UNIVERSITAT POLITÈCNICA DE VALÈNCIA

Doctoral Thesis:

Operations research models for the management of supply chains of perishable and heterogeneous products in uncertain contexts. Application to the agri-food and ceramic sectors.

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February, 2020

A Noa,
el motor de mi vida

Agradecimientos

Mi más profundo agradecimiento a todas las personas que de alguna manera han contribuido al desarrollo de esta tesis. A mis directores, Dr. Ángel Ortiz Bas y Dra. María del Mar Eva Alemany Díaz, por haber confiado en mí y haber invertido en mi formación, tanto académica como personal. Durante este tiempo he aprendido de vosotros el valor del esfuerzo y el sacrificio con el fin de poder alcanzar una meta, que me ha permitido ampliar mis conocimientos y formarme tanto en la investigación como en la docencia.

Quiero agradecer también, a mis compañeros del Centro de Investigación y Gestión en Ingeniería de Producción (CIGIP) y del Departamento de Organización de Empresas (DOE) de la Universitat Politècnica de València por su constante apoyo durante estos cuatro años de tesis doctoral. Muchas gracias a todos, en especial a la Dra. Josefa Mula Bru, el Dr. Francisco Campuzano Bolarín y el Dr. David Peidró Payá.

A los miembros del proyecto europeo RUC-APS, que me han proporcionado información y conocimiento acerca del sector agroalimentario. A los miembros de ALSIA, en especial a la Dra. Rina Iannacone, que me recibió durante tres meses para realizar mi estancia de investigación, así como a Pascale Zaraté (Toulouse 1 Capitole University), Guy Camilleri (Tolouse 1 Capitole University) y Mariana del Pino (Universidad de La Plata).

A mis amigos, por entender todos los cambios que han ocurrido en mi vida en los últimos años. Siempre habéis estado ahí, compartiendo y afrontando cada cambio y reto de mi vida. Gracias por seguir a mi lado.

A mi familia, que nunca ha dudado de mi capacidad para afrontar este reto y que ha depositado una fe ciega en mí. Sin vosotros, sin todo el apoyo que me habéis brindado, hubiera sido imposible que este proyecto hubiera salido adelante. Gracias por haber llevado vuestro orgullo por bandera, cada frase de apoyo ha sido una grandísima inyección de energía para mí.

Finalmente, mi agradecimiento más especial a mi hija, Noa. Quien a su corta edad ha sabido entender el esfuerzo que debía realizar para desarrollar este trabajo. Gracias por recibirme siempre con tu alegría y amor incondicional, que da la suficiente fuerza para afrontar este y otros muchísimos retos con el mayor de los optimismos.

Abstract

Some products are characterised by their lack of homogeneity, what means that products with different characteristics can be obtained from the same production process due to uncontrollable factors such as the nature of raw materials or the environmental conditions during production. There are four aspects that characterize the lack of homogeneity in the product: the homogeneous subtypes to be obtained from a production lot, the quantity of products that belong to each subtype, the value related to each of the subtypes and the state of the products.

The lack of homogeneity in the product hinders the management of the supply chain or company's processes at the time customers require the homogeneity among the acquired units of product. An example of this is produced in the ceramic tile sector, in which customers need all acquired ceramic tiles that are going to be jointly assembled to have the same colour, thickness and quality for aesthetic and safety reasons. Another example is the extracted from the agri-food sector, in which final markets require products that meet some characteristics such as a minimum size, a particular colour or flavour in the case of fruits. In addition, the agri-food sector has the added complexity produced by the deterioration of products over time, and the need of markets to offer to end consumers products with a minimum durability after sale.

In this Thesis, heterogeneous products are defined as products for which different subtypes can be obtained in a variable quantity while perishable products are those that, apart from being heterogeneous, have a lack of homogeneity in their state. According to these concepts, ceramic sectors would commercialize heterogeneous products while the agri-food sector would do so with perishable products.

This Thesis proposes conceptual frameworks and Operations Research models to support the management of supply chains with heterogeneous and perishable products in centralized and distributed decision-making processes related to strategic, tactical and operative decisional levels. The objective is to improve the supply chain competitiveness, sustainability and flexibility to adapt to market requirements under uncertain conditions. For this, both deterministic and uncertain Operations Research models have been proposed, whose results are compared concluding that results obtained with uncertain models better fit with the behaviour of real supply chains.

The proposed Operations Research models have contributed to three research areas: operational problems in the ceramic sector, strategic problems in the agri-food sector and planning problems in the agri-food sector.

Main novelties in the ceramic operational problems are the modelling of the characteristics of ceramic tile products, the consideration of homogeneity requirements between units from different order lines, and the possibility of making partial deliveries and delayed deliveries.

This Thesis contributes to strategic problems in agri-food products by designing an entire fresh agri-food supply chain considering the perishability of products and integrating tactical decisions, and by determining the real impact that considering the products' perishability has on the supply chain design process.

Regarding the planning in agri-food sector, one chapter addresses the crop planning process for perishable products in centralized and distributed ways, being the distributed proposals the first in the literature, and obtaining solutions near to the centralized optimum. These proposals model the uncertainty inherent to some parameters such as the yield or time requirements per farming activities that have not been previously modelled with fuzzy sets. The crop planning has also been addressed from a sustainable point of view in which three objectives related to the triple bottom line are modelled, and several non-dominated planning are obtained. In this case, a group decision support system is collaboratively used by planners to choose the solution of their preference, being the first tool combining mathematical programming and decision support systems in agri-food literature. Finally, a collaborative approach to plan the commercialization of products with different level of quality is proposed in which retailers can invest on farms in order to improve the quality of their products. The modelling by fuzzy numbers of the uncertainty in the proportion of quality products to be obtained and in the improvement of such proportion with the retailers' investments is a novel proposal of this Thesis.

The developed Operations Research models have been implemented by using Operations Research computer software and validated through their application to realistic ceramic and agri-food supply chains. A set of conclusions and managerial insights about the behaviour of ceramic and agri-food supply chains when considering the characteristics that make these sectors different from other industrial sectors, are extracted through the analysis of the results obtained in the experimentation.

Resumen

Algunos productos se caracterizan por su falta de homogeneidad, lo que significa que productos con diferentes características pueden ser obtenidos de un mismo proceso de producción debido a factores incontrolables como la naturaleza de las materias primas o las condiciones ambientales durante la producción. Hay cuatro aspectos que caracterizan la falta de homogeneidad en el producto: los subtipos homogéneos que se obtienen de un mismo lote de producción, la cantidad de productos que componen cada subtipo, el valor de cada uno de los subtipos, y el estado de los productos.

La falta de homogeneidad en el producto dificulta la gestión de los procesos de las empresas y cadenas de suministro en el momento en el que los clientes requieren homogeneidad entre las unidades de producto que adquieren. Un ejemplo de esto se produce en el sector de la cerámica, en el que los clientes requieren que todas las unidades que van a ser ensambladas juntas tengan el mismo color, espesor y calidad por razones estéticas y de seguridad. Otro ejemplo es el extraído del sector agroalimentario, en el que el mercado final requiere productos que cumplan con un tamaño mínimo, un color particular, o sabor en el caso de las frutas. Además, el sector agroalimentario tiene la complejidad añadida producida por el deterioro de los productos a lo largo del tiempo, y la necesidad de los mercados de ofrecer a los clientes productos con una mínima duración tras su venta.

En esta Tesis, se define como productos heterogéneos a aquellos productos que se pueden clasificar en subtipos homogéneos con una cantidad variable, mientras que los productos perecederos son aquellos que, además de ser heterogéneos, tienen falta de homogeneidad en su estado. De acuerdo con estos conceptos, el sector cerámico comercializa productos heterogéneos mientras que el sector agroalimentario comercializa productos perecederos.

Esta Tesis propone marcos conceptuales y modelos de Investigación Operativa que soporten la gestión de cadenas de suministro con productos heterogéneos y perecederos en la toma de decisiones centralizada y distribuidas relacionadas con los niveles de decisión estratégica, táctica y operativa. El objetivo es mejorar la competitividad, sostenibilidad y flexibilidad de la cadena de suministro para adaptarse a los requerimientos del mercado bajo condiciones de incertidumbre. Para esto, se han propuesto modelos de Investigación Operativa deterministas e inciertos, cuyos resultados se comparan concluyendo que los resultados obtenidos con los modelos inciertos se adaptan mejor al comportamiento real de las cadenas de suministros.

Los modelos de Investigación Operativa propuestos han contribuido a tres áreas de investigación: problemas operativos en el sector cerámico, problemas estratégicos en el sector agroalimentario y problemas de planificación en el sector agroalimentario.

Las principales novedades en los problemas operativos en el sector cerámico son el modelado de las características de las baldosas cerámicas, la consideración de los requerimientos de homogeneidad entre unidades de diferentes líneas de pedido, y la posibilidad de realizar entregas parciales y entregas con retraso.

Esta Tesis contribuye a los problemas estratégicos en el sector agroalimentario al diseñar una cadena de suministro completa de productos agroalimentarios frescos considerando el aspecto perecedero de los productos e integrando decisiones tácticas, y determinando el impacto real que tiene considerar el aspecto perecedero de los productos durante el diseño de la cadena de suministro.

En cuanto a la planificación del sector agroalimentario, un capítulo aborda el proceso de planificación de cultivo para productos perecederos de forma centralizada y distribuido, siendo las propuestas distribuidas las primeras en la literatura, y obteniendo soluciones cercanas al óptimo centralizado. Estas propuestas modelan la incertidumbre inherente a algunos parámetros como el rendimiento de las plantas, o el tiempo necesario para desarrollar las actividades de cultivo, que no han sido modeladas anteriormente con conjuntos difusos. La planificación de cultivo ha sido abordada también bajo un punto de vista sostenible en el que se modelan tres objetivos relacionadas con los tres aspectos de la sostenibilidad, donde se obtienen varias soluciones no dominadas. En este caso, un sistema grupal de apoyo a la toma de decisiones se utiliza colaborativamente por los planificadores para seleccionar una solución de su preferencia, siendo la primera herramienta que combina un modelo de programación matemática y un sistema de apoyo a la toma de decisiones en la literatura agroalimentaria. Finalmente, se propone un enfoque colaborativo para planificar la comercialización de productos con diferentes niveles de calidad en el que los minoristas pueden realizar inversiones sobre los agricultores con el fin de mejorar la calidad de sus productos. El modelado difuso de la incertidumbre en la proporción de productos de calidad obtenida en la cosecha, y en la mejora de dicha proporción con cada inversión son propuestas novedosas de esta Tesis.

Los modelos de Investigación Operativa propuestos han sido implementados usando software de Investigación Operativa y validados a través de su aplicación a cadenas de suministro cerámicas y agroalimentarias realistas. A través del análisis de los resultados obtenidos con la experimentación se extraen un conjunto de conclusiones y conocimientos de gestión sobre el comportamiento de las cadenas de suministro cerámicas y agroalimentarias al considerar las características que hacen estos sectores diferentes de otros sectores industriales.

Resum

Alguns productes es caracteritzen per la seua falta d'homogeneïtat, el que significa que productes amb diferents característiques poden ser obtinguts d'un mateix procés de producció degut a factors incontrolables com la naturalesa de les matèries primeres o les condicions ambientals durant la producció. Hi ha quatre aspectes que caracteritzen la falta d'homogeneïtat en el producte: els subtipus homogenis que s'obtenen d'un mateix lot de producció, la quantitat de productes que componen cada subtipus, el valor de cada un dels subtipus, i l'estat dels productes.

La falta d'homogeneïtat en el producte dificulta la gestió dels processos de les empreses i cadenes de subministrament en el moment en què els clients requerixen homogeneïtat entre les unitats de producte que adquirixen. Un exemple d'açò es produïx en el sector de la ceràmica, en el que els clients requerixen que totes les unitats que seran acoblades juntes tinguen el mateix color, grossària i qualitat per raons estètiques i de seguretat. Un altre exemple és l'extret del sector agroalimentari, en el que el mercat final requerix productes que complisquen amb una grandària mínima, un color particular, o sabor en el cas de les fruites. A més, el sector agroalimentari té la complexitat afegida produïda pel deteriorament dels productes al llarg del temps, i la necessitat dels mercats d'oferir als clients productes amb una mínima duració després de la seua venda.

En aquesta Tesi, es definix com a productes heterogenis a aquells productes que es poden classificar en subtipus homogenis amb una quantitat variable, mentres que els productes peribles són aquells que, a més de ser heterogenis, tenen falta d'homogeneïtat en el seu estat. D'acord amb aquests conceptes, el sector ceràmic comercialitza productes heterogenis mentres que el sector agroalimentari comercialitza productes peribles.

Aquesta Tesi proposa marcs conceptuals i models d'Investigació Operativa que suporten la gestió de cadenes de subministrament amb productes heterogenis i peribles en la presa de decisions centralitzada i distribuïdes relacionades amb els nivells de decisió estratègica, tàctica i operativa. L'objectiu és millorar la competitivitat, sostenibilitat i flexibilitat de la cadena de subministrament per adaptar-se als requeriments del mercat sota condicions d'incertesa. Per a açò, s'han proposat models d'Investigació Operativa deterministes i incerts, els resultats es comparen concloent que els resultats obtinguts amb els models incerts s'adapten millor al comportament real de les cadenes de subministraments.

Els models d'Investigació Operativa proposats han contribuït a tres àrees d'investigació: problemes operatius en el sector ceràmic, problemes estratègics en el sector agroalimentari i problemes de planificació en el sector agroalimentari.

Les principals novetats en els problemes operatius en el sector ceràmic són el modelatge de les característiques de les rajoles ceràmiques, la consideració dels requeriments d'homogeneïtat entre unitats de diferents línies de comanda, i la possibilitat de realitzar lliuraments parcials i lliuraments amb retard.

Aquesta Tesi contribueix als problemes estratègics en el sector agroalimentari al dissenyar una cadena de subministrament completa de productes agroalimentaris frescos considerant l'aspecte perible dels productes, integrant decisions tàctiques, i determinant l'impacte real que té considerar l'aspecte perible dels productes durant el disseny de la cadena de subministrament.

Pel que fa a la planificació del sector agroalimentari, un capítol aborda el procés de planificació de cultiu per a productes peribles de forma centralitzada i distribuït, sent les propostes distribuïdes les primeres en la literatura, i obtenint solucions properes a l'òptim centralitzat. Aquestes propostes modelen la incertesa inherent a alguns paràmetres com el rendiment de les plantes, o el temps necessari per desenvolupar les activitats de conreu, que no han estat modelades anteriorment amb conjunts difusos. La planificació de cultiu ha estat abordada també sota un punt de vista sostenible en què es modelen tres objectius relacionats amb els tres aspectes de la sostenibilitat, on s'obtenen diverses solucions no dominades. En aquest cas, un sistema grupal de suport a la presa de decisions s'utilitza col·laborativament pels planificadors per seleccionar una solució de la seva preferència, sent la primera eina que combina un model de programació matemàtica i un sistema de suport a la presa de decisions en la literatura agroalimentària. Finalment, es proposa un enfocament col·laboratiu per planificar la comercialització de productes amb diferents nivells de qualitat en el qual els minoristes poden realitzar inversions sobre els agricultors per tal de millorar la qualitat dels seus productes. El modelatge difús de la incertesa en la proporció de productes de qualitat obtinguda en la collita, i en la millora d'aquesta proporció amb cada inversió són propostes noves d'aquesta Tesi.

Els models d'Investigació Operativa proposats han estat implementats amb software d'Investigació Operativa i validats a través de la seva aplicació a cadenes de subministrament ceràmiques i agroalimentàries realistes. A través de l'anàlisi dels resultats obtinguts amb l'experimentació s'extrauen un conjunt de conclusions i coneixements de gestió sobre el comportament de les cadenes de subministrament ceràmiques i agroalimentàries al considerar les característiques que fan aquests sectors diferents d'altres sectors industrials

Contents

Chapter I:

Introduction

In this chapter, the Thesis called "Operations research models for the management of supply chains of perishable and heterogeneous products in uncertain contexts. Application to the agri-food and ceramic sectors" is introduced to readers. Section 1 presents the institutions that have supported this Thesis. In Section 2, a brief background of the research area to which the Thesis belongs is described. The purpose of the Thesis as well as their specific objectives are displayed in Section 3. The research methodology employed is explained in Section 4. Finally, Section 5 shows the structure of the Thesis and stablishes the relationship between the chapters that compose it including a Conclusion chapter where the main contributions of the Thesis and the future research lines are pointed out.

1 Context and supporting institutions

This Thesis has been developed in the Research Centre of Management and Production Engineering (CIGIP, for its acronym in Spanish "Centro de Investigación en Gestión e Ingeniería de Producción") of the Universitat Politècnica de València with the support of the predoctoral grant Programme of Formation of University Professors (FPU, for its acronym in Spanish "Formación de Profesorado Universitario") from the Spanish Ministry of Science, Innovation and Universities (Ref. FPU15/03595). The supervisors of this Thesis are Dr. Angel Ortiz, and Dra. María del Mar Alemany Diaz that are Professors in the Research Centre of Management and Production Engineering (CIGIP) of the Universitat Politècnica de València. The FPU grant has been endorsed by the supervisor Dr. Ángel Ortiz.

This Thesis has also been supported by the project 'RUC-APS: Enhancing and implementing Knowledge based ICT solutions within high Risk and Uncertain Conditions for Agriculture Production Systems' (Ref. 691249) funded by the EU under its funding scheme H2020-MSCA-RISE-2015, the project 'Methods and models for

operations planning and order management in supply chains characterised by uncertainty in production due to the lack of product uniformity' (PLANGES-FHP) (Ref. DPI2011-23597) funded by the Spanish Ministry of Economy and Competitiveness. The projects RUC-APS and PLANGES-FHP have been led by the one of the supervisors of this Thesis Dr. María del Mar Eva Alemany.

In order to obtain the international mention for this Thesis, three months of research stages have been made in the research agency Agenzia Lucana di Sviluppo e di Innovazione in Agricoltora, located in Metaponto (Italy). These stages, led by Dr. Rina Iannacone under the framework of the European project RUC-APS, were done in order to identify real agricultural problems that could be optimized through mathematical programming models and to better understand the real behaviour of the agri-food supply chains. In addition, collaboration with other partners from the European project RUC-APS such as University of La Plata (Argentina), Tolouse University (France), and Bretagne Development Innovation (France) has been carried out for the development of some chapters included in this Thesis.

2 Background

There are numerous applications of the Operations Research to diverse supply chains management processes such as their design [1–3], operation planning [4–8], and orders management [9–13]. Lowe and Preckel [14] identify that practices that are effective for some supply chains could not be directly extrapolated to others due to their particular characteristics. This is the case of supply chains that produce and commercialize products with lack of homogeneity in their characteristics such as the ceramic and agri-food ones.

The lack of homogeneity in products (LHP) is the absence of the homogeneity required by customers in the products [8]. The most important aspects that characterize the LHP are subtypes, subtype quantity, subtype value and subtype state [7]. Different **subtypes** appear when there are several references of the same LHP item, but with different characteristics that are relevant for the customer. For example, in the agricultural sector, fruits are classified according to size, colour and quality into different subtypes. This makes necessary the classification of produced units into homogeneous sublots (**subtype quantity**). Furthermore, subtypes for an item can have the same or different economic value (**subtype value**). Different economic values usually involve the existence of several qualities. Another aspect is that the value of the classification attributes (**subtype state**) may remain unchanged over time (static) or not (dynamic). For example, in the food sector, freshness decreases with time (decay or perishability).

In this Thesis, we identify as heterogeneous products those products characterized by the lack of homogeneity in the subtypes and subtype quantity while we define as perishable products those products with lack of homogeneity in subtypes, subtype quantity, and subtype state. The lack of homogeneity in the subtype state is in some cases related to the lack of homogeneity in the subtype value. In this sense, although ceramic and agri-food sectors are subject to the LHP, ceramic tile sector commercializes heterogeneous products while agri-food sector commercializes perishable products.

The lack of homogeneity in ceramic tiles causes several problems in the management of ceramic supply chains. The LHP is caused by uncontrollable factors such as the composition of the used clays and enamels, and the environmental conditions given during production [9]. As a result, products with different tones, gages and qualities are obtained [15]. Therefore, the 'subtype' and 'subtype quantity' categories of the LHP are present in the ceramic sector. The problem arises since products that are going to be assembled together need to be homogeneous for functional and aesthetic reasons [16]. Because of this, orders need to be fulfilled with homogeneous products during the order promising process, what implies that a projection of the homogeneous product to be obtained in the future production has to be previously estimated [12].

In their review of mathematical models to support the order promising process under LHP, Grillo et al. [7] affirm that few papers deal with the LHP and its inherent uncertainty in the order promising process, identifying a new research area. In addition, Alarcón et al. [17] state that, given the discrepancies that may occur between the planned and real homogeneous product obtained from production, the order promising process could not be enough and a reallocation of the available products to the already committed orders could be needed to obtain a new valid allocation of product. This reallocation process is called shortage planning process. Few models deal with the shortage planning process, by reallocating the stocked product [10,11,15] and the estimated homogeneous sublots to be produced [11] to already committed orders. All of them consider that the homogeneity of products should be guaranteed for the units that compose the same order line, classifying the homogeneous sublots obtained from production. A research gap was identified for those orders that require not only the homogeneity between units comprising one order line, but also the homogeneity between units of product belonging to different order lines that require a jointly assembly. This makes necessary to differentiate between the characteristics that characterize each sublot (tone, quality and gage), what has not been made in previous works.

Grillo et al. [2] also identify the agri-food sector as the sector where more characteristics of the LHP appear simultaneously. The lack of homogeneity in agri-food products appears in terms of the quantity of homogeneous sublots to be obtained from a single process and the quantity comprising each homogeneous sublot (LHP 'subtype' and 'subtype quantity' category). There are few models that model these categories of LHP in agri-food sector such as Amorim et al. [18] that differ between mainstream and local raw materials, Ahumada et al. [19] that consider the different qualities a product can acquire after harvest stating that a percentage of production correspond to each quality, Tan and Çömden [20] that models the different maturation and harvest periods that crops have in function of the planting date, or Munhoz and Morabito [21] that make the differentiation between different oranges varieties.

The lack of homogeneity in agri-food products appears also in the value and state of subtypes. The lack of homogeneity in the products value has been modelled by giving different prices to products with different quality [22], to different subtypes of product [23], to products of different sizes [24], to products with different brands [18] and so on. The lack of homogeneity in the state of the product is also present in the agri-food sector (LHP 'subtype state' category) since some characteristics of the product such as their quality, colour, freshness can vary along the time. The most representative characteristic of the state of agri-food products is its perishability. Some models deal with agri-food design and planning problems addressing the perishability of the agri-food products [18,25–29]. The limitation of the products shelf-life requires a precise planning of the transport and storage in order to reduce the deterioration of products and to preserve their value [30]. However, all identified models modelled these characteristics in a deterministic context, putting aside the inherent uncertainty of the products' perishability and modelling it by using "mean" values or the "most probable" value [31]. Therefore, the quantity of Operations Research models that include the LHP, and more concretely, the perishability of agri-food products in uncertain contexts is very scarce, what identifies another gap in the literature for which more research is required.

Following with this idea, Soto-Silva et al. [32] indicate in their review of Operations Research models applied to fresh fruits that there is a gap of models to design and manage fresh fruits supply chains highlighting the need to develop new tools that incorporate the own characteristics of the fresh fruit supply chains such as the shelf-life, quality decay, wastes, or prices dependent on time and freshness. This is also remarked by Ahumada and Villalobos [30] who state on their review of models to plan agri-food supply chains that new stochastic models to the tactical planning of agri-food products including more realistic characteristics such as the information uncertainty, the logistic integration, risk modelling, and quality, safety and perishability of products are needed. Ahumada and Villalobos [30,33] also noted the lack of models to plan the operative decisions in this area. In addition, given the uncertainty inherent to the agri-food sector, it is necessary to develop models that take into account the uncertain behaviour of parameters [32]. These authors conclude that the number of papers in this research area is scarce, although they identify an increase in the last years that is expected to be accentuated in the close future where the Operations Research are outlined as one of the ways to face the uncertainty in the agri-food supply chains [32]. It is also remarkable that most existing models to design and manage agri-food supply chains make it in a centralized way. However, decision-making process in agriculture uses to be distributed, what has received little attention in existing research [34]. In addition, it is well-known that supply chain performance and efficiency is benefit from a high level of centralization [35]. Thus, on one hand it is necessary to determine the impact that integrating distributed decisions have on the efficiency of the entire supply chain. On the other hand, it is necessary to determine the possibility to obtain a supply chain efficiency similar to the obtained with centralized approaches by including collaboration mechanisms in a distributed decision-making process. Finally, it is necessary to identify the level of unfairness produced between the members of the supply chain in centralized and distributed decision-making processes.

In addition, Prima Dania et al. [36] identify collaboration between members of agri-food supply chains as a powerful tool to increase the sustainability of supply chains and highlights the importance that collaboration has as a tool to empower farmers belonging to low social-economic communities. Collaboration is also vital to achieve safe and high-quality products for the consumer [37]. In this sense, few models use collaboration mechanisms to empower farmers and improve the quality of products such as the proposed by Sutopo et al. [38,39] and Wahyudin et al. [40] in which retailers invest on the development of small farmers to obtain better products. On the other hand, collaboration can also be used in order to reduce the negative impact generated by the uncertainty on the supply chain management [41]. It is concluded that research including collaboration mechanisms in the design and management of supply chains characterized by the LHP and perishable products as well as research stablishing the relationship between uncertainty and collaboration in this type of supply chains are still scarce.

Therefore, it is needed to investigate the best ways to design and operate integrated and global agri-food supply chains [30] taking into consideration the main characteristics of the agri-food products such as their lack of homogeneity and perishability and the uncertainty inherent to the sector. It is also needed to determine the impact that making decision in a distributed of centralized way has on the supply chain efficiency. Finally, the possibility of including collaboration mechanisms to increase the sustainability of the supply chain, increase the safety and quality of products and reduce the negative impact of uncertainty sources should be contemplated. Thus, it is needed to develop models and tools to support the decision-making process for both, the design and operation of agri-food supply chains, taking into consideration the continuous changes caused by the sources of uncertainty present in the sector that these chains should face [32].

3 Objectives

The main purpose of this Thesis is to propose new Operations Research models and their implementation in software tools to improve the management of supply chains characterized by the heterogeneity and perishability of products in centralized and distributed perspectives at the strategic, tactical and operative decisional levels and to validate them through their application to ceramic and agri-food supply chains. All of this taking into account the main characteristics of the ceramic and agri-food sectors, such as the homogeneity requirements between units of the same or different products in the ceramic sector, or the freshness requirements and the high level of uncertainty related to biological aspects, pests, weather, perishability, demand and price volatility in the agri-food sector as well as including collaborative aspects. Everything with the objective of improving the competitiveness, sustainability and flexibility of the supply chains to adapt to the market requirements under uncertain conditions.

To achieve the purpose of this Thesis, a set of specific objectives are defined:

1. To identify specific and real problems existing in supply chains that commercialize heterogeneous and perishable products.
2. To develop conceptual frameworks to characterize supply chains with heterogeneous and perishable products, the exogenous and endogenous sources of uncertainty present in these chains and their impact on the supply chain management.
3. To identify and analyse the Operations Research approaches used to deal with design and management problems and to address different types of uncertainty, as well as their advantages and limitations.
4. To develop integrated models to support the decision-making process during the design and management of supply chains with heterogeneous and perishable products under deterministic and uncertain contexts that consider the supply chain characteristics. Developed models should contribute to one or more of the following aspects:
    a. To properly manage the uncertainty present in supply chains with heterogeneous and perishable products.
    b. To provide solutions to situations where there is a discrepancy between planning and reality because of the uncertainty inherent to the heterogeneity and perishability of products.
    c. To analyse the impact of modelling the products' perishability in the design and management of supply chains in deterministic and uncertain context
    d. To analyse and assess the impact of making decisions in centralized or distributed ways on sectors with heterogeneous and perishable products.
    e. To identify collaboration mechanisms to improve the efficiency of the supply chains with heterogeneous and perishable products.

5. To implement the proposed models in software tools for deterministic and uncertain contexts and to compare both approaches.
6. To validate the results of the Thesis through its application to supply chains with heterogeneous and perishable products.

4 Methodology

The research methodology employed to develop this Thesis is comprised by five phases. The methodology has been applied to the following fields: i) operative problems with LHP in the ceramic sector, ii) strategic problems with LHP and perishability in agri-food sector, and iii) planning problems with LHP and perishability in agri-food sector. This complete methodology has also been used to build up those chapters of the Thesis that include a proposal of Operations Research models.

- *Phase I: Problem definition*

  In this phase the problems addressed in this Thesis, which have been primarily identified in the context of supporting projects related to real problems, are described. This phase contributes to the development of the specific objective 1 of this Thesis.

- *Phase II: Literature Review and Conceptual Framework*

  In this phase, a literature review is made for each of the addressed problems in which the characteristics considered by previous models as well as the approaches used to model it are identified. For cases in which a gap is identified in literature, such as the design of agri-food supply chains and the management of uncertainty through collaboration, a more extensive literature review and conceptual frameworks are developed. This phase contributes to the development of the specific objectives 2 and 3 of this Thesis.

- *Phase III: Proposal of Operations Research models*

  In order to fulfil the gaps identified in Phase I, different Operations Research models have been proposed. The steps to propose an Operations Research model depend on the used approach. To formulate mathematical programming models, first the nomenclature to be used by the model is set, and then the objectives optimized by the model as well as the constraints to which it is subject are defined. On the other hand, to formulate system dynamic models requires to define the nomenclature to be used by the model, a causal-loop diagram to show the cause-effect relations between the elements of the system and to create a flow chart where the simulated process is represented. This phase contributes to the achievement of the specific objective 4 of this Thesis.

- *Phase IV: Implementation of Operations Research models.*

  This phase consists in implementing the developed Operations Research models to solve them computationally. For that, the proposed Operations Research models are translated to a computer programming language and they are solved with the help of optimization (MPL+Gurobi) and simulation (Vensim) software. This phase contributes to the fulfilment of the specific objective 5 of this Thesis.

- *Phase V: Validation of Operations Research models and tools and Conclusions.*

  The proposed models and tools in phases II and III are validated through their application to ceramic and agri-food supply chains. For that, realistic data have been obtained with the collaboration of real companies and universities. In addition, a set of experiments have been designed to compare the behaviour of the model in various what-if situations, comparing also the results obtained for deterministic and uncertain situations. This phase contributes to the specific objective 6 of this Thesis.

This methodology has also been used to build up each of the chapters that include Operations Research models proposals that comprise this Thesis. The relationship between the phases that comprise the research methodology and the objectives of this Thesis is displayed in Figure 1.

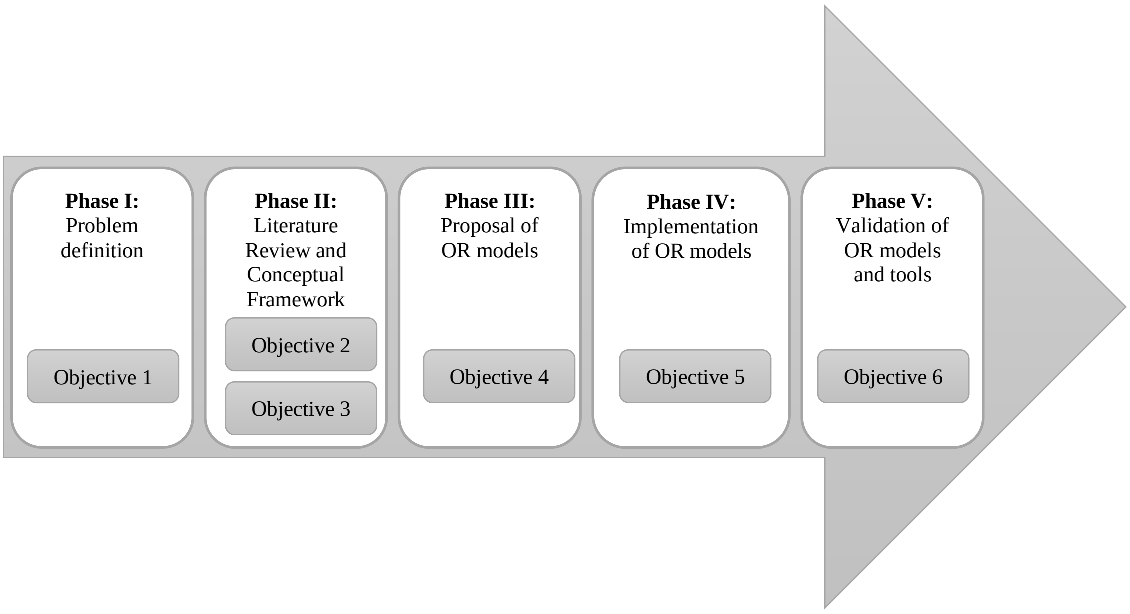

Figure 1. Relation between objectives and methodology phases

5 Structure of the Thesis

This Thesis is structured as a compendium of articles. Each article is presented as a chapter of this Thesis, except Chapter X that include the conclusions of the whole Thesis and the identified future research lines. The following chapters are included in the Thesis:

- **Chapter I:** Introduction.
- **Chapter II:** A multi-objective model for inventory and planned production reassignment to committed orders with homogeneity requirements.
- **Chapter III:** Simulation to reallocate supply to committed orders under shortage.
- **Chapter IV:** Conceptual framework for designing agri-food supply chains under uncertainty by mathematical programming models.
- **Chapter V:** Impact of perishability in the design of agri-food supply chains

- **Chapter VI:** Centralized and distributed optimization models for the multi-farmer crop planning problem under uncertainty: application to a fresh tomato Argentinean SC case study
- **Chapter VII:** Conceptual framework for managing uncertainty in a collaborative agri-food supply chain context.
- **Chapter VIII:** A collaborative model to improve farmers' skill level by investments in an uncertain context.
- **Chapter IX:** How to support group decision making in horticulture: an approach based on the combination of a centralized mathematical model and a group decision support system.
- **Chapter X:** Conclusions and future research lines.

Information related to the publication of the articles included in this Thesis is presented in Table 1, where data about the authorship and journal of publication is displayed. In total six indexed papers have been published with the following characteristics: Three of the papers are published in a journal classified as **Q1** in **JCR** and **SJR**, and three two papers are published in a journal classified as **Q3** in **SJR**. Finally, two papers have been submitted to **Q1** journals in **JCR**.

Table 2 details the objectives to which each chapter contributes, as well as the phases of the research methodology used to develop the articles.

Each article has been written in order to be easily read and understood independently, so each chapter stands alone. In the following, the relationship among the chapters is established to create a guiding thread throughout the Thesis.

The Thesis begins with the proposal of Operations Research models to manage the lack of homogeneity of products in the ceramic tiles sector. The main problem for the management in this sector arises from the need to meet customer orders with homogeneous products while products with different characteristics are obtained at production due to uncontrollable factors. Companies estimate the homogeneous product that planned to be produced in order to commit the customers' orders. However, this estimation usually differs from the real quantity of homogeneous product finally produced. In **Chapter II** a multi-objective operative model for the shortage planning process for products with lack of homogeneity in the ceramic sector is proposed. The shortage planning process consists on reallocate planned and real quantities of homogeneous products to already committed orders. Committed orders are comprised by one or more order lines. The units of the same product that belong to a same order line need to be homogeneous for all their attributes. However, units of products belonging to different lines of the same order need to be homogeneous for the gage attribute. This requirement comes up from the need of assembly together different products. The main novelty of this proposal is the consideration of the requirement of homogeneity between products from different order lines for the gage attribute. To guarantee that, the differentiation of the attributes that characterize each sublot should be modelled, representing other novelty of the model. In addition, a maximum delay is allowed for each order and the possibility of serving some of the lines that comprise an order (partial deliveries) is contemplated. This model aims to optimize three objectives: i) maximization of profits, ii) minimization of delayed deliveries, and iii) minimization of partial deliveries. The model can be solved by using both, the ε-constraint method when an implementable solution wants to be obtained for the company, and the weighted sum method when the behaviour of the shortage planning process wants to be tested. The last approach is used to validate four hypotheses: i) objectives pursued by the model are conflictive, ii) it is more difficult to serve orders when batches are divided in a bigger quantity of balanced homogeneous sublots, iii) serving orders is easier when more flexibility is allowed in deliveries, and iv) considering the homogeneity requirement between units of different lines increases the complexity of serving the orders.

Table 1. Structure of the Thesis

Ch	Authors	Journal	Impact factor	Categories	Ref
II	A. Esteso, M.M.E. Alemany, A. Ortiz, D. Peidro	Computers & Industrial Engineering	JCR: 3.518 SJR: 1.334	JCR: • Comp. science, interd. applic. (Q1) • Engineering, industrial (Q1) SJR: • Comp. science, (Q1) • Engineering, (Q1)	[16]
III	A. Esteso, J. Mula, F. Campuzano-Bolarín, M.M.E. Alemany, A. Ortiz	International Journal of Production Research	JCR: 3.199 SJR: 1.585	JCR: • OR & manag. science (Q1) • Engineering, industrial (Q2) • Engineering, manuf. (Q2) SJR: • Industrial and manuf. Eng.(Q1) • Manag. science and OR (Q1) • Strategy and management (Q1)	[42]
IV	A. Esteso, M.M.E. Alemany, A. Ortiz	International Journal of Production Research	JCR: 3.199 SJR: 1.585	JCR: • OR & manag. science (Q1) • Engineering, industrial (Q2) • Engineering, manuf. (Q2) SJR: • Industrial and manuf. Eng.(Q1) • Manag. science and OR (Q1) • Strategy and management (Q1)	[43]
V	A. Esteso, M.M.E. Alemany, A. Ortiz,	Submitted: Applied Mathematical Modelling	JCR: 2.841 SJR: 0.873	JCR: • Engineering, multidisciplinary (Q1) • Mathematics, interd. applic. (Q1) • Mechanics (Q1) SJR: • Modelling and simulation (Q1) • Applied mathematics (Q2)	
VI	M.M.E. Alemany, A. Esteso, A. Ortiz, M. del Pino	Submitted: Computers & Industrial Engineering	JCR:3.518 SJR: 1.334	JCR: • Comp. science, interd. applic. (Q1) • Engineering, industrial (Q1) SJR: • Comp. science, (Q1) • Engineering, (Q1)	
VII	A. Esteso, M.M.E. Alemany, A. Ortiz	IFIP Advances in Information and Communication Technology	SJR: 0.188	SJR: • Comp. networks and communications (Q3) • Information systems (Q4) • Inf. Systems and manag. (Q3)	[44]
VIII	A. Esteso, M.M.E. Alemany, A. Ortiz, C. Guyon	IFIP Advances in Information and Communication Technology	SJR: 0.188	SJR: • Comp. networks and communications (Q3) • Information systems (Q4) • Inf. Systems and manag. (Q3)	[45]
IX	P. Zaraté, M.M.E. Alemany, M. del Pino, A. Esteso, G. Camilleri	Lecture Notes in Business Information Processing	SJR: 0.243	SJR: • Business and international management (Q3) • Control and systems engineering (Q3) • Information systems (Q3) • Information systems and management (Q3) • Management information systems (Q3) • Modelling and simulation (Q4)	[41]

[1]The values of JCR and SJR correspond to the data of 2018 (last available)

Table 2. Relationship among chapters, objectives and research methodology

Chapter	Objectives						Research methodology				
	1	2	3	4	5	6	I	II	III	IV	V
II	X	X		X	X	X	X	X	X	X	X
III	X	X		X	X	X	X	X	X	X	X
IV	X	X	X				X	X			
V	X	X		X	X	X	X	X	X	X	X
VI	X	X		X	X	X	X	X	X	X	X
VII		X	X					X			
VIII				X	X	X			X	X	X
IX	X	X		X	X	X	X	X	X	X	X

Following this research line, an operative system dynamic-based simulation model is proposed in **Chapter III** to reallocate real and planned available quantities of product with lack of homogeneity to the committed orders during the order promising process in the ceramic sector. This graphic tool may help decision-makers to understand the shortage planning process and to make decisions. The proposed simulation model is based on a mixed integer linear programming model that aims to maximize the profits while partial deliveries and delayed deliveries are allowed. To the best of our knowledge, no research proposes a simulation-based model to address the shortage planning problem. The homogeneity requirement between the units that comprise an order line should be met. The simulation model is validated by comparing its results to the obtained with the mathematical programming model. For that, the number of orders lines accepted as well as economic results are analysed. Then what-if scenarios are simulated to study the performance of the system when different grades of flexibility are allowed for deliveries, and by testing different estimations of the distribution of production lots into homogeneous sublots. Results prove that i) it is easier to serve orders when few homogeneous sublots are obtained from production, and ii) the higher the flexibility in the orders delivery, the easier to serve orders. These conclusions, that coincides with the obtained in Chapter II, prove the validity, reliability and coherence of both models.

The LHP can be found in the number of subtypes into which the product can be classified (subtype), the quantity of products obtained for each subtype (subtype quantity), the economic value attributed to each subtype (subtype value), and the state of the attributes used to define the subtypes (subtype state) [2]. The lack of homogeneity in ceramic products is produced in terms of subtype and subtype quantity. However, to follow up with this Thesis, the agri-food sector is selected since it presents the LHP in terms of subtype, subtype quantity, subtype value and subtype state.

To start up with the agri-food sector, **Chapter IV** proposes a conceptual framework to identify the main characteristics that should be considered when developing a new mathematical programming model to design agri-food supply chains in uncertain contexts. The conceptual framework is divided into four dimensions: i) characteristics of the agri-food supply chain where the agri-food subsectors, supply chain stages, number of products, and characteristics of products are identified, ii) decisions characteristics where the design decisions as well as other related decisions and time horizons are defined, iii) modelling approach where the types of models, objective functions and constraints, and model applications are defined, and finally iv) uncertainty modelling where the modelling context, uncertainty types and uncertain parameters are identified. This conceptual framework can be used as a tool for developing a new mathematical programming model to design agri-food supply chains and as a tool to review existing literature. In Chapter IV, the conceptual framework is used to perform an up-to-date literature review in which it is identified the need to develop new mathematical programming models to design agri-food supply chains integrating planting and harvest and other planning activities and considering the perishability of agri-food products.

To fill this gap, **Chapter V** proposes a multi-period centralized mathematical programming model to design agri-food supply chains in which planting, cultivation, harvest, packing, inventory, operation and distribution decisions are addressed taking into consideration the perishability of products. Therefore, this model supports the strategic and planning decision-making process. The model aims to maximize the profits obtained by the supply chain. Design and planning decisions are included in all stages of the supply chain: farmers, packing plants, warehouses, and distribution centres. Perishability of products is addressed by modelling the products' shelf-life, what characterize the LHP, and fixing the minimum freshness that products need to have at the sales moment. The proposed model is used to determine the impact of the perishability of products on the agri-food supply chain design, concluding that different supply chain configurations are obtained for products with different shelf-life. The proposed model can be used to design/redesign an entire or partial agri-food supply chain, to plan tactical decisions once the configuration has been defined, and to determine the maximum investment that can be carried out to extend the shelf-life of the product.

As mentioned, Chapter V deals with the planning of planting and harvest in a centralized way. In addition, most existing models in literature that deal with this problem also addresses it in a centralized way. However, in the real agri-food sector, farmers usually make this planning in a distributed way, that is that farmers make their own decisions without knowledge of other farmers decisions. To study the impact that these different collaboration approaches can have on the supply chain performance, **Chapter VI** proposes a set of models to address the planting and harvest planning under different collaboration scenarios: i) distributed, ii) distributed with minimum and maximum areas to plant each crop, iii) distributed with information sharing, and iv) centralized. The uncertainty inherent to some aspects of the planting and harvest processes such as the time needed per activity, the minimum and maximum areas to be planted with each crop, the yield of plants, demand, prices, and wastes and unmet demand penalizations are modelled by using fuzzy sets systems. All models aim to maximize the profits for farmers in distributed approached and for the entire supply chain in the centralized model, while including a penalization for wastes and unmet demand to take into account the environmental and social aspects of sustainability. An auxiliary centralized model is used to assess the real performance that the supply chain will have when implementing the decisions made with the different distributed approaches in terms of gross margin, wastes, unmet demand and economic unfairness among farmers. It is also determined that a collaborative distributed approach can be used to obtain solutions near to the supply chain optimum while maintaining the independence of farmers in decision-making process.

Since collaboration is identified as one tool that can help to obtain better solutions for the components of the supply chain, more research related to collaboration is included in this Thesis. First, a conceptual framework to manage the uncertainty in agri-food supply chains in a collaborative context is proposed in **Chapter VII**. This chapter aims to identify the sources of uncertainty present in the agri-food supply chains, to determine if collaboration can be used to reduce the uncertainty in the agri-food supply chains, and finally, to determine which elements can compose a conceptual framework to manage the uncertainty in collaborative agri-food supply chains. With all this information, a conceptual framework that can be used to determine the best way to reduce each uncertainty source is proposed.

Following with the collaboration between the members of the agri-food supply chains, a mathematical programming model to centrally plan the commercialization of quality products in agri-food sector is proposed in **Chapter VIII**. This model includes the LHP since products with different qualities are obtained from harvest. In addition, the distribution of harvest into homogeneous sublots is unbalanced and uncertain. Products with different qualities are commercialized in different markets, so products with higher quality are related to higher prices. Modern retailers, who are responsible of selling quality products, can collaborate with small farmers through funding them for their own development with the objective of obtaining more quality product and consequently, increase the sales.

Finally, it is reflected that most Operations Research models used to design and manage supply chains do it in a centralized way, without taking into account the opinion of the supply chain stakeholders. **Chapter IX** proposes a tool to support the group decision-making in which a multi-objective mathematical programming model and a group decision support system are combined. This tool is designed to plan the planting and harvest of different varieties of tomatoes in a whole region considering the LHP and perishability of products. The objectives contemplated by the mathematical programming model represent the three pillars of sustainability: maximization of profits (economic), minimization of products waste (environmental), and minimization of the unmet demand (social). The mathematical programming model is solved by using the ε-constraint method with which several non-dominated solutions can be obtained for the same problem. Then, obtained solutions are introduced as input data in the group decision support system, that can be used by all people involved in the decisions to be made in order to collaboratively decide the solution to be finally implemented in the real supply chain.

Therefore, the chapters included in this Thesis contributes to the Operations Research literature by proposing models for deterministic and uncertain contexts that take into account the lack of homogeneity and perishability of products, and that have been validated through their application to ceramic and agri-food supply chains. The research areas to which each chapter contributes is displayed in Table 3.

Table 3. Characterization of chapters

Ch.	Sector		Research type			Operations Research approach			Decisional level			Process			Context		Product characteristics	
	C	AF	SoA	CF	ORM	MP	S	DSS	Str	Tac	Op	D	SP	Pl	Det	Unc	Het	Per
II	X				X	X					X		X		X		X	
III	X				X	X	X				X		X		X		X	
IV		X	X	X					X			X						
V		X			X	X			X	X		X		X	X		X	X
VI		X			X	X				X				X	X		X	X
VII		X	X															
VIII		X			X	X			X	X				X		X	X	
IX		X			X	X		X		X				X	X		X	

C: Ceramic, AF: Agri-food; SoA: State of the art, CF: Conceptual framework; ORM: Operations research model; MP: Mathematical programming, S: Simulation, DSS: Decision support system; Str: Strategic, Tac: Tactical, Op: Operational; D: Supply chain design, SP: Shortage planning, PHP: Planting and harvest planning; Det: Deterministic, Unc: Uncertain; Het: Heterogeneity, Per: Perishability

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Chapter II:

A multi-objective model for inventory and planned production reassignment to committed orders with homogeneity requirements

Certain industries are characterized by obtaining non-homogeneous units of the same product. However, customers require homogeneity in some attributes between units of the same and different products requesting in their orders. To commit such orders, an estimation of the homogeneous product to be obtained can be used. Unfortunately, estimations of homogenous product quantities can differ considerably from real distributions. This fact could entail the impossibility of accomplishing the delivery of customer orders in the terms previously committed. To solve this, we propose a multi-objective mathematical programming model to reallocate already available homogeneous products in stock and planned production to committed orders. The main contributions of this model are the consideration of the homogeneity requirement between units of different lines of the same order, the allowance of partial deliveries of order lines, and the specification of some relevant attributes of products to accomplish with the customer homogeneity requirement. Different hypotheses are proved through experiments and statistical analyses applied to a ceramic tile company. The ε-constraint method is used to obtain an implementable solution for the company. The weighted sum method is used when proving other hypotheses that offer some managerial insights to companies.

Keywords: Reallocation process, Mathematical programming, Lack of homogeneity in the product, Homogeneity among order lines, Deterministic

1 Introduction

Customers usually express requirements in their orders in terms of quantity and delivery date. However, several situations emerge where customers require homogeneity among units of the same product or different products for certain attributes that are relevant for them. These attributes refer to functional or aesthetical reasons because units of the same or different products need to be assembled, packed or presented together. For instance, customer orders in the agricultural sector should be served with units of the same fruit belonging to the same quality, size and weight. This is also valid for the furniture sector, where colour uniformity among units of the same product (e.g. chairs) or among products (e.g. chairs and table) impacts the final value of the products perceived by customers. Thus, colour and grain sorting are necessary.

Another example is the ceramic sector, where the nature of the raw material (clay) and components (frits and enamels) employed during ceramic tile production, and the variability of the environmental conditions during this process, means obtaining units with different tone, gage and quality attributes from a unique production batch [1,2]. In this sector, customers require product homogeneity for quality, tone and gage for all the units that compose an order line. Customers also require gage homogeneity for units of different order lines that are to be jointly installed for functional and aesthetic reasons. To ensure serving customer orders with the required homogeneity, classification stages are included during production processes.

The causes that generate product heterogeneity are mainly uncontrollable because the non-homogeneity of the raw material and components usually coming from the nature or the productive process itself. The above aspects make the homogeneous quantities of each product in planned production batches to be uncertain. In such a way, that only the homogeneous quantities of stocked products are really known. However, the Order Promising Process (OPP) should decide based on both, the uncommitted availability of products in stock and in planned batches, which customer order proposals to be committed and an accurate due date for them [3]. For this reason, the distribution of production batches into homogeneous sublots should be estimated during the OPP. However, due to the inherent aforementioned uncertainty, discrepancies between the estimated homogeneous quantities in batches and real ones are quite likely to occur. This circumstance can lead to some orders committed during the OPP not being served as there is not enough quantity of homogeneous product, although enough total quantity exists. This shortage situation can occur even with high stock levels and causes a poor customer service level since it is caused by homogeneity requirements (HR). One solution would be to simply refuse any orders that cannot be served [4]. However, this decision could very negatively impact both the customer and the company, so better solutions for the shortage problem are necessary.

One solution for minimising this problem is Shortage Planning (SP), which refers to the activities to be performed if stock becomes unavailable [5]. Some examples of SP activities are negotiation with customers (late supply, partial shipments, etc.) and decisions about supply alternatives (outsourcing, substitutive products, etc.). Another possible solution to this problem is reallocating inventories to previously committed orders to improve the customer service level and to increase profits [6,7]. Other strategies to improve customer satisfaction, such as postponement, are not possible in this case. The reason is that postponement attempts to delay product differentiation as much as possible until orders are received [8] in order to face uncertainty in customised orders. Delayed product differentiation has proven capable of reducing inventory requirements and ensuring high product availability at the same time [9]. However, in the problem under study, uncertainty is not on the customer orders' side because we deal with already committed orders and, therefore, known with certainty. On the contrary, uncertainty is on the supply side, because of the final availability of homogeneous quantities cannot be known until they have been produced and classified.

In this paper, a multi-objective mathematical programming (MOILP) model to reallocate available homogeneous stocked and planned quantities that are already committed orders in ceramic companies is proposed. Although some publications have addressed the SP problem in the ceramic sector [10-12], none has considered HR among units that comprise different order lines, nor the allowance of partial deliveries of order lines, which are some of the novelties of this proposal. This requires not only the differentiation among the homogeneous sublots from the same batch (as previously done), but also the attributes specification for each sublot. This model pursues maximisation of profits and minimisation of order lines served with delays, plus minimisation of the partial deliveries of order lines. The consideration of the last two objectives, as well as the combination of all the objectives, is another contribution of this paper. Some hypotheses are proposed that provide some managerial insights. The model is executed for a different set of scenarios, whose results are statistically analysed to prove the proposed hypotheses.

The rest of the paper is structured as follows: Section 2 describes the problem under study, while Section 3 presents a literature review on the SP problem. Section 4 introduces the MOILP model, which is validated through an experimental design applied to a ceramic tile company in Section 5. Finally, Section 6 offers the main conclusions and the identified future research lines.

2 Problem description

The starting situation contemplates the existence of orders previously committed to customers by means of the OPP. In an ideal situation where the homogeneous planned and real quantities coincide, customer orders are delivered during execution activities as promised. However, discrepancies between the planned and real homogeneous quantities usually occur due to the uncertainty in the homogeneous quantities of the same product in planned production batches. When this happens, it is necessary to verify that the obtained homogeneous quantities are sufficient to serve already committed orders. If not, it will not be possible to serve all the committed orders as previously planned.

To solve this situation, the reallocation of updated available homogeneous quantities both in stock and planned to already committed orders is proposed to minimise the negative impact for both the company and the customer. This reallocation process should meet not only the committed quantity and due date as usual, but also the HR among the units that comprise an order line in all its attributes, and among the units of different order lines that belong to the same series in the gage attribute.

The characteristics of the company and products, customers, orders and delivery flexibility involved in the problem, as well as the reallocation objectives, are described below.

Company and product characteristics:

- The existence of a ceramic production plant composed of several parallel production lines that work according to a Make-To-Stock strategy is assumed.
- The products, once produced, are classified into homogeneous sublots based on their attributes: quality, tone, and gage.
- The products that can be assembled together belong to the same series (e.g. units of two ceramic tiles products which are combined to form a mosaic floor, or units of ceramic skirting boards and ceramic tiles for paving which are assembled together).

Availability of products:

- The existing stock and planned quantities to be produced in the Master Production Schedule (MPS) are used during the reallocation process, but only for first quality products.
- The stocked quantities at the beginning of the planning horizon are already classified into homogeneous sublots. So, their attributes (tone and gage) are known.
- The production batches defined in the MPS (planned batches) are divided into different homogeneous sublots by an estimated distribution. The sum of all homogeneous sublots of a batch must equal the batch size.

Customers:

- The orders previously committed during the OPP (firm orders) are considered for reallocation.
- Two types of customers are distinguished when reallocating available homogeneous quantities to already committed orders: priority and non-priority customer orders.
- An order can be composed of one order line or more. For each order line, the required product and the demanded quantity are detailed. The same finished product can be claimed in more than one order line (e.g. two lines of an order can demand the same product if these quantities are to be assembled separately), but only one product can be requested in each order line.
- The committed due date for each order is known and previously agreed on with customers through the OPP. It is the same for all their order lines.
- An order line must be reserved with a homogeneous product so that all units of the product must have the first quality, and the same tone, and gage, but customers do not specify the tone and gage requested in their orders.
- The order lines with the products that belong to the same series must be booked with the products that present the same gage.
- An order can be served only if all the lines that comprise it are served.

Flexibility in delivery:

- A maximum delivery delay is defined for each order. The real delivery date of an order after the reallocation process is comprised during the period defined by the committed due date and the maximum allowed delay.
- Partial deliveries of order lines are allowed. This means that each line of the same order can be delivered on different dates if the maximum number of partial

deliveries and the maximum delay defined by the customer for this order are not exceeded.

- No partial deliveries of quantities of an order line are allowed. The entire quantity demanded by a customer in an order line must be served simultaneously.
- The reallocation objectives are: maximisation of obtained profits, minimisation of the order lines served with delays, and minimisation of partial deliveries of order lines.

To better understand the problem under study, let's assume two products that belong to the same series: wall tiles (k_1) and floor tiles (k_2). For simplicity, let's assume that each product can be classified into two tones (c_1 and c_2 for k_1; c_3 and c_4 for k_2) and two gages (g_1 and g_2 for both products). This implies that each batch of each product can be classified into four homogeneous sublots. Let's also assume the existence of a planned production batch for k_1 of 2000m^2 that the company estimates is divided into four homogeneous sublots of 650, 350, 700 and 300m^2 with the tone (c_i) and gage (g_i) represented in Figure 1. Finally, let's also assume the existence of two planned production batches, each of 1100m^2 for k_2, which the company estimates will be also divided into four homogeneous sublots of 250, 400, 300 and 150m^2 with the tone (c_i) and gage (g_i) represented in Figure 1.

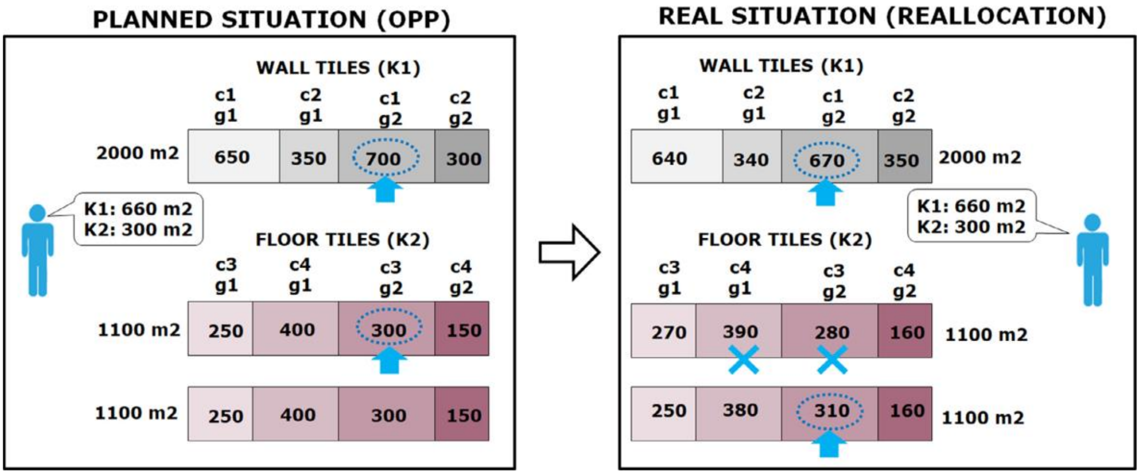

Figure 1. Example of the problem under study

Based on these planned homogeneous sublots, the ceramic company can commit during the OPP the request of 660m^2 of k_1 and 300m^2 of k_2 from a customer order proposal composed of two order lines. Given the HR among the units of the same product, the only possibility of committing this order is for the company to reserve 660m^2 from the homogeneous sublot of k_1 with tone c_1 and gage g_2 because it is the only homogeneous sublot whose size (700m^2) is bigger than the required quantity (660m^2). Since k_1 and k_2 belong to the same series, the homogeneous sublot used to reserve the 300m^2 of k_2 in the customer order should also be of gage g_2. The only sublot of k_2 with a size that equals or is bigger than 300m^2 and with gage g_2 are both the sublots of 300m^2 with tone c_3 and gage g_2. Therefore, the customer order proposal will be committed according to this estimation of the size of the homogeneous sublots.

However, given the inherent uncertainty in such companies, when planned production lots are produced and classified, real homogeneous quantities are likely to differ from the initial estimated ones. This can lead to a situation where if anything is made, the customer order cannot really be served.

Following the previous example, let's assume that once the three planned production batches have finally been manufactured, they are classified to provide the size of the homogeneous sublots depicted as "real situation" in Figure 1. In this new situation, the real homogeneous sublot of k_1 with tone c_1 and gage g_2 is 670m^2 instead of the previously estimated 700m^2. Even so, this discrepancy does not affect being able to serve the requested quantity of product k_1 because it is still enough to serve the 660m^2 requested by the customer. However, for product k_2, the real size of 280m^2 for the homogeneous sublot with tone c_3 and gage g_2 makes it impossible to serve the initial committed quantity of 300m^2 with the customer if nothing is done: a shortage situation occurs. Therefore, once the real homogeneous sublots are known, the initial assignment of customer orders becomes infeasible, which renders serving the customer impossible.

If the possibility of orders reallocation to homogeneous sublots exists, we might think about reserving 300m^2 from the 390m^2 homogeneous sublot of the first batch of k_2 with tone c_4 and gage g_1. However, this reallocation is not possible because product k_2 delivered to the customer should be of the same gage g_2 as product k_1. If only the first batch of k_2 had been manufactured, the customer order would not have been served. However, if all the quantities of the second batch of k_2 are uncommitted, the 300m^2 of k_2 requested by the customer would be served by reserving them from the homogeneous sublot of k_2 with a size of 310m^2 and tone c_3 and gage g_2. Without the availability of this second batch of k_2 only in case customer allows some delay, partial deliveries should be contemplated to solve the problem.

If we consider that ceramic companies manage hundreds of customer orders from several order lines and each product presents more than two tones and gages, the task of finding only a feasible solution to this reallocation problem is no trivial one. This reallocation procedure becomes even more complicated when there are one or more objectives to be optimised. In these situations, mathematical programming models have proved their validity.

3 Literature review

A search of publications about mathematical models for SP was performed. As very few publications on this topic were found, the search was extended to mathematical programming models for the OPP that include some characteristic of the problem to be solved. The reason was that, according to Framinan & Leisten [5], from a modelling point of view, SP deals with relaxing some constraints that have been previously considered in the OPP.

Note that this literature analysis does not intend to provide in-depth details of the features of the reviewed models, but of those closely linked to the problem at hand. Therefore, the employed analysis framework was divided into nine dimensions related to the previously described problem: (1) problem type; (2) availability; (3) manufacturing strategy; (4) customer segmentation; (5) customer orders; (6) homogeneity requirements; (7) flexibility in requirements; (8) objectives; (9) modelling approach. This literature review aims to identify which features have been addressed by existing models, and which represent a gap in the existing literature. The results of this analysis are shown in Tables 1 and 2, where the differences between existing models and the model proposed in this paper are also demonstrated.

Table 1. Literature review (Part I)

Ref.	Problem		Availability			Manufacturing strategy			Customer segmentation	Customer orders	Homogeneity requirements		Flexibility in requirements	
	OP	SP	ST	MPS	ATP	MTS	MTO	ATO	Yes	ML	HP	HL	DA	POL
[13]	X						X							
[10]		X	X			X				X	X		X	
[11]		X	X	X		X			X	X	X		X	
[14]	X				X	X			X	X	X			
[15]	X						X							
[16]	X						X						X	
[12]		X	X			X				X	X			
[17]	X				X		X							
[18]	X				X		X							
[19]	X				X		X			X				
[20]	X				X		X							
[21]	X				X		X			X				
[22]	X				X	X	X	X		X			X	
[23]	X				X		X						X	
[24]	X				X	X								
[25]	X				X	X			X				X	
[26]	X				X	X	X						X	
[27]	X						X							
[28]	X				X	X				X	X			
[29]	X						X		X				X	
[30]	X				X	X			X				X	
[31]	X				X	X				X			X	
[32]	X				X	X								
[33]	X				X	X							X	
[34]	X				X	X			X					
[35]	X				X		X			X			X	
[36]	X				X	X	X			X				
[37]	X				X			X					X	
[38]	X				X	X							X	
[39]	X				X		X							
[40]	X				X		X							
[41]	X				X	X								
[42]	X				X	X							X	
[43]	X						X						X	
[44]	X				X			X			X			
This paper		X	X	X		X			X	X	X	X	X	X

SP: Shortage planning; OP: Order promising; ST: Real quantities in stock; MPS: Planned quantities in MPS; ATP: Available-to-promise; MTS: Make-to-stock; MTO: Make-to-order; ATO: Assemble-to-order; ML: Multiline order: HP: Homogeneity between units of the same order line; HL: Homogeneity between units of different order lines; DA: Delivery delay allowed; POL: Partial deliveries of order lines.

The analysis of publications per problem type shows that only three of the 35 analysed articles address the SP problem, while the rest address the OPP. For SP problems, availability refers to the quantities used during the reallocation process. Alemany et al. [10] and Boza et al. [12] consider the reallocation of available quantities in stock, while Alemany et al. [11] consider the simultaneous reallocation of stocked and planned ones. For OPP problems, availability refers to the availability level checked when promising orders. 26 of the 32 OPP publications use the Available-To-Promise level, while the rest resort to other levels of availability, such as Capable-To-Promise, Deliver-To-Promise or Profitable-To-Promise [13,15,16,27,29,43].

Table 2. Literature review (Part II)

References	Objectives			Modelling approach										
	MP	MD	MSOL	LP	MILP	MOILP	NLP	INLP	FMP	HEU	HYB	SIM	SPP	DP
[13]									X	X				
[10]	X					X								
[11]	X								X					
[14]	X					X								
[15]								X			X		X	
[16]												X		
[12]	X					X								
[17]	X				X									
[18]	X				X									
[19]	X				X									
[20]	X								X	X	X			
[21]	X			X										
[22]					X									
[23]	X										X			
[24]									X					
[25]				X										
[26]	X					X								
[27]	X				X									
[28]	X				X									
[29]					X					X	X			
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[37]	X				X									
[38]				X										
[39]					X							X		
[40]	X				X									
[41]					X									
[42]	X							X		X	X	X	X	X
[43]	X				X									
[44]					X									
This paper	X	X	X			X								

MP: Maximise profit; MD: Minimise delayed deliveries; MSOL: Minimise partial deliveries; LP: Linear programming; MILP: Mixed integer linear programming; MOILP: Multi-objective integer linear programming; NLP: Non-linear programming; INLP: mixed integer non-linear programming, FMP: fuzzy mathematical programming; HEU: heuristics/metaheuristics; HYB: hybrid models; SIM: simulation; SPP: stochastic/probabilistic programming; DP: Dynamic programming.

When we examined the manufacturing strategy, we found that all the SP publications deal with the Make-To-Stock strategy, while OPP publications use different manufacturing strategies: Make-To-Stock in 41% of publications, Make-To-Order in 56% of them, and Assemble-To-Order in 25%. Percentages sum more than 100% as some references consider more than one manufacturing strategy [22,26,36].

In customer segmentation terms, only six papers consider it when treating some customers as priority [11,29,30,34], when prioritising those customer orders with an early delivery date [14], or when assigning priority to customers depending on the order size [25]. Furthermore, 31.4% of the analysed articles consider multiline orders, while the rest consider single line orders.

On the other hand, 17.1% of the analysed publications have HR among units of the same final product. So, customer orders must be served with homogeneous products. In the ceramic field, homogeneity is measured by the quality, tone and gage attributes of the final product [10-12,14]. In TFT-LCD production, homogeneity is given by the quality and materials used [28]. In the computers assembly field, different components have specifications that can make assembly compatible or incompatible [44]. No analysed reference deals with HR among the units that comprise different order lines. However, there are various sectors in which this requirement should be considered, such as the furniture industry or the ceramic sector.

Regarding the flexibility in deliveries requirements, 45.7% of the publications contemplate the possibility of making delayed deliveries. In contrast, none of the analysed articles consider the possibility of making partial deliveries of order lines, which will be another novelty of this proposal.

The analysis of the objectives proposed by previous literature works shows that 51.4% of the publications seek to maximise profits after SP or OPP processes. However, the minimisation of the order lines served with delays, and the minimisation of the partial deliveries of order lines, are not addressed in the analysed literature.

According to the analysed publications, the most widely used modelling approach for this problem is MILP, but other modelling approaches are used by some authors, such as linear programming, nonlinear programming, integer non-linear programming, simulation, heuristics and metaheuristics, fuzzy mathematical programming models, multi-objective integer linear programming, stochastic programming and dynamic programming.

To summarise, we conclude that, although there are publications that consider some of the characteristics of the problem, none addresses them all simultaneously. In addition, the joint consideration of the proposed objectives is a novelty as most are not addressed in the literature. Indeed, no publication addresses HR among order lines, nor the allowance of partial deliveries of order lines, which are the main novelties of this proposal. This requires not only the differentiation between homogeneous sublots from the same batch (as previously done), but also the attributes specification for each sublot. These features are the major contributions of the proposed model.

4 Model

This model is referred to hereinafter as the “Homogeneity Multi-Line Shortage-Planning Model” (HML-SP Model).

4.1 Nomenclature

The indices, sets of indices, parameters and decision variables that are subsequently used in the HML-SP Model are described in Table 3. As seen from the definition part of the model, to ensure achieving the HR among the units of the products that belong to the same and different order lines, the novel specification of the tones, gages, and series which characterise each product is necessary. This aspect obliges a new more complex formulation of the whole proposed model compared to others that consider HR and are reported in the literature review section. Furthermore, the modelling of the multiple objectives and the allowance of the partial deliveries of the order lines that belong to the same customer order constitute the other differentiation characteristic.

Table 3. Nomenclature

Indices			
f	Reallocation objective	g	Existing gage of the considered products
o	Customer order already committed	c	Existing tone of the considered products
l, l'	Order line that composes customer orders	m	Production line
k, k'	Finished product	t	Time periods in the reallocation planning horizon (t = $1, \ldots, T$)
s	Series to which a product can belong		
Set of indices			
O_k	Set of orders o requesting product k	C_k	Set of possible tones c for product k
L_k	Set of order lines l included in order o	G_k	Set of possible gages g for product k
KLO_{ol}	Set defining the product k required on order line l of order o	S_k	Set defining the serie s that product k belongs to.
LOK_{ok}	Set of order lines l of order o requesting product k	KS_s	Set of products k that belong to the same serie s
Parameters			
w_f	Weight assigned to objective f of the HML-SP Model	β_{kcg}	Fraction of the production lot of product k expected to have tone c and gage g after production
p_{ol}	Profit obtained when serving order line l of order o	$LDmax_o$	Maximum number of time periods that order o can be delayed
hc_k	Per unit inventory holding cost of product k per period t	$DOmax_o$	Maximum number of partial deliveries allowed for order o
q_{olk}	Requested quantity of product k in order line l of order o	$stock_{kcg}$	Initial stock of product k characterised by tone c and gage g
rc_o	Cost of rejecting order proposal o	mps_{kmt}	Planned quantity of product k to be produced on production line m during period t
no	Total number of orders o		
nl_o	Number of order lines included in order o		
dd_o	Committed due date for order o		
Decision variables			
Y_o	Binary variable takes a value of 1 when the entire order o is served, and 0 otherwise		
YL_{ol}	Binary variable takes a value of 1 when order line l from order o is served, and 0 otherwise		
D_{ol}	Binary variable takes a value of 1 when order o is partially or completely delivered during period t, and 0 otherwise		
DL_{olt}	Binary variable takes a value of 1 when order line l from order o is delivered during period t, and 0 otherwise		
AD_{ol}	Number of time periods during which the required product quantity in order line l of order o is reserved until it is delivered		
LDL_{ol}	Number of time periods of delay in the delivery of order line l of order o in relation to committed due date dd_o		
UDL_{ol}	Binary variable takes a value of 1 when order line l from order o is served with delay, and 0 otherwise		
$ATP0_{kcg}$	Stock available to promise quantity (ATP) of product k with tone c and gage g after the reallocation of the real and planned available		
ATP_{kcgmt}	Planned available to promise quantity (ATP) of product k with tone c and gage g to be produced on production line m during period t after the reallocation of the real and planned available quantities to the committed orders		
$U0_{olkcgs}$	Binary variable takes a value of 1 when the quantity of required product k on order line l of order o that belongs to series s is reserved from $stock_{kcg}$, and 0 otherwise		
$U_{olkcgmts}$	Binary variable takes a value of 1 when the quantity of required product k on order line l of order o that belongs to series s is reserved from planned lot mps_{kmt} with tone c and gage g, and 0 otherwise		

4.2 HML-SP model

The HML-SP Model is presented in this subsection. Firstly, the different objective functions are detailed. Secondly, the restrictions given by the characteristics of the problem are formulated.

4.2.1 Objective function

The first objective (1), called Z_P, consists in maximising profits during the reallocation process. Profits are made as the difference between the margin earned by serving order lines and the costs incurred when rejecting orders and holding quantities of product for an order until it meets its committed due date.

$$Max[Z_P] = \sum_{o}\left(\sum_{l\in L_o}\left(p_{ol}\cdot YL_{ol} - \sum_{k\in KLO_{ol}} hc_k\cdot AD_{ol}\cdot q_{olk}\right) - rc_o\cdot(1-Y_o)\right) \tag{1}$$

The second objective (2), called Z_D, consists in minimising the number of order lines served with delays.

$$Min[Z_D] = \sum_{o}\sum_{l\in L_o} UDL_{ol} \tag{2}$$

The third objective (3), called Z_{PD}, consists in minimising the number of partial deliveries of order lines. For an order, a partial delivery exists if the number of deliveries ($\sum_t D_{ot}$) is higher than one when the order is delivered ($Y_o = 1$). The total number of partial deliveries is calculated as the difference between the total number of deliveries and the number of served orders.

$$Min[Z_{PD}] = \sum_{o}\left(\sum_{t} D_{ot} - Y_o\right) \tag{3}$$

4.2.2 Constraints

Set of constraints (4) establishes that the updated stocked quantity of product k with tone c and gage g equals the initial stock of this product with tone c and gage g, minus the quantities reserved to serve orders.

$$ATP0_{kcg} = stock_{kcg} - \sum_{o\in O_k}\sum_{l\in LOK_{ok}}\sum_{s\in S_k} q_{olk}\cdot U0_{olkcgs} \qquad \forall k, c\in C_k, g\in G_k \tag{4}$$

Set of constraints (5) indicates that the available planned quantity of product k with tone c and gage g produced on production line m during period t equals the master production schedule quantity to be produced for this product, production line and period, multiplied by the probability of obtaining tone c and gage g, minus the quantities reserved to serve orders.

$$ATP_{kcgmt} = \beta_{kcg}\cdot mps_{kmt} - \sum_{o\in O_k}\sum_{l\in LOK_{ok}}\sum_{s\in S_k} q_{olk}\cdot U_{olkcgmts} \qquad \forall k, c\in C_k, g\in G_k, m, t \tag{5}$$

Set of constraints (6) ensures that an order line can be reserved only once to thus avoid the possibility of serving an order line with heterogeneous quantities.

$$\sum_{k\in KLO_{ol}}\sum_{c\in C_k}\sum_{g\in G_k}\sum_{s\in S_k}\left(U0_{olkcgs} + \sum_{m}\sum_{t} U_{olkcgmts}\right) = YL_{ol} \qquad \forall o, l\in L_o \tag{6}$$

Set of constraints (7) indicates that an order can be served only if all its order lines are served. These constraints also act contrariwise.

$$\sum_{l\in L_o} YL_{ol} = nl_o\cdot Y_o \qquad \forall o \tag{7}$$

Sets of constraints (8)–(10) force the real delivery date of an order line to be comprised during the period defined by the committed due date and the maximum delay allowed for that order.

$$\sum_{t} DL_{olt} \cdot t \geq dd_o \cdot YL_{ol} \qquad \forall o, l \in L_o \tag{8}$$

$$\sum_{t} DL_{olt} \cdot t = dd_o \cdot YL_{ol} + LDL_{ol} \qquad \forall o, l \in L_o \tag{9}$$

$$LDL_{ol} \leq LDmax_o \cdot UDL_{ol} \qquad \forall o, l \in L_o \tag{10}$$

Set of constraints (11) ensures that, if an order line is served without delays, then the binary variable that indicates if an order line is delayed equals zero.

$$LDL_{ol} \geq UDL_{ol} \qquad \forall o, l \in L_o \tag{11}$$

Set of constraints (12) indicates that an order cannot be delivered with delays if it is not served.

$$UDL_{ol} \leq YL_{ol} \qquad \forall o, l \in L_o \tag{12}$$

Set of constraints (13) ensures that an order line can be served only once if it is served.

$$\sum_{t} DL_{olt} \leq 1 \qquad \forall o, l \in L_o \tag{13}$$

Set of constraints (14) calculates the number of time periods during which a requested quantity of product is reserved until its real delivery date.

$$AD_{ol} = \sum_{t} DL_{olt} \cdot t - \sum_{k \in KLO_{ol}} \sum_{c \in C_k} \sum_{g \in G_k} \sum_{s \in S_k} \left(U0_{olkcgs} + \sum_{m} \sum_{t} U_{olkcgmts} \cdot t \right) \qquad \forall o, l \in L_o \tag{14}$$

Set of constraints (15) ensures that when an order line is served during period t, then a partial or complete delivery of that order is made during this period.

$$\sum_{l \in L_o} DL_{olt} \leq D_{ot} \cdot nl_o \qquad \forall o, t \tag{15}$$

Set of constraints (16) indicates that when an order is completely or partially delivered during period t, then at least one line of this order is delivered during that period:

$$\sum_{l \in L_o} DL_{olt} \geq D_{ot} \qquad \forall o, t \tag{16}$$

Set of constraints (17) ensures that the quantity of partial deliveries made for an order is less than or equals the maximum of partial deliveries allowed for that order.

$$\sum_{t} D_{ot} \leq DOmax_o \qquad \forall o \tag{17}$$

Set of constraints (18) ensures that the novelty requirement of two lines or more of the same customer order that belong to the same series s must be served with the quantities available with the same gage g:

$$\sum_{c} \left(U0_{olkcgs} + \sum_{m} \sum_{t} U_{olkcgmts} \right) = \sum_{c} \left(U0_{ol'k'cgs} + \sum_{m} \sum_{t} U_{ol'k'cgmts} \right) \tag{18}$$
$$\forall o, s, k \in KS_s, k' \in KS_s, l \in LOK_{ok}, l' \in LOK_{ok'}, g$$

Finally, set of constraints (19) shows the definition of the decision variables:

$$
\begin{array}{ll}
AD_{ol}, LDL_{ol} & INTEGER, \\
ATP0_{kcg}, ATP_{kcgmt} & CONTINUOUS, \\
Y_o, YL_{ol}, D_{ot}, DL_{olt}, UDL_{ol}, U_{olkcgmts}, U0_{olkcgs} & BINARY
\end{array}
\tag{19}
$$

4.3 Resolution methodology for the HML-SP Model

MOILP models can be solved by different methods regarding the phase in which decision makers express their preferences about the objectives [45]. In *a priori* methods, decision makers express their preferences before solving the model, while decision makers select the most satisfying solution from among a set of non-dominated solutions obtained by the model in *a posteriori* methods [46]. Thus, in *a posteriori* methods, decision makers express their preferences after solving the model. In this subsection, *a priori* and *a posteriori* methods to solve the HML-SP model are presented. These methods are later applied in Section 5.3.

4.3.1 A priori method: the weighted sum method

The weighted sum method consists in constructing a single global objective function by assigning weights to each objective and summing their results. The sum of the weights assigned to each objective should equal the unit $(w_P + w_D + w_{PD} = 1)$. The closer the weight assigned to an objective is to one, the stronger incidence that this objective has on the global objective function. It is necessary to scale each objective value by dividing them between the highest value that they can reach so they acquire values between 0 and 1. The benefit of serving all the committed orders with no cost, the total number of existing order lines, and the total number of allowed deliveries will be the maximum values for objectives Z_P, Z_D, and Z_{PD}, respectively. After applying the weighted sum resolution method, the resulting HML-SP model is formulated as follows:

$$
Max[Z] = w_P \cdot \frac{Z_P}{\sum_o \sum_{l \in L_o} p_{ol}} - w_D \cdot \frac{Z_D}{\sum_o nl_o} - w_{PD} \cdot \frac{Z_{PD}}{\sum_o DOmax_o} \tag{20}
$$

Subject to: Equations (4) – (19).

Note that Z_P, Z_D, and Z_{PD} are calculated through Equations (1) – (3).

The disadvantage of this method is that decision makers hardly know what their preferences are and/or how to quantify them [46]. So it is difficult to establish weights to objectives. To solve this, a method like the Analytic Hierarchy Process (AHP) can be employed to determine the objectives' weights [47].

4.3.2 A posteriori method: the ε-constraint method

To transform the multi-objective model into a single-objective model, the ε-constraint method is used [46,48,49] in which one of the objectives is selected as the model's objective function, while the other objectives are considered the model's constraints. In this case, maximisation of profits is maintained as the model's objective function, minimisation of the number of order lines served with delays, and minimisation of partial deliveries of order lines are transformed into the model's constraints. The new model is formulated as follows:

$$Max\ Z = \sum_{o} \left(\sum_{l \in L_o} \left(p_{ol} \cdot YL_{ol} - \sum_{k \in KLO_{ol}} hc_k \cdot AD_{ol} \cdot q_{olk} \right) - rc_o \cdot (1 - Y_o) \right) \tag{21}$$

subject to:

$$\sum_{o} \sum_{l \in L_o} UDL_{ol} \leq \varepsilon_D \tag{22}$$

$$\sum_{o} \left(\sum_{t} D_{ot} - Y_o \right) \leq \varepsilon_{PD} \tag{23}$$

and Equations (4) - (19).

To apply this method, a payoff table that determines the ranges of values that each objective modelled as a constraint can assume needs to be calculated. In this paper, the lexicographic optimisation for the payoff table proposed by Mavrotas [46] is used that provides with non-dominated solutions. It consists in solving the model each time for only one objective. Then, the model is solved for another objective, forcing the first objective to be equal to its optimal value by means of a constraint. This process is repeated for all the combination of objectives. For example, in a model with two objectives (f_1 and f_2), the optimum value for f_1 is obtained. Then objective f_2 is optimised by considering that f_1 must equal the optimal value obtained in the previous execution. To obtain another non-dominated solution, the process is repeated by firstly solving the model for objective f_2.

Then the grid points (ε_i) obtained when dividing the objective's range of values into equal intervals are used to obtain the non-dominated solutions to the problem. Finally, decision makers select the non-dominated solution that most satisfies them. Note that the payoff table, and therefore the grid points, differ for each data instance.

This approach is more appropriate for obtaining the solution to be implemented into a real company because it obtains non-dominated solutions, among which decision makers can choose. However, if the model needs to be executed for different sets of instances (scenarios), this approach becomes tedious, long and dependent on the decision maker's preference. So the experimental design could not be automated for this last reason. To avoid these disadvantages for the experimental design, an a priori method seems more adequate.

5 Experimental design: application to a ceramic tile company

The aims of the numerical tests defined in this section are threefold: 1) to validate the HML-SP Model; 2) to analyse the model's behaviour in different situations for the company under study to provide some managerial insights for the studied case and 3) to check computational efficiency by solving different scenarios. Before analysing these aspects, the data used in the experimentation are described.

5.1 Input data

The experimental design was conducted with data from a major company in the Spanish ceramic sector, and were slightly modified for confidentiality reasons, while maintaining the magnitude order.

A planning horizon of 12-time periods (weeks) was contemplated, which is approximately a 3-month planning. Ten final products were considered and classified into two different tones and three different gages, with six homogeneous subtypes. In addition, each product belonged to a series so, if products from the same series were required in the same order, it was necessary to ensure that all their units were homogeneous for the gage attribute.

There were 150 committed orders (firm orders) for the considered planning horizon. Fifty of these orders were considered priorities. Each order was made up of between one and ten order lines, with an average of 2.31 lines per order, and there were 347 total order lines. For each line that belonged to an order, the final requested product and the demanded quantity were known and ranged from a minimum of 20 m^2 to a maximum of 4,000 m^2, with an average of 150 m^2 per order line. The same final product could be requested on more than one order line of the same order. This is often done if a customer requires a very large amount of a given product and does not require all this quantity to be homogeneous, but only parts of it (for example, large builders).

Each order was associated a committed due date, which was the same for all its order lines. For each order, the maximum delivery delay (one-time periods) and the maximum partial deliveries allowed (two for multiline orders and one for single line orders) were also known.

It was assumed that current stocks were classified according to their attributes and the planned batches of the MPS were known. Current stocks varied by subtype, ranging from 0 m^2 and 3,500 m^2. In addition, the distribution of production batches into homogeneous sublots was estimated.

Table 4 shows the unitary margin, unitary holding cost and unitary rejection cost per product. Note that unitary rejection costs were estimated as 75% of the unitary margin for each product. An increase of 20% in the rejection costs for priority orders was assumed to reflect the company's preference for them to be firstly served.

Table 4. Economic data per product

Final product *k*	Unitary profit (€/m^2)	Unitary rejection cost (€/m^2)	Unitary holding cost (€/m^2·week)
1	7.00	5.25	0.064
2	18.00	13.50	0.052
3	12.00	9.00	0.040
4	10.00	7.50	0.036
5	5.00	3.75	0.036
6	11.00	8.25	0.052
7	13.00	9.75	0.040
8	12.00	9.00	0.036
9	6.00	4.50	0.052
10	15.00	11.25	0.045

Two new data instances were created to assess the complexity of the HML-SP model in light of the different problem sizes and their respective resolution times. A smaller instance was built by considering the data for the first six time periods of the original instance. Similarly, a larger instance was generated by duplicating the data provided by the company and comprised a 24-time period planning horizon. To avoid equality between the data from the first 12 time periods and the other periods, the due dates between the 13th and 24th time periods were randomly attributed.

5.2 Defining the hypotheses

The purpose of the experimental design was to validate the HML-SP Model and to provide some managerial insights as the following hypotheses:

H1. There may be some conflict with the HML-SP model objectives when obtaining optimum values.

H2. Given a master plan, the greater the division of a batch into homogeneous sublots (more subtypes) and the more uniform its size, the more difficult it will be to serve the committed orders from the homogeneous product.

H3. The results should improve if the number of allowed partial deliveries and/or the maximum allowed delay for each order increases as these measures increase the feasible area and, therefore, the possibility of finding better solutions.

H4. The difficulty of serving orders should grow significantly when considering HR among order lines.

The hypotheses were demonstrated by executing different sets of scenarios and a statistical analysis of the obtained results. For clarity reasons, these demonstrations are explained fairly in Section 5.3.

In addition, an analysis of the model's computational complexity was done in Section 5.4, where the problem size, the resolution time and the GAP for each execution are displayed. For the scenarios in which the optimal solution was not found during the time limit defined as 18,000 seconds, a GAP was obtained and represents the difference between the best-found solution and the best-bound explored one. The average GAP for the original data instance was 0.24%. The GAP varied from 0.00% to 0.63% in the proposed scenarios that came very close to zero. This denotes that the obtained solutions presented in next section are optimum solutions or come very close to them.

5.3 Experimental results to prove the hypotheses

In this subsection, different sets of scenarios were solved with the proposed model to prove the defined hypotheses. The original data instance provided by the company (a 12 time-period planning horizon) was used for all the executions.

5.3.1 Objectives' conflict

A partial correlation analysis of the non-dominated solutions for the HML-SP model was made to prove the existing conflict between the model's objectives (H1). When the model was solved with the ε-constraint method, a payoff table comprised by the non-dominated solutions was needed. To find out these non-dominated (Pareto optimal) solutions (Table 5), lexicographic optimisation, as explained in Section 4.3.2, was employed.

Table 5. Payoff table

#	Z_P	Z_D	Z_{PD}
1	267162.717	78	30
2	267162.717	86	25
3	222613.882	0	0
4	266856.842	149	0

A partial correlation analysis of these solutions can be made to study the relations between the results of the objectives, and to therefore discover if there is any conflict between the different objectives considered in the HML-SP model (Table 6).

Table 6. Partial correlation coefficient

	Z_P	Z_D	Z_{PD}
Z_P	1	0.9996	0.9990
Z_D	0.9996	1	-0.9985
Z_{PD}	0.9990	-0.9985	1

The values of the profits and order lines served with delays positively and perfectly correlated (0.9996 ≈ 1) in such a way that when profits increased, the number of required delayed order lines also increased. Similarly, profits and partial deliveries also perfectly and positively correlated (0.9990 ≈ 1), in such a way that the partial deliveries increased as profits improved. As the purpose of the model was to maximise profits while minimising the number of delayed order lines and partial deliveries, this analysis proved the conflict between maximisation of profits and the other objectives.

The number of delayed order lines and the number of partial deliveries correlated perfectly and negatively (-0.9985 ≈ -1). This means that one of them increased, while the other decreased. As the model intended to minimise both objectives, this result ensured a conflict between them. This proved the existence of conflict among all the proposed objectives and proved Hypothesis H1.

5.3.2 Distribution of batches into homogeneous sublots

Five scenarios were proposed to prove Hypothesis H2, according to which it was more difficult to serve committed orders with homogeneous product when a production lot was divided into more sublots and their size was more uniform. These scenarios (Table 7) differed in the considered distribution of a production batch into homogeneous sublots (β_{kcg}). It was assumed that a maximum of three homogeneous sublots could be obtained by each production batch (β_{k11}; β_{k12}; β_{k23}). The homogeneous sublot β_{k11} was defined by tone 1 and gage 1, sublot β_{k12} was defined by tone 1 and gage 2, and finally, the sublot β_{k23} was defined by tone 2 and gage 3.

Table 7. Distribution of batches into homogeneous sublot scenarios

Scenario	β_{k11}(%)	β_{k12}(%)	β_{k23}(%)
1 homogeneous sublot	100	--	--
2 unbalanced homogeneous sublots	70	30	--
3 unbalanced homogeneous sublots	70	20	10
2 balanced homogeneous sublots	50	50	--
3 balanced homogeneous sublots	40	30	30

As explained in the last paragraph of Section 4.3.2, the weighted sum method was employed given its suitability for solving sets of scenarios. To determine the weight distribution between the objectives that comprised the global objective function, AHP was used. This technique is based on the paired comparisons of the elements among which weights were to be distributed.

The scale used to make judgements was the proposed by Saaty [47], where 1 means that both elements are of the same importance, and 3, 5, 7, and 9 mean that one element is moderately, strongly, very strongly, or extremely important over another element, respectively. If one of the above numbers is assigned to element x when compared with the element y, then y has the reciprocal value when compared with x [47]. With this scale, the pairwise comparison matrix and weight distribution were obtained (Table 8).

Table 8. Pairwise comparison matrix

	Z_P	Z_D	Z_{PD}	w_f
Z_P	1	5	5	0.66
Z_D	1/5	1	1/3	0.09
Z_{PD}	1/5	3	1	0.25

A maximum delivery delay of one period $(LDmax_o = 1)$ and a maximum of two partial deliveries per order $(DOmax_o = 2)$ were allowed. Both HR were considered: homogeneity among units of the same order line and among units of different order lines.

The results (Figure 2) show that the values of the profits and the global objective function became worse as the division of a batch into homogeneous sublots increased. This was because it is more difficult to serve orders with homogeneous product when lots were more heterogeneous. Therefore, the profits made in the "One homogeneous sublot" scenario practically duplicated those made in the scenarios where the lack of homogeneity in the product was considered.

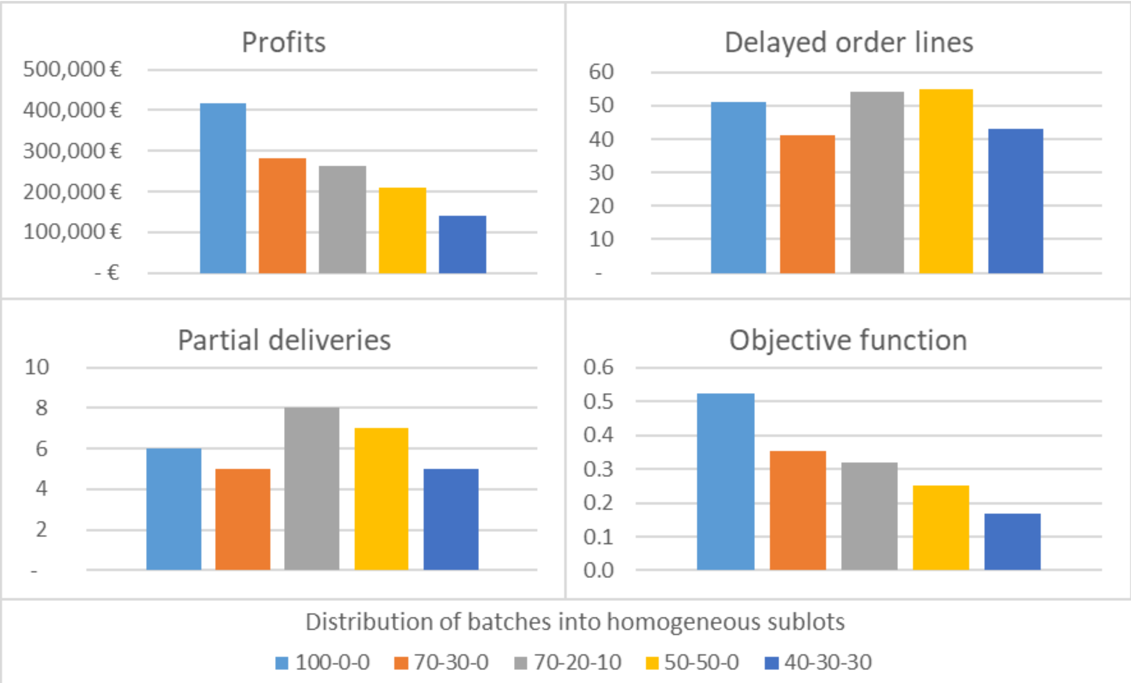

Figure 2. Results of the distribution of batches into homogeneous sublot scenarios

This same logic was not seen in the other objectives partly since the weights assigned to them in the global objective function were relatively small compared to the profits weight. A scatter plot of the distribution of batches into homogeneous sublots and the number of orders served in each scenario (Figure 3) shows how the quantity of served orders decreased as the number of homogeneous sublots increased and consequently their size decreased. To obtain this scatter plot, it was necessary to first transform each homogeneity distribution, composed of three terms (β_{k11}, β_{k12}, and β_{k23}), into a numerical value. The homogeneity coefficient value is supposed to be high when just one homogeneous sublot is obtained from the same production batch and to decrease its value as more sublots are obtained. Similarly, this coefficient should decrease its value as the different obtained sublots are more uniform in size. Thus, AHP was employed again, and conferred much preference to obtain only one homogeneous sublot rather than obtaining two, and even more preference rather than obtaining three sublots in the same lot. The weights obtained with this process ($w_{\beta_{k11}} = 0.60$; $w_{\beta_{k12}} = 0.36$; $w_{\beta_{k23}} = 0.04$) were multiplied to the different terms of each homogeneity distribution to obtain a homogeneity coefficient β (Table 9), which was used in the statistical analysis of the results.

Table 9. Homogeneity coefficient β obtainment

Homogeneity distribution β_{k11}-β_{k12}-β_{k23}	Homogeneity coefficient β
100-00-00	100 * 0.60 + 0 * 0.36 + 0 * 0.04 = 60
70-30-00	70 * 0.60 + 30 * 0.36 + 0 * 0.04 = 53
70-20-10	70 * 0.60 + 20 * 0.36 + 10 * 0.04 = 50
50-50-00	50 * 0.60 + 50 * 0.36 + 0 * 0.04 = 48
40-30-30	40 * 0.60 + 30 * 0.36 + 30 * 0.04 = 36

A correlation coefficient of 0.97 demonstrated the clear relation between the number of orders served and the homogeneity coefficient. In addition, a scatter plot showing the relation between these variables is displayed in Figure 3. Thus, when the homogeneity coefficient rose, the number of served orders also increased. This proved hypothesis H2 and showed the importance of allocating product quantities to customer orders considering HR in those industries characterised by the lack of homogeneity in the product.

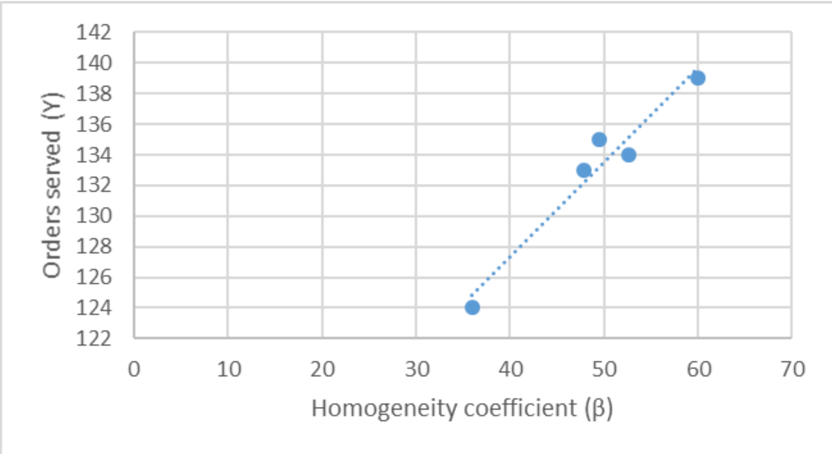

Figure 3. Scatter plot: Orders served vs. β

5.3.3 . Flexibility in order deliveries

This subsection aimed to demonstrate that flexibility in order deliveries impacted the reallocating process. In the HML-SP model, flexibility in deliveries can be modified by allowing more/less partial deliveries per orders ($DOmax_o$) and/or shorter/larger delays ($LDmax_o$) of deliveries. For this reason, two sets of scenarios were proposed to prove the independent effect that partial and delayed deliveries had on the results (Table 10). In all, 22 scenarios were executed.

For these scenarios, the same weight distribution among the objectives was assumed ($w_P = 0.66; w_D = 0.09; w_{PD} = 0.25$), as was the division of production batches into the most usual three unbalanced homogeneous sublots ($\beta_{k11} = 0.7; \beta_{k12} = 0.2; \beta_{k23} = 0.1$).

Table 10. Conditions of "Flexibility in Order Deliveries" scenarios

Set of scenarios	Scenario	Number of scenarios	$DOmax_o$	$LDmax_o$
Flexibility in the maximum allowed delay	i periods delay allowed $i \in (0, T-1)$	12	1	$min(i, T - dd_o)$
Flexibility in partial deliveries	j deliveries per order $j \in (1, 10)$	10	$min(j, nl_o)$	$Domax_o - 1$

In the "Flexibility in the Maximum Allowed Delay" scenarios, the maximum delay allowed per order had to equal the minimum between the general maximum delay allowed and the difference between the planning horizon and the due date for this order. This assumption ensured that any order could be served after the planning horizon. Only one delivery was allowed per order to study the independent effect that delays had on the model.

The results showed how the profits and the objective function value improved as the general maximum allowed delay increased (Figure 4). The same relation was not found in the number of order lines served with delay because this objective had a lower weight in the objective function. The part of the partial deliveries in Figure 4 is empty because no partial deliveries were allowed.

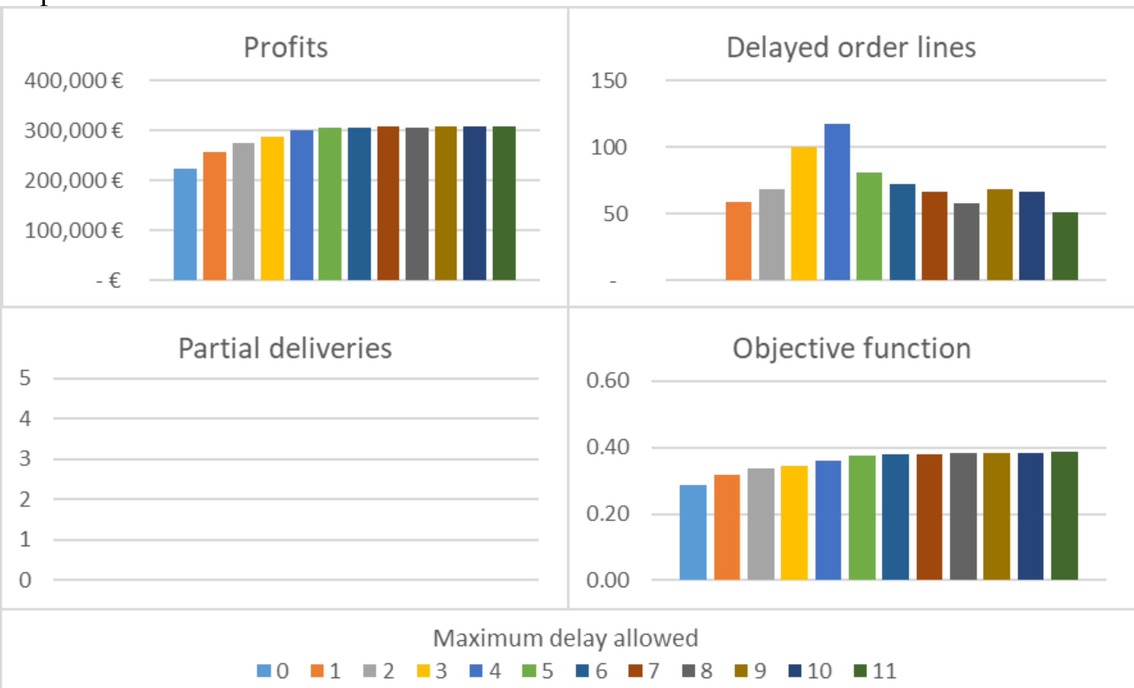

Figure 4. Results of the flexibility in the maximum allowed delay scenarios

To statistically prove that the objective function value improved as the maximum delay allowed increased, a correlation analysis of these variables was run. This was proved with a correlation coefficient of 0.90, which determined that both variables would simultaneously improve or worsen. Figure 5 shows a scatter plot of these variables, where their relation can be seen.

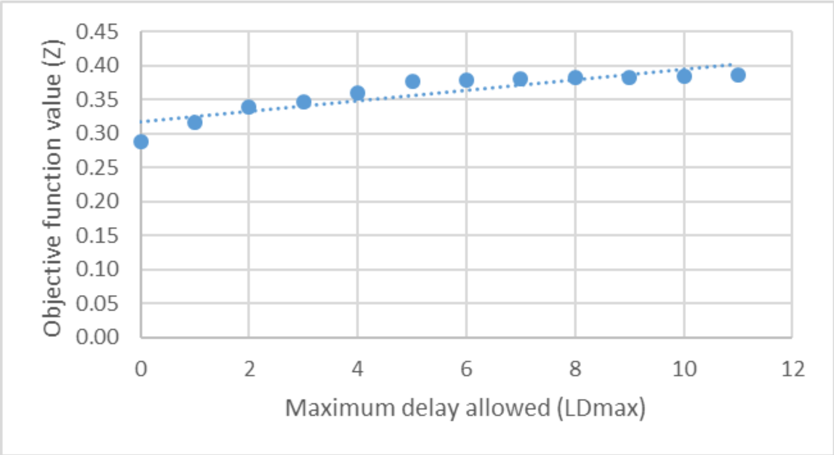

Figure 5. Scatter plot: Maximum delay allowed vs. Objective function value

In the "Flexibility in Partial Deliveries" set of scenarios, the number of deliveries allowed per order was modified to analyse how this factor impacted on the results of the model. For each scenario it was assumed that the maximum delay allowed per order was equal to the partial deliveries allowed in this scenario, minus one. The objective of this assumption was to ensure that enough delivery periods were available to make us of all the allowed deliveries. In addition, it was assumed that the number of deliveries allowed per order could be at most equal to the number of lines that comprise the order (Table 10).

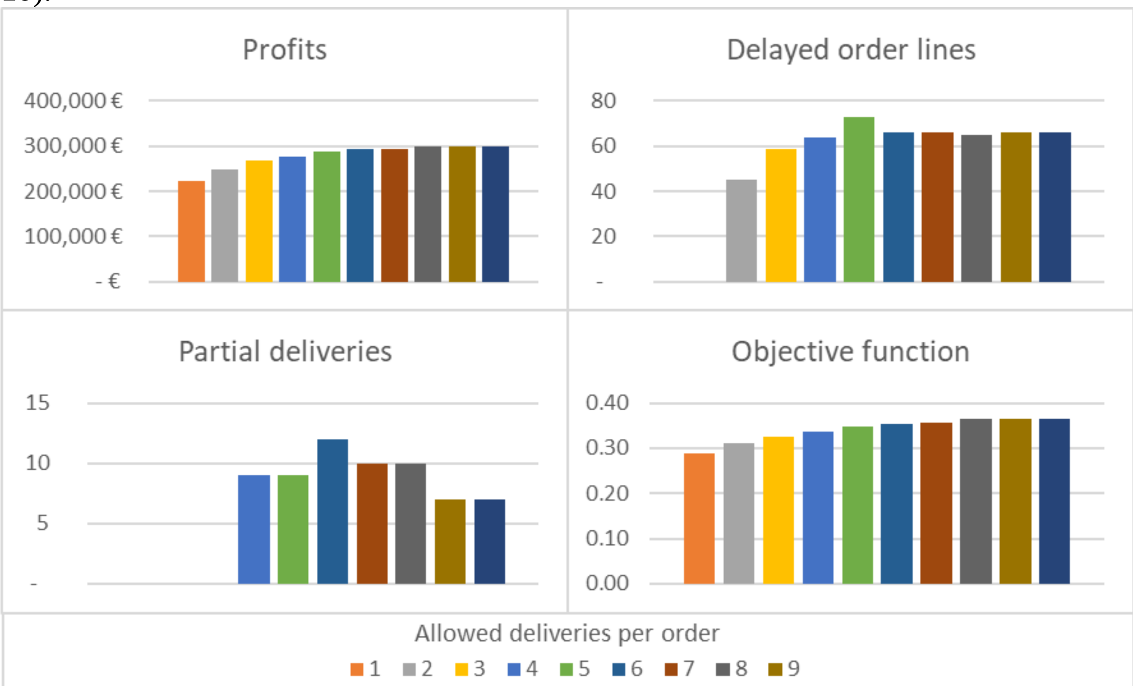

Figure 6. Results of the flexibility in partial deliveries scenarios

The results (Figure 6) showed how both profits and the objective function value improved as the number of allowed deliveries per order increased. Besides, the number of order lines served with delays and the number of partial deliveries made did not seem to follow a pattern related to the flexibility in the allowed partial deliveries. As in the other scenarios, it was produced because the weight that the last two objectives had on the global objective function was low compared to maximisation of profits.

A correlation analysis between the global objective function value and the number of partial deliveries allowed and a scatter plot between these variables (Figure 7) were done. The relation between these variables was proved by a correlation coefficient of 0.94, which demonstrates that when these variables improve, the value of the other one also increases.

Figure 7. Scatter plot: Partial deliveries allowed vs. Objective function value

We hence concluded that delivery flexibilities led to better results for the global objective function of the HML-SP Model, and Hypothesis H3 was demonstrated. So these results can be employed by manufacturers to decide which policy to apply to their customers as to delays and partial deliveries if negotiation is possible.

5.3.4 Flexibility in the homogeneity requirement

To prove Hypothesis H4, the scenarios solved in Section 5.3.3 when considering HR among units of different order lines were compared to the homologues without considering this requirement. For these scenarios, the real weight distribution among the objectives $(w_P = 0.66; w_D = 0.09; w_{PD} = 0.25)$ and the division of production batches into the most usual three unbalanced homogeneous sublots $(\beta_{k11} = 0.7; \beta_{k12} = 0.2; \beta_{k23} = 0.1)$ were assumed.

Figure 8. Results of Flexibility in the homogeneity requirements scenarios

Figure 8 shows the comparison of these results for the scenarios proving the flexibility in the maximum allowed delay and the flexibility in partial deliveries. The scenarios that considered HR among order lines obtained worse global objective function values than the homologues scenarios that did not consider this requirement. This was because considering HR implies a reduced feasible area, which hinders the reallocation process.

Box and Whiskers plots were used to show the main differences between the results distribution in those cases in which HR among the units of different order lines were or were not considered. For both cases, in the scenarios that proved flexibility in the number of deliveries allowed or in the allowed delay, the obtained values for the objective function were higher when HR was not considered. Also, in the scenarios where the flexibility in the allowed delay is analysed, the range of the objective function values was wider when HR were not considered.

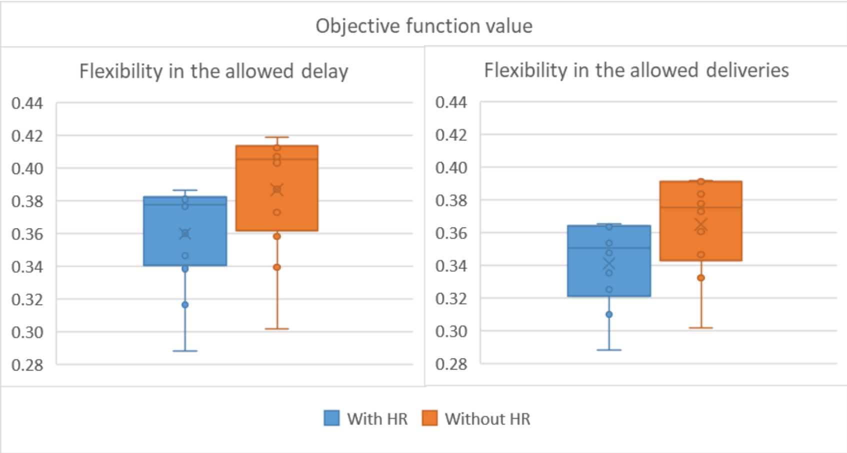

Figure 9. Box and Whiskers plots

We conclude that absence of HR among order lines gave better results for the global objective function of the HML-SP Model and proved Hypothesis H4.

5.4 Computational efficiency

The proposed model was implemented in modelling language MPL® 5.0 and was resolved with solver Gurobi™ 7.0.2. Input data and the values that the decision variables and objectives acquired after resolving the model were stored in a Microsoft Access database. The computer used to solve different scenarios had an Intel® Xeon® CPU E5-2640 v2 with two 2.00 GHz processor, with an installed capacity of 32.0 GB and a 64-bits operating system.

The maximum time resolution was limited to 18,000 seconds (5 h) for each proposed scenario. The model was solved for the different instances comprised by a 6-, 12- or 24-time period planning horizon to determine the model’s complexity regarding the size of the problem and its impact on both, the resolution time and the quality of the obtained solutions.

Table 11 shows the problem size for each scenario set, which was evaluated by the number of constraints and the continuous, integer and binary variables. After analysing it, we found that all the scenarios corresponding to the same instance had the same number of continuous, integer and binary variables and these quantities augmented when the instance became bigger (more customer orders and larger planning horizon). The considerable presence of binary variables, which represented between 95-98% of the variables in all instances, should be emphasised. We observed that the number of constraints lowered for all the instances when HR among the units of different order lines were not considered by the model. This confirmed that the model's size was bigger in those scenarios that included this requirement and comprised more customer orders and larger planning horizon.

Table 11. Problem size

	Planning horizon	Set of scenarios			
		Distribution of batches into homogeneous sublots	Flexibility in order deliveries	Flexibility in HR: with HR	Flexibility in HR: without HR
Constraints	6	5,505	5,505	5,505	4,284
	12	10,795	10,795	10,795	8,896
	24	28,730	28,730	28,730	24,932
Continuous variables	6	1,140	1,140	1,140	1,140
	12	2,220	2,220	2,220	2,220
	24	4,380	4,380	4,380	4,380
Integer variables	6	450	450	450	450
	12	694	694	694	694
	24	1,388	1,388	1,388	1,388
Binary variables	6	28,122	28,122	28,122	28,122
	12	83,842	83,842	83,842	83,842
	24	329,516	329,516	329,516	329,516
Total variables	6	29,712	29,712	29,712	29,712
	12	86,756	86,756	86,756	86,756
	24	335,284	335,284	335,284	335,284

If an optimal solution was not found for a particular scenario during the fixed resolution time (RT) of 18,000 seconds, a GAP was displayed. It represented the difference between the best-found solution and the best-bound explored one. Thus, a GAP of 0.5% meant that the global objective function value for this solution had to improve by 0.5% to reach the best bound. The resolution time and GAP obtained for each scenario and instance are shown in Table 12.

When using the small instance (the 6-time period planning horizon), an optimal solution was found in 20 of the 27 scenarios, with an average resolution time of 7,895 seconds (132 minutes). With the original instance (the 12-time period planning horizon), the optimal solution was reached only in 11 of the 39 scenarios. Finally, no optimal solution was found for any scenario when solving the large instance (the 24-time period planning horizon), although the GAP was quite small and reached near optimal solutions. These results proved that the size of the instance influenced the time in which to optimally solve the model (Table 12).

The increasing complexity of solving the model with the size of the instance was also seen when comparing the GAP average for all the scenarios. For the small instance, an average GAP of 0.03% was obtained, whereas an average GAP of 0.24% and 0.73% were obtained for the original and large instance respectively. In addition, the GAP of almost all the scenarios with no optimal solution came close to zero, which denotes that the obtained solutions came close to the optimum solution.

Table 12. Resolution time and GAP per scenario and instance

Set of scenarios / Scenario	6 periods PH		12 periods PH		24 periods PH	
	RT (s)	GAP	RT (s)	GAP	RT (s)	GAP
Distribution of batches into homogeneous sublots (HS):						
• 1 HS	663	-	18,000	0.11%	18,000	0.61%
• 2 unbalanced HS	540	-	188	-	18,000	0.64%
• 3 unbalanced HS	429	-	18,000	0.20%	18,000	0.95%
• 2 balanced HS	2,597	-	2,396	-	18,000	0.53%
• 3 balanced HS	895	-	680	-	18,000	0.33%
Flexibility in the maximum delay allowed (with HR):						
• 0 periods of delay	84	-	148	-	18,000	0.25%
• 1 period of delay	137	-	4,054	-	18,000	0.85%
• 2 periods of delay	173	-	4,004	-	18,000	1.47%
• 3 periods of delay	18,000	0.13%	18,000	0.17%	18,000	1.35%
• 4 periods of delay	18,000	0.15%	18,000	0.34%	18,000	1.62%
• 5 periods of delay	18,000	0.21%	18,000	0.49%	18,000	0.76%
• 6 periods of delay	-	-	18,000	0.46%	18,000	0.87%
• 7 periods of delay	-	-	18,000	0.39%	18,000	0.96%
• 8 periods of delay	-	-	18,000	0.51%	18,000	1.15%
• 9 periods of delay	-	-	18,000	0.52%	18,000	0.97%
• 10 periods of delay	-	-	18,000	0.63%	18,000	1.00%
• 11 periods of delay	-	-	18,000	0.43%	18,000	0.97%
Flexibility in the maximum delay allowed (without HR):						
• 0 periods of delay	74	-	1,127	-	18,000	0.37%
• 1 period of delay	137	-	18,000	0.11%	18,000	0.52%
• 2 periods of delay	648	-	18,000	0.15%	18,000	0.43%
• 3 periods of delay	2,389	-	18,000	0.28%	18,000	0.33%
• 4 periods of delay	18,000	0.14%	18,000	0.21%	18,000	0.97%
• 5 periods of delay	18,000	0.16%	18,000	0.17%	18,000	0.33%
• 6 periods of delay	-	-	18,000	0.18%	18,000	0.38%
• 7 periods of delay	-	-	18,000	0.17%	18,000	0.33%
• 8 periods of delay	-	-	18,000	0.19%	18,000	0.38%
• 9 periods of delay	-	-	18,000	0.28%	18,000	0.38%
• 10 periods of delay	-	-	18,000	0.11%	18,000	0.49%
• 11 periods of delay	-	-	18,000	0.12%	18,000	0.27%
Flexibility in partial deliveries (with HR):						
• 1 delivery per order	84	-	148	-	18,000	0.25%
• 2 deliveries per order	492	-	15,470	-	18,000	0.76%
• 3 deliveries per order	2,434	-	18,000	0.50%	18,000	0.95%
• 4 deliveries per order	18,000	0.15%	18,000	0.25%	18,000	1.21%
• 5 deliveries per order	18,000	0.22%	18,000	0.42%	18,000	1.53%
• 6 deliveries per order	18,000	0.24%	18,000	0.37%	18,000	1.59%
• 7 deliveries per order	-	-	18,000	0.52%	18,000	1.65%
• 8 deliveries per order	-	-	18,000	0.28%	18,000	1.20%
• 9 deliveries per order	-	-	18,000	0.23%	18,000	1.16%
• 10 deliveries per order	-	-	18,000	0.26%	18,000	1.25%
Flexibility in partial deliveries (without HR):						
• 1 delivery per order	81	-	1,127	-	18,000	0.37%
• 2 deliveries per order	221	-	4,845	-	18,000	0.27%
• 3 deliveries per order	150	-	18,000	0.52%	18,000	0.23%
• 4 deliveries per order	4,009	-	18,000	0.43%	18,000	0.40%
• 5 deliveries per order	18,000	0.22%	18,000	0.37%	18,000	
• 6 deliveries per order	16,362	-	18,000	0.38%	18,000	0.50%
• 7 deliveries per order	-	-	18,000	0.26%	18,000	
• 8 deliveries per order	-	-	18,000	0.22%	18,000	
• 9 deliveries per order	-	-	18,000	0.17%	18,000	0.40%
• 10 deliveries per order	-	-	18,000	0.22%	18,000	0.30%

When comparing the resolution time and the GAP of each specific scenario, they increased as the instance became bigger. The difference between the average GAP of the scenarios that considered (0.05% for the small instance, 0.31% for the original instance and 1.08% for the large instance) or did not consider (0.02% for the small instance, 0.21% for the original instance and 0.41% for the large instance) HR among units of different order lines demonstrated that the computational efficiency was greater in those scenarios that did not take HR into account.

5.5 Managerial insights

As shown in the previous section, HML-SP model proved to be a suitable tool for decision makers in charge of delivering already committed orders to customers. During this process, it is usual that real quantities of homogeneous sublots do not match the planned ones in LHP contexts. If nothing is made, some orders could not be served with the initial assignation made. Therefore, an efficient resolution method is necessary to reallocate the real homogeneous availabilities to orders to find a satisfactory solution for both, customers and the company.

From the managerial point of view, the HML-SP model allows an optimal or nearly optimal solution to be found within a very acceptable time range for this type of decisions. A maximum 5-hour execution implies that the model can be executed at the end of one period, in which discrepancies in homogeneous sublots are detected, to the next, for which a new solution for delivery is necessary. Proof of the conflicting objectives (H1) indicates that the final reallocation solution of availability to orders should be a trade-off among different objectives. Therefore, no solution exists that simultaneously optimises all the pursued objectives.

From the customers' relationship point of view, the positive impact on objective function when increasing flexibility of partial deliveries and/or of the maximum allowed delay, provides valuable information to negotiate delivery conditions with customers when it is not possible to serve all of them on time. Incrementing profits when allowing flexibility in deliveries can be used to define discounts for customers in case they are not served as promised, but to ensure them still being profitable for company. Management of priority orders/customers can be made by not allowing any delay and/or increasing rejection costs of them.

The negative impact of heterogeneity on lots (H2) shows the importance of investing in technology to obtain more uniform product quantities. Unfortunately, this is not possible for all companies with LHP, especially for those that obtain products directly from nature.

Until a technology solution that eliminates LHP is found, efforts should be made on the planning and product design sides. In line with this, it is very important when defining the master plan and executing the OPP that the heterogeneity in the production lots and customer order sizes and their uncertainty should be taken into account [50]. This provides more robust promised conditions with customers, as reflected by the minor reallocations required and the major fulfilment of the initial conditions committed with customers during the OPP.

As Hypothesis H4 proved that the results worsened with HR among units of different order lines, efforts should be made when designing products that are jointly sold to avoid this additional homogeneity requirement.

6 Conclusions and future research lines

The uncertainty inherent to the lack of homogeneity in the product in the ceramic sector constantly leads to discrepancies between planned and available homogeneous quantities. This aspect can result in certain previously committed orders not being served under the conditions previously agreed on as there is not sufficient homogeneous quantity, which entails a shortage situation. To reduce the negative impact on both customers and company profitability, an optimisation model for SP in ceramic sector companies is presented in this article. The reallocation of planned and real available quantities to firm orders is proposed as a solution to possible shortage. Moreover, partial deliveries of order lines and delayed deliveries are allowed if the HR imposed by customers are respected during available quantities reallocation. What all this represents is an attempt to optimise different conflicting objectives. One of the main contributions of this article is to treat the above aspects as we are unaware of any previous study that has jointly addressed all the characteristics of the problem under study. Moreover, partial deliveries of order lines and HR among order lines/products have not been addressed as far as we know.

Two resolution methods are applied to the model, depending on whether it is being used to obtain an implementable solution for the company (ε-constraint method) or to prove the behaviour of the shortage planning process (weighted sum procedure).

In this paper, four hypotheses are proved by applying the model to a ceramic tile company: 1) conflict exists among the model's objectives; 2) worse results are obtained as a batch is divided into many sublots and these are more uniform; 3) the results improve when more flexibility in deliveries is allowed; 4) HR among units of different order lines makes it more difficult to serve orders. The hypotheses were demonstrated by comparing the results obtained with the experiments and by a statistical analysis of these results.

As a future research line, an uncertain modelling of the distribution of batches into homogeneous sublots can be considered. The model proposed in this paper is specifically designed for the ceramic sector as it considers the attributes that characterise it. However, the application of this model can be extended to other sectors by replacing the ceramic attributes with the new sector ones. One example would be to implement the HML-SP Model into the furniture sector where homogeneity among different products that make up a set (chairs, tables, etc.) is also required for raw material (e.g. pine wood, cherry wood, birch wood), colour (e.g. wood, red, white), and quality. In this case the sets or ambiences in furniture sector should be equivalent to the series in the ceramic sector, and each combination of material-colour-quality in the furniture sector should be equivalent to a specific gage.

7 Publication data

Figure 10 shows the first page of the article published in the journal Computers & Industrial Engineering (ISSN: 0360-8352).

Computers & Industrial Engineering 124 (2018) 180–194

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

A multi-objective model for inventory and planned production reassignment to committed orders with homogeneity requirements

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ARTICLE INFO

Keywords:
Reallocation process
Mathematical programming
Lack of homogeneity in the product
Homogeneity among order lines
Deterministic

ABSTRACT

Certain industries are characterized by obtaining non-homogeneous units of the same product. However, customers require homogeneity in some attributes between units of the same and different products requesting in their orders. To commit such orders, an estimation of the homogeneous product to be obtained can be used. Unfortunately, estimations of homogenous product quantities can differ considerably from real distributions. This fact could entail the impossibility of accomplishing the delivery of customer orders in the terms previously committed. To solve this, we propose a multi-objective mathematical programming model to reallocate already available homogeneous products in stock and planned production to committed orders. The main contributions of this model are the consideration of the homogeneity requirement between units of different lines of the same order, the allowance of partial deliveries of order lines, and the specification of some relevant attributes of products to accomplish with the customer homogeneity requirement. Different hypotheses are proved through experiments and statistical analyses applied to a ceramic tile company. The ε-constraint method is used to obtain an implementable solution for the company. The weighted sum method is used when proving other hypotheses that offer some managerial insights to companies.

1. Introduction

Customers usually express requirements in their orders in terms of quantity and delivery date. However, several situations emerge where customers require homogeneity among units of the same product or different products for certain attributes that are relevant for them. These attributes refer to functional or aesthetical reasons because units of the same or different products need to be assembled, packed or presented together. For instance, customer orders in the agricultural sector should be served with units of the same fruit belonging to the same quality, size and weight. This is also valid for the furniture sector, where colour uniformity among units of the same product (e.g. chairs) or among products (e.g. chairs and table) impacts the final value of the products perceived by customers. Thus, colour and grain sorting are necessary.

Another example is the ceramic sector, where the nature of the raw material (clay) and components (frits and enamels) employed during ceramic tile production, and the variability of the environmental conditions during this process, means obtaining units with different tone, gage and quality attributes from a unique production batch (Alemany, Alarcón, Ortiz, & Lario, 2008; Grillo, Alemany, & Ortiz, 2016). In this sector, customers require product homogeneity for quality, tone and gage for all the units that compose an order line. Customers also require gage homogeneity for units of different order lines that are to be jointly installed for functional and aesthetic reasons. To ensure serving customer orders with the required homogeneity, classification stages are included during production processes.

The causes that generate product heterogeneity are mainly uncontrollable because the non-homogeneity of the raw material and components usually coming from the nature or the productive process itself. The above aspects make the homogeneous quantities of each product in planned production batches to be uncertain. In such a way, that only the homogeneous quantities of stocked products are really known. However, the Order Promising Process (OPP) should decide based on both, the uncommitted availability of products in stock and in planned batches, which customer order proposals to be committed and an accurate due date for them (Kiralp & Venkatadri, 2010). For this reason, the distribution of production batches into homogeneous sublots should be estimated during the OPP. However, due to the inherent aforementioned uncertainty, discrepancies between the estimated homogeneous quantities in batches and real ones are quite likely to occur. This circumstance can lead to some orders committed during the

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https://doi.org/10.1016/j.cie.2018.07.025
Received 2 October 2017; Received in revised form 7 May 2018; Accepted 16 July 2018
Available online 17 July 2018

Figure 10. Publication data

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Chapter III:

Simulation to reallocate supply to committed orders under shortage

This article aims to deal with the reallocating supply problem in both its real and planned contexts, to orders that result from the order promising process under shortage. To this end, we propose a system dynamics-based simulation model to facilitate modelling for order managers, and to provide a graphic support tool to understand the process and to make decisions. The basis of the simulation model's structure is a mixed-integer linear programming approach that intends to maximise profits by considering the possibility of making partial and delayed deliveries. To illustrate this, we consider a real-world problem from the ceramic sector that contemplates 35 orders. We obtained a solution by a mathematical programming model and a simulation model. The results show the simulation model's capacity to obtain near-optimum results, and to provide a simulated history of the system.

Keywords: Available-to-promise; Lack of homogeneity; Shortage; Simulation; System dynamics; Ceramic sector

1 Introduction

According to Olhager [1], the order penetration point defines the stage in the manufacturing value chain where a particular product is linked to a specific customer order through different product delivery strategies, such as make-to-stock, assemble-to-order, make-to-order and engineer-to-order. In this paper, we consider a manufacturing make-to-stock environment. During the order promising (OP) process, companies normally make commitments with customers about the quantities and due dates of their orders. These commitments usually focus on make-to-stock companies and on the available-to-promise (ATP) quantities of finished goods calculated as the current stock and planned production defined in the master production schedule (MPS), minus any past orders promised.

However, from the time we commit an order until we must serve it, unexpected events may occur that could lead to a shortage of products. There are several causes of these unexpected events: (i) arrival of more priority customer orders that require already reserved products; (ii) delays in raw materials or components; (iii) machine breakdowns; (iv) workers absenteeism, among others. Some of these events might lead to discrepancies between planned and real production quantities and can, in turn, lead to a shortage situation.

Consequently, the previous allocation of products to orders may become suboptimum, or even unfeasible. In this case, the company might be unable to meet previously agreed conditions with customers. This situation becomes relevant because it could very negatively impact not only the company's profits but also customer satisfaction. Furthermore, if this situation occurs often, it can seriously harm customer loyalty and the company's future sustainability. In this context, the shortage planning process intends to find a solution when stock (component or finished products) is unavailable. Solutions include making decisions on supply alternatives (outsourcing, substitute products), late supply, partial shipments, etc. [2]. Indeed, the solutions to these shortage situations seriously impact the reliability of OP processing. Therefore, the recognised relevance of OP processing in the literature to better deal with demand requirements with high service level and customer satisfaction standards [3,4] supports the importance of shortage planning (SP).

The frequency of unexpected events increases when companies are characterised by lack of homogeneity in the product (LHP), which renders having to execute the SP process more frequently. LHP is an important issue because it appears in several industries like ceramics, textile, wood, marble, horticulture, tanned hides and leather goods, among others [5]. LHP implies the company producing to provide units of the same product with different relevant characteristics for customers. Indeed customers require homogeneity among the units of a particular product that comprises their orders (e.g. in the horticulture sector, fruit should present the same quality and calibre; in the ceramic sector, tiles should be of the same quality, tone (colour) and calibre (thickness)).

In the ceramic sector, the main causes of LHP are the origin and composition of raw materials, and changes in environmental conditions during production (e.g. temperature, humidity). Thus, a particular production lot leads to product units that may differ in terms of (i) quality, (ii) tone (colour) and (iii) calibre (thickness). This aspect would not become a management problem if customers were not sensitive to such differences. However, customers require homogeneity among the ordered units of a particular product for aesthetic and functional reasons. Therefore, after manufacturing a production lot, it is necessary to classify it into different sublots that comprise product units that are homogeneous to one another for all the above-cited characteristics [6].

Companies with LHP are obliged to classify production lots into different homogeneous sublots to comply with customers' homogeneity requirements. Moreover, the quantity of products that comprises each homogeneous sublot is not known for certain until lots are manufactured and classified after manufacturing and classifying the production lot. This means that it is necessary to estimate the distribution of homogeneous sublots in the MPS during OP processing. However, given the uncertainty in this distribution, discrepancies usually appear between the planned and real homogeneous sublots obtained after production. These discrepancies might render it impossible to serve or fulfil some committed orders according to previously agreed conditions because there are not enough homogeneous quantities to fulfil all the orders.

Evidently, we can deduce that the shortage situation occurs very often in companies with LHP. So, developing a method to solve this problem is crucial for such companies. One possible SP solution could involve reallocating available (in stock and planned) quantities to previously committed orders to serve those orders which, in the new circumstances, optimise the objective set by the company [7].

Finding a solution for the reallocation problem in the ceramic sector that is not only optimal, but also feasible, is an extremely complicated task. The main causes of this complexity are: (i) numerous references to be managed (classification of lots into homogeneous sublots entails increasing the number of product references to be handled); (ii) some orders include more than one product; (iii) having to comply with customer homogeneity requirements; (iv) the usually very short time available to reallocate. So it is necessary to develop new tools to help decision making during the process of reallocating homogeneous sublots to committed orders under shortage.

One of the most widely used tools to tackle this problem is mathematical programming. Table 1 shows a literature review of the models used for the allocation/reallocation of available quantities to orders in the ceramic sector, and a comparison made with the characteristics of the model herein proposed. For each existing model, we analysed: (i) the tackled problem, namely OP processing, or SP; (ii) the modelling context, namely deterministic, or uncertain; (iii) available quantities, namely real stock, planned production for SP or ATP for OP processing; (iv) delivery flexibility, namely delays allowed, or partial deliveries of order lines; (v) the modelling approach, namely mathematical programming or system dynamics.

Table 1. Literature review of the allocation/reallocation models

Reference	Problem tackled		Modelling context		Product origin			Delivery flexibility		Modelling approach	
	OP	SP	D	U	RS	PP	ATP	DA	POL	MP	SD
[8]		X	X		X					X	
[9]	X		X				X			X	
[10]		X	X		X					X	
[11]		X		X	X	X		X		X	
This paper		X	X		X	X		X	X	X	X

D: deterministic; U: uncertain; RS: real stock; PP: planned production; DA: delays allowed; POL: partial deliveries of order lines; MP: mathematical programming; SD: system dynamics

Alemany et al. [8] formulated a mixed-integer linear programming (MILP) model to solve the SP problem in LHP contexts. The model reallocates only existing stocks of multiple products to multiple-line orders, while ensuring homogeneity between the product units that comprise each order line. The objectives of this model are to (i) maximise profits and (ii) maximise the number of orders delivered with the earliest due date. It does not allow either delayed deliveries or partial deliveries of order lines. Subsequently, Boza et al. [10] extended this model and used it as a basis for a decision-support system.

Alemany et al. [9] also proposed a MILP model, but one to support OP processing in LHP contexts that relates closely to SP. This model estimates the distribution of planned production lots in the MPS into homogeneous sublots for ATP computation purposes. Then the model decides on the acceptance/rejection of customer order proposals and allocates the homogeneous ATP quantities of multiple products to the accepted multiple-line orders. It does not anticipate subtypes in sublots because customer orders only need serving with homogeneous units despite subtypes. Apart from the traditional objective of maximising profits, these authors implemented the maximisation of exhausted ATPs when allocating homogeneous ATP to customer orders. This model allows delays in deliveries, but not partial deliveries of order lines.

Finally, Alemany et al. [11] presented a fuzzy mixed-integer programming model to solve the SP problem in LHP contexts. This model considers uncertainty in the distribution of planned production lots in homogeneous sublots. The model reallocates both real and planned homogeneous quantities of products to already committed order lines. It considers multiple products and customer orders comprise more than one order line. The objective of this model is to maximise the profits made and it allows delays in deliveries, but not partial deliveries of order lines.

Although the above mathematical programming models are most valuable, they may require long computation times to optimally solve them when there are many numbers in the orders, products, subtypes and periods of time of the planning horizon. This can be particularly relevant for the SP problem for two reasons. During SP, all the previously committed orders by the company should be taken into account. This aspect implies problem size becoming very large. At the same time, as the time between the time of the real homogeneous quantities is known and the delivery of orders is very limited, methods are needed to provide a solution to the SP problem in a short time.

The theoretical framework used for the modelling and analyses in this research work is system dynamics [12,13]. In this paper, we propose a system dynamics approach, validated with an also novel MILP model, to overcome the above-cited drawbacks. To the best of our knowledge, no research proposes a simulation-based model to address the OP processing or SP problem. Our proposal also allows partial deliveries of order lines not previously addressed, which is the main novelty of the proposed MILP model. Besides its shorter computation times, simulation-based models can explain how process performance indicators react to changes in controllable factors or in the environment. Accordingly, managers can benefit from simulation models in several ways. They can contribute to: (i) study the system changes in the model; (ii) verify analytical solutions; (iii) provide a view about key variables and how they interact; (iv) experiment with new situations that involve risk or uncertainty; (v) test new policies and decision rules [14,15].We refer readers to Tako and Robinson [16] and to Jeon and Kim [17] for extensive reviews of simulation models applied to logistics, supply chains and to production planning and control contexts.

For this reason, the present article aims to design a system dynamics-based simulation model to support the SP process in the ceramic sector. The proposed solution is to reallocate homogeneous quantities of product to committed orders in order to optimise the company's objectives. To that end, this model considers not only the real homogeneous sublots of product in stock, but also the planned homogeneous sublots to be produced. It is important to highlight that as each homogeneous sublot is unique, sublots from different production lots cannot be combined to serve an order. When reallocating supply to customer orders, partial deliveries and/or some delays become flexible. The working basis of this simulation model is a mathematical programming model. Thus, analytical models offer optimum solutions, whereas simulation models: (i) reflect a suitable degree of realism and accuracy in describing the system; (ii) are capable of robustly and efficiently providing scenarios or what-if and sensitivity analyses [18-20]. All this provides a better evaluation and understanding of the problem under study.

The rest of the paper includes: Section 2 describes the problem. Section 3 presents the MP model, taken as a basis for reallocating real homogeneous stocks and planned homogeneous sublots to committed orders. Section 4 shows the simulation model devised for planning shortages in the ceramic sector. Section 5 describes the model's application, its validation in the ceramic sector, and analyses the results. Finally, Section 6 offers the obtained conclusions and the future research lines identified while conducting this work.

2 Description of the problem

As previously mentioned, this paper aims to provide solutions to the SP problem by reallocating (real and planned) available homogeneous quantities to already committed orders in the ceramic sector. LHP characterises the ceramic sector, which means that a particular production lot leads to units of the same product having different attributes. In this sector, such attributes are (i) quality, (ii) colour and (iii) calibre. Uncontrollable causes can be the reason for these products' heterogeneity, which are mainly the composition of raw materials and/or changes in the environment during production. This means that the available homogeneous quantities obtained from the MPS are not known with certainty until they have been manufactured and classified. At the same time, customers require homogeneity in the above-mentioned attributes for the product units that comprise each order line for aesthetic and assembly reasons.

During OP processing, customer orders are not only committed with the homogeneous quantities of product available in warehouses, but also with the planned homogeneous quantities that derive from the MPS. Therefore, it is necessary to initially estimate the distribution of lots into homogeneous sublots. Once production finishes, we can know the real distribution with certainty. Discrepancies between the estimated and real distribution of lots into homogeneous sublots can cause a shortage situation. As a result, it is not possible to serve some previously committed orders on the due date because there would be not enough homogeneous product. The SP intends to reallocate homogeneous quantities to orders to maximise the customer service level for the company as efficiently as possible.

It is necessary to consider the homogeneity attributes of products when following the SP process in ceramic companies because of having to serve customers not only with the agreed quantity and due date, but to also meet customers' homogeneity requirements.

We solve the SP process here by reallocating the real and planned products' homogeneous quantities to the previously committed orders that resulted from OP processing. This paper examines a company that works according to the following assumptions:

- The orders committed during OP processing can include one order line or more.
- For each order line, the customer specifies the required product and quantity to be served with homogeneous units.
- All the lines of the same customer order present the same due date, which coincides with the committed due date that results from OP processing.

- It is not possible to serve an order line through partial deliveries because it implies having to deliver all the quantity that comprises an order line during the same time period. Not serving an order line involves penalisation by rejecting costs.
- The model allows partial deliveries of complete order lines. It assumes that customers pick up their orders at the company and are in charge of the associated costs. For this reason, the number of partial deliveries does not affect the company's profit.
- If it is not possible to serve all the orders on the committed due date after the reallocation process, it contemplates a maximum delay allowed to deliver each order. Therefore, it is necessary to compromise the final delivery date of each customer order line between the interval defined by an earliest and latest due date where:
    - the earliest due date that a customer accepts a delivery is the committed due date provided by OP processing.
    - the latest due date that a customer accepts a delivery is the earliest due date, plus the maximum delays allowed for his/her order.

Figure 1 shows how the delivery terms are defined from the committed due date provided by the OP process (dd) and the maximum delay allowed for each order (maxd). This figure also shows how the homogeneous product allocated to a specific order is reserved until its committed due date. For example, if an order is to be served with product that is available before the order's due date, it is necessary to reserve (R) this product until the due date and to hold it in inventory until delivery (e.g. Orders 1 and 2 in Figure 1). In other cases, such as that represented in Order 3, the order is served with the product planned to be produced during the same or a later period to the committed due date. In these cases, the allocated product will not be reserved after production, but sent directly to the customer.

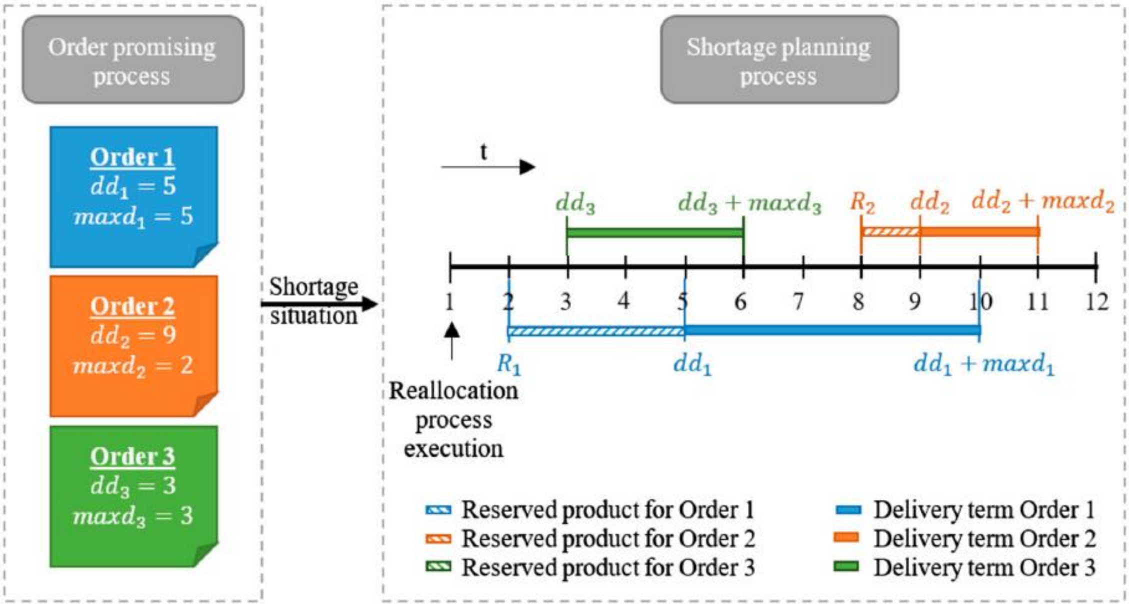

Figure 1. Delivery term definition.

To serve customer orders on time, prioritisation is possible by means of the maximum delays allowed: the shorter the maximum delays allowed for a customer order, the greater the priority of serving this order on the committed due date by OP processing.

- As the maximum allowed delays manage the priority of serving customers on time, it does not contemplate any penalty costs of late deliveries as regards the initial due date of OP processing.
- The homogeneous quantities of product available in stock are known. The model estimates the distribution of a production lot into different homogeneous sublots by the so-called coefficients of homogeneity. These coefficients represent the fraction of a lot considered homogeneous (i.e. of the same subtype).
- The company's objective is to maximise the profits calculated as the difference between the income from serving customer orders and the costs generated by rejecting and/or reserving products in advance to the committed due dates (holding costs).
- Economic data per product unit are known (profit, rejecting costs and holding costs).

3 MP model formulation

By following these assumptions, we propose a MILP model for reallocating available homogeneous quantities to committed orders. Table 2 presents the notation employed in the model.

The objective of the model, Equation (1), is to maximise profits, calculated as the difference between the income obtained when serving orders and the costs of rejecting orders and reserving quantities of product for future deliveries.

$$Max\ Profit = \sum_o \sum_k D_{ok} \cdot [p_k \cdot YK_{ok} - rc_k \cdot (1 - YK_{ok}) - hc_k \cdot AD_{ok}] \qquad (1)$$

Subject to:

$$A0_{ks} = stock_{ks} - \sum_o D_{ok} \cdot U0_{oks} \qquad \forall k, s \qquad (2)$$

$$A_{kst} = \beta_{ks} \cdot mps_{kt} - \sum_o D_{ok} \cdot U_{okst} \qquad \forall k, s, t \qquad (3)$$

$$\sum_s U0_{oks} + \sum_s \sum_t U_{okst} = YK_{ok} \qquad \forall o, k \qquad (4)$$

$$\sum_t DK_{okt} \cdot t \geq dd_o \cdot YK_{ok} \qquad \forall o, k \qquad (5)$$

$$\sum_t DK_{okt} \cdot t = dd_o \cdot YK_{ok} + LDK_{ok} \qquad \forall o, k \qquad (6)$$

$$LDK_{ok} \leq maxd_o \qquad \forall o, k \qquad (7)$$

$$\sum_t DK_{okt} \leq 1 \qquad \forall o, k \qquad (8)$$

$$AD_{ok} = \sum_t DK_{okt} \cdot t - \sum_s \sum_t U_{okst} \cdot t - \sum_s U0_{oks} \qquad \forall o, k \qquad (9)$$

$$\begin{aligned}&A0_{ks}, A_{kst} \quad Continuous\\&AD_{ok}, LDK_{ok} \quad Integer\\&YK_{ok}, DK_{okt}, U_{okst}, U0_{oks} \quad Binary\end{aligned} \tag{10}$$

Equation (2) calculates the uncommitted quantity of product k and subtype s available in stock after reallocating orders. This quantity equals the real stock of this product k and subtype s, minus the customer order lines served with this stock. Similarly, Equation (3) computes the uncommitted planned quantity of product k and subtype s available during period t after reallocating orders. This quantity equals the planned quantity of this product and the subtype to be produced during time period t, minus the customer order lines served with product k and subtype s through it. Equation (4) ensures serving each order line from a particular homogeneous quantity (subtype), while Equation (5) ensures serving an order if the delivery of all its order lines is complete. This means that it is not possible to serve only some order lines or part of the order line quantities. Moreover, Equations (5)–(7) guarantee that the delivery of an order line takes place within the date range specified by the committed due date and the maximum delay allowed. Equation (8) indicates serving an order line only during one time period. Equation (9) determines which products are reserved during the time periods until their delivery date. Finally, Equation (10) defines the nature of each variable by distinguishing among binary, continuous or integer variables.

Table 2. Nomenclature for the MP model

Indices	
o	Overall committed customer orders
k	Finished products required in the committed orders
s	Existing subtypes of all the finished products in the committed customer orders
t	Time periods
Parameters	
D_{ok}	Quantity of product k demanded in customer order o
p_k	Per unit price of product k
rc_k	Per unit reject cost of product k
hc_k	Per unit inventory holding costs of product k
$stock_{ks}$	Total available stock of subtype s of product k
mps_{kt}	Planned quantity of product k which becomes available during time period t
nl_o	Number of order lines in customer order o
dd_o	Committed due date of customer order o
$maxd_o$	Maximum delay allowed for customer order o in relation to the committed due date
β_{ks}	Fraction of each lot of product k of subtype s
Decision variables	
$A0_{ks}$	Uncommitted available quantity of subtype s of product k after the reallocation process
A_{kst}	Uncommitted available quantity of subtype s of product k derived from pskt after the reallocation process
$U0_{oks}$	It identifies if the requested quantity of finished product k in customer order o is completely served by the uncommitted stock with subtype s
U_{okst}	It identifies if the requested quantity of finished product k in customer order o is completely served by the uncommitted planned product in mpskt
YK_{ok}	It identifies if the order line of customer order o that corresponds to finished product k is completely served
AD_{ok}	Number of time periods where the required quantity of product k in customer order o is reserved until its delivery
LDK_{ok}	Number of time periods of delay in delivering product k in customer order o in relation to committed due date ddo
DK_{okt}	It identifies if finished product k in customer order o is served during time period t

4 SD model formulation

In order to develop the system dynamics model to reallocate available homogeneous products to committed orders, we used the following methodology: (i) propose the casual-loop diagram; (ii) create the flow chart that represents the process; (iii) generate the equations that define the system dynamics model's behaviour; (iv) validate and perform the system dynamics model to evaluate the what-if scenarios and sensitivity analyses.

The causal-loop diagram (Figure 2) shows the cause–effect relations between the different system elements, which help to understand them and to subsequently draw the flow chart of the inventory reallocation model. Arrows depict these relations. Arrows take a positive sign if the two variables are directly proportional, namely a change in the origin variable leads to a change in the destination variable in the same sense. An arrow relates elements, otherwise the relation between the two variables is inversely proportional and the arrow takes a negative sign.

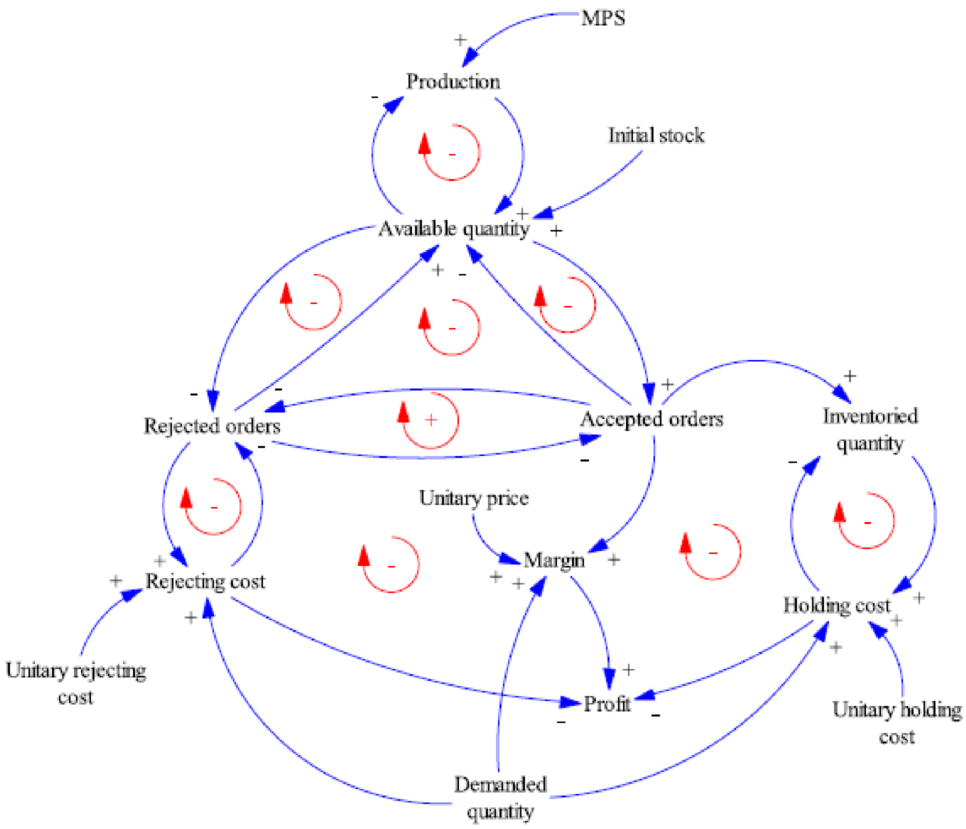

Figure 2. The casual-loop diagram of the reallocation process.

As the causal-loop diagram shows, the quantity planned to be produced in the MPS determines production. The produced quantities form part of the available quantity of product, which demonstrates their positive relation. Whenever any simulation of this system starts, a quantity of available product remains in the warehouse that comprises the initial stock. So the larger the initial stock, the more the available quantity.

In the process followed to reallocate available quantities to committed orders, we see that the relation between the available quantities of product and accepted orders is positive (the bigger the quantity of available product, the more committed orders served), while the relation between the available quantities of product and orders rejected is negative (the bigger the quantity of available product, the fewer committed orders rejected). We can also read these relations in the reverse sense; the more committed orders served, the smaller quantity of remaining available product. Similarly, the more orders rejected, the bigger the quantity of remaining available product. A relation exists between the accepted and rejected orders since the accepted quantity of orders increases when the rejected quantity of orders reduces, which establishes a negative relation. Moreover, when the quantity of accepted committed orders increases, it is necessary to reserve a bigger quantity of product beforehand until the committed due date of the order.

Regarding margin, we observe that the number of served orders and the quantity of products demanded in such orders have a positive impact on the margin to be obtained. The margin is also directly proportional to the unitary price of each product. Similarly, the costs of rejecting orders increase when the unitary costs of rejecting a product rise, and also with the number of rejected orders and the quantity of demanded products in such orders.

The holding costs derive from reserving MPS quantities of product until their due date. Holding costs may be null if the intended quantity of product to serve a particular order proceeds from the MPS that corresponds to the time period which coincides with customers' due dates. Similarly, holding costs may be null when serving the customer order with a delay. Therefore, holding costs increase with the quantity of reserved products, and also with the unitary holding cost per product.

Finally, the company's total profit increases when the obtained margin goes up. In turn, the total profit goes down when the costs from rejecting orders or from storing a reserved product increase.

The closed chains of the relations between variables results in loops, which can be positive or negative. Negative loops act like system stabilisers as they lead the system to a specific objective. However, positive loops have the opposite effect on the system. The dominance of negative or positive loops determines the system's final performance. In this case, the causal-loop diagram shows that the system is hyperstable as the vast majority of its loops (all except one) are negative. With the causal-loop diagram, one can develop a flow chart or a Forrester diagram. This diagram represents the system under study and allows the simulation of the SP problem. For this purpose, we first identified the level, flow and auxiliary variables needed to define the Forrester diagram. Table 3 offers the notation and respective units of measure, where index o refers to the customer order, index k denotes the product and index s represents the product subtype.

Figure 3 depicts the flow chart of the inventory reallocation model that adapts to the real system. This model is good for running experiments to study the system's performance in different scenarios. The Vensim® simulation software implements the model. To this end, we design the equations that define the performance of each level and flow variable, and we assign the values that correspond to the auxiliary variables.

We now go on to briefly describe the notation employed to represent the model:

- The flow variables notation is accompanied by (t), which denotes that the value of such variables depends on each time period.
- Level variables represent the addition or subtraction of different flow variables over time, represented in this notation by the integral, from the beginning of the simulation to the corresponding period of time, of the addition or subtraction of flow variables. The level variables notation comes with (t), which denotes that the value of such variables depends on each time period.

- We use nested braces to represent ‘if…then…else’ decisions. It is possible to concatenate several ‘if…then…else’ decisions by representing a nested brace inside another nested brace.

Table 3. Nomenclature

Level variables	
AQW_{ks}	Available quantity of finished product k and subtype s (m^2)
RQW_{ok}	Reserved quantity of finished product k to serve customer order o on its committed due date dd_o (m^2)
D_{ok}	Quantity of product k demanded in customer order o
DS_k	Total quantity of demand of product k served to customers (m^2)
DR_k	Total quantity of demand of product k rejected to customers (m^2)
COL_{ok}	Committed order lines during the OP process (Dmnl)
AOL	Total number of accepted order lines during the inventory reallocation process (Dmnl)
POL	Total number of rejected order lines during the inventory reallocation process (Dmnl)
P	Total profit (€)
HC	Total holding cost of reserved quantities (€)
RC	Total rejecting cost (€)
Flow variables	
AQ_{ks}	Available quantity of product k and subtype s during each time period (m^2/week)
RQ_{oks}	Reserved quantity of finished product k and subtype s during each time period to serve customer order o on its committed due date dd_o (m^2/week)
SQ_{ok}	Served quantity of finished product k to customer order o during each time period (m^2/week)
SQ'_{oks}	Served quantity of finished product k with subtype s to customer order o during each time period (m^2/week)
DQ_{ok}	Demanded quantity of product k in a customer order o during each time period (m^2/week)
RD_{ok}	Rejected demand of product k in a customer order o during each time period (m^2/week)
SD_{ok}	Served demand of product k in a customer order o during each time period (m^2/week)
AL_{ok}	Identifies if the delivery of product k of order o is accepted during a time period (Dmnl/week)
RL_{ok}	It identifies if the delivery of product k of order o is rejected during this time period (Dmnl/week)
WM	Total margin obtained during each time period (€/week)
WHC	Total holding cost of the quantities reserved during each time period (€/week)
WRC	Total rejecting cost during each time period (€/week)
Auxiliary variables	
β_{ks}	Coefficient of homogeneity or percentage of a lot of product k which will be subtype s after production (Dmnl)
mps_k	Planned quantity of finished product k (m^2)
$prod_{ks}$	Produced quantity of finished product k with subtype s (m^2)
$stock_{ks}$	Total available stock of subtype s of finished product k (m^2)
dem_{ok}	Quantity demanded of product k by customer order o (m^2)
dd_o	Committed due date of customer order o (week)
$maxd_o$	Maximum delay allowed for customer order o related to the committed due date dd_o (week)
hc_k	Inventory holding costs per unit of product k and time period (€/m^2/week)
rc_k	Rejecting cost per product k unit (€/m^2)
p_k	Price per product k unit (€/m^2)
AQA_{oks}	Identifies if an order o is committed with a certain product k and subtype s (Dmnl)

This model’s performance commences as follows: when simulation starts, the only available quantities of product are those that comprise the initial stock. During the following time periods, homogeneous quantities of product become available when produced. The quantities of product planned in the MPS define production, as does the coefficient of homogeneity that defines the homogeneity between manufactured product units.

A set of committed orders is known at the beginning of simulation. The model has information about the products demanded in each order, the demanded quantities, the agreed due date and the maximum delivery delays allowed. No order line is served or rejected during the first time period.

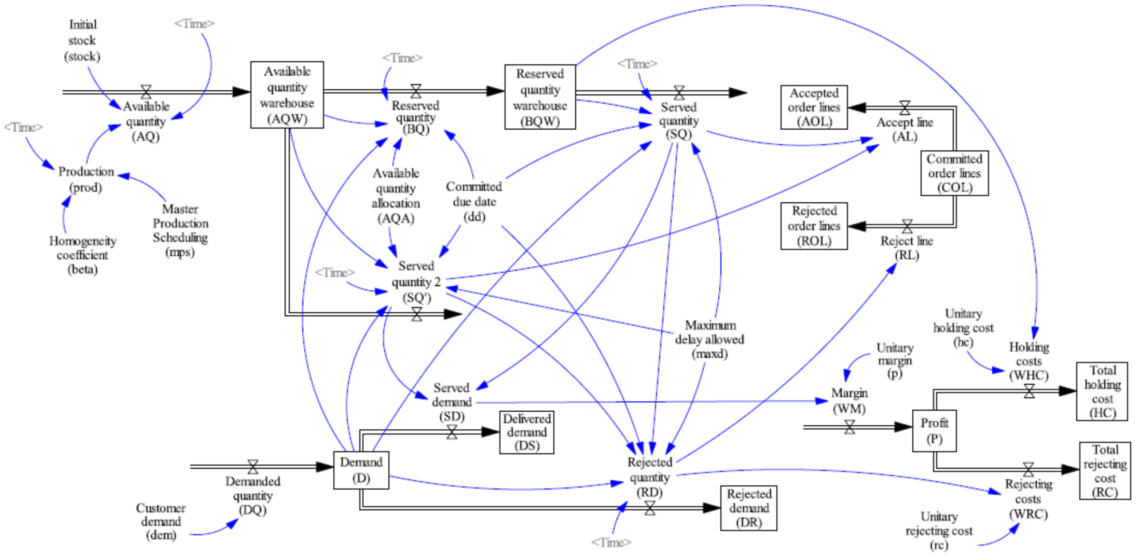

Figure 3. Flow chart of the reallocation process

For each order line and during each time period, the model verifies if it is necessary to serve each one with a particular available amount of product by defining the homogeneous subtype. If the current time period comes before the agreed due date during this allocation, it is necessary to reserve these quantities until the due date. If the current time period equals or is later than the due date, it is necessary to check if the maximum delays allowed has been exceeded. If this were the case, it is necessary to reject the customer order line, otherwise we must directly serve the customer order line.

At the same time, we need to update the counters for the number of accepted or rejected committed order lines as their demand is accepted or rejected. Similarly, we update the economic data during simulation to obtain the total profit made by the company.

More details about the model's performance are available with the explanation of the equations that comprise it. Although Equations (12)–(24) determine the system's performance, the other equations are useful for analysing this performance. Equation (12) defines the quantity of product to be produced during each time period, calculated by multiplying the quantity of product planned to be produced in the MPS for each time period and the homogeneity coefficient. This coefficient characterises the distribution of a production lot into homogeneous sublots.

$$prod_{ks} = mps_k \cdot \beta_{ks} \tag{12}$$

Equation (12) calculates the value for flow variable AQ_{ks} for each time period.

$$AQ_{ks}(t) = \begin{cases} stock_{ks}, & if\ t = 0 \\ prod_{ks}, & otherwise \end{cases} \qquad \forall k, s \tag{13}$$

We used level variable AQW_{ks} to know the exact units of each product and each subtype available per time period. This acts as a virtual warehouse of available quantities because it does not really exist but displays the same performance as a real warehouse. Equation (14) defines AQW_{ks} as the available quantities that arrive at the virtual warehouse, minus the quantities used to serve or reserve orders.

$$AQW_{ks}(t) = \int_{t_0}^{t} \left[AQ_{ks}(t) - \sum_{o} \left(RQ_{oks}(t) + SQ'_{oks}(t) \right) \right] dt; \qquad AQW_{ks}(t_0) = 0 \quad \forall k,s \tag{14}$$

We include variable AQA_{oks} for its use while validating the model by detailing which order is to be served and with which product and subtype.

Variable SQ'_{oks}represents the quantity of product with a specific subtype, served directly from the available quantities in the virtual warehouse. We can serve a quantity directly if the current time period equals or comes after the agreed due date. We calculate flow variable SQ'_{oks} as indicated in Equation (15).

$$SQ'_{oks}(t) = \begin{cases} if\ t \geq dd_o \begin{cases} if\ AQA_{oks} = 1 \begin{cases} D_{ok}(t), & if\ AQW_{ks}(t) \geq D_{ok}(t) \\ 0, & otherwise \end{cases} \\ 0, \quad otherwise \end{cases} \\ 0, \quad otherwise \end{cases} \qquad \forall o,k,s \tag{15}$$

Equation (16) represents the reserve of a quantity of product with a specific subtype to serve a particular order on its due date, RQ_{oks}. It is only possible to reserve a quantity to serve an order if the current time period comes before the agreed due date.

$$RQ_{oks}(t) = \begin{cases} if\ t < dd_o \begin{cases} if\ AQA_{oks} = 1 \begin{cases} D_{ok}(t), & if\ AQW_{ks}(t) \geq D_{ok}(t) \\ 0, & otherwise \end{cases} \\ 0, \quad otherwise \end{cases} \\ 0, \quad otherwise \end{cases} \qquad \forall o,k,s \tag{16}$$

Equation (17) defines RQW_{ok} as the reserved quantities that arrive from the virtual warehouse of available quantities, minus the quantities used to serve orders.

$$RQW_{ok}(t) = \int_{t_0}^{t} \left[\sum_{s} RQ_{oks}(t) - SQ_{ok}(t) \right] dt; \quad RQW_{ok}(t_0) = 0 \qquad \forall o,k \tag{17}$$

Variable SQ_{ok} represents the quantity of product served to customers after being reserved for one time period or more. We can only serve a quantity if the current time period equals or comes after the agreed due date. We define SQ_{ok} as stated in Equation (18).

$$SQ_{ok}(t) = \begin{cases} if\ RQW_{ok}(t) = D_{ok}(t) \begin{cases} if\ t \geq dd_o \begin{cases} D_{ok}(t), & if\ t \leq dd_o + maxd_o \\ 0, & otherwise \end{cases} \\ 0, \quad otherwise \end{cases} \\ 0, \quad otherwise \end{cases} \qquad \forall o,k \tag{18}$$

Note that both variables SQ'_{oks} and SQ_{ok}indicate the quantity of products that we must serve to customers during each time period. However, these variables are not the same. When talking about variable SQ'_{oks}, we directly serve orders from the available product quantities. However when we refer to variable SQ_{ok}, we first reserve the product quantities to serve each order until their due date, and then we serve these products.

Equation (19) assigns the quantities demanded for each order and the particular product to variable DQ_{ok} .

$$DQ_{ok}(t) = dem_{ok} \qquad \forall o,k \tag{19}$$

Flow variable RQ_{ok} represents the quantity of rejected product during each time period per order. Equation (20) determines that, if the demand of a product in a particular order exceeds zero, then we must check if the current time period equals the last time period of the simulation horizon. If this condition is met, demand is rejected if it is not served during this time period. However, if the current time period does not equal the last time period of the simulation horizon, and is less than or equals the agreed due date, plus the maximum delays allowed, demand is also rejected.

$$RD_{ok}(t) = \begin{cases} if\ D_{ok}(t) > 0 \begin{cases} if\ t = T \begin{cases} D_{ok}(t), & if\ \left[SQ_{ok}(t) + \sum_s SQ'_{oks}(t)\right] = 0 \\ 0, & otherwise \end{cases} \\ otherwise \begin{cases} 0, & if\ t \le dd_o + maxd_o \\ D_{ok}(t), & otherwise \end{cases} \end{cases} \\ 0, \quad otherwise \end{cases} \quad \forall o, k \tag{20}$$

Flow variable SD_{ok} determines the quantity of product served to customers during each time period per order. We calculate the served demand presented in Equation (21) as the sum of both variables, and show the served quantities of product per order (SQ'_{oks} and SQ_{ok}).

$$SD_{ok}(t) = SQ_{ok}(t) + \sum_s SQ'_{oks}(t) \qquad \forall o, k \tag{21}$$

We employ level variable D_{ok} to know the existing demand of products during each time period. Equation (22) defines D_{ok} as the new demand that arrives during each time period, minus the rejected and served demands for each time period.

$$D_{ok}(t) = \int_{t_0}^{t} [DQ_{ok}(t) - RD_{ok}(t) - SD_{ok}(t)]\, dt; \quad D_{ok}(t_0) = 0 \qquad \forall o, k \tag{22}$$

We use the level variable called DS_k to control the total quantity of the demanded product served to customers (23).

$$DS_k(t) = \int_{t_0}^{t} \left[\sum_o SD_{ok}(t)\right] dt; \quad DS_k(t_0) = 0 \qquad \forall k \tag{23}$$

Similarly, we employ the level variable called DR_k to control the total quantity of rejected demanded product (24).

$$DR_k(t) = \int_{t_0}^{t} \left[\sum_o RD_{ok}(t)\right] dt; \quad DR_k(t_0) = 0 \qquad \forall k \tag{24}$$

Equations (25)–(29) establish the control of the number of served/rejected order lines. Flow variable AL_{ok} determines the time period when an order line has been accepted/served, as shown in Equation (25).

$$AL_{ok}(t) = \begin{cases} 1, & if\ SQ_{ok}(t) > 0 \\ otherwise & \begin{cases} 1, & if\ \sum_s SQ'_{oks}(t) > 0 \\ 0, & otherwise \end{cases} \end{cases} \qquad \forall o, k \tag{25}$$

Flow variable RL_{ok} determines the time period o when an order line is rejected, as shown in Equation (26).

$$RL_{ok}(t) = \begin{cases} 1, & if\ RD_{ok}(t) > 0 \\ 0, & otherwise \end{cases} \qquad \forall o, k \tag{26}$$

At the start of simulation, we commit all the known order lines, and the value of binary variable COL_{ok} equals one for all the existing orders and order lines. As shown in (27), this variable takes a value that equals zero when an order line is rejected or served.

$$COL_{ok}(t) = \int_{t_0}^{t} -[AL_{ok} + RL_{ok}]\, dt; \quad COL_{ok}(t_0) = 1 \qquad \forall o, k \tag{27}$$

Level variables AOL and ROL are useful for measuring the total number of accepted or rejected order lines, respectively. Equation (28) shows how the total number of accepted order lines equals those per time period. Similarly, Equation (29) indicates that the total number of rejected order lines equals these per time period.

$$AOL(t) = \int_{t_0}^{t} \left[\sum_{o} \sum_{k} AL_{ok}(t) \right] dt; \quad AOL(t_0) = 0 \tag{28}$$

$$ROL(t) = \int_{t_0}^{t} \left[\sum_{o} \sum_{k} RL_{ok}(t) \right] dt; \quad ROL(t_0) = 0 \tag{29}$$

Equations (30)–(35) provide the economic results obtained during simulation. Equation (30) defines the margin obtained by serving customer orders during each time period. This we calculate as the total demand served per unitary price of each product type.

$$WM(t) = \sum_{o} \sum_{k} SD_{ok}(t) \cdot p_k \tag{30}$$

Equation (31) defines the holding costs of reserving products allocated to order lines until their due date per time period.

$$WHC(t) = \sum_{o} \sum_{k} RQW_{ok}(t) \cdot hc_k \tag{31}$$

Equation (32) defines the rejection costs obtained by rejecting customer orders during each time period.

$$WRC(t) = \sum_{o} \sum_{k} RD_{ok}(t) \cdot rc_k \tag{32}$$

Profit (P) is the level variable to maximise, which we calculate as shown in Equation (33).

$$P(t) = \int_{t_0}^{t} [WM(t) - WHC(t) - WRC(t)]\, dt; \quad P(t_0) = 0 \tag{33}$$

Finally, Equations (34) and (35) present the total holding costs and the total rejecting costs.

$$HC(t) = \int_{t_0}^{t} [WHC(t)]\, dt; \quad HC(t_0) = 0 \tag{34}$$

$$RC(t) = \int_{t_0}^{t} [WRC(t)]\, dt; \quad RC(t_0) = 0 \tag{35}$$

Moreover, we identify the key element of this system's performance and, therefore, the element on which improvement proposals focus, as variable AQA_{oks} because this variable determines which order lines we serve and which product subtypes we can serve these lines with. This decision conditions the system's performance for several reasons, which depend on: (i) the rule used to reallocate the available quantities to committed orders, when we can serve more or fewer order lines; (ii) if we accept order lines, we can make more or less profit (this also implies a higher or lower cost of rejecting order lines); (iii) the product subtype chosen to serve an order line allows us to serve this order line with or without delay; (iv) with the product subtype chosen to serve an order line, we can serve more or fewer orders because of homogeneity requirements.

5 Applying the system dynamics model

We employed data based on a real Spanish ceramic company's problem to define the different types of variables. We also considered the assumptions set out below while simulating the model:

- The simulation run length is the equivalent to 12 time periods, where each time period represents 1 week.
- The company's objective consists in maximising the profits made after reallocating the available quantities to previously committed orders.
- We contemplate 35 orders made up of 10 order lines with 10 different products.
- Each order line requires a quantity of between 20 and 4000 m2 of the final product, and the total demand is approximately 52,200 m2 of the product.
- When simulation commences, we know the product quantity available in the warehouse, which we classify according to the homogeneous subtype to which it belongs.
- We cannot classify the quantities planned in the MPS into homogeneous sublots before they are manufactured. In this case, we estimate the distribution of a lot into homogeneous subtypes according to probabilistic distributions.
- The customer requires homogeneity among all the units that each particular order line comprises.
- We need to serve customers' orders within the time interval defined by the committed due date during OP processing, and the maximum delay detailed by the customer.
- The customer allows us to make the same number of deliveries as the number of lines that the order includes. However, partial deliveries of order lines are not possible.

Table 4 presents the economic data per unit of each product.

Table 4. The economic data of each product

Final product (k)	Unitary margin (p_k)	Unitary rejecting cost (rc_k)	Unitary holding cost (hc_k)
1	7.00	5.25	0.064
2	18.00	13.50	0.052
3	12.00	9.00	0.040
4	10.00	7.50	0.036
5	5.00	3.75	0.036
6	11.00	8.25	0.052
7	13.00	9.75	0.040
8	12.00	9.00	0.036
9	6.00	4.50	0.052
10	15.00	11.25	0.045

We also set the initial value for level variable COL_{ok} to 1, while the rest of the level variables take a null initial value.

5.1 Validation

We ran several of the tests proposed by Sterman [13] to validate the contemplated model. The first one was the dimensional consistency test, which checks that the measure units employed in the model are correct. Secondly, we ran the reproduction test of known performances. The computer used to solve the models has an Intel® Xeon® CPU E5-1620 v2© 3.70 GHz processor, with an installed capacity of 32 GB and a 64-bits operating system.We achieved the results obtained by mathematical programming with the MPL® tool and solver Gurobi™ 6.0.4, and we ran simulation in Vensim®.We used the same input data for both tests. Moreover in the simulation model, auxiliary variable Available quantity allocation (AQA_{oks}) indicated which subtype we must serve each order line with. Afterwards, we obtained the results that appear in Table 5, which we used to validate the model. Thirdly, we ran an extreme-conditions test in two situations: no existing demand and no existing production.

Table 5. Comparison of mathematical programming and system dynamics results (35 orders)

Variable	Mathematical programming	System dynamics
AOL	286	286
ROL	64	64
HC	1,981.38 €	1,981.00 €
RC	171,233.25 €	171,200.00 €
$\sum_t WM$	308,561.00 €	308,554.00 €
P	135,346.37 €	135,300.00 €
Resolution time	33.18 s	38 s

We carried out another test to compare the results obtained by the mathematical programming and the system dynamics models. The intention of this test was to compare their performance for larger problems. For this case, we contemplated 70 orders and we duplicated the data about the MPS and initial stocks. The results (Table 6) show that the mathematical programming model needs almost 10 hours to provide a solution, whereas the system dynamics model instantaneously provides a solution.

Table 6. Comparison of mathematical programming and system dynamics results (70 orders)

Variable	Mathematical programming	System dynamics
AOL	578	578
ROL	122	122
HC	2,500.5 €	2,496 €
RC	330,598.5 €	330,600 €
$\sum_t WM$	632,946 €	642,946 €
P	299,847 €	299,850 €
Resolution time	9 h 13 min 20 s	40 s

The mathematical programming model was also solved for an instance of data comprised by 140 orders. In this case, a near-optimum solution was found in 48 h, with a GAP of 0.17%. This GAP represents the difference between the best solution found and the best bound one. However after a 96-h execution, the GAP did not decrease. The computational results showed how the time needed to solve the MILP model increased with the number of already committed orders.

5.1.1 Sensitivity analysis

With the sensitivity analysis, we examined the model's performance by modifying the values assigned to its constant parameters. In this model, one parameter in particular can substantially change the model's performance, which can actually imply a certain degree of uncertainty. This parameter is bks, which represents the distribution of a lot into homogeneous sublots. We carried out a Monte Carlo sensitivity analysis on this parameter, where we assigned the distribution function to follow, as well as its minimum and maximum values. We studied the effects that these changes had on the Profit (Figure 4) and Accepted Order Lines (Figure 5) level variables. It is important to note that the first 4 weeks belonged to the warm-up simulation period. As we contemplated only 13 time periods, we did not achieve the steady state with the Profit level variable because the profit calculations were higher than the costs on the simulation horizon. Nevertheless the average profit reached the steady state, as shown in Figure 6. As Accepted Order Lines was a level variable, it accumulated the accepted orders without reaching a steady state. Figure 7 presents the average Accepted Order Lines where the steady state is reached.

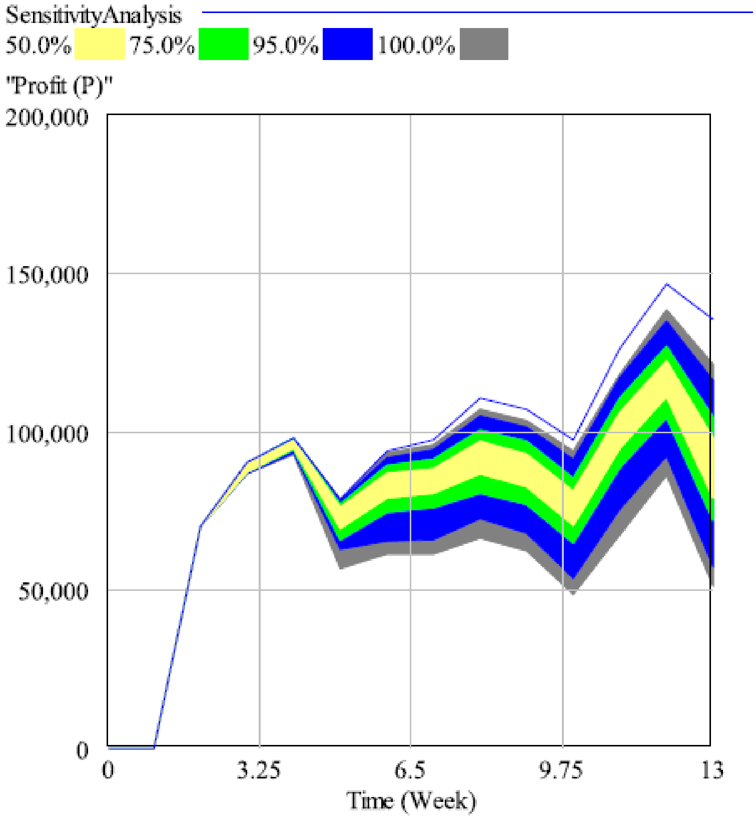

Figure 4. Profit. Sensitivity analysis

Considering that a robust model maintains a fixed design and still accommodates plenty of changes in uncontrollable environmental factors, we were able to ensure the model's robustness as the decision made about product allocation to orders was limited. We verified this robustness when we observed that the values obtained by a sensitivity analysis for the studied level variables were lower than those initially obtained. This was because not enough homogeneous product was available when assigning the different values to the homogeneity coefficient to serve some order lines that could be served beforehand. Thus we made less profit and served fewer order lines, which were the results that we expected with the model. Although we carried out other sensitivity tests with several parameters (maximum deliveries allowed, initial stock, etc.), we concluded that they had no significant effect on the model, and the homogeneity coefficient had the strongest impact on LHP. Due to space requirements, we do not provide these sensitivity analyses here.

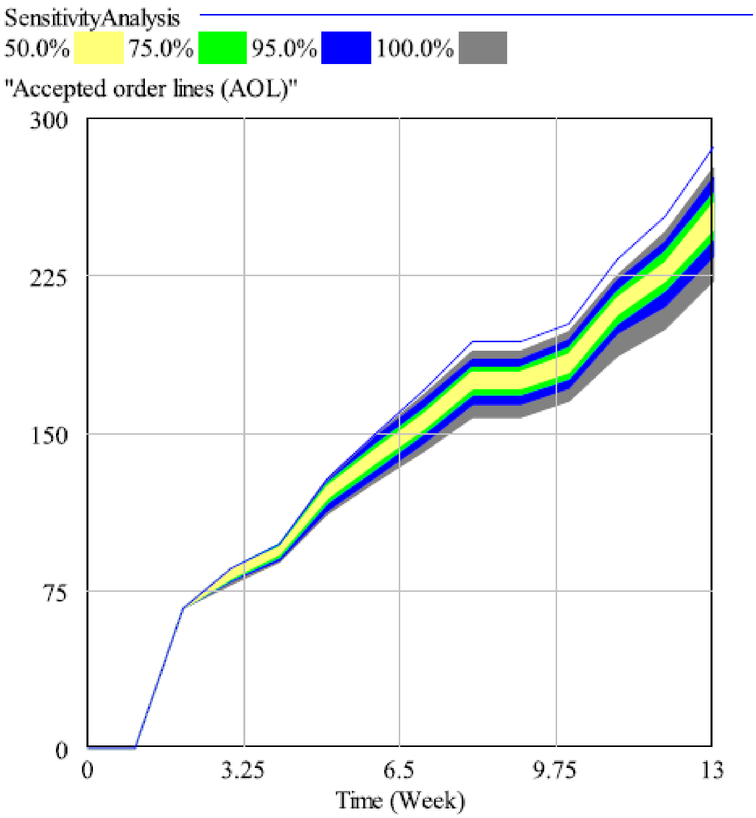

Figure 5. Accepted order lines. Sensitivity analysis

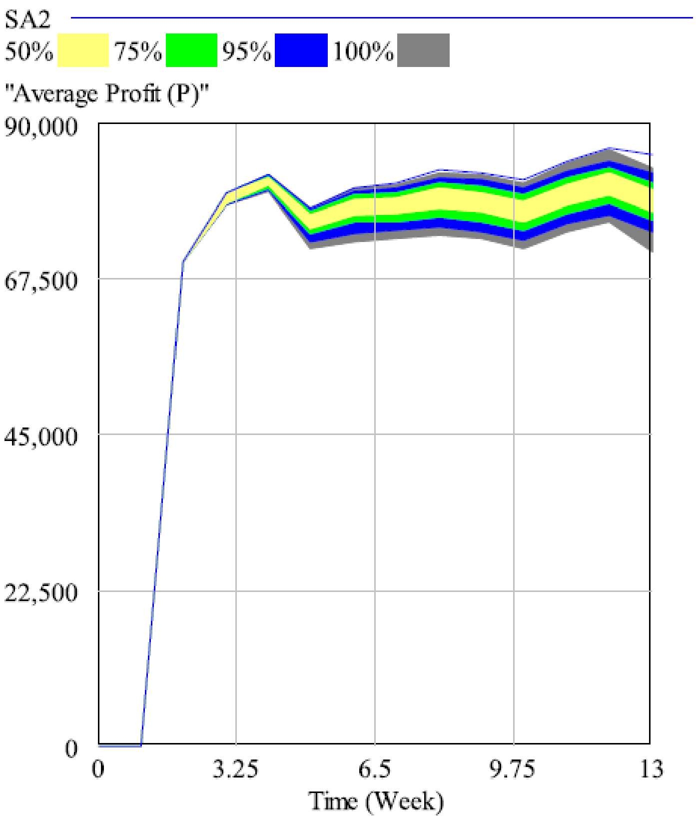

Figure 6. Average profit. Sensitivity analysis

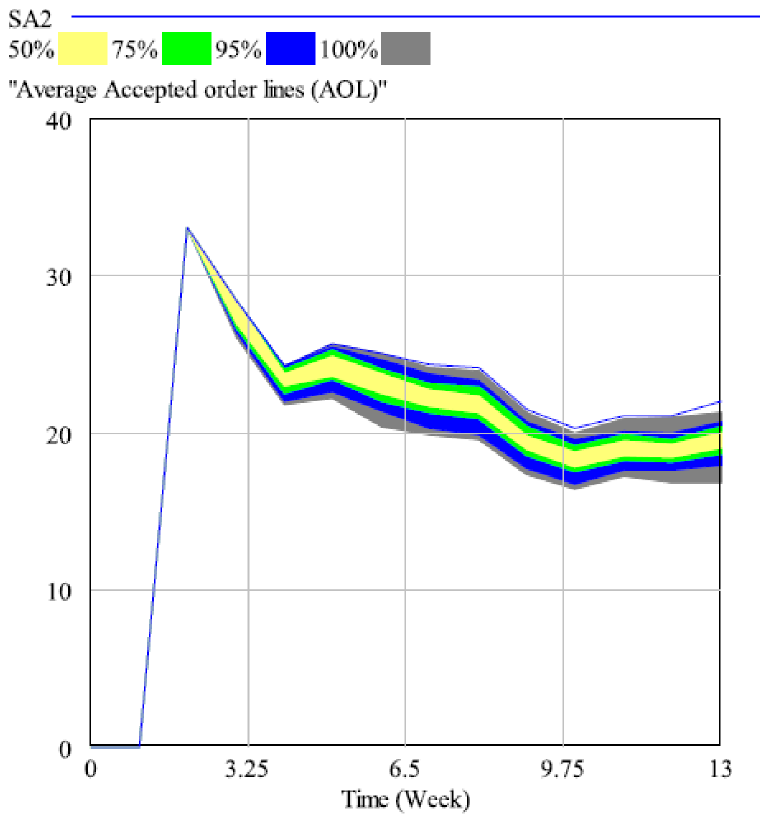

Figure 7. Average accepted order lines. Sensitivity analysis

5.2 Simulating scenarios

We proposed a series of scenarios that intend to improve the method, according to which we allocated the available quantities to previously committed orders. Up to this point, we did this with auxiliary variable AQA_{oks}, which we deleted from the model and we used a different method to allocate the available quantities to committed orders. In Scenario 1, we considered serving the committed by the available quantities. This meant reserving no product quantities and, therefore, holding costs always equalled zero.

Flow variable SQ'_{oks} defines the relation between the available quantities of homogeneous product and committed orders. So we need to reformulate the equation that determines this variable's performance. During the reallocation process, we made the decisions presented in (36): if the current period comes before the due date, we do not serve the order line. However, if the current time period comes after the range of dates defined by the committed due date and the maximum deliveries allowed, then we do not serve the order line. If we have already served this order line during the same period of time, but with a different homogeneous subtype, we cannot serve the order line. If the available quantity of product is greater than or equals the sum of the order line demand, plus the quantity of available product destined to serve other orders, then we serve the order lines with the product that has this homogeneous subtype.

$$SQ'_{oks} = \begin{cases} if\ t \geq dd_o \begin{cases} if\ t \leq dd_o + maxd_o \begin{cases} 0, & if \sum_{s'}^{s} SQ'_{oks'}(t) > 0 \\ otherwise \begin{cases} D_{ok}, & if\ AQW_{ks}(t) \geq D_{ok}(t) + \sum_{o'}^{o} SQ'_{o'ks}(t)\ \forall o,k,s \\ 0, & otherwise \end{cases} \end{cases} \\ 0, \quad otherwise \end{cases} \\ 0, \quad otherwise \end{cases} \tag{36}$$

This equation must represent each order, product and subtype and 1260 equations (35 orders · 10 products · 36 subtypes) constitute flow variable SQ'_{oks}.

Based on the system considered in Scenario 1, we ran two experiments in which the company's policies about delivering orders changed. Scenario 2 contemplates what would happen if the company did not allow delays in order deliveries. Scenario 3 recreates a situation in which there is no maximum allowable delay, orders can be served until the end of the simulation horizon. The intention of these scenarios is to assess the influence that flexibility in deliveries would have on the assessed system.

Subsequently, we proposed three experiments in which the homogeneity coefficient (distribution of a production lot into homogeneous sublots) changed. For this purpose, the values assigned to auxiliary variable bks vary. We considered each production lot to be divided into three homogeneous sublots. Then we defined the homogeneity coefficient as β_{ks} = β_{k1}–β_{k2}–β_{k3}, where β_{k1}, β_{k2} and β_{k3} are the proportion of the production lot classified as homogeneous subtypes 1, 2 or 3, respectively. In Scenario 1, we divided each production lot into three unbalanced homogeneous sublots, and by following distribution β_{ks} = 0.7–0.2–0.1 in Scenario 4, we obtained a single homogeneous lot after production (β_{ks} = 1.0– 0.0–0.0). In Scenario 5, we obtained two balanced homogeneous sublots with a production lot (β_{ks} = 0.5–0.5–0.0) and, to finish, we obtained three unbalanced homogeneous sublots in Scenario 6 with the production lot with distribution β_{ks} = 0.4–0.3–0.3. These scenarios assessed the influence of LHP on the process of reallocating available quantities to committed orders.

5.3 Assessing the results

For each scenario, we analysed the maximum deliveries allowed in deliveries ($maxd_o$), the number of order lines accepted and rejected, and the economic results comprised of the total rejecting costs, total margin and total profit made. Table 7 offers the results obtained after running the simulations which correspond to the first, second and third scenarios. We designed this set of scenarios to assess the effect of flexibility on the deliveries of orders.

These results reveal that the greater the flexibility allowed in order deliveries, the better the obtained results. Scenario 1 allows a maximum delay of two time periods per order. Here the profit made duplicate the results obtained by Scenario 2, which allows no delays. Moreover, the delay allowed in Scenario 1 enables us to serve 29 more order lines than when not permitting delays. From the results obtained in Scenario 3, which set no limit to the time in which to make deliveries, we serve even more order lines (39 more than in Scenario 1). Therefore, we conclude that the results considerably improve by allowing flexibility when delivering orders.

Table 8 presents the results obtained for the scenarios that assess system performance when making changes to the homogeneous sublots obtained with each production lot.

Table 7. Results of the scenarios with flexibility in deliveries

Variable	Scenario 1	Scenario 2	Scenario 3
$maxd_o$	2 time periods	0 time periods	unlimited
AOL	316	287	326
ROL	34	63	24
RC	149,600 €	189,974 €	116,051 €
$\sum_t WM$	337,468 €	283,573 €	382,138 €
P	187,900 €	93,599 €	266,087 €

AOL: order lines accepted; ROL: order lines rejected; RC: rejecting cost; $\sum_t WM$: total margin; P: total profit obtained.

Table 8. Results of the scenarios with homogeneity in distribution

Variable	Scenario 1	Scenario 4	Scenario 5	Scenario 6
β_{ks}	0.7-0.2-0.1	1.0-0.0-0.0	0.5-0.5-0.0	0.4-0.3-0.3
AOL	316	328	322	310
ROL	34	22	28	40
RC	149,571 €	127,544 €	137,185 €	168,613 €
$\sum_t WM$	337,468 €	366,813 €	353,959 €	312,055 €
P	187,873 €	239,269 €	216,774 €	143,442 €

AOL: order lines accepted; ROL: order lines rejected; RC: rejecting cost; $\sum_t WM$: total margin; P: total profit obtained.

From the obtained results, we conclude that we can serve more order lines when homogeneous sublots include a bigger lot fraction. This positively affects the profits made as we reject fewer orders, and we obtain a higher margin for the served products. Additionally, readers are referred to the following url to open with Vensim® the simulation model as a published version at:

http://www.cigip.upv.es/docs/2017_IJPR_Esteso_et_al_Publish.vpm

6 Conclusions

This article presents a system dynamics model for the SP process in the ceramic sector based on reallocating stocked and planned available quantities to previously committed orders. This model considers partial deliveries of order lines and the customer's requirement of homogeneity among the units that comprise an order line, which makes the task of serving orders even more difficult. A mathematical programming model with the same purpose is proposed and used to validate the systems dynamics model. The comparison made between both models shows that the systems dynamics model performs better as the number of orders increases with near-optimum solutions in a very short time.

Once the system dynamics model validation was proved, different what-if scenarios were simulated to assess the system's real performance in such a scenario. For this purpose, the number of order lines accepted/rejected and economic results were analysed. Firstly, a new policy for the reallocation process based on serving orders with the older available quantity that meet customers' requirements was defined. This policy was used for all the following scenarios. Secondly, we compared the system's performance when changing the maximum delay allowed per order. Here we found that more orders could be served with increasing flexibility in deliveries. Finally, we generated three scenarios to verify the system's performance in light of the different distributions of a production lot into different homogeneous sublots. From this set of scenarios, we conclude that it is easier to serve orders with homogeneous products when a few sublots are obtained from a production lot. Therefore, the fewer the sublots obtained from a lot, the better the achieved results.

International Journal of Production Research, 2018
https://doi.org/10.1080/00207543.2018.1493239

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Simulation to reallocate supply to committed orders under shortage

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(*Received 28 June 2017; accepted 20 June 2018*)

This article aims to deal with the reallocating supply problem in both its real and planned contexts, to orders that result from the order promising process under shortage. To this end, we propose a system dynamics-based simulation model to facilitate modelling for order managers, and to provide a graphic support tool to understand the process and to make decisions. The basis of the simulation model's structure is a mixed-integer linear programming approach that intends to maximise profits by considering the possibility of making partial and delayed deliveries. To illustrate this, we consider a real-world problem from the ceramic sector that contemplates 35 orders. We obtained a solution by a mathematical programming model and a simulation model. The results show the simulation model's capacity to obtain near-optimum results, and to provide a simulated history of the system.

Keywords: available-to-promise; lack of homogeneity; shortage; simulation; system dynamics; ceramic sector

1. Introduction

According to Olhager (2003), the order penetration point defines the stage in the manufacturing value chain where a particular product is linked to a specific customer order through different product delivery strategies, such as make-to-stock, assemble-to-order, make-to-order and engineer-to-order. In this paper, we consider a manufacturing make-to-stock environment. During the order promising (OP) process, companies normally make commitments with customers about the quantities and due dates of their orders. These commitments usually focus on make-to-stock companies and on the available-to-promise (ATP) quantities of finished goods calculated as the current stock and planned production defined in the master production schedule (MPS), minus any past orders promised.

However, from the time we commit an order until we must serve it, unexpected events may occur that could lead to a shortage of products. There are several causes of these unexpected events: (i) arrival of more priority customer orders that require already reserved products; (ii) delays in raw materials or components; (iii) machine breakdowns; (iv) workers absenteeism, among others. Some of these events might lead to discrepancies between planned and real production quantities and can, in turn, lead to a shortage situation.

Consequently, the previous allocation of products to orders may become suboptimum, or even unfeasible. In this case, the company might be unable to meet previously agreed conditions with customers. This situation becomes relevant because it could very negatively impact not only the company's profits but also customer satisfaction. Furthermore, if this situation occurs often, it can seriously harm customer loyalty and the company's future sustainability. In this context, the shortage planning process intends to find a solution when stock (component or finished products) is unavailable. Solutions include making decisions on supply alternatives (outsourcing, substitute products), late supply, partial shipments, etc. (Framinan and Leisten 2010). Indeed the solutions to these shortage situations seriously impact the reliability of OP processing. Therefore, the recognised relevance of OP processing in the literature to better deal with demand requirements with high service level and customer satisfaction standards (Alemany et al. 2015a; Grillo, Alemany, and Ortiz 2016) supports the importance of shortage planning (SP).

The frequency of unexpected events increases when companies are characterised by lack of homogeneity in the product (LHP), which renders having to execute the SP process more frequently. LHP is an important issue because it appears in several industries like ceramics, textile, wood, marble, horticulture, tanned hides and leather goods, among others (Grillo et al. 2018). LHP implies the company producing to provide units of the same product with different relevant characteristics

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Figure 8. Publication data

In the literature, system dynamics models focus mainly on strategic problems [16,17]. However, the computational efficiency of the proposed system dynamics model proves that it is also an excellent operational tool to reallocate available products to committed orders. Managerial implications focus on integrating the system dynamics model into the information system of companies. It is also possible to use the tool to do what-if analyses according to managers' requirements. Specific system dynamics training for managers would be desirable to obtain more flexible and robust simulation models.

Some future improvements for the current proposal were detected. In this work, we particularly managed to adjust the SP process in such a way that real and planned available quantities of products were reallocated to previously committed orders. This process was held at the start of the simulation in order to decide if the produced units were to be stocked, reserved to serve a committed order until its due date, or directly served to customers. In future works, different inventory reallocation policies could be employed; e.g. instead of serving an order with the oldest homogeneous sublot, we could serve it with the smaller homogeneous sublot that meets the order requirements. This would reduce the number of small homogeneous sublots available in the company, and would increase the probability of serving big amounts of product with homogeneous products. Furthermore, the simulation could consider different sized orders. It would better represent reality as each order could be comprised by a different number of order lines. Similarly, it would be possible to consider the same product being demanded in more than one line of the same order. Finally, the system dynamics model could be extended by assuming that two lines or more of the same order need to be homogeneous. This would be most valuable for ceramic industries as they need to ensure that the products to be assembled together display homogeneity with one another.

7 Publication data

Figure 8 shows the first page of the article published in the International Journal of Production Research (ISSN: 0020-7543).

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Chapter IV:

Conceptual framework for designing agri-food supply chains under uncertainty by mathematical programming models

Agri-food sector performance strongly impacts global economy, which means that developing optimisation models to support the decision-making process in agri-food supply chains (AFSC) is necessary. These models should contemplate AFSC's inherent characteristics and sources of uncertainty to provide applicable and accurate solutions. To the best of our knowledge, there are no conceptual frameworks available to design AFSC through mathematical programming modelling while considering their inherent characteristics and sources of uncertainty, nor any literature reviews that address such characteristics and uncertainty sources in existing AFSC design models. This paper aims to fill these gaps in the literature by proposing such a conceptual framework and state of the art. The framework can be used as a guide tool for both developing and analysing models based on mathematical programming to design AFSC. The implementation of the framework into the state of the art validates its. Finally, some literature gaps and future research lines were identified.

Keywords: Agri-food supply chain; Design; Uncertainty; Conceptual framework; Literature review

1 Introduction

Agri-Food Supply Chains (AFCS) are responsible for bringing agricultural products from the farm to the fork [1]. Since these supply chains (SC) comprise the largest manufacturing sector in Europe, and contribute to the economy with 4.25 million employees and a turnover over €1 trillion, it is critical to develop effective and efficient models and methods to support AFSC decision-making processes and to optimise AFSC performance [2,3].

Such performance is strongly influenced by factors such as uncertainty sources (e.g. weather, diseases, pests) and product characteristics (e.g. perishability), which differentiate AFSC from other industrial SC. Therefore, generic decision-making models and methods for designing and operating SC cannot be easily extrapolated to the agri-food sector since they do not represent real AFSC performance.

A first step, and one of the most critical ones for optimising AFSC performance, is to adequately design them as tactical and operational decisions, as well as their impact on overall SC performance, will depend on their configuration [4]. Tsolakis et al. [5] point out that despite the significance of SC configuration decisions and a number of papers that address them in the general SC management context, the relevant agri-food literature on this topic is limited. This is probably due to the difficulties imposed by the structure and complexity of an entire agri-food chain's relationships, and to incoming uncertainties that characterise this particular network type.

In their review of operational research models applied to fresh fruit SC, Soto-Silva et al. [6] state that there is a gap of models to design and manage such SC. These authors note that practically all models consider a constant price over time without taking into account fruit seasonality or loss in the product's value due to product deterioration. They point out the need for tools that incorporate fresh fruit SC's characteristics, such as shelf life, quality deterioration, waste, and prices that depend on time and product freshness. They also indicate that given the uncertainty and risk that surround the fresh fruit sector, it is necessary to develop models that include these characteristics. Along these lines, Nakandala et al. [7] proposed a hybrid model for assessing risk in fresh food supply chains.

Since inherent sources of uncertainty in AFSC have a negative impact on their performance and sustainability, several authors [5,8-12] state the need to develop AFSC design models that contemplate the effect of existing uncertainty sources and product perishability throughout the chain.

In order to formulate such models, it is necessary to: 1) define AFSC's characteristics, uncertainty sources, decisions and mathematical programming approaches that can be addressed and employed when designing AFSC; 2) establish the state of the art of such items to know current research and to detect existing gaps in the literature.

For the purpose of determining if previous works have met these needs, a review of existing conceptual frameworks (CF) covering the AFSC design problem and literature reviews (LR) of AFSC design models was done. It is worth mentioning that this review was restricted to CF that deal with the strategic decision "Configuration of SC category" within the Hierarchical Decision Framework for AFSC management proposed by Tsolakis et al. [5]. Consequently, other CF types that address strategic decisions of other categories are beyond scope of this research. This is the case of the CF of Hobbs and Young [13] and the CF of Zhang and Aramyan [14], which deal with the strategic decision

"Fostering SC Partnering Relationship category" (see [5]). This is why they are not analysed herein.

The results of this review (Table 1) showed that existing CF focus mainly on providing managerial insights for the AFSC design process. It was also determined that: 1) existing CF are not based on or developed to think in mathematical programming models; 2) do not consider AFSC's inherent characteristics; nor 3) sources of uncertainty simultaneously. The studied LR do not define the main AFSC's inherent characteristics and uncertainty sources, nor which have been addressed by existing models, or how they have been modelled.

This paper aims to fill these literature gaps by following a research methodology that comprises two phases. The first phase is to propose a CF to develop and/or analyse AFSC design mathematical programming models, while considering AFSC's inherent characteristics and uncertainty sources. The second phase consists in using the proposed CF for reviewing existing AFSC design models to determine if such characteristics have been addressed and to identify possible literature gaps. This second phase validates the proposed framework.

The results of this paper show that existing AFSC design models have not addressed product characteristics simultaneously, such as perishability, food quality, food safety or product heterogeneity. Uncertainty is considered in a few papers, but they have not modelled the AFSC's own uncertainty sources (e.g. weather, food quality, food safety, perishability), rather the generic ones found in SC from different sectors (e.g. demand, lead time).

The remainder of the paper is structured as follows. Section 2 proposes a CF to design AFSC, while considering their inherent characteristics and uncertainty sources through mathematical programming modelling. Since the different items to be contemplated while designing AFSC are defined within this framework, Section 3 uses them to establish the current state of the art of AFSC design models and to detect any possible gaps in them. Finally, Section 4 sets out the conclusions and future research lines.

2 Conceptual framework for AFSC design models

This section describes the proposed CF to design AFSC whose purpose is to be used as a guide tool to both develop accurate mathematical programming models to design specific AFSC and to analyse existing ones.

The proposed CF aim to identify all the inherent characteristics to the AFSC design problem. For this reason, some of their characteristics are common to other generic SC design models as they deal with the same problem (SC design), whereas other characteristics are specific for the agri-food sector. As justified in the Introduction, these AFSC specific features strongly impact AFSC performance and efficiency, which render their consideration necessary. Therefore, employing already existing generic models to design AFSC could lead to poorer SC performance than the performance expected when using AFSC design models considering inherent characteristics to the agri-food sector. For example, if the product freshness requirement is not considered when designing AFSC, a SC with very long transport times can be designed, during which products will lose their freshness and then, become unmarketable.

Table 1. Literature review

Type	Ref.	Application	Dimensions	Novelty	Conclusions
CF	[15]	Assessing the suitability of a combined stochastic and dynamic modelling approach to design and control a responsive fresh product SC network.	System characteristics Context factors Performance indicators	It considers the importance of product perishability and supply and demand uncertainties during the SC design process.	Need to incorporate product perishability into both design and control models. A hybrid approach that combines simulation and optimisation is a promising research direction.
	[16]	Optimising the design, planning and operation of AFSC by implementing appropriate green SC management and logistics principles. Tool for reducing CO2 emissions through the design, planning and operation of AFSC.	Sustainable farming Supply chain management Marketing Environmental management Reverse logistics Corporate social responsibility	This CF measures SC performance by focusing on environmental performance, while previous literature focuses on efficiency and other economic-related performance.	The proposed framework is expected to foster sustainable regional socio-economic development on two major axes, namely rural development and the agriculture sector. CF focus on developing green operations that will lead to new environmentally benign SC designs and operations to replace less sustainable practices.
	[17]	To support the analysis and design of robust food SC. Tool guide for managing process disturbances and designing robust SC.	Description of the SC scenario and identification of KPIs. Identification and characterisation of unexpected events and disturbances in processes that impact performance robustness. Assessment of performance robustness Identification of sources of vulnerability Identification of appropriate redesign principles and strategies.	This CF fills the gap caused by lack of an integral framework that guides companies to manage process disturbances and design robust SC.	Process disturbances can be detected and typified by analysing the performance robustness of specific scenarios. Each disturbance is related to a set of sources of vulnerability that represent a direct/indirect cause of disturbance. A set of redesign principles and strategies is identified to prevent disturbance. More research is needed to extend and validate these findings. More research that models and quantifies the impact on key SC performance indicators for alternative SC scenarios is needed.
LR	[12]	Bringing location-allocation applications in agriculture to the forefront.	Product type Model description Model type Solution procedure Special features	First review of applications of location models in the agriculture sector.	Production-distribution models have emerged in agri-business and authors expect them to continue. It is important to consider globalisation and sources of uncertainty when designing any global SC. Global SC models should surface.
	[18]	Establishing a generic state of the art in AFSC location problems related to mathematical programming models.	Type of location problem Type of mathematical programming model Type of solution method Aspects covered by papers	Up-to-date review of AFSC location models.	Models including product perishability, waste and the stochastic behaviour of some variables are required. Dynamic models should be employed to locate facilities in perishable AFSC. Future models should contemplate different transport types that allow the organoleptic properties of products to be conserved.

The CF is based on that proposed by Grillo et al. [19] to characterise quantitative models by contemplating Lack of Homogeneity in the Product (LHP) characteristics and/or uncertainty during the Order Promising Process (OPP), where LHP is identified to be present in AFSC. In this paper, this framework was extended and adjusted to the AFSC design problem in the following way.

The "Environment" dimension was replaced with the "AFSC characteristics" dimension where the main agri-food issues to be considered when designing AFSC were defined (Section 3.1). The OPP-related dimensions were replaced with the "Decision characteristics" where design decisions were focused on (Section 3.2). The "Modelling approach" dimension was extended by adding the constraints to be contemplated when designing AFSC (Section 3.3.). Finally, the way of modelling sources of uncertainty was also included in the "Uncertainty modelling" dimension (Section 3.4).

Therefore, the proposed CF was divided into four blocks (Figure 1) that represent the pillars needed to develop an AFSC design model. Each block was divided into a series of specific categories of the problem under study that differentiated this CF from that proposed by Grillo et al. [19].

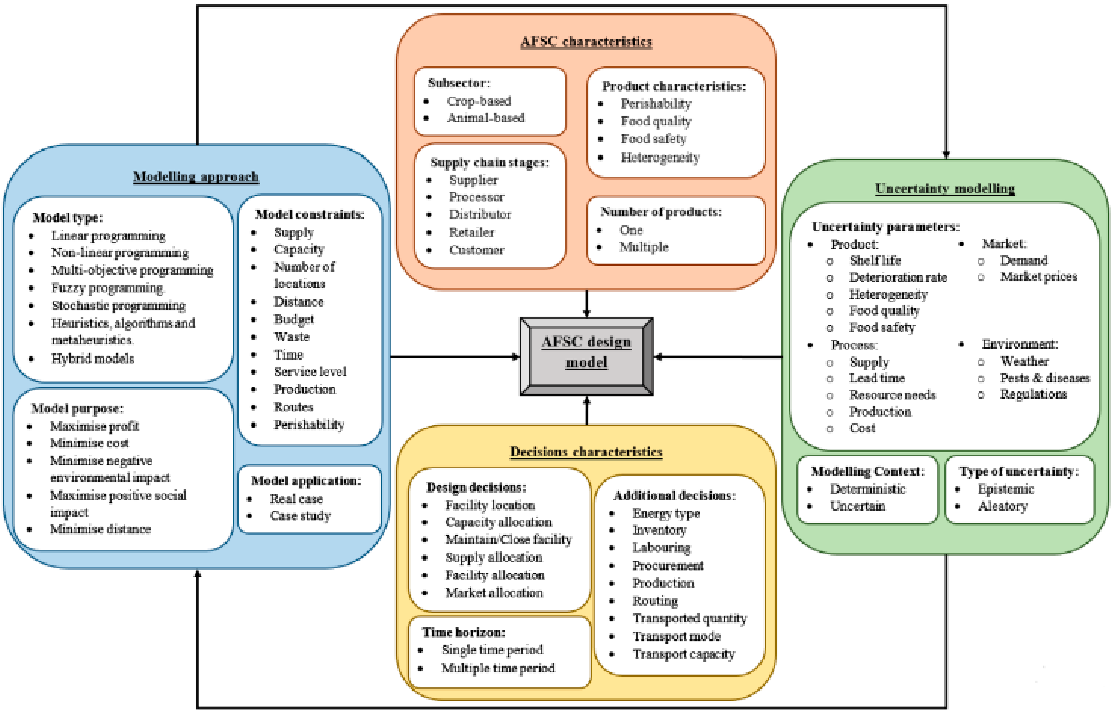


Figure 1. Conceptual framework for designing AFSC.

2.1 AFSC characteristics

This dimension is composed of four categories: 1) Subsector, where the agri-food sector is subdivided into subsectors; 2) SC stages showing the existing AFSC stages; 3) number of products where the different products produced by AFSC were identified; 4) product characteristics, where the characteristics inherent of agri-food products were identified.

2.1.1 Subsector

Many products can be obtained from AFSC, such as rice, beef, carrots or apples. These SC products are different in terms of the needed productive processes, product characteristics and legislation, which makes their management and design very different.

For this reason, it is necessary to classify the agri-food sector into subsectors. This CF proposes distinguishing between: 1) crop-based AFSC and 2) animal-based AFSC as their products and productive processes vastly differ. In addition, it is interesting to subdivide the crop-based AFSC into: 1.a) highly perishable AFSC (vegetables and fruits), and 1.b) slightly perishable AFSC (cereals, tubs, nuts) [8].

2.1.2 Supply Chain Stages

According to Chopra and Meindl [20], SC can be divided into five stages:

- Supplier
- Processor.
- Distributor.
- Retailer.
- Customer.

In this sector, farmers are considered the suppliers of SC, although they have, in turn, their own suppliers (e.g. seed or fertilizer companies). They all perform add-value activities with products, such as packaging in fresh fruit SC, or slaughtering, cutting up and packaging in beef SC, and are considered processors. Distributors are responsible for storing and distributing products to retailers, who sell the finished product to end customers. Finally, customers represent the market's final demand.

2.1.3 Number of Products

AFSC can be designed to manage one product or more, which makes SC management more complicated when more products are simultaneously managed. However, given product seasonality in some agri-food subsectors (e.g. vegetables and fruits), it is interesting to design AFSC capable of simultaneously managing more than one product variety (e.g. different varieties of apples) or even different products (e.g. spinach, lettuce and cauliflower).

2.1.4 Product Characteristics

Agri-food products are characterised mainly by their perishability, represented by considering products' remaining shelf life until they become inedible for humans and/or by contemplating a product deterioration rate that depends on time and/or environmental factors (e.g. temperature or humidity). New technologies allow the monitoring of relevant attributes of products in real time. For instance, it is possible to use sensors to estimate the remaining shelf-life of agri-food products during their transport and management, what allows to determine prices dependent on the remaining shelf-life [21].

Other characteristics of agri-food products are the food quality and food safety requirements imposed by end customers and/or governments. Food quality is measured by a product's physical attributes (e.g. taste, texture, colour) and customers' perceptions of them, while food safety can be measured as a binary variable to determine if a product is allowed for consumption or not to prevent illnesses caused by contaminated products [9].

Finally, agri-food products are also characterised by heterogeneity between units of the same product in physical attributes and perishability terms. For example, two apples harvested at the same time from one same tree, or two similarly fed chickens of similar age, can present different physical attributes (weight, colour, taste, texture, etc.) and distinct deterioration rates.

In some cases, product characteristics can be interrelated and considered equivalents, but this does not occur in all AFSC types. For example, some authors claim that product quality is linked directly to its freshness, whereas others state that product quality and freshness can be considered differentiated characteristics according to AFSC [22]. Therefore, depending on the specific case for which the AFSC design model is developed, researchers and practitioners can decide to either consider these characteristics separately or, on the contrary, integrate some of them in order to lessen the model's complexity.

2.2 Decision characteristics

This dimension is composed of three categories: 1) Design decisions, where the possible decisions to be made when designing AFSC are identified; 2) Additional decisions, where planning and/or operational decisions made while designing AFSC are exposed; 3) Time horizon, where the horizon to be considered needs to be decided.

2.2.1 Design decisions

Chopra and Meindl [20] proposed four decisions to design SC (facility role, facility location, capacity allocation, market & supply allocation). This approach has been extended in this CF by considering the following decisions:

- Facility role: defining the processes to be performed at each facility and/or the facility type to be opened at each location
- Facility location: deciding where to locate a facility
- Capacity allocation: defining the capacity to allocate each facility
- Maintain/Close facility: decision as to whether to close or keep open locations over the horizon
- Supply allocation: selecting which suppliers will provide each processor
- Facilities allocation: defining the connections among AFSC's nodes
- Market allocation: selecting which facilities will serve each retailer or end customer

It is necessary to differentiate between models developed to design SC and models developed to design a particular facility. SC design models will pursue objectives that benefit the whole SC such as in Allaoui et al. [23]. Meanwhile, a facility design model will only look for the benefit of the particular facility, such as in Meneghetti and Monti [24].

2.2.2 Additional decisions

Design decisions are not usually isolated but are accompanied by other SC decisions. Melo et al. [25] proposed a list of five planning decisions to be considered when designing

SC, which has been extended in this CF to represent the most important decisions in AFSC:

- Energy type: energy source to be used in each AFSC process
- Inventory: product quantities to store per facility and time period
- Labouring: number of labourers needed at each facility
- Procurement: amount of raw materials or products to buy from suppliers
- Production: amount of product to be manufactured in each production plant
- Routing: definition of the routes to follow during product distribution
- Transported quantity: product quantity to be transported between locations
- Transport mode: transport mode to be used for each delivery
- Transport capacity: allocation of transport capacity

2.2.3 Time horizon

An AFSC can be designed by considering a single time period or multiple time periods. Depending on the problem to be addressed (considered design decisions, additional decisions and AFSC characteristics), it might be more appropriate to consider one time period or more when designing AFSC. The correct selection of the time horizon to be considered when designing AFSC can lead to more accurate results for AFSC behaviour, but also to more complex models.

2.3 Modelling approach

This dimension is made up of four categories: 1) Model type, where the employed modelling type is decided; 2) Model purpose, where the model's objectives are set; 3) Model constraints, where the model constraints are decided; 4) Model application, where the model application to real cases or cases studies is stated.

2.3.1 Model type

The taxonomy proposed by Mula et al. [26] for classifying model types is adopted in this category:

- Linear programming: it can be divided into Linear programming (LP) and Mixed integer/Integer linear programming (MILP)
- Non-linear programming: it can be divided into Non-linear programming (NLP) and Mixed integer/Integer non-linear programming (INLP)
- Multi-objective programming: it can be divided into Multi-objective linear programming (MOLP), Multi-objective integer linear programming (MOILP), Multi-objective non-linear programming (MONLP) and Multi-objective non-linear integer programming (MONLIP)
- Fuzzy programming: composed of Fuzzy mathematical programming (FMP)
- Stochastic programming (SP)
- Heuristics, algorithms and metaheuristics (HEU)
- Hybrid models (HYB)

Another classification of optimisation approaches can be adopted when considering multiple models to solve specific problems. This is the case of the multi-level, multi-stage or multi-echelon modelling approaches. Multi-level models are applied to decentralised planning problems with multiple decision makers who sequentially make decisions based on his/her own model in a multi-level or hierarchical organisation. Bi-level programming is a specific case of the multi-level type, but with only two decision makers at two different hierarchical levels [27]. Multi-stage models deal with a single decision maker who must make a sequence of decisions over time to react to changing conditions. Both these optimisation approaches are normally used as decomposition techniques that divide the complex problem into inter-connected simpler subproblems to diminish the complexity of the solution. Finally, and broadly speaking, the multi-echelon inventory theory is concerned with a variety of inventory problems that comprise two interrelated supply or production facilities or more [28]. The places where the inventory is kept in the SC are called "echelons". Usually the complexity of a SC is related to the number of echelons that it incorporates [29].

2.3.2 Model purpose

Models can pursue different objectives that can be related to various sustainability aspects. According to Farahani et al. [30], a SC is sustainable when it considers economic, environmental and social aspects. However, it is called a "Green supply chain" if it considers environmental and economic aspects, or is known as a "Lean supply chain" when it considers only the economical aspect.

The agri-food sector has a huge impact on Europe's economy (€1 trillion turnover), the environment (25.7% of Europe's energy use) and society (4.25 million employees) [3,31]. In order to attempt to optimise AFSC performance and generate a positive impact on a nation's sustainability, it is important to develop models that pursue objectives related to the three pillars of sustainability: 1) economical aspect (maximise profits or minimise costs), 2) environmental aspect (minimise CO2 emissions, water/energy use and waste); 3) social aspect (e.g. maximise employment creation, customer satisfaction, or minimise delivery times).

2.3.3 Model constraints

When designing a SC, it is important to consider the constraints that limit the decision-maker power of decisions. As the AFSC design problem is usually addressed while devising planning and/or operational decisions, the constraints related to these decisions should also be considered. Therefore, the constraints to be contemplated depend on the decisions to be made.

Some possible constraints to be considered are those related with: 1) supply (e.g. available quantity in suppliers); 2) capacity (e.g. capacity of facilities, transport capacity); 3) number of locations (e.g. minimum, maximum or the exact number of locations to be opened or operated simultaneously); 4) distance (e.g. minimum or maximum allowable distance between locations, maximum transport distance); 5) budget (e.g. budget available to open locations); 6) product flow (e.g. maximum quantity to be handled at a facility); 7) time (e.g. maximum transport time, deliveries time window, working time limitations); 8) service level (e.g. minimum service level); 9) production (e.g. minimum production required to open a plant); 10) routes (e.g. useable routes during each time period); 11) perishability (e.g. product's minimum remaining shelf life when being delivered).

2.3.4 Model application

Two methods are normally used to validate the proposed models, namely a case study application or a real case application. A model can also be validated by applying both methods. A case study application consists in solving the proposed model by using simulated data. In real case applications, the used data are obtained from a real SC.

2.4 Uncertainty modelling

This dimension comprises three categories: 1) the modelling context, where models are identified as being deterministic or uncertain; 2) uncertain parameters, where the existing sources of uncertainty in AFSC are identified; 3) type of uncertainty, where the different ways of modelling uncertainty are exposed.

2.4.1 Modelling context

When developing a mathematical programming model to support a decision-making process, it must first be decided if this model should either consider uncertainty sources (uncertain context) or ignore them (deterministic context). In order to develop models that accurately represent AFSC behaviour, the uncertainty sources that strongly impact AFSC performance should be modelled.

2.4.2 Uncertain parameters

The existing sources of uncertainty in crop-based AFSC have been categorised by Esteso et al. [32] by classifying them into four blocks depending on whether they are related to the product, process, market or environment. This categorisation is adapted to the whole AFSC by adding the "cost uncertainty" to process uncertainties, and by changing the "harvesting yield uncertainty" (which refers to crop-based AFSC) per "supply uncertainty" (in order to consider the different AFSC types):

- Product uncertainties: (i) product shelf-life; (ii) deterioration rate; (iii) product heterogeneity; (iv) food quality; (v) food safety uncertainties. Product shelf-life consists in the time during which a product can be consumed. Deterioration rate denotes a product's deterioration speed. Product heterogeneity refers to the difference of attributes between units of the same product. Food quality measures customer satisfaction and legal requirements. Food safety consists in assuring a product's non-contamination.
- Process uncertainties: (i) supply characteristics; (ii) lead time; (iii) resource needs; (iv) costs; (v) production uncertainties. Supply characteristics refer to the quantity, quality and arrival time of the supply. Lead time denotes the time needed to complete processes. Resource needs consists in the requirements of machines and labourers to follow processes. Costs are the unitary costs generated by each activity. Production uncertainty refers to the uncertainty produced by not knowing the real quantity and quality of ingredients when producing a final product.
- Market uncertainties: (i) demand; (ii) market prices uncertainties. Both these items are usually interrelated in the agri-food sector.

- Environment uncertainties: (i) weather; (ii) pests and diseases; (iii) regulations uncertainties. Weather uncertainty has a stronger impact on crop-based AFSC where product characteristics strongly depend on the weather. Pests and diseases are usually unpredictable and strongly influence product safety. Finally, changes in the regulations that deal with food quality and safety have a huge impact on AFSC and their content cannot be known in advance.

2.4.3 Uncertainty type

In their review of perspectives of uncertainty, Samson et al. [33] mainly identify two uncertainty types according to the grade of known information: epistemic and aleatory uncertainty.

Decisions are made under aleatory uncertainty when the possible consequences (or results) of such decisions are known. In addition, the probability of each consequence occurring is usually known or can be estimated before making decisions. Some approaches, such as SP, can be used to model this uncertainty type. In fact, the aleatory uncertainty and stochastic uncertainty concepts can be used interchangeably [34].

Moreover, we fall within the scope of making a decision under epistemic uncertainty when the possible consequences for this decision are unknown and not even meaningful. Therefore, as we do not recognise the possible consequences, the probability of each one occurring is impossible to know. Some approaches, such as fuzzy set theories, can be employed for modelling epistemic uncertainty.

After identifying which uncertainty type better represents the real source of uncertainty present in an AFSC, the function that characterises the behaviour of the source of uncertainty should be selected. For example, aleatory uncertainty could be represented by a distribution function (normal distribution, Weibull distribution, etc.), while epistemic uncertainty could be represented by a membership function (trapezoidal function, triangular function, etc.).

3 Analysing AFSC design models

The proposed CF was used to analyse the existing mathematical programming models used to design an AFSC to validate it by establishing the current state of the art and identifying possible gaps in this research area.

The literature review was done by using the process proposed by Seuring and Müller [35] to analyse content: 1) Material collection, where the material to be collected is defined and delimitated; 2) Descriptive analysis, where the material's formal aspects are assessed; 3) Category selection, where structural dimensions and related analytic categories are selected; 4) Material evaluation, where the material is analysed according to the structural dimensions and categories.

Material collection was carried out in well-known scientific databases (Google Scholar, Web of Science, Scopus, Elsevier, Emerald, Taylor & Francis and Springer) using the following keywords:

- Agri-food supply chain
- Agro-food supply chain
- Food supply chain

- Agriculture
- Supply chain design
- Network design
- Location
- Optimisation
- Operation research
- Mathematical programming

Although a vast amount of papers related to the proposed keywords were found, not all these publications proposed mathematical programming models to design AFSC. To identify the papers that dealt with this problem, two refining processes were conducted in each paper: 1) reading the title, abstract and keywords in order to eliminate those that did not focus on AFSC; 2) verifying the proposal of mathematical programming models that dealt with at least one of the SC design decisions proposed by Chopra and Meindl [20]. For this reason, some papers that modelled some of the main AFSC characteristics, such as Dellino et al. [36], Huang and Song [37], and Rong et al. [38], but did not make decisions about SC design, were ruled out. Having finished the refining process, reference and citation analyses were done to find older and more recent contributions.

Finally, 30 papers needed to be further analysed, of which 22 were scientific journal publications, six were conference proceedings and two were book chapters (Table 2). References spanned 15 years, although 83% of the papers have been published in the last 6 years (Figure 2), which demonstrates the increasing interest of researchers in AFSC design through mathematical programming models.

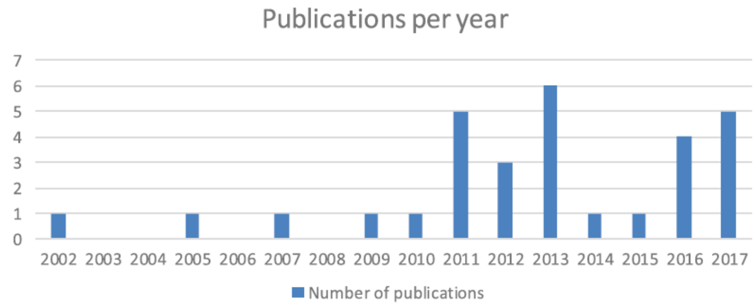


Figure 2. Number of publications per year.

The structural dimensions and categories employed to analyse the selected literature were those that comprise the proposed CF. The covering degree of each structural dimension allowed the current state of the art and future research lines to be identified.

The state of the art is structured as follows: firstly, the results obtained for each category that comprised the CF dimensions were analysed independently. Secondly, the relationship between the results obtained for each category that made up a dimension was established in an additional subsection called "Findings", which was included at the end of each dimension section (Subsections 3.1.5, 3.2.4, 3.3.5, and 3.4.4). For example, the "Findings" of "Uncertainty Modelling" established the relation among the results obtained in categories "Modelling Context", "Uncertain Parameters", and "Type of Uncertainty". Finally, a global literature analysis for all the dimensions and categories was carried out in the Conclusions section from which the main conclusions were drawn and gaps in the literature were identified.

Table 2. Number of publications per source.

Sources	References	%
Advanced Methods for Computational Collective Intelligence	1	3.3
Advances in Mechanical and Electronic Engineering	1	3.3
Annals of Operations Research	1	3.3
Applied Mathematical Modelling	1	3.3
British Food Journal	2	6.7
Computers & Operations Research	1	3.3
Computers and Electronics in Agriculture	1	3.3
European Journal of Operational Research	3	10.0
Information	1	3.3
International Conference on Management Science and Engineering	1	3.3
International Conference on Fuzzy Systems and Knowledge Discovery	1	3.3
International Conference on Service Operations, Logistics, and Informatics	1	3.3
International Conference on Communications, Computing and Control Applications	1	3.3
International Conference on Management and Service Science	1	3.3
International Conference on Artificial Intelligence, Management Science and Electronic Commerce	1	3.3
International Journal of Computer Science Issues	1	3.3
International Journal of Production Economics	2	6.7
Journal of Cleaner Production	1	3.3
Jornal of Food Engineering	2	6.7
Key Engineering Materials	1	3.3
OR Spectrum	1	3.3
Production Planning & Control	1	3.3
Puente Revista Científica	1	3.3
South African Journal of Industrial Engineering	1	3.3
Transportation Research Record: Journal of the Transportation Research Board	1	3.3
Total	30	100

3.1 AFSC characteristics

This dimension provides an overview of the characteristics inherent to AFSC, which have been considered in previous models. The AFSC characteristics considered by each paper are analysed in Table 3.

3.1.1 Subsector

Most references (83%) proposed generic AFSC models. This means that they can be applied to more than one product type (crop-based or animal-based products). Of these generic models, 72% were validated in potatoes [39], rice [4], meat [40-47], chocolate manufacturers [48], grains [49,50], vegetables and fruits [51,52], apples and by-products [53,54], or bakery [55] SC.

Whereas 16.7% of the papers proposed models to design SC of a specific product, such as pea-based novel protein food [56], sugar cane [57,58], or dairy products [59,60].

3.1.2 Supply chain stages

The most considered stages when designing AFSC were processor and retailer stages (73.3%), followed by the distributor stage (53.3%) and the supplier stage (46.7%). Most models (96.7%) took into account more than one SC stage when designing AFSC, and only one model designed a one-stage SC. It should be stressed that each stage could comprise one member or more, as in Apaiah and Hendrix [56], where only the processor stage was considered by locating three different types of processing facilities.

The suppliers considered by models were mainly farmers [23,45-47,49,50,53,54,59]. However, other models mentioned generic suppliers [2] and the rest detailed type of farmers, such as sugar cane fields [58], crops [39], supply regions [57], or milk regions, defined as groups of farmers [60].

Some models considered the processor stage and included more than one facility type (20.0% of the models). This is the case of Allaoui et al. [23], who considered different types of processing facilities, and Ding [49], who included grain elevators and final processors. Jouzdani et al. [59] considered processing factories and dairy manufacturers, while Neungmatcha et al. [58] distinguished between sugar cane loading stations and mill factories. Zhao and Dou [53] and Zhao and Lv [54] included plants of semi-finished products and plants of finished products. All the other models referred to the processor stage when they mentioned packaging and processing plants [39], factories [2,50], processors [56,57], manufacturers [4,62], production node/location [44,52], production plants [55,60], slaughterhouses [40-43] or abattoirs [45-47].

When considering the distributor stage, some models referred to distribution centres [4,23,51,60-62,65], warehouses [39,63,64], hubs [44,52], regional sale markets [53,54], or a combination of a central warehouse and a set of transit points [48].

In the analysed papers, the authors referred to the retailer stage as retailers [2,4,23,45-47,62], customer clusters, defined as a set of retailers [40-43], points of demand [39], delivery points [48], customer/consumer zone [61,63], stores [50], consumption nodes/locations [44,52], customer points [64], demand points [51] or points of requirement [65].

AFSC were designed by considering two stages in 46.7% of the models, where the interactions among supplier-processor (10.0% of models), distributor-retailer (20.0% of models), processor-retailer (13.3% of models) or processor-distributor (3.3% of models) were represented. Three-stage AFSC were designed in 43.3% of the models by considering these combinations: supplier-processor-retailer (20.0% of the models), processor-distributor-retailer (13.3% of the models) or supplier-processor-distributor (10.0% of the models). Finally, 6.7% of the models designed AFSC by considering four stages: supplier, processor, distributor and retailer.

3.1.3 Number of products

The models that considered a single product (60.0%) were more commonplace than those that took into account multiple products (40.0%), although this tendency has changed over the years.

Two ways to model multiple products were identified: 1) simultaneously managing different products in each process (e.g. apples and pears) [4,23,42,43,63,64], 2) differentiating between raw materials and processed products [59]. Some models considered both multiple products ways simultaneously [2,53,54,57,60].

Table 3. Classification of AFSC characteristics.

Reference	Subsector	SC stages					No. of products		Product characteristics			
		Supplier	Processor	Distributor	Retailer	Customer	One	Multiple	Perishability	Food quality	Food safety	Heterogeneity
[39]	Agri-food	X	X	X	X		X					
[23]	Agri-food	X	X	X	X			X				
[2]	Agri-food	X	X		X			X	X	X		X
[56]	Pea-based food		X				X					
[4]	Agri-food		X	X	X			X				
[40]	Agri-food		X		X		X					
[41]	Agri-food		X		X		X					
[42]	Agri-food		X		X			X				
[43]	Agri-food		X		X			X				
[48]	Agri-food			X	X		X					
[61]	Agri-food			X	X		X		X			
[49]	Agri-food	X	X				X					
[50]	Agri-food	X	X		X		X					
[44]	Agri-food		X	X	X		X					
[52]	Agri-food		X	X	X		X					
[62]	Agri-food		X	X	X		X		X			
[57]	Sugar	X	X		X			X				
[59]	Dairy	X	X					X				
[45]	Agri-food	X	X		X		X					
[46]	Agri-food	X	X		X		X			X		
[47]	Agri-food	X	X		X		X					
[58]	Sugar	X	X				X					
[63]	Agri-food			X	X			X				
[64]	Agri-food			X	X			X	X			
[55]	Agri-food		X	X			X					
[60]	Dairy	X	X	X				X				
[51]	Agri-food			X	X		X		X			
[53]	Agri-food	X	X	X				X	X			
[54]	Agri-food	X	X	X				X	X			
[65]	Agri-food			X	X		X		X			
Total		14	24	16	22	0	18	12	8	2	0	1
%		46.7	80.0	53.3	73.3	0.0	60.0	40.0	26.7	6.7	0.0	3.3

Real AFSC usually manage a wide variety of products that interact until the final product required by end customers is obtained. Thus, in order to obtain more accurate AFSC design models that represent the real complexity of the agri-food sector, new models should simultaneously consider several products.

3.1.4 Product characteristics

One of the most important characteristics of agri-food products is perishability, which was considered in 26.7% of the models by modelling the products' remaining shelf life after being produced [2] or when reaching the retailer [64], the maximum consecutive time periods during which a product can be stored [62], or a product's deterioration rate while being transported [51,53,54,61,65] or stored [61].

Food quality was modelled in two papers. Mohammed and Wang [46] considered food quality by maximising the healthiness of the livestock transported to slaughterhouses and the freshness of meat pieces transported from slaughterhouses to retailers. Amorim et al. [2] considered this factor by assuming that local raw material was of better quality than non-local raw materials.

Product heterogeneity was modelled only in Amorim et al. [2], where the combination of two raw material types determined the branding of final products (local or mainstream), which differentiated them in remaining shelf life, quality and price terms. Finally, food safety was not dealt with in any analysed model.

3.1.5 Findings

The results showed that more effort was required to develop SC design models to appropriately address agri-food sector characteristics Given the significant differences between animal-based and crop-based AFSC production processes, it is necessary to develop models to appropriately design these two SC types.

No model contemplated the customer stage when designing AFSC. This is reasonable since customers in the agri-food sector are responsible for buying demanded products at retailers. Thus, retailers represent end customers' demand. However, in order to develop AFSC design models that represent the whole SC, the supplier, processor, distributor and retailer stages should at least be considered.

Some agri-food products need to be processed to meet consumer requirements. For example, raw materials that need to be cut to obtain different end products (e.g. beef cut into chuck, rib, brisket), products composed of combining different raw materials (e.g. salad made of lettuce, tomato and carrot) or final products obtained by applying different cooking procedures to one same raw material (e.g. cream, buttermilk, and yoghurt made with milk). This shows the huge complexity that AFSC face when managing products. In order to accurately represent this complexity, AFSC design models should simultaneously take into account more than one product.

Finally, the analysed models did not appropriately address the product characteristics that strongly influenced AFSC performance, such as product perishability, food quality, food safety and product heterogeneity. Surprisingly, 63.3% of the models did not consider any inherent product characteristic of AFSC. Most of the models that addressed the product perishability characteristic did so in the AFSC that comprised more than one stage close to customers (regardless of the number of managed products). It is also noteworthy that food quality and heterogeneity characteristics were addressed in two models and one model, respectively, by considering the whole AFSC. Making the effort to develop models that address these last characteristics, even simultaneously, is highly recommended to ensure AFSC's good performance and efficiency.

3.2 Decisions characteristics

This section aims to identify the decisions made by each analysed model and the time horizon considered in them (Table 4).

3.2.1 Design decisions

Almost all the reviewed models (96.7%) decided the location of one facility or more, such as production plants (66.7% of the models), distribution centres (43.3% of the models), or retailers (6.6% of the models). In 16.7% of the models, the level of capacity allocated to each location was also defined.

The role that each facility was to play was decided in 23.3% of the references, with decisions such as the products to be produced in each plant [23,53,54,57], or the processes to be performed at each open location [39,57,59,60].

Once facilities had been opened, 6.7% of the models made the decision to maintain or close facilities during each time period depending on costs, emissions generated, water use, efficiency and employment created when opening, maintaining or closing a facility [23] or according to the costs of opening and closing locations [64].

The connections among different AFSC members were defined in all the models (100%), of which 43.3% defined the suppliers that supplied each processor, 46.7% stated the existing relations among processors, distributors or processors-distributors, and 86.7% decided which distributors or processors were to serve each retailer.

3.2.2 Additional decisions

The most considered decision was transportation (63.3% of models), for which the quantity to be transported between the supplier and the production plant (36.7%), production plants (40.0%), the plant and DC (26.7%), DC and retailer (23.3%) or, the production plant and the retailer (20.0%) was decided. Only 23.3% of the models considered transportation of products over the whole AFSC [2,23,39,45-47,57]. In addition, 16.7% of the models defined the transport mode that was to be used depending on the related costs and/or environmental impact, and 3.3% of them determined the vehicle to be used according to the required capacity.

The route to follow during distribution was defined in 10.0% of the models by choosing among several possible routes [4], by defining the best route to minimise costs and the environmental impact [62], or by solving a classical travelling salesman problem [43].

The amount of product to be manufactured at each facility was defined in 23.3% of the models. The quantity of raw material to be bought from suppliers was considered in 16.7% of the models. Among them, Amorim et al. [2] also differentiated between the quantity to be produced with regular and overtime production.

In addition, one of these models decided which energy type to employ when processing a product according to generated emissions, and also to the water used by it [23].

Table 4. Classification of decisions characteristics

Ref.	Design decisions							Additional decisions									Time horizon	
	FR	FL	CA	MC	SA	FA	MA	ET	Inv	Lab	Proc	Prod	Rou	TQ	TM	TC	ST	MT
[39]	X	X	X		X	X	X							X			X	
[23]	X	X	X	X	X	X	X	X			X	X		X	X			X
[2]					X	X	X		X		X	X		X				X
[56]		X				X						X		X	X		X	
[4]		X				X	X						X	X			X	
[40]		X					X										X	
[41]		X					X										X	
[42]		X					X										X	
[43]		X					X						X				X	
[48]		X					X										X	
[61]		X					X										X	
[49]		X			X	X								X			X	
[50]		X			X		X							X			X	
[44]		X				X	X							X			X	
[52]		X				X	X							X	X		X	
[62]		X				X	X		X			X	X	X		X		X
[57]	X	X	X		X	X	X							X				X
[59]	X	X				X								X				X
[45]		X			X		X							X			X	
[46]		X			X		X			X				X			X	
[47]		X			X		X			X				X			X	
[58]		X	X		X												X	
[63]		X	X				X										X	
[64]		X		X			X							X			X	
[55]		X					X										X	
[60]	X	X			X	X	X				X	X		X			X	
[51]		X					X										X	
[53]	X	X			X	X	X				X	X		X	X		X	
[54]	X	X			X	X	X				X	X		X	X		X	
[65]		X					X										X	
Total	7	29	5	2	13	14	26	1	2	2	5	7	3	19	5	1	25	5
%	23.3	96.7	16.7	6.7	43.3	46.7	86.7	3.3	6.7	6.7	16.7	23.3	10.0	63.3	16.7	3.3	83.3	16.7

Notes: FR: Facility role, FL: Facility location, CA: Capacity allocation, MC: Maintain/Close facility, SA: Supply allocation, FA: Facility allocation, MA: Market allocation; ET: Energy type, Inv: Inventory, Lab: Labouring, Proc: Procurement, Prod: Production, Rou: Routing, TQ: Transported quantity, TM: Transport mode, TC: Transport capacity; ST: Single time period, MT: Multiple time period.

The amount of products to store as inventory at all the facilities during each time period was defined in only 6.7% of the models. These models simultaneously represented product perishability using its remaining shelf life. In these cases, it was important to not only ensure that products did not exceed the maximum consecutive time periods during which a perishable product could be stored [62], but to also be aware of the age of each stored product [2].

The number of labourers needed at each facility to complete the involved processes requirements was defined in 6.7% of the models, where the working rates per labourers, their cost per hour, and the minimum required hours for contracting labourers were considered.

3.2.3 Time horizon

The majority of the models (83.3%) were developed to design AFSC by considering data from a single time period. Multiple period models (16.7%) simultaneously contemplated strategic decisions about facilities and tactical/operational decisions, such as inventory, transport, procurement or production decisions.

As 66.7% of the models simultaneously addressed strategic, planning and/or operational decisions, and given some of the agri-food sector's time-dependent characteristics (e.g. product perishability), it would be logical to develop models to design AFSC that considered a multiple period horizon time. This could ensure that the obtained results would be more accurate in relation to real AFSC behaviour and performance.

Note that most of the models which considered product perishability, which is a time-dependent characteristic, contemplated a one-time period horizon. In these cases, perishability was modelled by a product deterioration rate during its transport

[51,53,54,61,65] and was employed to decide where to locate AFSC facilities because, if two facilities were far from one another, a product could deteriorate while being transported between them. Moreover, the models that considered product perishability in a multiple time periods horizon usually modelled it by contemplating a product's remaining shelf life during each time period [2,62]. These models were the only ones that addressed inventory decisions, for which knowledge of a product's remaining shelf life is important.

3.2.4 Findings

The agri-food sector is under strong pressure to improve its resilience capabilities due to severe environmental conditions, government food safety regulations and the global market increasingly demanding requirements in product quality, variety and personalisation terms. And all this is to respond to abrupt changes in the quality, quantity and availability of resources, especially with unexpected environmental circumstances caused by existing uncertainty related to climate, pests and diseases, and also by volatile market conditions, prices of raw materials, etc.

In order to achieve rapid, flexible and efficient responsiveness, AFSC need to adopt integrated strategies from raw material production to product distribution to end customers in order to align demand and supply in the most competitive and dynamic way. Thus, simultaneously solving design and tactical/operational decisions can improve AFSC performance in the long, mid, and short terms. Given the special features of AFSC, it would be interesting to develop models that address design, procurement, production, storage and transport decisions to obtain AFSC configurations capable of meeting market requirements in product freshness, quality, safety and homogeneity terms, while minimising product losses. This can only be possible by considering AFSC's inherent product characteristics.

Despite the need for flexible design solutions, we found from the literature review that most models used a single period approach to represent a static decision-making process, where decisions were made at one time horizon point. These decisions need to be respected during successive time periods by limiting subsequent tactical/operational decisions and determining future SC performance.

In order to obtain more flexible and adaptable AFSC, design decisions should be made dynamically. To this end, multiple time periods and design decisions allowing changes in SC configurations (e.g. opening, maintaining or closing facilities, and changing the allocation of processes/products to facilities, the capacity of facilities and the connections between facilities) should be considered during each time period depending on stakeholders' needs.

3.3 Modelling approach

The objective of this section is to characterise the analysed models to identify their modelling type, model purpose, constraints and application. This analysis is useful to identify the commonest characteristics and the possible gaps in existing AFSC design models (Tables 5 and 6).

Table 5. Classification of the modelling approach (Part I)

Ref.	Model type							Model purpose			
	LP	MILP	MOILP	INLP	SP	FMP	ALG/ HEU	Max. profit	Min. Cost	Min. negative environmental impact	Max. positive social impact
[39]	X								X		
[23]			X				X		X	X	X
[2]					X		X	X			X
[56]	X								X		
[4]				X				X			
[40]		X							X		
[41]		X							X		
[42]		X							X		
[43]		X							X		
[48]			X						X	X	
[61]		X					X		X		
[49]					X		X		X		
[50]					X		X		X		
[44]		X							X		
[52]		X					X		X		
[62]			X				X		X	X	
[57]		X						X			
[59]						X			X		
[45]						X			X		X
[46]			X				X		X		X
[47]						X	X		X	X	X
[58]		X					X		X		
[63]					X				X		X
[64]		X							X		
[55]		X					X		X		
[60]		X							X		
[51]		X							X		
[53]		X					X		X		
[54]		X					X		X		
[65]		X							X		
Total	2	16	4	1	4	3	13	3	27	4	6
%	6.7	53.3	13.3	3.3	13.3	10.0	43.3	10.0	90.0	13.3	20.0

3.3.1 Model type

The most employed modelling type was MILP, which was used in 53.3% of the analysed models, followed by MOILP and SP used by 13.3%. The analysed stochastic models could, in turn, be categorised as either stochastic mixed integer linear programming [2,49,50] or multi-objective stochastic non-linear programming [63]. Two LP models and one MONLP model were identified.

FMP was employed in 10.0% of the analysed models, although two types of FMP were identified: Fuzzy multi-objective integer linear programming [45,47] and Fuzzy non-linear mixed integer programming [59].

MILP models were NP-hard problems whose resolution proved to be time-consuming and computationally intractable in medium-large problems [54]. For this reason, 45% of the analysed references proposed a MILP model, and simultaneously presented algorithms/heuristics to solve the model in a reasonable time. Similarly, algorithms/heuristics were used to solve 57.1% of uncertain models.

In order to also cope with model complexity, 16.6% of the studied references [2,23,40-42] applied two-stage optimisation techniques, where the entire problem was decomposed into two problems and each problem was sequentially solved. The result obtained in the first stage was used as input to solve the second stage.

Table 6. Classification of the modelling approach (Part II)

Reference	Model constraints											Model application	
	Supply	Capacity	No. of location	Distance	Budget	Waste	Time	Service	Production	Routes	Perishability	Real case	Case study
[39]		X											X
[23]	X	X											X
[2]	X	X											X
[56]													X
[4]		X			X					X		X	
[40]		X											X
[41]		X											X
[42]		X											X
[43]		X										X	
[48]		X		X									X
[61]			X										X
[49]		X	X	X									X
[50]				X				X					X
[44]	X	X		X								X	
[52]	X	X		X									X
[62]		X	X				X						X
[57]	X	X											X
[59]		X								X			X
[45]	X	X											X
[46]	X	X					X						X
[47]	X	X					X						X
[58]	X	X											X
[63]		X											X
[64]		X		X									X
[55]		X											X
[60]	X		X									X	
[51]			X										X
[53]	X						X		X				X
[54]	X						X		X				X
[65]		X				X							X
Total	12	23	5	6	1	1	5	1	2	2	0	4	26
%	40.0	76.7	16.7	20.0	3.3	3.3	16.7	3.3	6.7	6.7	0.0	13.3	86.7

It is also worth mentioning that two of the analysed papers employed the MOILP [23] and the multi-objective FMP [45] model types, along with multi-attribute decision-making (MADM) approaches to simultaneously consider multiple performance indicators in a simplified manner. MADM approaches were used to identify the best option from a limited number of alternatives whose attributes were known [66]. Allaoui et al. [23] applied MADM techniques in a first step to assess potential partners from a limited set which, once selected, were taken as input in the second step for the MOILP model to decide the AFSC design. Mohammed and Wang [45] firstly proposed a fuzzy multi-objective model to design an AFSC, which provided them with limited Pareto-optimal solutions. Secondly, an MADM method was used to seek the best Pareto solution as a trade-off decision when optimising three conflicting objectives.

Finally, Govindan et al. [62] studied a two-echelon facility location problem, while Mohammed and Wang [47] developed a product distribution planner for a three-echelon green meat SC design.

3.3.2 Model purpose

All models pursue economic objectives, and for 90.0% of the models this implies minimising costs and maximising profits for 10.0% of the models, while considering the dependence of price on product branding [2] or season [57], or on markets [4]. The costs accounted in each model are identified in Table 7, and the most widely used costs are related to the location of facilities (67% of the models), production (47% of the models) and transportation (100% of the models). Other models represented the costs incurred by inventory (23.3%), procurement (16.7%), product waste (13.3%), unmet demand (10.0%), RFID uses (10.0%), closing locations (6.7%), energy use (3.3%) or labouring (3.3%). It is worth noting that very little attention was paid to minimising waste (13.3%) when designing AFSC, despite it being an important source of inefficiencies.

The environmental aspect of sustainability was considered in 13.3% of the models. Allaoui et al. [23] minimised the total produced CO2 emissions and the water used when locating and operating a facility, and also when transporting products. Colicchia et al. [48] minimised CO2 emissions while transporting and storing products. Govindan et al. [62] reduced the general environmental impact when transporting, producing and handling products, or when opening a facility. Mohammed and Wang [47] proposed minimising CO2 emissions when opening facilities and transporting products. Although Accorsi et al. [39] and Boudhari et al. [41,43] did not consider any environmental impact-related objective, but assumed its minimisation by assigning a related cost to the whole chain. Carbon trading mechanisms can also be used by AFSC actors to minimize carbon emissions and to comply with carbon cap-and trade regulations [67].

The social aspect of sustainability was addressed by 20.0% of the models. For this purpose, models aimed to minimise total delivery times [45,47,63], maximise customer satisfaction, measured as the degree of demand fulfilment [46,47], and maximise product quality [46], job creation [23] and the conditional value-at-risk of customer services [2].

Thus according to the classification by Farahani et al. [30], we found that 100% of the analysed models were designing Lean SC, 23.3% of the models designed Green AFSC and 6.67% of them designed Sustainable AFSC. Sustainability performance of AFSC could be analytically evaluated with methodologies such as the proposed by Yakovleva et al. [68]. For a recent review of quantitative models to address issues in sustainable food supply chains, see Zhu et al. [69].

Table 7. Costs accounted in economic objectives.

Reference	Costs										
	Locating facility	Production	Transport	Inventory	Product loss	Procurement	Unmet demand	Energy	Closing location	RFID	Labouring
[39]	X		X								
[23]	X	X	X			X			X		
[2]		X	X	X		X					
[56]		X	X			X					
[4]	X	X	X	X			X				
[40]	X		X								
[41]	X		X								
[42]	X		X								
[43]	X		X								
[48]			X								
[61]	X	X	X	X	X						
[49]	X	X	X		X						
[50]	X	X	X								
[44]	X		X								
[52]	X		X								
[62]	X	X	X	X			X				
[57]	X	X	X								
[59]	X		X								
[45]			X							X	
[46]			X							X	X
[47]		X	X							X	
[58]	X	X	X								
[63]	X		X	X		X					
[64]	X		X				X	X	X		
[55]	X		X								
[60]		X	X			X					
[51]	X		X		X						
[53]		X	X	X							
[54]		X	X	X							
[65]			X		X						
Total	20	14	30	7	4	5	3	1	2	3	1
%	66.7	46.7	100.0	23.3	13.3	16.7	10.0	3.3	6.7	10.0	3.3

3.3.3 Model constraints

The most widely considered constraint was the capacity limitation of facilities (76.7% of the references), followed by supply constraints (36.7% of the models) that determine the maximum quantity to be provided from suppliers.

The constraints related to the number of locations to be opened (20.0% of the models) referred to the maximum [58,60,62], the minimum [49] or the exact number [51,61] of locations to be opened.

The maximum distance to be covered when transporting/distributing products was addressed in 16.7% of the models to ensure the proximity of AFSC members [49,50], sales of local products [44,52], or a minimum product's remaining shelf life when delivered to customers [64]. In contrast, Colicchia et al. [48] considered the minimum distance between opened locations to avoid the crossing replenishment flows from two locations.

Similarly, 16.7% of the models considered a time limitation; e.g. the maximum allowable time for transportation [53,54], the minimum working hours to contract labourers [45,46] or considering time windows for deliveries [62].

Other constraints covered by the models included considering existing routes to transport products [4,59], the maximum allowed budget to open locations [4], the maximum flow of product to go through each facility [65], the minimum service level to be ensured [50] and the minimum production to open a new facility [53,54].

3.3.4 Model application

The majority of analysed papers (86.7%) validated their models and showed their applicability using a case study. Conversely, only 13.3% of the publications validated their models by applying them to a real AFSC.

3.3.5 Findings

This result of the dimension showed that many AFSC design models were MILP models, which are time-consuming and even computationally intractable in medium-large problems. Thus algorithms/heuristics are needed to solve these models in reasonable computing times. Algorithms/heuristics are also employed when models are extremely complex to solve due the vast amount of parameters, decision variables, objectives and/or constraints to be considered.

Only four models dealt with different objectives from the economical one, and only one simultaneously dealt with three sustainability dimensions. All these models used MOILP, and some combined it with multi-attribute decision-making techniques. Models for designing sustainable AFSC are needed, especially those that focus on the environmental and social dimensions, which can be respectively represented by reducing generated emissions and water/resource use, and by creating jobs. Given the conflicting nature of these dimensions and the necessity to include them in AFSC design processes, it would be appropriate to apply multi-objective programming and/or other modelling types combined with MADM approaches within multi-level optimisation frameworks.

The most modelled constraints were related to the capacity of facilities, available quantities at suppliers, times and distances. Some product characteristics-related constraints were lacking, such as products' minimum remaining shelf life needed in each SC stage, minimum food quality ensured at retailers, a constraint to ensure products' food safety, or a constraint to meet customer requirements in product homogeneity terms. Therefore, more effort needs to be made to develop models that consider constraints related to agri-food product characteristics.

Finally, more real applications of models are needed to identify the real benefits of considering specific AFSC characteristics when making decisions, e.g., designing SC.

3.4 Uncertainty modelling

The aim of this section is to identify which uncertainty sources present in AFSC have been covered by existing design models, and how they have been dealt with (Table 8).

3.4.1 Modelling context

The majority of models did not consider any source of uncertainty when designing AFSC (73.3% of the models). However, some other models contemplated at least one source of uncertainty. This was consistent with the model type employed by the authors who proposed uncertain models as they employed SP or FMP.

3.4.2 Uncertain parameters

The most considered source of uncertainty was uncertainty on demand (20.0% of the models), followed by uncertainty on supply and on costs (13.3% of the models for each one). Uncertainty in supply was considered in the limitation of the quantity to be supplied [2,47,50], or when modelling possible disruptions in processors, distribution centres and retailers [4]. The costs considered to be uncertain in the analysed models included the cost of opening locations [49,50], spot deal purchasing costs [2], and transportation costs, RFID costs and handling costs [47]. Finally, uncertainty on lead time was also considered [2] specifically in the supply lead time.

3.4.3 Uncertainty type

Only eight papers modelled at least one source of uncertainty for AFSC. Of these cases, 62.5% of the models considered aleatory uncertainty when assigning a probability function to uncertain parameters. Amorim et al. [2] modelled the purchasing cost of raw material and the available quantity of raw materials as normal distribution functions, demand as a gamma distribution depending on product age, and the supplier lead time as exponential negative offset. Baghalian et al. [4] considered that demand followed a normal distribution function, and that supply uncertainty was characterised by disruption probabilities for manufacturers. Ding [49,50] employed normal distribution functions to model the quantity of grain sold by suppliers and the cost of opening locations. Reza-Nasiri and Davoudpour [63] also modelled demand with a normal distribution function.

Epistemic uncertainty was considered by other models (37.5%). For this reason, uncertain parameters were modelled as either triangular fuzzy numbers [59] or trapezoidal membership functions [45,47].

Table 8. Classification of uncertainty modelling

Ref.	Modelling context		Uncertain parameters															Uncertainty type	
			Product						Process					Market		Env.			
	Det	Unc	SL	DR	H	FQ	FS	S	LT	RN	Pr	C	D	MP	W	PD	R	Ep	Al
[39]	X																		
[23]	X																		
[2]		X						X	X			X	X						X
[56]	X																		
[4]		X						X					X						X
[40]	X																		
[41]	X																		
[42]	X																		
[43]	X																		
[48]	X																		
[61]	X																		
[49]		X										X							X
[50]		X						X				X							X
[44]	X																		
[52]	X																		
[62]	X																		
[57]	X																		
[59]		X											X					X	
[45]		X											X					X	
[46]	X																		
[47]		X						X				X	X					X	
[58]	X																		
[63]		X											X						X
[64]	X																		
[55]	X																		
[60]	X																		
[51]	X																		
[53]	X																		
[54]	X																		
[65]	X																		
Total	22	8	0	0	0	0	0	4	1	0	0	4	6	0	0	0	0	3	5
%	73.3	26.7	0	0	0	0	0	13.3	3.3	0	0	13.3	20.0	0	0	0	0	10.0	16.7

Notes: Env: Environment; Det: Deterministic, Unc: Uncertain; SL: Shelf life, DR: Deterioration rate, H: Heterogeneity, FQ: Food quality, FS: Food safety; S: Supply, LT: Lead time, RN: Resource needs, Pr: Production, C: Costs; D: Demand, MP: Market prices; W: Weather, PD: Pests/diseases, R: Regulations; Ep: Epistemic, Al: Aleatory.

3.4.4 Findings

The results of this dimension showed that a few mathematical programming models dealt with sources of uncertainty when designing AFSC. In addition, the sources of uncertainty considered by the models were not specific of the agri-food sector, but actually existed in any SC type regardless of the sector. As far as we know, no AFSC design models exist that consider inherent uncertainty in both product characteristics and the environment. This is a very surprising finding and one that constitutes a wide gap in the literature.

The uncertainties inherent to AFSC cause major imbalance between supply and demand in terms of product varieties, quantities, qualities, customer requirements, times and prices. The mismanagement of such sources of uncertainty for AFSC can very negatively impact the quality, safety, sustainability and logistic efficiency of products and processes throughout the AFSC [70] and in waste.

Since sources of uncertainty negatively impact AFSC performance, future models should design AFSC in an uncertain context to obtain results that faithfully represent AFSC behaviour. To this end, a study on the influence of sources of uncertainties on AFSC performance is required. The best way to model each source of uncertainty should be identified (epistemic or aleatory uncertainty). After establishing the knowledge-base in this area, future models can use this information to evaluate what sources of uncertainty to cover when designing AFSC and how to model them.

AFSC design models are needed that consider sources of uncertainty related to the product (shelf life, deterioration rate, heterogeneity, food quality, food safety), process (resources needs, production), market (product price) and the environment (weather, pests, diseases, regulations).

4 Conclusions and future research lines

Lack of both CF to design AFSC by mathematical programming modelling and state-of-the-art of mathematical programming models to design AFSC motivated this research. The objective of this paper was to fill these two gaps in the research literature.

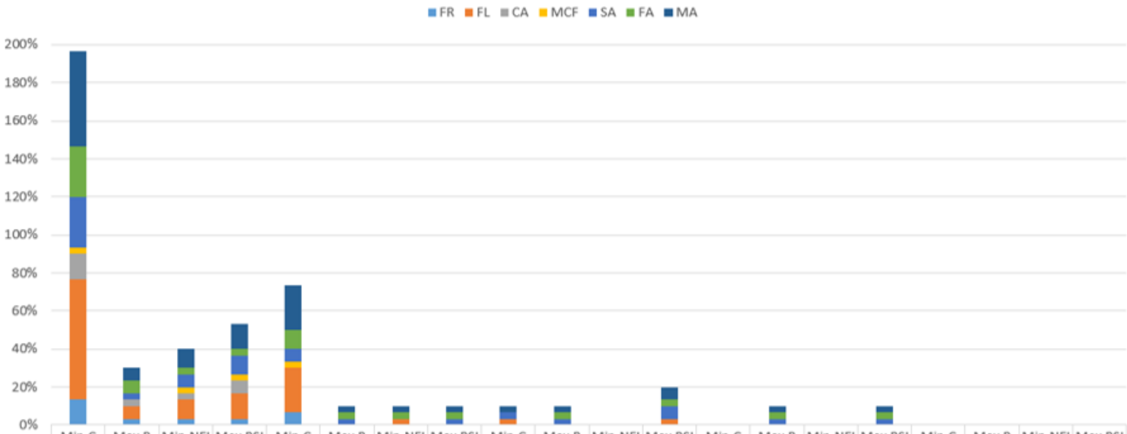
For this purpose, firstly CF to design AFSC by mathematical programming models was proposed. This framework is composed of four blocks that describe the characteristics of both the problem under study and the mathematical programming models that can be used to address the problem. CF can be used as a tool to either analyse existing mathematical programming models to design AFSC or to develop new models that apply to specific situations. Then a complete existing state-of-the-art mathematical programming model to design AFSC was carried out with the proposed CF. This allowed the framework to be validated.

The analysis results showed that most existing models design generic AFSC without considering all SC stages. Very few took into account the existence of multiple products and the product characteristics that strongly influenced AFSC performance. During the decision process, most models simultaneously considered design and tactical/operational decisions by a single time period approach. Thus given the complexity of the addressed problems, some mathematical programming models needed to be solved by algorithms/heuristics or by multi-stage optimisation methods. Those models basically considered economic objectives, while some also considered optimising the chain's environmental or social impacts. Very little attention was paid to minimise waste (13.3%) when designing AFSC. This is surprising knowing that food waste and losses is a major concern in AFSC, as reflected in FAO's [71] future trends. Since waste originates mainly from perishability and food quality, once again these aspects demand more attention. Most models were validated by them being applied to a case study.

It is interesting to observe how the consideration of product characteristics is related to the purpose of the AFSC design model and to the related design decisions (Figure 3). Food quality and product heterogeneity are related to socio-economic objectives, which makes sense as these two characteristics can be associated easily with customers' perception of the product. Similarly, product perishability is related to economic, social, and environmental objectives because it is not only related to customers' perception of a product, but also to the quantity of waste generated through AFSC. When considering product characteristics, related decisions are also related mainly to the allocation of the connections between the different SC stakeholders.

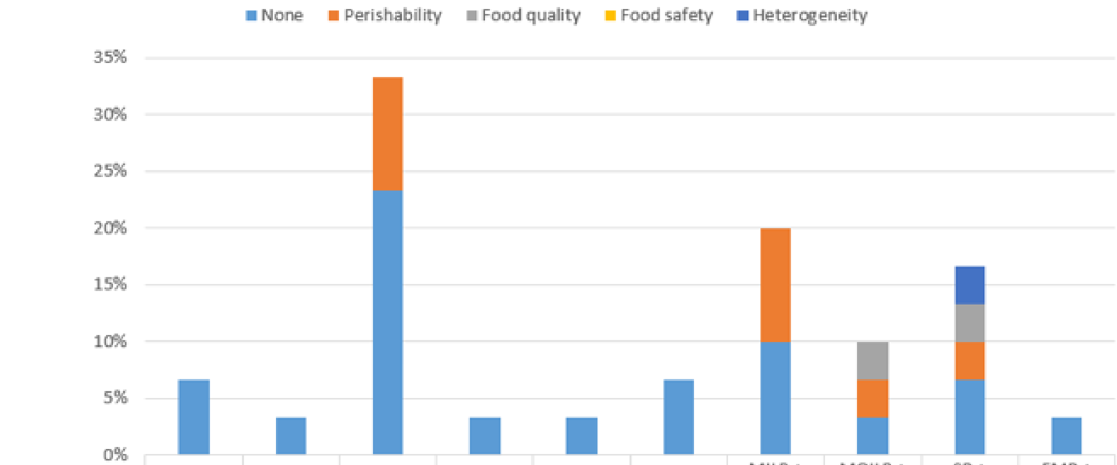
Generally, the complexity of models increases when considering one agri-food product characteristic or more, and algorithms/heuristics are often needed to solve these models (Figure 4). The cases which contemplate perishability, but do not use algorithms to solve the model, correspond to the models with few constraints and decisions, one time period, one objective and two SC stages. So they can be considered small problems.

Very few papers considered sources of uncertainty in their models. In addition, the sources of uncertainty (supply, lead time, cost, demand) modelled in the analysed models were present in each SC, regardless of the sector, and did not make a considerable contribution to uncertainty modelling research in the agri-food sector. Despite the negative impact of uncertainties on AFSC performance, no models were found that included any uncertain parameter related with either product characteristics or the environment. Therefore, it is necessary to include these inherent AFSC sources of uncertainty to obtain a proper and more robust AFSC design.



	None				Perishability				Food quality				Heterogeneity				Food safety			
	Min.C	Max.P	Min.NEI	Max.PSI	Min.C	Max.P	Min.NEI	Max.PSI	Min.C	Max.P	Min.NEI	Max.PSI	Min.C	Max.P	Min.NEI	Max.PSI	Min.C	Max.P	Min.NEI	Max.PSI
MA	50%	7%	10%	13%	23%	3%	3%	3%	3%	3%		7%		3%		3%				
FA	27%	7%	3%	3%	10%	3%	3%	3%		3%		3%		3%		3%				
SA	27%	3%	7%	10%	7%	3%		3%	3%	3%		7%		3%		3%				
MCF	3%		3%	3%	3%															
CA	13%	3%	3%	7%																
FL	63%	7%	10%	13%	23%		3%		3%			3%								
FR	13%	3%	3%	3%	7%															

Figure 3. Design decisions versus model purpose and product characteristics.



	LP	INLP	MILP	MOILP	SP	FMP	MILP + ALG/HEU	MOILP + ALG/HEU	SP + ALG/HEU	FMP + ALG/HEU
Heterogeneity									3%	
Food safety										
Food quality								3%	3%	
Perishability			10%				10%	3%	3%	
None	7%	3%	23%	3%	3%	7%	10%	3%	7%	3%

Figure 4. Model type versus product characteristics.

Lastly from this state of the art, the following future research lines are presented. Firstly, there is a need to make a distinction in models for designing crop-based and animal-based AFSC because their production process and product characteristics are not the same. These models should at least consider the supplier, processor, distributor and retailer stages of the SC, the existence of multiple products (and/or subproducts) and the characteristics of these products (perishability, food quality, food safety and heterogeneity). It is noteworthy that, to the best of our knowledge, no AFSC design model has dealt with the food safety characteristic before.

International Journal of Production Research, 2018
https://doi.org/10.1080/00207543.2018.1447706

Conceptual framework for designing agri-food supply chains under uncertainty by mathematical programming models

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(*Received 16 September 2017; accepted 23 February 2018*)

Agri-food sector performance strongly impacts global economy, which means that developing optimisation models to support the decision-making process in agri-food supply chains (AFSC) is necessary. These models should contemplate AFSC's inherent characteristics and sources of uncertainty to provide applicable and accurate solutions. To the best of our knowledge, there are no conceptual frameworks available to design AFSC through mathematical programming modelling while considering their inherent characteristics and sources of uncertainty, nor any there literature reviews that address such characteristics and uncertainty sources in existing AFSC design models. This paper aims to fill these gaps in the literature by proposing such a conceptual framework and state of the art. The framework can be used as a guide tool for both developing and analysing models based on mathematical programming to design AFSC. The implementation of the framework into the state of the art validates its. Finally, some literature gaps and future research lines were identified.

Keywords: agri-food supply chain; design; uncertainty; conceptual framework; literature review

1. Introduction

Agri-food supply chains (AFCS) are responsible for bringing agricultural products from the farm to the fork (Esteso, Alemany, and Ortiz 2017b). Since these supply chains (SC) comprise the largest manufacturing sector in Europe, and contribute to the economy with 4.25 million employees and a turnover over €1 trillion, it is critical to develop effective and efficient models and methods to support AFSC decision-making processes and to optimise AFSC performance (Amorim et al. 2016; FoodDrink Europe 2016).

Such performance is strongly influenced by factors such as uncertainty sources (e.g. weather, diseases, pests) and product characteristics (e.g. perishability), which differentiate AFSC from other industrial SC. Therefore, generic decision-making models and methods for designing and operating SC cannot be easily extrapolated to the agri-food sector since they do not represent real AFSC performance.

A first step, and one of the most critical ones for optimising AFSC performance, is to adequately design them as tactical and operational decisions, as well as their impact on overall SC performance, will depend on their configuration (Baghalian, Rezapour, and Farahani 2013). Tsolakis et al. (2014) point out that despite the significance of SC configuration decisions and a number of papers that address them in the general SC management context, the relevant agri-food literature on this topic is limited. This is probably due to the difficulties imposed by the structure and complexity of an entire agri-food chain's relationships, and to incoming uncertainties that characterise this particular network type.

In their review of operational research models applied to fresh fruit SC, Soto-Silva et al. (2016) state that there is a gap of models to design and manage such SC. These authors note that practically all models consider a constant price over time without taking into account fruit seasonality or loss in the product's value due to product deterioration. They point out the need for tools that incorporate fresh fruit SC's characteristics, such as shelf life, quality deterioration, waste and prices that depend on time and product freshness. They also indicate that given the uncertainty and risk that surround the fresh fruit sector, it is necessary to develop models that include these characteristics. Along these lines, Nakandala, Lau, and Zhao (2017) proposed a hybrid model for assessing risk in fresh food supply chains.

Since inherent sources of uncertainty in AFSC have a negative impact on their performance and sustainability, several authors (Lucas and Chhajed 2004; Ahumada and Villalobos 2009; Akkerman, Farahani, and Grunow 2010; Tsolakis

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Figure 5. Publication data.

It is also necessary to develop multiple time periods AFSC design models to reflect the dynamic characteristics of products (limited shelf life, deterioration, seasonality in prices, production yields, etc.) and the environment. Considering multiple time periods also allows design decisions to be made during each time period by allowing the SC to adapt to requirements at all times. All the design decisions should be addressed by these models, and it would be interesting to simultaneously address the procurement, production, storage and transport decisions and product characteristics to obtain accurate solutions to real AFSC performance. Inclusion of multiple objectives related to economic, environmental and social aspects seems mandatory if different sustainability dimensions are to be addressed. In doing so, and given their usual conflicting nature and the inherent complexity of AFSC, adopting multi-objective programming models might be suitable. Combining other mathematical programming models with MADM techniques also seems adequate to provide MADM with a limited number of AFSC design solutions (alternatives) to be evaluated by different criteria. This can be used also to simplify the

AFSC design problem by previously using MADM techniques to consider some objectives and to rule out the worst solutions from part of the AFSC design.

Future models should design AFSC in an uncertain context. For this purpose, more research on sources of uncertainty is needed. We propose conducting a study of the degree of influence that each source of uncertainty has on AFSC performance, followed by identifying the best way to address each uncertainty source. The results of this research could help researchers to decide which sources of uncertainty to address in future AFSC design models.

5 Publication data

Figure 5 shows the first page of the article published in the International Journal of Production Research (ISSN: 0020-7543).

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Chapter V:

Impact of perishability in the design of agri-food supply chains

This paper proposes a novel mixed integer linear programming model to design agri-food supply chains integrating tactical decisions and considering products' shelf-life. The model contribution lies in the joint modelling of the design, planting, cultivating, harvest, labouring, packing, inventory, transport, operation, wastes and unmet demand decisions, considering the entire supply chain, multiple products, multiple period horizon, and capacity, perishability and planting constraints. The purpose of this paper is to determine the impact that products' perishability has on the agri-food supply chain design, being this the main contribution of the paper. For that, a set of scenarios is generated by varying the products' shelf-life. It is concluded that products' perishability impact on the agri-food supply chain design when commercializing perishable products. Model can be used to determine the maximum investment that can be made to extend the products' shelf-life in function of the profits that will be obtained in return. The proposed model can also be applied to partially design a supply chain and to perform tactical planning for already designed chains.

Keywords: Supply chain design; Planting; Harvest; Optimization; Shelf-life

1 Introduction

Agri-food sector is the largest manufacturing sector in Europe, employing more than 4 million of people and producing a revenue of more than 1 trillion euros [1]. Up to 88 million of food tons are wasted each year in Europe, accounting for 20% of production [2]. Therefore, the economic and environmental sustainability of European countries is in some extent linked to the sustainability of agri-food supply chains (AFSC). This means that any improvement on the economic and environmental efficiency of AFSCs will have a positive impact on European inhabitants.

Having this objective on mind, researchers have proposed mathematical programming models (MPM) to solve agri-food tactical and operational problems optimizing the AFSC efficiency [3–5]. However, this could not be enough to optimize the AFSC efficiency since AFSC performance is highly influenced by its configuration [6]. In fact, the AFSC configuration limits the possible decisions that can be carried out.

To reduce the AFSC environmental impact, [7–9] remark the importance of considering the products' perishability during the AFSC design. Perishability impacts on the economic, environmental and social aspects of AFSC since it is related to the customers' perception of products and wasted generated [1]. Additionally, one of the main goals in the distribution of agri-food products is to guarantee the products' freshness [10], what is related to the products' perishability. Although models exist considering perishability at the tactical and operational level [11,12], few design models contemplate this aspect.

This paper proposes an AFSC design MPM integrating tactical decisions and considering products' shelf-life. The model contribution lies in the joint modelling of the design, planting, cultivating, harvest, labouring, packing, inventory, transport, operation, wastes and unmet demand decisions, considering the entire supply chain, multiple products, multiple period horizon, and capacity, perishability and planting constraints. This model combines strategic and tactical decisions with the consideration of the products' shelf-life, what represents the real AFSC characteristics and improves the AFSC performance in the long-, mid- and short-term [1].

Up to our knowledge, no previous studies compare the optimal AFSC configuration considering or not considering the products' perishability. To fill this gap, the model is solved for a set of scenarios in which products' have different shelf-life to respond the research question: Should products' perishability be modelled when designing AFSCs? To answer this question some tactical decisions mentioned above should be considered.

The rest of the paper is structured as follows. Section 2 analyses previous MPMs to design AFSC and highlights the main contributions of the paper. Section 3 describes the problem under study and section 4 explains the proposed MPM. Section 5 exposes the defined experimentation and main results. Section 6 draws conclusions and future research lines.

2 Related literature analysis and contributions of this study

Most relevant MPMs to design AFSCs or generic supply chains (SC) commercializing perishable products are analysed. This review does not intend to establish the current state of the art in this area (see [1]) but to analyse those characteristics relevant for this work. The characteristics of the proposed model are included in the last line of each table, referred to as TP (this paper).

Table 1 shows agri-food characteristics modelled. The number of models considering the entire AFSC during its design is growing although it is still scarce. Most models are designed for mono-product AFSC. However, the tendency is changing since mainly multi-product models have been published over the last two years.

Products’ perishability is modelled in AFSC design by including a product deterioration rate during storage [13–16] or distribution [14–21], a quality decay rate [9,22], a percentage of loss at warehouse storage [23], a fixed shelf-life for products [7,8,10,24–27] or pallets [28], a limitation on the duration of transportation [15,16] or storage [29], and a minimum shelf-life [27] or quality [9] required at markets.

Table 1. AFSC characteristics

Ref	Supply chain stages					No. of products		Product's perishability
	Supplier	Processor	Distributor	Retailer	Customer	One product	Multiple products	
[30]	X	X	X			X		
[31]		X				X		
[17]			X	X		X		X
[13]	X		X	X		X		X
[18]			X	X		X		X
[19]			X	X		X		X
[32]		X	X			X		
[33]		X		X		X		
[14]			X	X		X		X
[34]	X	X				X		
[15]	X	X	X				X	X
[16]	X	X	X				X	X
[35]		X		X		X		
[36]		X		X			X	
[37]			X	X			X	
[6]		X	X	X			X	
[38]		X		X			X	
[39]	X	X		X		X		
[40]		X	X	X		X		
[7]	X		X	X		X		X
[41]	X	X					X	
[42]	X	X				X		
[8]			X	X		X		X
[29]		X	X	X		X		X
[20]	X	X		X			X	X
[43]		X	X	X		X		
[44]	X	X	X	X		X		
[24]	X	X		X			X	X
[45]			X	X		X		
[25]		X	X	X			X	X
[22]	X	X	X	X			X	X
[26]		X	X	X		X		X
[46]	X	X		X			X	
[47]	X	X		X		X		
[48]	X	X		X		X		
[49]	X	X		X		X		
[10]			X	X		X		X
[23]	X	X	X	X			X	X
[50]	X	X	X	X			X	
[28]	X		X	X			X	X
[21]		X	X	X			X	X
[27]			X	X			X	X
[51]	X	X	X	X			X	
[9]	X	X		X			X	X
TP	X	X	X	X	X		X	X

Table 2. Model characteristics

Ref	Decisions													Constraints			Horizon	
	FL	SA	FA	MA	P	H	C	Pa	I	T	W	UD	L	P	Ca	Pe	SP	MP
[30]	X	X	X	X						X							X	
[31]	X		X							X							X	
[17]	X			X											X		X	
[13]	X			X					X								X	
[18]	X			X											X		X	
[19]	X			X													X	
[32]	X			X													X	
[33]	X			X											X		X	
[14]	X			X													X	
[34]	X	X	X							X					X		X	
[15]	X	X	X	X		X				X							X	
[16]	X	X	X	X		X				X							X	
[35]	X			X											X		X	
[36]	X			X											X		X	
[37]	X			X											X		X	
[6]	X		X	X						X					X		X	
[38]	X			X						X					X		X	
[39]	X	X		X						X							X	
[40]	X		X	X						X					X		X	
[7]	X			X					X								X	
[41]	X		X							X					X			X
[42]	X	X													X		X	
[8]	X			X					X								X	
[29]	X		X	X					X	X					X			X
[20]	X									X					X			
[43]	X		X	X						X					X		X	
[44]	X	X	X	X						X					X		X	
[24]		X	X	X					X	X					X			X
[45]	X			X											X		X	
[25]	X			X					X	X							X	
[22]	X	X	X	X					X	X							X	
[26]	X								X	X					X			X
[46]	X	X	X	X						X					X			X
[47]	X	X		X						X					X		X	
[48]	X	X		X						X			X		X		X	
[49]	X	X		X						X			X		X		X	
[10]	X			X						X					X		X	
[23]	X	X	X	X						X					X		X	
[50]	X	X	X	X						X					X			X
[28]	X					X			X	X					X			X
[21]	X									X					X		X	
[27]	X			X						X		X			X		X	
[51]	X								X	X					X			X
[9]	X				X	X			X	X	X			X	X	X		X
TP	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X		X

FL: Facility location, SA: Supply allocation, FA: Facility allocation, MA: Market allocation, P: Planting, C: Cultivation, H: Harvest, Pa: Packing, I: Inventory, T: Transport, W: Wastes, UD: Unmet demand, L: Labouring; Ca: Capacity, Pe: Perishability, SP: Single period, MP: Multiple period

Table 2 identifies the characteristics of the design models. Most models addressed facility location (98%), and market allocation (85%) design decisions. Tactical decisions such as transport (68%) and inventory (25%) are usually included in design models. Less modelled decisions include the planting (2%) and harvest (9%) of crops, labouring decisions in slaughterhouses (5%), and wastes and unmet demand (2%). 80% of models consider a single-period horizon to design AFSC and are mainly focused on strategic decisions and tactical decisions (transport).

Regarding constraints, most models limit the transport (34%), production (43%) or inventory (23%) capacity in one or more facilities. [9] limits the area to be planted per product due to legislative or practical reasons. In perishable contexts, [9] constraints the maximum age at which products can be sold while [27] fixes the minimum freshness that products must have at markets.

After the review, it is concluded that models contemplating the entire AFSC and multiple products are needed as highlighted in [1]. Products' perishability has been modelled particularly in models designing partial AFSCs commercializing one product. To fill these gaps, the proposed model designs a five-stage AFSC commercializing multiple products with limited shelf-life.

Most models deal with design decisions combined with one or two tactical decisions such as transport or inventory. AFSC design models addressing planting, cultivating or harvest activities are very scarce although specific characteristics of AFSC makes necessary to include harvesting decisions into the AFSC design [9]. Planting should also be addressed to better balance the product flow along the SC, reducing production peaks and their impact on the AFSC design. Considering planting, production, storage and distribution decisions and products' perishability while designing AFSC ensures the adjustment to markets requirements and improves the SC performance in the short-, mid- and long-term [1]. The proposed model in this paper integrates design decisions with planting, cultivation, harvest, labouring, packing, storage, operation, wastes and unmet demand decisions.

Modelled constraints are mainly related to storage and production capacity of facilities. This paper limits the capacity for managing products in warehouses and DC, what has not been previously considered in literature. This constraint prevents using cross-docking points to manage an infinite quantity of product per period.

Constraints related to products' perishability should be contemplated to ensure the safety of products sold. In the proposed model, a minimum freshness at markets is fixed to ensure a minimum duration of products after sale, in order to keep suitable products properties for consumption, sometime after the consumer purchase. Finally, multiple period horizon needs to be contemplated in cases in which products' perishability is included in the model and planting and harvest decisions are made, since it can lead to more accurate results [1].

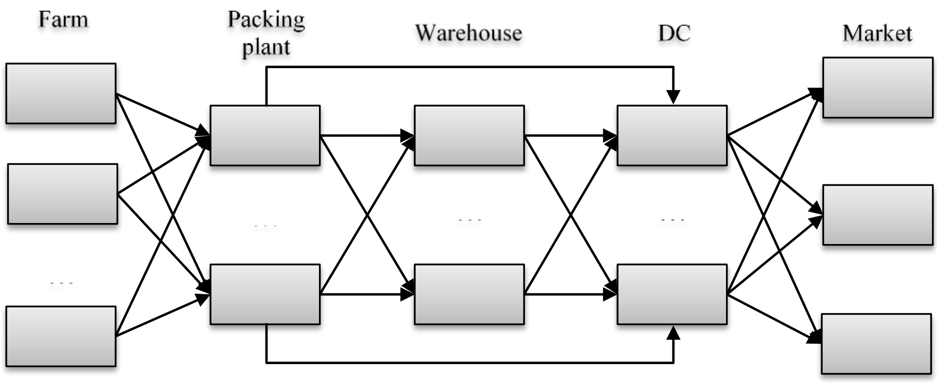
The main contributions to multi-period AFSC design modelling is the joint integration planting, cultivation, harvest, labouring, packing, inventory, transport, operation, wastes and unmet demand decisions to the design of an entire AFSC that commercialize multiple perishable products. Cultivation, labouring in farms, packing, and operation decisions have not been previously addressed in AFSC design models. Constraints related to the capacity of production, storage and products' management, the minimum freshness of products at sales time, and minimum planting areas are modelled. The proposed model is used to determine the impact of products' perishability on the AFSC design, being this another contribution of the paper.

In short, more realistic models are necessary in order to include the inherent characteristics of AFSC and to study the impact of modelling them. Following sections aim to throw some light to this matter.

3 Problem description

A typical AFSC for fresh fruits and vegetables (short shelf-life products) is modelled. It is comprised by five stages: farmers, packing plants (PP), warehouses, DCs, and markets (Figure 1). Farmers plant, cultivate and harvest crops. Once harvested, products are transported to PPs where are stored and packed. Packed products can either be transported to warehouses or DCs, where product can be stored. Warehouses and DCs can also be used as cross-docking points. Finally, products are transported from DCs to markets, who represent the demand of end-consumers [1].

Figure 1. Agri-food supply chain (based on [50])



The assumptions made to define the problem are described below.

- The facilities that can be opened as well as their role (farm, PP, warehouse, and DC), capacity (available area at farms, processing and storage capacity at PPs, operation and storage capacity at warehouses and DCs), and opening costs are known.
- Only crops from annual plants can be planted. Planting can be done with seeds or seedlings and the planting density is known. Planting periods depend on the crop planted. There is a crop-dependent fixed cost related to the planting and cultivation of plants.
- Plants are cultivated from the planting period until the last harvest period. Cultivation activities include irrigation of plants, application of phytosanitary products, and plant-related activities such as pruning.
- Harvest depend on the crop and planting date. Plants are harvested at all harvest periods although the harvest frequency (harvest pattern) per period can be chosen.
- The yield of the plant, that is the quantity of product obtained from a plant, depends on the crop, the planting and harvest dates, and the used harvest pattern.
- Once harvested, products shelf-life is limited depending on the crop and harvest period. Products need to be sold with a minimum remaining shelf-life (freshness).
- Planting, cultivation and harvest activities are handmade by seasonal and temporary laborers. Time needed to carry out these activities is known as well as the capacity of laborers. The available laborers to be hired is limited. Seasonal laborers have an associated hiring cost in addition to their salary whereas the only cost for temporary laborers is their salary.

- Products can be stored at PPs until their packing. Packing has an associated cost due to the use of materials and energy. Wastes are produced when products last their shelf-life before being sold. Penalty costs are associated to wastes.
- Packed products are transported to warehouses and DCs for their storage and distribution to markets. Transportation costs among SC nodes are known.
- Markets, demand and prices of products are known. Unmet demand is economically penalized.

4 MPM to design AFSC considering products' shelf-life

4.1 Nomenclature

Nomenclature used to define the model is described in Tables 4-5.

Table 4. Nomenclature

Indices			
v	Vegetable	f	Farmer
p	Planting period	c	PP
h	Harvest period	s	Warehouse
t	Period of time	d	DC
w	Harvesting patterns	m	Market
Set of indices			
P_v	Set of planting periods p in which vegetables v can be planted	HP_v^h	Set of planting periods p for vegetables v that allow harvest at period h
H_v	Set of harvest periods h in which vegetables v can be harvested	PC_v^t	Set of periods t in which vegetables v planted in p need to be cultivated
PH_v^p	Set of periods h in which vegetable v planted in p can be harvested	W_v	Set of harvest patterns w that can be used with plants of vegetable v
Parameters			
p_{vm}^t	Sales price for the vegetable v in the market m at the period t	de_{vm}^t	Demand of vegetable v in the market m at the period t
cwa_v	Penalization cost for wasting one kg of vegetable v	cud_{vm}	Penalization cost for not meeting one kg of demand of vegetable v at market m
cf_v	Cost to plant and cultivate one plant of vegetable v	$cpack_v$	Cost to pack one kilogram of vegetable v
$ctfp_{fc}$	Cost to transport one kg of vegetable from farmer f to PP c	tfc_{fc}	Time needed to transport product from farmer f to PP c
$ctpw_{cs}$	Cost to transport one kg of vegetable from PP c to warehouse s	tcs_{cs}	Time needed to transport product from PP c to warehouse s
$ctpd_{cd}$	Cost to transport one kg of vegetable from PP c to DC d	tcd_{cd}	Time needed to transport product from PP c to DC d
$ctwd_{sd}$	Cost to transport one kg of vegetable from warehouse s to DC d	tsd_{sd}	Time needed to transport product from warehouse s to DC d
$ctdm_{dm}$	Cost to transport one kg of vegetable from DC d to market m	tdm_{dm}	Time needed to transport product from DC d to market m
tpa_v	Time required to pack one kilogram of vegetable v	$capp_c$	Available packing capacity in the PP c during a period
chp_{vc}	Holding cost for vegetable v at PP c for one period	$capip_c$	Available storage capacity in the PP c during a period
chw_{vs}	Holding cost for vegetable v at warehouse s for one period	$capw_s$	Available storage capacity in the warehouse s during a period
chd_{vd}	Holding cost for vegetable v at DC d for one period	$capd_d$	Available storage capacity in the DC d during a period

Table 5. Nomenclature

Parameters			
cow_{vs}	Operation cost for vegetable v at warehouse s for one period	$capow_{s}$	Available operation capacity in the warehouse s during a period
cod_{vd}	Operation cost for vegetable v at DC d for one period	$capod_{d}$	Available operation capacity in the DC d during a period
cff_{f}	Cost for opening farm f	cfw_{s}	Cost for opening warehouse s
cfp_{c}	Cost for opening PP c	cfd_{d}	Cost for opening DC d
a_{f}	Available area at farm f	d_{v}	Density of planting for the vegetable v
am_{v}	Minimum area to be planted per period with vegetable v due to technical aspects in case it is decided to be planted	y_{vw}^{ph}	Yield of a plant of vegetable v at period h if planted at p and harvested with pattern w
tp_{v}	Time needed to plant one plant of vegetable v	mls_{f}	Minimum number of seasonal laborers hired by farmer f
tc_{v}	Time required to cultivate one plant of vegetable v	Mls	Maximum number of seasonal laborers available to be hired
th_{vw}	Time required to harvest a plant of vegetable v with pattern w	Mlt	Maximum number of temporal laborers available to be hired
hw	Capacity of a labourer during a period	cls	Weekly cost for a seasonal labourer
chs	Cost for hiring one seasonal labourer	clt	Weekly cost for a temporary labourer
sl_{v}^{h}	Shelf-life for vegetable v if planted in period p and harvested at h	msl_{v}	Minimum shelf-life that vegetable v needs to have in the moment of its sale
$capt$	Capacity of transportation in one truck		

Decision variables	
YF_{f}	Binary variable with value 1 when farm f is open, and 0 otherwise.
YPA_{c}	Binary variable with value 1 when PP c is open, and 0 otherwise
YW_{s}	Binary variable with value 1 when warehouse s is open, and 0 otherwise
YD_{d}	Binary variable with value 1 when DC d is open, and 0 otherwise
YP_{vf}^{p}	Binary variable with value 1 when vegetable v is planted by farmer f in the planting period p, and 0 otherwise.
NP_{vf}^{p}	Number of plants of v planted by farmer f at period p
NC_{vf}^{t}	Number of plants of v cultivated by farmer f at period t
NHW_{vfw}^{ph}	Number of plants of v planted by farmer f at t and harvested at h with harvest pattern w
QH_{vf}^{ph}	Quantity of v planted by farmer f at period p that is harvested at period h
QP_{vc}^{ht}	Quantity of v harvested at h packed at the PP c at period t
WP_{vc}^{ht}	Quantity of v harvested at h wasted at the PP c at period t
$QTFP_{vfc}^{ht}$	Quantity of v harvested at h by farmer f transported to PP c at period t
$QTPW_{vcs}^{ht}$	Quantity of v harvested at h transported from PP c to warehouse s at period t
$QTPD_{vcd}^{ht}$	Quantity of v harvested at h transported from PP c to DC d at period t
$QTWD_{vsd}^{ht}$	Quantity of v harvested at h transported from warehouse s to DC d at period t
$QTDM_{vdm}^{ht}$	Quantity of v harvested at h transported from DC d to market m at period t
$NTFP_{fc}^{t}$	Number of trucks that go from farm f to PP c in period t
$NTPW_{cs}^{t}$	Number of trucks that go from PP c to warehouse s in period t
$NTPD_{cd}^{t}$	Number of trucks that go from PP c to warehouse s in period t
$NTWD_{sd}^{t}$	Number of trucks that go from warehouse s to DC d in period t
$NTDM_{dm}^{t}$	Number of trucks that go from DC d to market m in period t
IP_{vc}^{ht}	Existing inventory at period t in PP c of vegetable v harvested in h
IW_{vs}^{ht}	Existing inventory at period t in warehouse s of vegetable v harvested in h
ID_{vd}^{ht}	Existing inventory at period t in DC d of vegetable v harvested in h
HLS_{f}^{t}	Seasonal laborers hired by farmer f in period t
LS_{f}^{t}	Seasonal laborers working at farm f in period t
FLS_{f}^{t}	Seasonal laborers fired by farmer f in period t
LT_{f}^{t}	Temporary laborers working at farm f in period t
QTS_{vm}^{ht}	Quantity of v harvested at h and sold at market m in period t
UD_{vm}^{t}	Quantity of unmet demand of v at market m in period t

4.2 Agri-food supply chain design considering products' shelf-life model

The model aims to maximize the SC profits, calculated as the difference between sales and costs derived from opening locations, planting, packing, transport, inventory, operation, workforce, wastes, and unmet demand.

$$\begin{aligned}
Max\ Z_1 = &\sum_{v}\sum_{m}\sum_{h\in H_v}\sum_{t} p_{vm}^{t}\cdot QTS_{vm}^{ht} - \sum_{v}\sum_{f}\sum_{p\in P_v} cf_v\cdot NP_{vf}^{p} \\
&-\sum_{v}\sum_{c}\sum_{h\in H_v}\sum_{t} cpack_v\cdot QP_{vc}^{ht} - \sum_{f}\sum_{c}\sum_{t} ctfp_{fc}\cdot NTFP_{fc}^{t} \\
&-\sum_{c}\sum_{s}\sum_{t} ctpw_{cs}\cdot NTPW_{cs}^{t} - \sum_{c}\sum_{d}\sum_{t} ctpd_{cd}\cdot NTPD_{cd}^{t} \\
&-\sum_{s}\sum_{d}\sum_{t} ctwd_{sd}\cdot NTWD_{sd}^{t} - \sum_{d}\sum_{m}\sum_{t} ctdm_{dm}\cdot NTDM_{dm}^{t} \\
&-\sum_{v}\sum_{h\in H_v}\sum_{t}\left(\sum_{c} chp_{vc}\cdot IP_{vc}^{ht} + \sum_{s} chw_{vs}\cdot IW_{vs}^{ht} + \sum_{d} chd_{vd}\cdot ID_{vd}^{ht}\right) \\
&-\sum_{v}\sum_{h\in H_v}\sum_{t}\left(\sum_{c}\sum_{s} cow_{vs}\cdot QTPW_{vcs}^{ht} + \sum_{c}\sum_{d} cod_{vd}\cdot QTPD_{vcd}^{ht}\right. \\
&\left.+\sum_{s}\sum_{d} cod_{vd}\cdot QTWD_{vsd}^{ht}\right) - \sum_{f}\sum_{t}\left(chs\cdot HLS_f^{t} + cls\cdot LS_f^{t} + clt\cdot LT_f^{t}\right) \\
&-\sum_{v}\sum_{c}\sum_{h\in H_v}\sum_{t} cwa_v\cdot WAH_{vc}^{ht} - \sum_{v}\sum_{m}\sum_{t} cud_{vm}\cdot UD_{vm}^{t} \\
&-\sum_{f} cff_f\cdot YF_f - \sum_{c} cfp_c\cdot YPA_c - \sum_{s} cfw_s\cdot YW_s - \sum_{d} cfd_d\cdot YD_d
\end{aligned} \tag{1}$$

The model is subject to the following constraints. At the farm level, the planted area during a year cannot exceed the available area at the farm (2). If a vegetable is decided to be planted at a farm in one period, a minimum and maximum area must be planted because of technical reasons (3). Vegetables can only be planted at one farm in case it is open (4).

$$\sum_{v}\sum_{p\in P_v}\frac{NP_{vf}^{p}}{d_v} \le a_f\cdot YF_f \qquad \forall f \tag{2}$$

$$am_v\cdot YP_{vf}^{p} \le \frac{NP_{vf}^{p}}{d_v} \le a_f\cdot YP_{vf}^{p} \qquad \forall v,f,p\in P_v \tag{3}$$

$$YP_{vf}^{p} \le YF_f \qquad \forall v,f,p\in P_v \tag{4}$$

Cultivating (5) and harvest (6) activities are made on all plants that require so on one period. The harvest pattern to be used in each plant can be decided.

$$NC_{vf}^{t} = \sum_{p\in PC_v^{t}} NP_{vf}^{p} \qquad \forall v,f,t \tag{5}$$

$$\sum_{w\in W_v} NHW_{vfw}^{ph} = NP_{vf}^{p} \qquad \forall v,f,h\in H_v,p\in HP_v^{h} \tag{6}$$

The quantity of vegetables obtained during harvest is function of the yield of the plant (7). Harvested vegetables should be transported to PPs in the harvest period (8).

$$QH_{vf}^{ph} = \sum_{w \in W_v} y_{vw}^{ph} \cdot NHW_{vfw}^{ph} \qquad \forall v, f, p \in P_v, h \in PH_v^p \tag{7}$$

$$\sum_{p \in HP_v^h} QH_{vf}^{ph} = \sum_{c} QTFP_{vfc}^{ht} \qquad \forall v, f, h \in H_v, t = h \tag{8}$$

When products arrive to a PP, they can be packed, stored or wasted (9). The packing capacity is limited (10). Once products are packed, they are transported to warehouses or DCs in the same period of their packing (11).

$$IP_{vc}^{ht} = IP_{vc}^{ht-1} + \sum_{f} QTFP_{vfc}^{ht-tfc_{fc}} - QP_{vc}^{ht} - WP_{vc}^{ht} \qquad \forall v, c, h \in H_v, h \leq t \leq h + sl_v^h - msl_v \tag{9}$$

$$\sum_{v} \sum_{t-sl_v^h+msl_v \leq h \leq t} tpa_v \cdot QP_{vc}^{ht} \leq capp_c * YPA_c \qquad \forall c, t \tag{10}$$

$$QP_{vc}^{ht} = \sum_{s} QTPW_{vcs}^{ht} + \sum_{d} QTPD_{vcd}^{ht} \qquad \forall v, c, h \in H_v, h \leq t \leq h + sl_v^h - msl_v \tag{11}$$

Vegetables are necessarily transported to markets from DCs. All vegetables arriving to markets are sold at the same period (12). If transported product is not enough to meet demand, unmet demand would be produced (13).

$$QTS_{vm}^{ht} = \sum_{d} QTDM_{vdm}^{ht-tdm_{dm}} \qquad \forall v, m, h \in H_v, h \leq t \leq h + sl_v^h - msl_v \tag{12}$$

$$\sum_{t-sl_v^h+msl_v \leq h \leq t} QTS_{vm}^{ht} + UD_{vm}^{t} = de_{vm}^{t} \qquad \forall v, m, t \tag{13}$$

Seasonal and temporary laborers needed to do handmade activities at farms vary in function of the plants that need some operation (14). A balance of laborers where hiring and firing actions are considered is needed for seasonal laborers (15) while it is not for temporary laborers as their contracts are defined for just one period. A minimum and maximum number of seasonal and temporary laborers must be contemplated (16-18).

$$\sum_{v} \left(\sum_{p=t} tp_v \cdot NP_{vf}^{p} + tc_v \cdot NC_{vf}^{t} + \sum_{p \in P_v} \sum_{w} \sum_{h=t} th_{vw} \cdot NHW_{vfw}^{ph} \right) \leq hw \cdot \left(LS_f^t + LT_f^t \right) \qquad \forall f, t \tag{1}$$

$$LS_f^t = LS_f^{t-1} + HLS_f^t - FLS_f^t \qquad \forall f, t \tag{2}$$

$$LS_f^t \geq mls_f \cdot YF_f \qquad \forall f, t \tag{3}$$

$$\sum_{f} LS_f^t \leq Mls \qquad \forall t \tag{4}$$

$$\sum_{f} LT_f^t \leq Mlt \qquad \forall t \tag{5}$$

The number of trucks that make each route depends on the quantity of vegetables to transport and the truck capacity (19-23). Products can only be transported from and to a location in case it is open (24-27).

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} QTFP_{vfc}^{ht} \le NTFP_{fc}^{t} \cdot capt \qquad \forall f,c,t \tag{19}$$

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} QTPW_{vcs}^{ht} \le NTPW_{cs}^{t} \cdot capt \qquad \forall c,s,t \tag{20}$$

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} QTPD_{vcd}^{ht} \le NTPD_{cd}^{t} \cdot capt \qquad \forall c,d,t \tag{21}$$

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} QTWD_{vsd}^{ht} \le NTWD_{sd}^{t} \cdot capt \qquad \forall s,d,t \tag{22}$$

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} QTDM_{vdm}^{ht} \le NTDM_{dm}^{t} \cdot capt \qquad \forall d,m,t \tag{23}$$

$$\sum_{c} \sum_{t} NTFP_{fc}^{t} \le M \cdot YF_f \qquad \forall f \tag{24}$$

$$\sum_{f} \sum_{t} NTFP_{fc}^{ht} + \sum_{s} \sum_{t} NTPW_{cs}^{t} + \sum_{d} \sum_{t} NTPD_{cd}^{t} \le M \cdot YPA_c \qquad \forall c \tag{25}$$

$$\sum_{c} \sum_{t} NTPW_{cs}^{t} + \sum_{d} \sum_{t} NTWD_{sd}^{t} \le M \cdot YW_s \qquad \forall s \tag{26}$$

$$\sum_{s} \sum_{t} NTWD_{sd}^{t} + \sum_{m} \sum_{t} NTDM_{dm}^{t} \le M \cdot YD_d \qquad \forall d \tag{27}$$

The inventory of a vegetable in warehouses and DCs is equal to the inventory in the previous period, plus product coming from other locations less the product transported to other facilities. In case of warehouses, products come from PPs and are transported to DCs (28). In case of DCs, products come from both PPs and warehouses and are transported to markets (29).

$$IW_{vs}^{ht} = IW_{vs}^{ht-1} + \sum_{c} QTPW_{vcs}^{ht-tcs_{cs}} - \sum_{d} QTWD_{vsd}^{ht} \tag{28}$$

$$\forall v,s,h \in H_v, h \le t \le h + sl_v^{ph} - msl_v$$

$$ID_{vd}^{ht} = ID_{vd}^{ht-1} + \sum_{c} QTPD_{vcd}^{ht-tcd_{cd}} + \sum_{s} QTWD_{vsd}^{ht-tsd_{sd}} - \sum_{m} QTDM_{vdm}^{ht} \tag{29}$$

$$\forall v,d,h \in H_v, h \le t \le h + sl_v^{h} - msl_v$$

Existing inventory at facilities per period cannot exceed the storage capacity of such facilities (30-32). The total inventory at the end of the horizon should be equal to zero in all locations (33).

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} IP_{vc}^{ht} \le capip_c * YPA_c \qquad \forall c,t \tag{30}$$

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} IW_{vs}^{ht} \le capw_s * YW_s \qquad \forall s,t \tag{31}$$

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} ID_{vd}^{ht} \le capd_d * YD_d \qquad \forall d,t \tag{32}$$

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} \left(\sum_{c} IP_{vc}^{ht} + \sum_{s} IW_{vs}^{ht} + \sum_{d} ID_{vd}^{ht} \right) = 0 \qquad \forall t = 52 \tag{33}$$

The quantity of vegetables managed in warehouses and DCs per period is limited (34-35).

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} \left(\sum_{c} QTPW_{vcs}^{ht-tcs_{cs}} + \sum_{d} QTWD_{vsd}^{pht} \right) \le capow_s * YW_s \qquad \forall s,t \tag{34}$$

$$\sum_{v} \sum_{t-sl_v^h+msl_v \le h \le t} \left(\sum_{c} QTPD_{vcd}^{ht-tcd_{cd}} + \sum_{s} QTWD_{vsd}^{ht-tsd_{sd}} + \sum_{m} QTDM_{vdm}^{ht} \right) \le capod_d * YD_d \qquad \forall d,t \tag{35}$$

To ensure that no products remain in a truck at the end of the horizon, constraint (36) equals the total quantity of sales with the total quantity of product transported to markets.

$$\sum_{v} \sum_{m} \sum_{h \in H_v} \sum_{t} QTS_{vm}^{ht} = \sum_{v} \sum_{d} \sum_{m} \sum_{h \in H_v} \sum_{h \le t \le h+sl_v^h-msl_v} QTDM_{vdm}^{ht} \tag{36}$$

Finally, nature of decision variables is defined (37).

$$\begin{array}{ll} Continuous: & QH_{vf}^{ph}, QP_{vc}^{ht}, UD_{vm}^{t}, W_{vf}^{ht}, QTFP_{vfc}^{ht}, QTPW_{vcs}^{ht}, QTPD_{vcd}^{ht}, QTWD_{vsd}^{ht} \\ & QTDM_{vdm}^{ht}, IP_{vc}^{ht}, IW_{vs}^{ht}, ID_{vd}^{ht}, QTS_{vm}^{ht} \\ Integer: & NP_{vf}^{p}, NC_{vf}^{t}, NHW_{vfw}^{ph}, HLS_f^t, LS_f^t, FLS_f^t, LT_f^t \\ & NTFP_{fc}^{t}, NTPW_{cs}^{t}, NTPD_{cd}^{t}, NTWD_{sd}^{t}, NTDM_{dm}^{t} \\ Binary: & YF_f, YP_{vf}^{p}, YPA_c, YW_s, YD_d \end{array} \tag{37}$$

4.3 Model extensions

Although the model is formulated to cover the entire AFSC design, it can also be used to design/redesign only a part of the chain. For that, binary variables related to the opening of already open locations are set to one by including constraint (38) for farmers, (39) for PPs, (40) for warehouses and (41) for DCs.

$$YF_f = 1 \qquad \forall f \tag{6}$$

$$YPA_c = 1 \qquad \forall c \tag{7}$$

$$YW_s = 1 \qquad \forall s \tag{8}$$

$$YD_d = 1 \qquad \forall d \tag{9}$$

Once AFSCs have been designed, the model can be used to carry out the tactical-operative planning by including only those indexes corresponding to open locations, and fixing the binary variables referring to opening locations to one, by including constraints (38-41).

5 Computational experiments

This section aims to validate the proposed model and to determine the impact of products' perishability on the AFSC design. For that, a set of scenarios where products are characterized by different shelf-life are solved with the model.

5.1 Data

Data used to validate the model and carry out the experimentation are inspired in a realistic case study from the region of La Plata in Argentina. An agricultural area composed by ten farmers grouped in four regions is considered. Farms belonging to the same region are very close each other, so distance between them is negligible. The available area at each farm and related opening costs are detailed in Table 6.

Table 6. Farmers information

Farmer	Available area (ha)	Opening cost (€)
1	110	162,800
2	150	222,000
3	190	281,200
4	230	340,400
5	270	399,600
6	250	370,000
7	210	310,800
8	170	251,600
9	130	192,400
10	290	429,200

Three types of crops can be planted. Due to technical reasons, a minimum of 200 plants of the same variety are planted when it is decided to do so in a period. The density of planting is 22000 plants/ha for crops A and B, and 19000 plants/ha for crops C. The costs of planting one plant of each variety are 0.095, 0.092 and 0.068 €/plant, respectively.

Crops can be planted in three planting seasons: July, October and January. Cultivation and harvest activities depend on planting dates as showed in Figure 2 where week 1 corresponds to the first week of July. Cultivation activities ensure the correct grow up of plants such as irrigation, application of phytosanitary products, or pruning and staking up of plants. Four harvest patterns defined in [53] can be used during harvest. Times needed to plant, cultivate and harvest crops are defined in Table 7.

These activities are handmade by laborers that work 48 hours week. Farmers hire a minimum of one seasonal worker per each ten available hectares at farm. A maximum of 450 seasonal and 350 temporary laborers are available with a salary of 42.5 and 69 €/week respectively. Seasonal workers have also an associated hiring cost of 42.5€.

Figure 2. Planting, cultivation and harvest dates for tomatoes

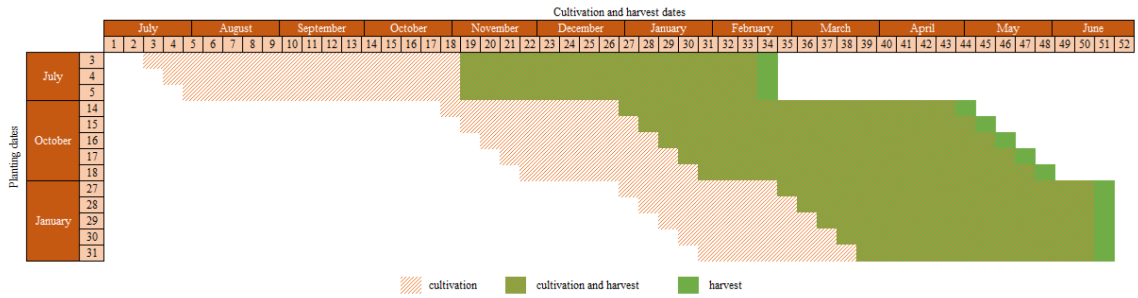


Table 7. Time requirements at farm level

		Crop		
		A	B	C
Time to plant (min/plant)		0.1309	0.1309	0.1516
Time to cultivate (min/plant)		0.0342	0.0342	0.0396
Time to harvest (min/plant)	Pattern I (harvest every day)	0.0682	0.0682	0.1579
	Pattern II (harvest every two days)	0.0614	0.0614	0.1421
	Pattern III (harvest thrice a week)	0.0545	0.0545	0.1263
	Pattern IV (harvest twice a week)	0.0477	0.0477	0.1105

According to expertise of farmers, the yield of plants per period ranges between 0.14-0.66 kg/plant for crop A, 0.13-0.58 kg/plant for crop B and 0.02-0.18 kg/plant for crop C depending on the planting and harvest dates, and harvest pattern used. Once harvested, crops are transported to PPs where 0.15 minutes are used to pack one kilogram of product. Packing and wasting one kilogram of product costs the 6% and 5% of the mean price of the product, respectively.

Eight PPs, four warehouses and eight DCs can be opened. The opening cost, processing, management and storage capacity for each type of facility are displayed in Table 8. The same data are used for all facilities of the same nature. Holding costs are calculated as 0.25% of the mean price of each product per week.

Table 8. Facility related data

Facility	Processing capacity (min/week)	Management capacity (kg/week)	Storage capacity (kg)	Opening cost (€)
Packing plant	270,000		36,000	720,000
Warehouse		19,200,000	3,600,000	1,000,000
Distribution centre		4,800,000	240,000	4,800,000

The cost of transporting one truck between two facilities is calculated in function of the distances between facilities (Tables 9-12). Each truck can transport a maximum of 24,000 kg of products. Time needed to transport product between facilities ranges between zero and two periods.

Table 9. Transport cost between farms and packing plants (€/truck)

Region	Farm	Packing plant							
		1	2	3	4	5	6	7	8
1	1, 2, 3	224	439	525	494	821	754	1,576	866
2	4, 5, 6	238	308	730	692	679	637	1,435	1,030
3	7, 8	431	673	31	108	559	515	1,315	375
4	9, 10	483	789	124	23	658	631	1,403	445

Table 10. Transport cost between packing plants and warehouses/DCs (€/truck)

PP	Warehouse				DC							
	1	2	3	4	1	2	3	4	5	6	7	8
1	515	704	665	1,379	65	352	446	434	641	711	1,030	1,017
2	731	521	482	1,200	293	64	596	649	462	528	1,169	1,100
3	52	568	549	1,251	525	768	176	118	473	545	583	514
4	49	654	634	1,337	551	838	246	138	559	631	642	599
5	594	58	23	710	617	554	480	594	92	69	890	670
6	573	69	25	744	576	513	438	554	61	70	897	677
7	1,331	769	766	193	1,363	1,293	1,218	1,341	827	800	1,444	1,224
8	386	675	730	1,325	903	996	417	442	693	637	270	168

Table 12. Transport cost between warehouses and distribution centre (€/truck)

Warehouse	Distribution centre							
	1	2	3	4	5	6	7	8
1	577	790	199	90	513	585	623	554
2	645	582	492	609	100	48	863	642
3	604	539	466	582	82	66	887	668
4	1,318	1,258	1,182	1,296	780	755	1,486	1,265

Table 13. Transport cost between packing plants and distribution centre (€/truck)

Distribution centre	Market			
	1	2	3	4
1	69	628	1,461	1,131
2	293	734	1,403	1,215
3	635	141	1,324	641
4	561	155	1,438	663
5	558	428	925	908
6	628	503	897	834
7	1,262	506	1,523	41
8	1,228	441	1,304	228

Four markets are considered in the model. Supply and market prices were extracted from the Buenos Aires Central Market website for different tomato varieties. Supplies are used to randomly generate the demand for the model to preserve the order of magnitude. Unmet demand is penalized with the 50% of the mean product price in each market.

5.2 Experimental design and results

To determine if products' perishability impacts on the AFSCs configuration, the model is solved for five scenarios in which the shelf-life is varied from one to five periods. Figure 3 displays the objective function value per scenario. Worst values are obtained for AFSCs with very short shelf-life products and values improve as the products' shelf-life increases until a stable value is reached for products with shelf-life ranged between three and five.

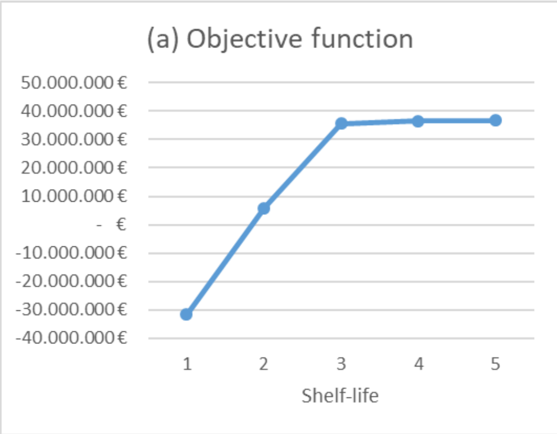


Figure 3. Objective function

Figure 4 displays economic results. Sales and planting and cultivation, packing, transport, operation, inventory and labouring costs (Figures 4a-g) increase as shelf-life do so for products with one to three-weeks shelf-life. This is because more product is produced as shelf-life increases, decreasing the level of unmet demand (Figure 4i).

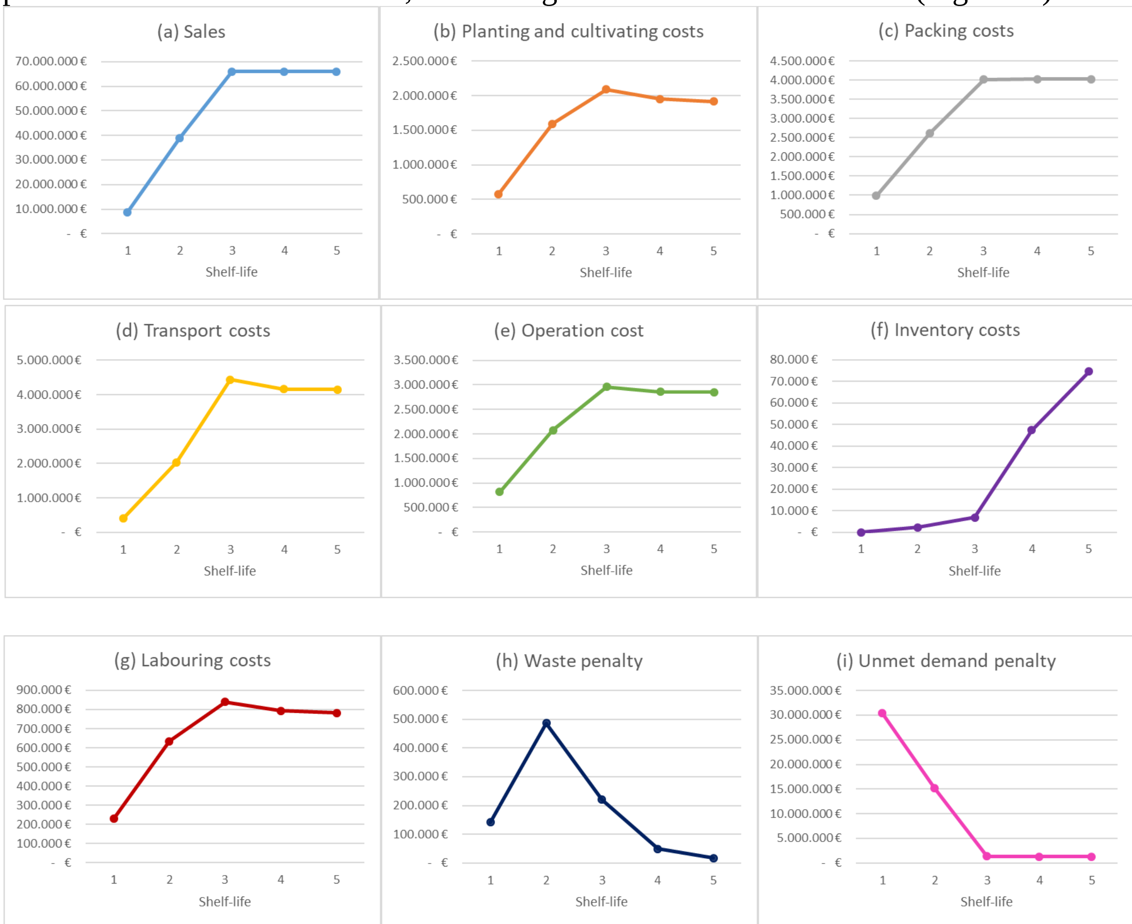


Figure 4. Economic results

For scenarios with three-week shelf-life or longer, sales and packing costs are stabilized while planting and cultivation, transport, operation and labouring costs remain similar, showing a little decrease in their values as the shelf-life increases. The reason is that more products are stored as shelf-life increases, making it possible to plant less plants, having less production and wastes while meeting the same demand level.

This is reinforced in Figure 5 where the percentage of product wasted, and demand met per scenario and market are exposed. When products have one-week shelf-life, only demand from one market can be met, wasting products that cannot be sold in the same period of its harvest. Wastes increase for AFSC with two-week shelf-life products since more product has to be produced to meet demand from three markets. When shelf-life is equal or longer than three-weeks, wastes highly decrease since products can be stored, reducing the quantity of products to produce during the year. In these cases, almost all demand from all markets can be met.

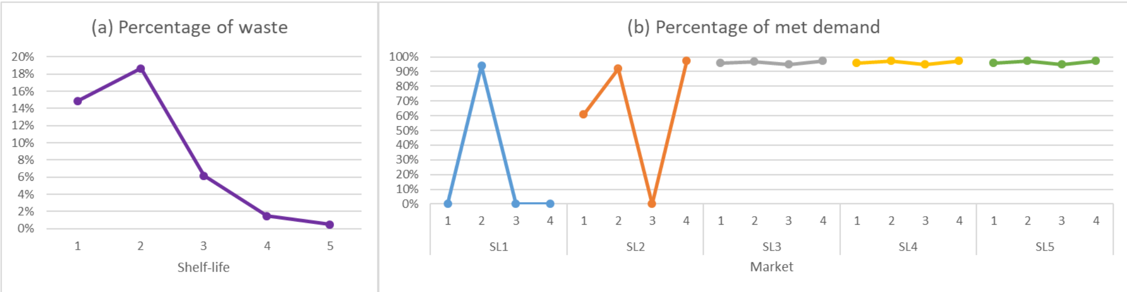


Figure 5. Percentage of wastes and met demand

To determine why the solution is stabilized for scenarios with three-week shelf life or longer, the AFSC configurations are analysed (Table 13). AFSC commercializing products with one-week shelf-life are configured by three facilities that are very close each other. In this case, only the demand of the market located in the same region than the open farm can be partially met while demand from other markets cannot be met. In case of products with two-week shelf-life, more facilities are open allowing farmers to meet demand from three markets that are close enough to the farming region. However, products cannot arrive to one market without losing their properties. This problem is solved for AFSC with products with three-week shelf-life or longer, where products have longer enough shelf-life to meet demand of all markets, obtaining in these cases the same AFSC configuration and similar economic results.

Table 13. AFSC configuration per scenario

SL	Farm										PP								Warehouse				DC							
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	1	2	3	4	1	2	3	4	5	6	7	8
1										X				X												X				
2							X	X	X				X	X					X							X				
3						X	X	X	X	X	X		X	X					X				X			X				
4			X				X	X	X	X	X		X	X					X				X			X				
5			X				X	X	X	X	X		X	X					X				X			X				

It is concluded that the optimal AFSC configuration when maximizing profits for the Argentinean case study varies in function of the products' perishability for cases of products with short shelf-life (one or two). However, it gets to the point in which products' perishability does not influence the AFSC configuration with the cost structure under study. For such cases, the model could be used to determine the maximum investment that could be made to extend the products' shelf-life based on the profit's increase that this investment would produce.

5.3 Computational efficiency

An Intel® Xeon® CPU E5-2640 v2 with two 2.00 GHz processor, with an installed capacity of 32.0 GB and a 64-bits operating system is used to solve the model. The model was implemented in MPL® 5.0 and solved with Gurobi 8.0.1 solver. Microsoft Access databases were used to store input data and export the values for decisions variables. Model statistics and computational efficiency per execution are presented in Table 14.

Table 14. Model statistics and computational efficiency

Shelf-life	Continuous variables	Integer variables	Binary variables	Constraints	Iterations	Solution time (seconds)	% GAP
1	31,254	19,210	210	190,432	2,513	2	-
2	51,054	19,210	210	190,432	69,452	76	-
3	71,354	19,210	210	190,432	2,335,686	2,344	-
4	88,854	19,210	210	190,432	27,668,979	29,682	-
5	106,854	19,210	210	190,432	85,075,072	86,400	0.32%

Constraints, integer and binary variables remains the same for all experiments as are independent of products' perishability. The continuous variables increase as shelf-life grows since these variables are mostly related to the flow of perishable products along the AFSC. It also increases the complexity of the model.

Executions of the model are limited to 24 hours (86,400 seconds). Time needed to optimally solve the model and number of iterations increase with the complexity of the model. The same happens to the GAP that represents the difference between the best solution obtained and the best bound investigated.

6 Conclusions and future research lines

A MPM to design realistic AFSCs considering the products' perishability is proposed. This model integrates tactical decisions like planting, cultivating, harvest, labouring, packing, storage, operation, and distribution of products to the design decisions, what improves the performance of the AFSC in the long-, mid- and short- terms [1]. Some of these decisions have been previously modelled in literature, while others like labouring, cultivating and operation decisions are integrated to the AFSC design model for the first time. The proposed model can be used to make a partial design/redesign of the AFSC, and to plan tactical decisions once the AFSC configuration has been defined.

The model is used to determine if the products' shelf-life influences the AFSCs design. For that, AFSCs for products with different shelf-life are designed. Results for the Argentinean case study show that different configurations are obtained for AFSCs commercializing short shelf-life products, demonstrating that shelf-life should be considered when designing this type of chains. Since the obtained AFSC configuration for long shelf-life products is the same, the model could be used to provide decision-makers with information about the maximum investment to be made to extend the shelf-life of products.

In the future, it could be determined if considering the uncertainty of products' perishability impacts on the AFSC configuration. On the other hand, a multi-objective MPM could be proposed including the maximization of products' freshness at the sales time as an objective of the model. Finally, the configuration of AFSC commercializing products with various shelf-life should be analysed to determine if perishability impacts on this type of chains.

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Chapter VI:

Centralized and distributed optimization models for the multi-farmer crop planning problem under uncertainty: application to a fresh tomato Argentinean supply chain case study

Imbalance between supply and demand of crops frequently occurs in markets originating an excess or shortage of supply in relation to demand. This causes high volatility and uncertainty in market prices, unmet demand and wastes, especially for fresh crops due to their limited shelf-life. This imbalance is mainly due to the inherent uncertainty present in the agricultural sector, the perishability of fresh crops and the lack of coordination among farmers when making planting and harvesting decisions. Despite farmers usually plan the planting and harvesting in an individual way, there is a scarcity of research addressing the crop planning problem in a distributed manner and, even less, assessing their impact on the SC as a whole. In this paper, we developed a set of novel mathematical programming models to plan the planting and harvest of fresh tomatoes under a sustainable point of view for multi-farmer supply chains under uncertainty in different decision-making scenarios: i) distributed, ii) distributed with maximum and minimum land area constraints to be planted for each crop, iii) distributed with information sharing, and iv) centralized. Then, for each distributed scenario, we integrate all the individual solution per farmer as regards the planting and harvesting decisions per crop to obtain the overall supply in order to satisfy SC market demands assessing the real performance measures per farmer and the impact on the SC as a whole. We also compare the results obtained for each scenario with the centralized model in terms of economic, environmental and social impact. The experimental design shows that *when integrated these solutions in the whole SC significant differences between planned and real results obtained in each scenario as regards the gross margin per hectare, unmet demand, wastes and unfairness between farmers exist, being the distributed model with information sharing, that most similar to the centralized one. The experimental design shows that uncertainty consideration in models improves the gross margin per ha and the unfairness among farmers in all scenarios and under planned and real evaluation.*

Keywords: Planting; Harvesting; Fuzzy optimization; Centralized and distributed decision-making, Fresh tomato supply chain

1 Introduction

The crop planning problem consists of deciding at the beginning of each production cycle, which crops farmers are going to plant in each of their parcels [1] and their acreage, in case more than one crop is allowed to be planted in the same period and parcel. Farmers usually made crop planning decisions in function of the expected benefits per crop that mainly depends on the market prices. However, the real crop prices are highly influenced by the crop supply-demand balance [2]. Prices influence the behavior of both, consumers and producers: higher prices encourage more production by the producers but less consumption by the consumers, while low prices discourage production by the producers and encourage consumption by the consumers [3]. If during one specific year most of farmers decide to cultivate the crops that were more profitable the previous year, there will be a high probability that the supply of these crops will exceed their demand. This excess would provoke a decrease of the crop's sales price, turning it less profitable. Simultaneously, the supply of less profitable crops would be lower than their demand, resulting in an increase of their final price and, therefore, in their conversion into more profitable crops. Although this behavior is well known, this pattern is repeated year after year, provoking high economic losses for farmers.

Other aspects that can partly explain the usual imbalance between supply and demand affecting market price fluctuations are the lack of knowledge about demand forecasts and the non-collaborative decision-making among farmers. In fact, it is usual for farmers to decide the production of each crop individually without any type of collaboration among them. This absence of coordination and the extended custom among farmers of increasing production of the most profitable crops of the previous year, lead the existence of some crops with over production and others with under production, fact that decrease and increase market prices, respectively. Moreover, this cyclic behavior does not only affect benefits of the own farmers and market prices but also have a great impact on waste and unmet demand quantities. Waste has a negative impact on the environment because it uses resources (land, seeds, fertilizers, human laboring, etc.) to produce food not reaching customers, meanwhile the unmet demand has a negative social impact due to not satisfaction of human needs. In short, reduction of food losses and unmet demand benefits farmers, consumers, and the environment [4].

The complexity to match supply with demand becomes more difficult task for fresh crop SCs because of the impossibility of totally controlling the production (yield quantities and dates) and the shelf-life that limits the storage of harvested quantities. The limited shelf-life and its inherent uncertainty also affects the increasing of wastes.

Therefore, it is necessary to define strategies to manage and mitigate the risks associated with the crop price volatility [5]. Farmers can reduce the risk of economic losses by planting more than one crop, since each crop has different trends of price and yield [6] and can be harvested in different time periods. A very widespread way of implanting this diversification strategy consists of limiting the maximum and minimum areas to be planted for each crop. Although these limits highly impact on the results obtained, surprisingly, the calculation of them is not usually justified in existing cropping plan decision support tools. Another strategy to reduce price volatility could be intending to balance supply and demand which implies to know the demand forecasts. If market demand forecasts per crop and region exist, to centrally deciding about the planting and harvesting for all the farmers in that region represents a way to balance supply and demand avoiding the drop in prices. Another situation that makes sense to centrally making decisions comprises vertically integrated corporations in which the processing facility and the farms are owned by the same entity [7].

However, this centralized approach could produce inequalities in the profits obtained by farmers, leading to the unwillingness to cooperate and contribute to the collaborative crop planning, and to the farmers unacceptance of the obtained planning [8]. It draws attention that despite almost all research adopts a centralized approach, we have only found one paper [9] in the agriculture sector considering this aspect. They propose a centralized model for an investor to define contracts to many smallholder farmers. In order to find a fair solution for all farmers, they introduce some constraints in their model limiting the difference in profits obtained among farmers. In addition, implementing centralized decision making is not always possible due to organizational, information and mistrust barriers. These aspects limit the centralized approach applicability. Up to our knowledge there is only one paper that implements a distributed decision-making approach for the cropping plan problem [10].

In this situation, an increasing number of recent research works recognize the necessity of implementing collaboration mechanisms among the members of fruit and vegetable SCs for achieving sustainability [11], increase revenues and customer satisfaction and reduce the negative impact of uncertainty [12]. Simatupang and Sridharan [13] distinguish three interrelated dimensions of collaboration: information sharing, decision synchronization, and incentive alignment. Handayati et al. [14] affirm that still, research on coordination-related issues in an agricultural supply chains is in its early development and not cover coordination of the whole supply chain. They state that studies on the coordination of processed fruits and vegetables products have been more widely studied than the coordination of fresh produce. In their review Handayati et al. [14], also identify mathematical modelling as one methodology used in agri-food supply chain coordination. They conclude that studies on supply chain coordination in agri-food sector with a particular focus on small-scale farmers is very scarce.

Prima Dania et al. [15] pointed out the relevance of achieving sustainability when dealing with the complexity of agri-food supply chain to remain competitive in the triple bottom line (TBL), i.e. in the economic, environmental, and social dimensions. These implies to consider more than one goal. Along these lines Sarker and Quaddus [16] formulate a nationwide crop-planning problem as a goal program considering the minimization of deviations from import, investment and contributions. Plà et al. [17] identify as new opportunities for operations research in agri-food SC better predictive modelling of the decision-making behavior of actors in the natural resources system and multiple stakeholder decision analysis. They state that research on coordination issues in agricultural SCs is in its early development. Moreover, research addressing coordination among actors in the same stage specifically at the farmer stage is even more scarce. This aspect highlights the need of effectively matching demand and supply in the agri-food supply chain processes [18].

On the other hand Behzadi et al. [19] highlight as a conclusion of their review of quantitative models for agribusiness supply chain risk management that although quantitative modeling approaches have been applied to agricultural problems for a long time, adoption of these methods for improving planning decisions in agribusiness supply chains under uncertainty is still limited. This draws attention since the agribusiness is one of the sectors affected by most sources of uncertainty such as, for instance, the number of qualities obtained (subtypes), their quantity, their limited shelf-life and their value [18,20,21]. Esteso et al. [22] classifies uncertainties in crop-based Agri-food Supply Chains in product, process, market and environmental ones. Therefore, there is a need to consider the existing uncertainties in agri-food supply chains during decision making processes in order to obtain realistic solutions.

Under uncertainty, Zeng et al. [23] pointed out that for the cropping plan problem the estimation of proper distribution of uncertain parameters such as surface water withdrawal, crop yield, price, irrigation volume, is not always a simple task. This is due to different factors: (i) historical data of some parameters cannot easily be obtained (in general terms, collecting precise data is very hard because the system's environment is unstable or such collection entails high information costs [24], (ii) variance and mean are difficult to obtain and (iii) stochastic programming with parameters modeled by probability distributions has a negative effect on the computational efficiency and sometimes lack right meaning. In situation like this, characterized by uncertainty associated with vagueness, imprecision, inexact statements, incomplete, lack of information and/or unobtainable information on a particular element of the problem under study, Fuzzy Sets Theory has proved their validity to manage uncertainty [25,26]. Along these lines, Arunkumar and Jothiprakash [27] affirm that crop production becomes more uncertain because of the vagueness and impressions in regard to the price of crops, crop yields, non-availability of land and water resources. Arunkumar and Jothiprakash [27] recommend the Fuzzy Set Theory as the most suitable approach to handle such vagueness in multi-objective planning and imprecise parameter values, as crisp deterministic approaches are not sufficient to model such complex situations.

In view of all above, the present study seeks to provide an answer to the following research questions that, in turn, constitute the contributions of this paper:

- RQ1: Which is the impact of different widespread farmers' agricultural practices and collaborative scenarios on the gross margin, waste and unmet demand on each farmer, the whole SC, and the unfairness among farmers?
- RQ2: Is it possible to define a collaboration approach in a real distributed situation that allow obtain solutions nearly optimal as compared the centralized decision-making approach minimizing the unfairness among farmers?
- RQ3: Which optimization models can be developed in each scenario to support farmers when deciding on the crops to be planted from a sustainable point of view that considers the own characteristics of crops that mature over time (fresh tomato)?
- RQ4: How affect the modelling of uncertainty on the solutions obtained and the answer to the above research questions?

To provide a response to the above research questions, a set of novel distributed and centralized mathematical programming models for the cropping plan problem for fresh tomato SC have been proposed in a deterministic and uncertain context by Fuzzy Set Theory under different Scenarios.

The rest of the paper is structured as follows. The analysis of related research and the contributions of this study as regards existing literature on fresh tomato SCs are presented in detail in Section 2. The problem description is made in Section 3, while the formulation of the distributed and centralized mathematical programming models in deterministic and uncertain context for the cropping plan problem involving multiple farmers under different Scenarios are presented in Section 4. Section 5 details the methodology adopted for solving the fuzzy models. In Section 6, the validation and result analysis of the proposed models for each Scenario is performed by their application to a case study of an Argentine Tomato Supply Chain. Finally, in Section 7 conclusions and future research lines are outlined.

2 Related literature analysis and contributions of this study

Previous section has provided insights about the scarcity of distributed models and collaboration mechanisms implementation in the agricultural sector in general and the cropping plan problem, in particular. This section intends to show the contribution of our paper as compared existing literature on the planting and/or harvesting problems in fresh tomato SCs. In doing so, first the existing specific mathematical programming models (MPMs) for addressing the planting and/or harvesting problems in tomato SCs and generic MPMs applied to tomato SCs are analyzed as regards the most relevant aspects of our proposal (Table 1, 2 and 3). Second, an identification of research gaps based on the previous characterization is made, in order to finally show the contribution of our paper taking into account insights of Section 1 and Section 2.1.

Fifteen papers dealing with the development of MPMs for the planting and/or harvesting problems in either tomato SCs or generic MPMs applied to tomato SCs have been found (Table 1, 2 and 3).The first three papers (shaded in grey) only consider the harvesting decisions, meanwhile the rest consider planting decisions along with other decisions. Finally, the characteristics of the set of models developed in this paper are reported (shaded in orange).

As it can be seen in Tables 1 and 2, the papers have been analyzed as regards those dimensions more relevant for our proposal: crops, the spatial level, the decision-making approach, the objective function, the demand faced by farmers, the decisions and problem characteristics addressed. The uncertain modelling features are reflected in Table 3.

In view of the literature analysis (Tables 1 and 2), only two models considering exclusively harvesting but not planting decisions [4, 28] have been developed ad hoc for tomato. Therefore, it can be stated that none of the revised planting MPM have been specifically developed for tomato not considering, therefore, the specific characteristics of this crop. Instead, they have been formulated in a generic form and then applied to several crops including the fresh tomato.

At the spatial level, papers exist that consider only one farmer [1, 29-32]. Other papers consider multiple planting locations that can be assumed to belong to one or several farmers [4,28,33-34], meanwhile the remaining papers are developed at the regional level [35-38].

Table 1. Characteristics of MPMs for planting and/or harvest planning of fresh tomato

Ref.	Crops		Spatial Level			Decision making approach		Objectives			Demand faced by Farmers		
	Only Tomato	Tomato & Others	Single Farmer	Multiple Farmer	Region	Centralized	Distributed	Max. profits	Min. costs	Others	Markets	Production plants	Contracts
[39]	X			X		X			X			X	
[28]	X	X	X	X		X		X			X		X
[4]	X		X	X		X		X			X		X
[35]	X	X			X	X		X		X			
[40]	X	X	X	X		X		X					X
[33]	X	X	X	X		X		X					
[34]	X	X	X	X		X		X					X
[29]	X	X	X			X		X					
[1]	X	X	X			X		X					X
[30]	X	X	X			X					X		
[31]	X	X	X			X		X					
[32]	X	X	X			X		X					
[36]	X	X			X	X		X					
[37]	X	X		X	X	X		X			X		
[38]	X	X		X	X	X		X			X		
This paper	X			X		X	X	X			X		

Despite the existence of multiple farmers for these last ones, all the revised models assume a centralized decision-making approach, existing also a lack of distributed models in crop planning models for the fresh tomato SCs. This finding reinforces the statement of Handayati et al. [14] that research on coordination-related issues in an agricultural supply chains is in its early development. Besides, all the centralized MPMs integrating several farmers aim at either maximizing profits or minimizing costs: none of them introduce any mechanism to ensure that optimal solution benefits all SC members. Therefore, the result of these approaches may yield a win-lose situation in which some members of the SC would obtain high profits and some other would have losses [8]. Thus, unless the decision-maker control the overall supply chain, the injured parties could decide not to accept the model's solution and to act on their own, penalizing the results achieved by the SC as a whole.

So, there is a need to develop new models to manage agri-food SCs while filling this gap. For that, some solutions could be to either minimize the differences on the results obtained across the SC's members or to establish a distribution method to share the optimal results between SC members. We have only found two models facing this issue but not including tomato crop, reason for which they do not appear in the literature analysis of the previous section. Li et al. [9] propose a centralized model to support the definition of a crop rotation schedule for an investor that offers contracts to many smallholder farmers. This model takes into account both the objective of maximizing the profits of smallholder farmers, while minimizing the differences in profits among farmers. For doing this a threshold of the profit gap between each farmer and the average profit of all farmers is introduced. On the other hand, we have only found one distributed model for perishable crops SCs not developed or applied to fresh tomato [10]. This distributed model addresses the particular problem of agricultural cooperatives by means defining appropriate contracts by an auction mechanism. However, the results of these two papers are not transferable to our case that does not fit neither with cooperatives nor with contract signature. The case addressed in this paper assumes that farmers act independently to face the market demand, which is in concordance with the reality in several regions (e.g. Brittany, Argentine).

Table 2. Characteristics of MPMs for planting and/or harvest planning of fresh tomato

Ref.	Decisions												Problem characteristics			
	Planting	Cultivating	Harvesting	Packing	Inventory	Transport	Labour	Wastes	Unmet demand	Backlog	Irrigation	Technology	Min./Max. area (agricultural policy)	Harvest patterns	Yield dependent on harvest patterns	Products shelf-life
[39]			X	X	X					X						
[28]			X	X	X	X	X	X						X	X	X
[4]			X	X	X	X	X	X						X	X	
[35]	X										X		X			
[40]	X		X	X	X	X	X						X			X
[33]	X		X	X		X	X						X			
[34]	X															
[29]	X										X		X			
[1]	X										X					
[30]	X		X		X			X	X							X
[31]	X		X										X			
[32]	X															
[36]	X										X		X			
[37]	X		X	X		X					X	X	X			
[38]	X		X	X	X	X					X	X	X			
This paper	X	X	X	X	X	X	X	X	X				X	X	X	X

There are six planting models [29,31-33,35-36] that do not take into account any demand quantities, assuming that the whole yield of the planted area is harvested and consequently sold, instead they all except Otoo et al. [32], define minimum and/or maximum area to be planted for each crop. Not considering market demand when deciding about the crops to be planted and their acreage will contribute to produce more than demanded of those crops initially more profitable. The excess in supply of these crops will saturate the market causing not only the decrease in prices but also the increase in waste.

As regards the considered decisions in the MPMs, none of the revised papers has considered the cultivating operations. It is noteworthy that cultivating operations of different crop varieties can compete for the scarce resources, due to their possible overlapping with planting and harvesting activities when planting several crops or varieties. Other less considered decisions are the unmet demand [30], backlogs [39] and technology selection [37-38]. Furthermore, despite the imbalance between supply and demand is one of the main problems of the fresh fruit and vegetables SCs that causes high levels of unmet demand and waste due to the limited shelf-life of crops, only one study [30] includes the waste decision variable for the planting and harvesting problem and only two studies [4,28] for the harvesting problem.

In total eight from the twelve planting models include constraints about the minimum and maximum planted area per crop but despite their impact on the solution, except Sinha et al. [36] any justification is provided about the value adopted for them. Only one paper [32] no considers any limits in the planted area per crop. In absence of other constraints, this could lead to only cultivate the more profitable crop leading to an excess in its supply originating simultaneously the impossibility of selling all the produced quantities, the increase of wastes and the drop down of prices. It is important to note that the value of the profits for the solution obtained from these models (planned solution) can be very far from reality (real solution) because of the real quantities sold and their price could greatly differ. Therefore, more research is needed to analyze the impact of not considering market demand in crop planning models and the widespread managerial policy of limiting the planted areas not only in a planned situation but also in a real one, when all the farmers' decisions are integrated.

Only two harvesting models but none planting model include the possibility of chosen several harvesting patterns that are characteristic for tomato crops that mature overtime. Surprisingly, although the limited shelf-life is one of the most relevant characteristics of fresh crops, only two planting models [30,40] and one harvesting model [28] have considered it.

As it can be seen in Table 3, only four models include uncertainty: three of them, model uncertain parameters as stochastics [30,33-34] and only one model them as fuzzy [39], but this last one not for planting decisions. Stochastic approaches imply that it is possible to estimate the probability distribution of random parameters [12]. However, in most cases this information is either not known or historical data is not available, being impossible to obtain the stochastic distribution functions that characterize the behavior of the parameters. In such cases, the fuzzy approach has demonstrated to be useful.

Up to our knowledge, uncertainty has not been considered in parameters such as: times for planting, cultivating and harvesting activities and lower and upper limits of planted area. Despite the impact of the maximum and minimum area of land to be planted for each crop on the solution obtained, these values are considered deterministic and mostly defined arbitrarily or not justified. Although costs such as unmet demand, backlogs or waste are subjective defined in order to penalize their inclusion in the optimal solution, cost of unmet demand has been considered uncertain only by Miller et al. [39] and backlog and waste cost has not been modelled under uncertainty

In view of the literature analysis, this paper aims to contribute to the following gaps detected in the literature (in parenthesis their relationships with the corresponding RQs):

- To model the planting problem anticipating harvesting decisions for a multi-farmer fresh tomato SCs in a distributed and centralized manner under several scenarios considering different collaboration situations and farmers' agricultural practices. Up to our knowledge this comparison among different distributed and centralized models have not been previously addressed (RQ1&RQ2).
- To propose novel deterministic mathematical programming models for each scenario to support the planting and harvesting decisions of fresh tomatoes in a multi-farmer context. These models include aspects not previously modelled for the planting problem of such SCs: harvesting patterns, cultivating activities,

consideration of imbalance between supply and demand and their impact in terms of unmet demand and inventory that can become waste because of the shelf-life consideration (RQ3).

Table 3. Uncertain modelling of MPMs for planting and/or harvest planning of fresh tomato

Ref.	MC		UM		UP																
	Deterministic	Uncertain	Stochastic	Fuzzy	Harvest capacity	Gassing capacity	Overtime limit	Time to plant	Time to apply phytosanitary products	Time to stake up plants	Time to prune plants	Time to harvest	Time to pack	Yield	Maturation period	Min./Max. area (risk diversification)	Cost of waste	Cost of unmet demand	Backlog cost	Demand	Price
[39]	X	X		X	X	X	X						X	X				X		X	
[28]	X																				
[4]	X																				
[35]	X																				
[40]	X																				
[33]		X	X											X							X
[34]		X	X											X	X	X				X	
[29]	X																				
[1]	X																				
[30]		X	X																	X	
[31]	X																				
[32]	X																				
[36]	X																				
[37]	X																				
[38]	X																				
This paper		X		X				X	X	X	X	X	X	X		X	X	X		X	X

MC: Modelling context, UC: Uncertain modelling, UP: Uncertain parameters

- To formulate the above deterministic mathematical models, considering the uncertainty by fuzzy sets, in parameters previously not considered (times required to make cultivating activities, maximum and minimum planted areas per crop, yield depending on the harvesting patterns, unmet demand costs, waste costs, demand and price markets) (RQ4).
- To obtain the real performance measures for each farmer and for the whole SC when all the individual planting and harvesting decisions per farmer from the distributed models are integrated to satisfy SC market demands. This allows to calculate the real performance measures per farmer based on his/her final sold quantities and the impact on the SC as a whole for each scenario. The real performance is measured from a sustainable point of view taking into account not only the economic aspect, but also the environmental (wastes) and social (unmet demand and unfairness among farmers) ones in deterministic and uncertain contexts (RQ1, RQ2, RQ3 & RQ4).

The following sections describe the problem under study and formulates the set of mathematical programming models.

3 Problem description

The SC under study is integrated by several independent farmers that directly supply fresh tomato varieties to different markets without any intermediary (Figure 1). The commercialized tomato is for fresh consumption. In the considered SC, farmers are responsible for almost all the activities of the chain. In some regions like La Plata (Argentine) or Florida (EEUU), it is a practice for producers (farmers) to not only plant, cultivate and harvest as usual, but also pack and ship their product to the markets. These producers are often termed grower-shippers [4]. Indeed, several policies exist that intend to prioritize the smallholder family farming and to rebalance the farmers' position in the food chain by promoting this type of agricultural SCs with direct marketing channels to avoid the participation of intermediaries.

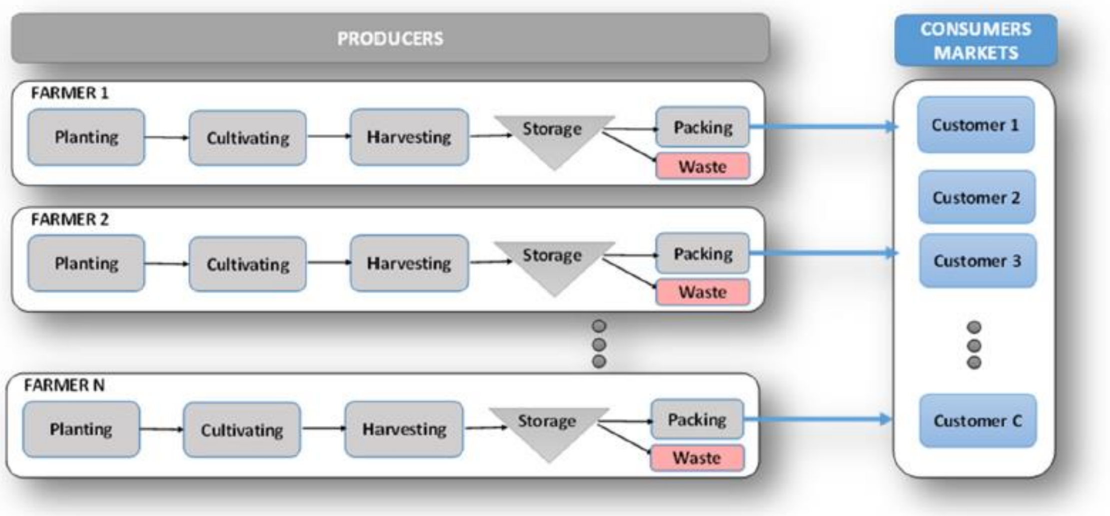

Figure 1. Fresh tomato supply chain

Each area of farmers' land can only be planted once per season. Different weeks exist for planting tomato varieties along the year. The planting week determine the time interval for cultivating, during which several activities are carried out that require manual labor. These cultivating activities include some that are specific for land (e.g. irrigation, fertilization, and weeding) while others that are performed over the tomato plants (e.g. stake, pruning, phytosanitary application). If any material is needed for these activities, it is purchased from different suppliers.

The planting week also determines the time periods to harvest tomatoes. Because tomatoes mature over time, to harvest ripe tomatoes, plants require to be harvested all weeks along the harvesting time periods. In doing so, it is also possible to perform several harvesting passes along the same piece of land during the same time period. Based on the frequency of harvesting passes in a time period, several harvesting patterns can be defined (i.e, every day, every two days, once a week, etc). It is possible to apply different harvesting patterns in the same time period in different land areas and, in the same area of land along different time periods. Yield and manual labor required are dependent on the harvesting pattern selected: more harvesting passes imply higher yields but also higher needs of manual labor and vice-versa.

The farmers' production of each tomato variety is destined to satisfy the demand in different markets that depends on the tomato variety and the time period (seasonal demand). The selling price of tomato is assumed to be dependent on the variety, market and time period. Although there is a relationship between the selling price and the ratio of demand and supply, in this paper it is assumed that the price is exogenous to our models. Instead, uncertainty is considered in both demand and selling price with the aim of reflecting their volatility.

Although the vast majority of planting models do not include the perishability aspect, our model takes it into account by means the definition of a limited shelf-life. Harvested tomatoes can be stored but they should be delivered inside their shelf-life. It is assumed that tomatoes are in stock from the date they are harvested until they are transported to the markets. The tomatoes are packed just before being transported to markets. The transport time from farmers to markets are assumed to be lower than the time period. The shelf-life inclusion ensures that tomatoes reach markets with the appropriate freshness contributing, therefore, to the food security.

It is assumed that all the tomatoes quantities transported to each market are to be sold, otherwise they are not transported. On the other hand, the harvesting quantities not being consumed during their shelf-life become waste. This is a consequence of the excess of supply in relation to the demand. In the opposite way, our models also compute the unmet demand per time period as a consequence of the shortage of supply in comparison with demand.

Weeks exist that is possible to plant, cultivate and harvest different pieces of land simultaneously. Besides, some activities performed for planting, cultivating, harvesting and packaging tomatoes require capacity of manual labor that depends on the variety (i.e. there are varieties that consume more labor capacity than others, such as the cherry tomato). These activities can overlap significantly in time, competing therefore for the limited capacity of laborers. In order to ensure a feasible planting, cultivating, harvesting and packaging plan to satisfy market demand, the labor capacity consumed to perform all these activities jointly with availability of laborers are taking into account as [28], but in our case additional activities related to the cultivation in greenhouses are included. Proposed models support the decision on the necessary seasonal and temporary laborers per time period and farm-land. However, only hiring and firing in seasonal laborers have associated costs. For the temporary laborers it is not necessary to calculate variations, because they can be hired weekly as needs arise, but at a premium. Maximum number of seasonal and temporary laborers exist reflecting the competitions among farmers for this scarce resource.

In short, the proposed models assumed that farmers should decide about the selection of crops to be planted, their acreage and the planting dates. Planting decisions affect the quantities and timing of cultivating and harvesting activities that, in turn, condition the packing and transportation of harvested tomatoes to the markets. The distribution of products will impact on the satisfied demand, the storage and the waste. For this reason, the models proposed in this paper do not consider only the usual cropping plan decisions but also anticipate other strongly related later decisions in an attempt of looking ahead for improving the solutions obtained. Therefore, the solution to our models support farmers as regards three main groups of decisions related to: 1) when and how much to plant, cultivate and harvest per tomato variety and harvesting mode, 2) when and how much to storage, distribute and sell of each tomato variety in each market and 3) the size of labor resources required to perform the different activities per time period. In order to properly reflect the tomato shelf-life and the temporality of the above decisions, a discrete time period models have been developed that cover the complete planting season of a year divided into weeks.

Definition of these decision variables allow us to take the three dimensions of sustainability into account in the objective function: economic, environmental and social. In doing so, our models try to maximize the gross margin (economic) of farmers penalizing the post-harvest waste (environmental) and the unmet demand (social). Besides, including these penalizations in the objective function will contribute to diminish the imbalance between supply and demand, that in turn will contributes to reduce the market price uncertainties. On the other hand, when evaluating collaboration scenarios and the uncertainty in models another social aspect is taken into account: the unfairness among farmers.

In the following section, the description of scenarios to be addressed is made followed by the formulation of their corresponding models.

4 Description of scenarios

There are multiple ways of organization among farmers that can even coexist in the same region. They can range from farmers acting individually without any type of coordination or collaboration among them to farmers fully coordinated. The first situation involves a distributed decision-making situation with many decision-makers as farmers exist, meanwhile in the last one, there is a single decision-maker that makes the decision in a centralized way for all farmers. Although in most cases farmers act individually, it is surprising the absence in the literature of distributed decision-making models for the crop planning problem (see Sections 1 and 2). This study intends to cover this gap. For doing so, several scenarios representing different managerial practices and levels of collaboration among farmers are defined and modeled by a set of distributed models in order to provide an answer to the RQ1 and RQ2. The organizational situation of a fully centralized decision-making is also analyzed and taken as a benchmark. The next subsection characterizes the scenarios addressed meanwhile the other subsections provide a detailed description of the mathematical programming models formulated to support the decision-making in each scenario.

In this paper, five scenarios have been defined with the following characteristics (Table 4) that require the formulation of different MPMs:

- **Distributed scenario (Scenario D)**. In this scenario there is no collaboration among farmers and there are as many MPMs as farmers exist. It is assumed that each farmer based on its own MPM independently decides when and how much to plant, harvest, package, storage and distribute to markets for each tomato variety. Therefore, a distributed decision-making is assumed. Besides, farmers do not have any knowledge about neither the market demand nor the other farmers' decisions. Because no knowledge exists about markets demand, they implicitly assume that all quantities harvested will be completely sold.
- **Distributed scenarios with limited land areas**. These scenarios are mainly the same as the Scenario D, but in an attempt to diversify their investment and reduce risk, farmers limit the minimum and maximum area allocated to each crop along the horizon. Although many crop planning models in the literature implement this managerial policy very little attention is paid to the values assigned to these limits.

With the aim of analyzing the effect of the maximum and minimum area allowed for each crop on the solutions obtained, three scenarios have been defined:

- **Fixed Area Percentages (Scenario DAf)**: lower and upper area limits are arbitrarily set (that is the common practice in the research models) for each tomato variety to 25% and 50% of the farmer land area, respectively.
- **Percentages proportional to the crop expected gross margin (Scenario DAm)**: This scenario attempts to model the usual practice of farmers of increasing the produce of more for the more profitable crops. For this, the mean gross margin along the horizon is calculated based on the price of each time period and market for each tomato variety and divided by the sum of the mean gross margins for all varieties. The obtained percentage for each crop variety is multiplied by 1.1 and 0.9 for defining the upper and lower percentages, respectively. This provides with the following values for each variety: round tomato [40%,49%], pear tomato [38%,47%], cherry tomato [12%,14%]. The obtained percentages for each crop variety is multiplied by the total land area of each farmer obtaining the minimum and maximum land area to be planted per variety $\widetilde{am}_v$ and $\widetilde{aM}_v$, respectively.
- **Percentages inversely proportional to the crop expected gross margin (Scenario DAim)**: This scenario attempts to model, the hypothetical situation that farmer decides to produce more for the more profitable crops of the previous year that results in the less profitable crops in the present year due to the excess in supply. In this scenario, first the inverse of the margin for each tomato variety is calculated. Then, the same process as the previous scenario is applied but, in this case, starting from these new inverse values for the margin. This provides with the following values for each variety: round tomato [16%,20%], pear tomato [17%,22%], cherry tomato [56%,69%].

- **Distributed scenario with information sharing (Scenario DIS)**: In this scenario, cropping plan decisions are also made in a distributed manner by each farmer, but unlike the previous scenarios, farmers have been provided by information about the market demand forecasts for each tomato variety according to their areas. This implicitly assumes that there is some mediator (e.g. government agency) that have knowledge not only on the market demand forecasts for each crop, but also on the area of every farmer. This agency provides with this information to each farmer in order to contribute to a more balanced situation between supply and demand.
- **Centralized scenario (Scenario C)**: In this situation, decisions for all farmers are made in a centralized way by means only one MPM representing the highest level of collaboration. This scenario assumes that a single decision-maker exists with completely knowledge of all farmers as well as the market demand forecasts for each tomato variety.

A summary of the main characteristics of each scenario is presented in Table 4. As it can be observed, Scenarios D, DAf, DAm and DAim do not involve any type of collaboration, meanwhile Scenario DIS and C assume collaboration based on information sharing and joint decision-making, respectively. All scenarios, except Scenario C, assume a distributed decision-making with as many mathematical models as farmers exist in the

SC. Information about market demand is incorporated only in the two last scenarios: in Scenario DIS, farmers know the market demand proportional to their area for each tomato variety and time period; in Scenario C knowledge about global market demand per tomato variety and time period is known, and farmers should jointly decide in a centralized manner the production to face this demand.

Table 4. Characterization of scenarios for the cropping plan problem.

Scenario	Collaboration		Decision making		No. of models (Decision-Makers)		Information on market demand		Min/Max land areas limits (Minimize risk)	
	No	Yes	Dis	Cen	NF	One	No	Yes	No	Yes
D	X		X		X		X		X	
DAf	X		X		X		X			% fixed
DAm	X		X		X		X			% crop margin
DAim	X		X		X		X			% inv. crop margin
DIS		Information sharing	X		X			X	X	
C		Joint decisions		X		X		X	X	

Dis: Distributed, Cen: Centralized; NF: No. farmers

Next subsections present the mathematical formulation and the description of the MPMs representing each Scenario.

5 MPMs for the cropping plan problem involving multiple farmers in different scenarios

5.1 MPM for each farmer in distributed Scenario D

In this scenario farmers make their cropping plan decisions in a decentralized manner based on the following MILP model without any type of collaboration among them or with other entities. Therefore, the number of MILP models coincides with the number of farmers. All the information available for each farmer appears in Table 5. Uncertain parameters are modelled by fuzzy sets indicated by the symbol (~). The deterministic model will be obtained from the fuzzy one by removing (~) from the corresponding uncertain parameters. It is worth mentioning that decision variables for the distributed scenarios finalize in “F” in order to highlight that the model is used for each farmer independently.

This model aims at optimizing the gross margin obtained by the farmer as a difference between the incomes per sales and the total costs (1). As the farmer does not have information about the demand of tomatoes, for calculating the incomes per sales, he/she assumes that all tomatoes sent to markets are going to be sold. The total costs include costs for planting and cultivating, holding costs, waste costs, transport costs, costs for hiring seasonal workers, and costs for seasonal and temporary labor.

Table 5. Nomenclature for the Distributed MPM for Scenario D

Indices			
v	Tomato variety	w	Harvesting patterns
p	Planting period	t	Time period in general
h	Harvest period	m	Market
Set of indices			
P_v	Set of planting dates p in which tomatoes of variety v can be planted.		
H_v^p	Set of harvest dates h that correspond to each planting date p and tomato variety v		
PS_v^t	Set of planting dates p for tomato variety v that requires stake up activities at t		
PC_v^t	Set of planting dates p for tomato variety v that requires pruning activities at t		
PK_v^t	Set of planting dates p for tomato variety v that requires phytosanitary application at t		
PH_v^h	Set of planting dates p for tomato variety v that enables harvest at h		
Parameters			
aF	Total available area for planting tomatoes at farmer (ha)		
d_v	Density of cultivation of variety of tomato v (plants/ha)		
$amin_v$	Minimum area to be planted per period and variety, in case the variety is decided to be planted in that period (ha). This is due to technical reasons (not to minimize risk) and its value is known with certainty.		
$\tilde{y}_{vw}^{ph}$	Quantity of tomatoes obtained from a plant of variety v if planted at period p and harvested at period h following the pattern w (kg/plant)		
$\widetilde{tp}_v$	Time needed to plant one tomato plant of variety v (min/plant)		
$\widetilde{ts}_v$	Time needed per period to stake up one tomato plant of variety v (min/plant)		
$\widetilde{tc}_v$	Time needed per period to prune one tomato plant of variety v (min/plant)		
$\widetilde{tk}_v$	Time needed per period to apply phytosanitary products in one plant of variety v (min/plant)		
$\widetilde{th}_{vw}$	Time needed to harvest a tomato plant of variety v under pattern w (min/plant)		
$\widetilde{tpa}_v$	Time needed to pack one kilogram of tomato of variety v (min/kg)		
sl_v^{ph}	Shelf-life of tomato variety v if planted at period p and harvested in period h (week)		
hw	Available capacity per worker in a week (min/week)		
$MinLS$	Minimum number of seasonal workers per week		
$MaxLS$	Maximum number of seasonal workers per week		
$MaxLT$	Maximum number of temporary workers per week		
$\tilde{p}_{vm}^t$	Selling price for each tomato variety v at market m and period t (€/kg)		
cf_v	Cost incurred for planting and cultivating one tomato plant (€/plant).		
$c\widetilde{wa}_v$	Penalty unitary cost for wasting tomato of variety v after harvest (€/kg)		
ch_v	Holding cost of one kilogram of tomato of variety v per period (€/kg·week)		
ctF_{vm}	Cost of transporting one kilogram of tomato of variety v from farmer to market m (€/kg)		
chs	Fixed cost of hiring one seasonal worker (€)		
cls	Cost per week for one seasonal worker (€/week)		
clt	Cost per week for one temporary worker (€/week)		
Decision variables			
NPF_v^p	Number of plants of tomato variety v planted at period p by the farmer (plant)		
YPF_v^p	Binary variable with a value of one if tomato variety v is planted by the farmer at planting date p and with a value of zero otherwise.		
NSF_v^t	Number of plants of tomato variety v to be staked and stringed up at period t (plant)		
NCF_v^t	Number of plants of tomato variety v to be pruned at period t (plant)		
NKF_v^t	Number of plants of tomato variety v that require the application of phytosanitary products at period t (plant)		
$NHWF_{vw}^{ph}$	Number of plants of tomato variety v planted in period p harvested in period h by pattern w (plant)		
QHF_v^{ph}	Quantity of tomatoes of variety v harvested at period h from plants planted at p (kg)		
$WAHF_v^{ph}$	Quantity of wasted tomato variety v planted at period p and harvest at period h (kg). These wastes are originated by the harvested tomatoes perishing before transported to markets.		
QPF_v^{pht}	Quantity of tomato of variety v planted at planting period p, harvested at period h and packed at period t (kg). Product is packaged after storage just for being transported to markets, for this reason the harvesting time period could be different from the period when is packaged.		
QTF_{vm}^{pht}	Quantity of tomato variety v planted at period p, harvested at period h and transported from farmer to market m at period t (kg). It represents the supply in the demand-supply balance.		
LSF^t	Number of seasonal laborers working at week t		
$HLSF^t$	Number of seasonal laborers hired at week t		
$FLSF^t$	Number of seasonal laborers fired at week t		
LTF^t	Number of temporary laborers working at week t		
PrF	Profit obtained by the farmer (€)		

$$Max[PrF] = \sum_{v}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t}\tilde{p}_{vm}^{t}\cdot QTF_{vm}^{pht} - \sum_{v}\sum_{p\in P_v} cf_v\cdot NPF_v^p - \sum_{v}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t} ch_v\cdot(t-h)\cdot QTF_{vm}^{pht} - \sum_{v}\sum_{p\in P_v}\sum_{h\in H_v^p}\widetilde{cwa}_v\cdot WAHF_v^{ph} - \sum_{v}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t} ctF_{vm}\cdot QTF_{vm}^{pht} - \sum_{t}(chs\cdot HLSF^t + cls\cdot LSF^t + clt\cdot LTF^t) \tag{10}$$

$$\sum_{v}\sum_{p\in P_v}\frac{NPF_v^p}{d_v}\le aF \tag{11}$$

$$\frac{NPF_v^p}{d_v}\ge amin_v\cdot YPF_v^p \qquad \forall v,p\in P_v \tag{12}$$

$$\frac{NPF_v^p}{d_v}\le aF\cdot YPF_v^p \qquad \forall v,p\in P_v \tag{13}$$

$$NSF_v^t = \sum_{p\in PS_v^t} NPF_v^p \qquad \forall v,t \tag{14}$$

$$NCF_v^t = \sum_{p\in PC_v^t} NPF_v^p \qquad \forall v,t \tag{15}$$

$$NKF_v^t = \sum_{p\in PK_v^t} NPF_v^p \qquad \forall v,t \tag{16}$$

$$\sum_{w} NHWF_{vw}^{ph} = NPF_v^p \qquad \forall v,h,p\in PH_v^h \tag{17}$$

$$\sum_{w}\tilde{y}_{vw}^{ph}\cdot NHWF_{vw}^{ph} = QHF_v^{ph} \quad \forall v,p\in P_v,h\in H_v^p \tag{18}$$

$$QHF_v^{ph} = \sum_{m}\sum_{h\le t\le h+sl_v^{ph}} QTF_{vm}^{pht} + WAHF_v^{ph} \qquad \forall v,p\in P_v,h\in H_v^p \tag{19}$$

$$QPF_v^{pht} = \sum_{m} QTF_{vm}^{pht} \qquad \forall v,p\in P_v,h\in H_v^p,t\ge h \tag{20}$$

$$\sum_{v}\sum_{p=t}\widetilde{tp}_v\cdot NPF_v^p + \sum_{v}\widetilde{ts}_v\cdot NSF_v^t + \sum_{v}\widetilde{tc}_v\cdot NCF_v^t + \sum_{v}\widetilde{tk}_v\cdot NKF_v^t + \sum_{v}\sum_{p\in P_v}\sum_{w}\sum_{h=t}\widetilde{th}_{vw}\cdot NHWF_{vw}^{ph} + \sum_{v}\sum_{p\in P_v}\sum_{h\in H_v^p}\widetilde{tpa}_v\cdot QPF_v^{pht} \le hw\cdot(LS^t + LT^t) \quad \forall t \tag{21}$$

$$LSF^t = LSF^{t-1} + HLSF^t - FLSF^t \qquad \forall t \tag{22}$$

$$MinLS \le LSF^t \le MaxLS \qquad \forall t \tag{23}$$

$$LTF^t \le MaxLT \qquad \forall t \tag{24}$$

$$\begin{array}{ll} PrF, QPF_v^{pht}, QHF_v^{ph}, WAHF_v^{ph}, QTF_{vm}^{pht} & CONTINUOUS \\ NPF_v^p, NSF_v^t, NCF_v^t, NKF_v^t, NHWF_{vw}^{ph}, HLSF^t, LSF^t, FLSF^t, LTF^t & INTEGER \\ YPF_v^p & BINARY \end{array} \tag{25}$$

Since available land area at farms can only be planted once per season, set of constraints (2) ensure the total area planted with the different tomato varieties plants along all the planting periods is not higher than the available farmer area to be planted.

Set of constraints (3) fixes the minimum area each time a specific variety of tomatoes is planted. It is noteworthy that this constraint is defined due to technical reasons and not to minimize the risk.

Set of constraints (4) forces the binary variable YPF_v^p to be 1 if the tomato variety v has been planted during period p, ensuring that the minimum area to be planted is respected by constraint (3). These two set of constraints also act in the opposite way, i.e. if a specific variety is not planted, constraint (3) obliges YPF_v^p to be zero. The number of plants to be staked up in each period t depends on the number of plants planted at planting periods p that require this operation to be done at t (5). Analogously to constraints (5), constraints (6) and (7) calculate the number of plants to be pruned and to applicate phytosanitary products in each period, respectively.

Set of constraints (8) ensure that the total number of plants per tomato variety v harvested during period h with the different harvesting patterns w is equal to the total number of plants planted during time period p where harvesting at h is possible. This constraint assumes that all the plants planted at period p that can be harvested at period h, are harvested. It is important to note that the same plant planted at period p can be harvested during different time periods h because tomatoes mature over time.

The amount of each tomato variety v planted at p and harvested during time period h is equal to the sum of the amount of the same tomato variety harvested by the different patterns (9). Since each harvesting pattern represent different number of passes along the same land area, the yield obtained is different. We assume that the yield considers only the quantity of tomato ready to be sold.

By means constraint (10) it is ensured that the quantity of tomato variety v planted at p and harvested h will be equal to the quantity of tomatoes transported and sold at all markets during at most their corresponding shelf-life and the waste originated for product that perish. Because all ripened tomato should be harvested, waste could exist due to not enough labor capacity for packing. The freshness of the product delivered at the market will be equal to $(t-h)/sl_v^{ph}$.

Constraint (11) assumes that the same quantity of each tomato variety that is going to be transported to all markets m in period t is going to be packaged in the same time period t. This means that the tomatoes cannot be stored when packaged.

The time used to do planting, cultivating (staking, pruning, application of phytosanitary products), harvesting and packing activities for all the planted areas per period cannot exceed the available capacity of seasonal and temporary workers for the period (12).

Set of equations (13) allows to calculate the number of seasonal workers hiring and firing at each time period. A minimum and maximum number of seasonal workers exist for all periods in the farm (14). Similarly, the available temporary workers are limited (15). Set of constraints (16) defines the nature of the decision variables of the model.

5.2 MPM for each farmer with limited land areas per variety in distributed Scenarios DAf, DAm and DAim

In these scenarios as in the previous one, farmers have no knowledge about market demand but in these scenarios, each farmer tries to minimize risk by diversifying the tomato varieties to be planted. For doing so, limits about the minimum and maximum land area to be planted per tomato variety along the year are defined for each farmer. In order to reflect these changes, the model for Scenario D should be modified by including new parameters representing the lower and upper limits on the area planted per tomato variety (Table 6) and a new constraint (17) that forces to accomplish with these limits. Differences between Scenario DAf, DApm and DAipm rely on the value defined for the minimum and maximum area per tomato variety. The way of calculating them has been explained in subsection 4.1.

Table 6. New parameters to the Distributed MPM with limited land areas per variety (DAf, DAm and DAim).

Parameters	
$\widetilde{am}_v$	Minimum area to be planted per variety v during the horizon at farmer (ha)
$\widetilde{aM}_v$	Maximum area to be planted per variety v during the horizon at farmer (ha)

$$Max\ Z = PrF \tag{1}$$

Subject to:

Constraints (2) to (16)

$$\widetilde{am}_v \leq \sum_{p \in P_v} \frac{NPF_v^p}{d_v} \leq \widetilde{aM}_v \qquad \forall v \tag{26}$$

5.3 MPM for each farmer with shared information about market demands for the distributed Scenario DIS.

As previously highlighted, Scenario DIS considers that each farmer knows the market's demand for each variety of tomato proportionally to their own area. This situation involves the existence of some organism like public agencies providing farmers with the market demand for each tomato variety proportional to his/her land area in comparison with other land areas. The demand per period and tomato variety for each farmer is calculated by distributing the total demand among farmers according to the farmer area available to grow tomatoes in each of the fields (18).

$$\widetilde{deF}_{vm}^{t} = \frac{\widetilde{de}_{vm}^{t} \cdot aF}{ta} \qquad \forall v, m, t \tag{27}$$

where $\widetilde{de}_{vm}^t$ represents the regional demand per time period t for each tomato variety v and market m, aF represents the land area available to plant tomatoes for a farmer, ta the total area available for planting tomatoes in the region calculated as a sum of the available area of all farmers and, $\widetilde{deF}_{vm}^t$ represents the demand per tomato variety v and market m in each time period t that farmer should satisfy.

Unlike the previous scenarios not considering demand, it is possible that unmet demand appears. Harvested tomato variety will become waste when its demand is lower than its supply during their shelf-life once harvested meanwhile, unmet demand will appear when supply is lower that the market demand. For modelling these two situations, new decision variables computing unmet demand and quantity finally sold as well as their associated costs should be defined (Table 7). The new model appears below.

Because penalties for unmet demand exists, the objective function of this scenario should be modified by considering them (19). Through these penalties the decision-maker seeks for a more sustainable production because not only the economic results are taken into account but also the environmental (wastes) and social (unmet demand) ones.

Table 7. New parameters and decision variables to the distributed MPM with shared information about market demand per farmer (DIS).

Parameters	
$\widetilde{deF}_{vm}^{t}$	Proportional demand of farmer for the tomato variety v at market m and period t (kg)
$\widetilde{cud}_{vm}$	Penalty unitary cost for not fulfilling tomato of variety v at market m (€/kg)
Decision variables	
UD_{vm}^{t}	Quantity of unmet demand of tomato variety v at period t in market m (kg)
QSF_{vm}^{pht}	Quantity of tomatoes of variety v planted at p, harvested at h and sold at period t in market m (kg)

$$\begin{aligned} Max\ PrF = & \sum_{v}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t}\tilde{p}_{vm}^{t}\cdot QSF_{vm}^{pht} - \sum_{v}\sum_{p\in P_v} cf_v \cdot NPF_v^p \\ & -\sum_{v}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t} ctF_{vm}\cdot QTF_{vm}^{pht} \\ & -\sum_{v}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t} ch_v\cdot(t-h)\cdot QTF_{vm}^{pht} \\ & -\sum_{v}\sum_{p\in P_v}\sum_{h\in H_v^p}\widetilde{cwa}_v\cdot WAHF_v^{ph} - \sum_{v}\sum_{m}\sum_{t}\widetilde{cud}_{vm}\cdot UD_{vm}^{t} \\ & -\sum_{t}(chs\cdot HLSF^t + cls\cdot LSF^t + clt\cdot LTF^t) \end{aligned} \quad (28)$$

Subject to:

$Constraints\ (2)-(16)$

$$QTF_{vm}^{pht} = QSF_{vm}^{pht} \qquad \forall v,m,p\in P_v, h\in H_v^p, t \quad (29)$$

$$\sum_{p\in P_v}\sum_{h\in H_v^p} QSF_{vm}^{pht} + UD_{vm}^{t} = \widetilde{deF}_{vm}^{t} \qquad \forall v,m,t \quad (30)$$

$$QSF_{vm}^{pht}, UD_{vm}^{t} \qquad CONTINUOUS \quad (31)$$

Because no waste is allowed at markets, through constraint (20) all the tomatoes quantities transported to each market are assumed to be sold, otherwise they are not transported. The unmet demand of each tomato variety at each market and time period should be equal to the total demand allocated to this farmer minus the sold quantity (21). Finally, the nature definition of the new decision variables is stated in (22).

5.4 MPM for all farmers in centralized Scenario C

This scenario assumes the existence of one decision-maker with knowledge about the market demand forecasts and all the characteristics of farmers including their available land area. The decisions are made to optimize the farmers' profit as a whole, that is at the region or SC level. For this reason, the global demand for each market should be satisfied considering the production of all farmers. In order to differentiate among the decisions related to each farmer, a new index f representing farmers has been defined. This index should be considered in all data and decision variables affecting one farmer in particular. The resulting nomenclature for modelling this scenario can be consulted in Table 8.

The objective function (23) tries to maximize the profits of the region calculated as the difference between the incomes per sales in different markets and the total costs. The costs include those related to planting and cultivating, storage costs, wastes penalty costs, costs for transporting the tomatoes from all the fields of farmers to markets, penalty costs for unmet demand and labor costs. In the same way as the model for Scenario DIS, this model contemplates the three aspects of sustainability by considering not only the profit (economic) but also the penalties of waste (environmental) and unmet demand (social).

Table 8. Nomenclature for the Centralized Model of Scenario C.

Indices			
v	Tomato variety	t	Time period in general
p	Planting period	f	Farmer
h	Harvest period	m	Market
w	Harvesting patterns		
Set of indices			
P_v	Set of planting dates p in which tomatoes of variety v can be planted.		
H_v^p	Set of harvest dates h that correspond to each planting date p and tomato variety v		
PS_v^t	Set of planting dates p for tomato variety v that requires stake up activities at t		
PC_v^t	Set of planting dates p for tomato variety v that requires pruning activities at t		
PK_v^t	Set of planting dates p for tomato variety v that requires phytosanitary application at t		
PH_v^h	Set of planting dates p for tomato variety v that enables harvest at h		
Parameters			
$\tilde{p}_{vm}^t$	Selling price for each tomato variety v at market m and period t (€/kg)		
$\widetilde{de}_{vm}^t$	Demand of the tomato variety v at market m and period t (kg)		
cf_v	Cost per plant and cultivate one plant of tomato variety v (€/planta).		
$c\widetilde{wa}_v$	Penalty cost for wasting one kilogram of variety tomato v after harvest (€/kg)		
ct_{vfm}	Cost of transporting one kilogram of tomato variety v from farmer f to market m (€/kg)		
ch_v	Unitary holding cost of tomato variety v per period (€/kg·week)		
$\widetilde{cud}_{vm}$	Penalty cost for not fulfilling one kilogram of tomato variety v at market m (€/kg)		
chs	Cost of hiring one seasonal worker (€)		
cls	Cost per time period for one seasonal worker (€/week)		
clt	Cost per time period for one temporary worker (€/week)		
a_f	Available area for planting tomatoes at farmer f (ha)		
d_v	Density of cultivation of variety of tomato v (plants/ha)		
$amin_v$	Minimum area to be planted per period and variety, in case the variety is decided to be planted (ha) due to technical aspects (no managerial aspects)		
$\tilde{y}_{vw}^{ph}$	Quantity of tomatoes obtained from a plant of variety v at period h if planted at period p (kg/plant)		
$\widetilde{tp}_v$	Time needed to plant one tomato plant of variety v (min/plant)		
$\widetilde{ts}_v$	Time needed per period to stake up one tomato plant of variety v (min/plant)		
$\widetilde{tc}_v$	Time needed per period to prune one tomato plant of variety v (min/plant)		
$\widetilde{tk}_v$	Time needed per period to apply phytosanitary products in one plant of variety v (min/plant)		
$\widetilde{th}_{vw}$	Time needed to harvest a tomato plant of variety v under pattern w (min/plant)		
$\widetilde{tpa}_v$	Time needed to pack one kilogram of tomato of variety v (min/kg)		
sl_v^{ph}	Shelf-life of tomato variety v if planted at period p and harvested in period h (week)		
hw	Available capacity per worker in a time period (min/week)		
$MinLS_f$	Minimum number of seasonal workers per time period at farm f		
$MaxLS$	Maximum number of seasonal workers per time period		
$MaxLT$	Maximum number of temporary workers per time period		
Decision variable			
NP_{vf}^p	Number of plants of tomato variety v planted at period p by the farmer f (plant)		
YP_{vf}^p	Binary variable with a value of 1 if tomato variety v is planted by the farmer f at planting date p, and with a value of 0, otherwise.		
NS_{vf}^t	Number of plants of tomato variety v to be staked and stringed up by the farmer f at period t (plant)		
NC_{vf}^t	Number of plants of tomato variety v to be pruned by the farmer f at period t (plant)		
NK_{vf}^t	Number of plants of tomato variety v that require the application of phytosanitary products by the farmer f at period t (plant)		
NHW_{vfw}^{ph}	Number of plants of tomato variety v planted by farmer f in period p to be harvested in period h by pattern w (plant)		
QH_{vf}^{ph}	Quantity of tomato variety v harvested by farmer f at period h from plants planted at p (kg)		
WAH_{vf}^{ph}	Quantity of tomato of variety v planted by farmer f at planting period p and wasted at the farm level after harvest at period h (kg). These wastes are produced by the tomatoes harvested not transported to markets.		
QP_{vf}^{pht}	Quantity of tomato of variety v planted at planting period p, harvested at period h and packed by farmer f at period t (kg).		
QT_{vfm}^{pht}	Quantity of tomato of variety v planted at planting period p, harvested at period h and transported from farmer f to market m at period t (kg).		
QS_{vfm}^{pht}	Quantity of tomatoes variety v planted in farm f at period p, harvested at h and sold at period t at market m (kg)		
UD_{vm}^t	Quantity of unmet demand of tomato variety v at period t in market m (kg)		
HLS_f^t	Number of seasonal laborers hired by farmer f at period t		
LS_f^t	Number of seasonal laborers working at farm f at period t		
FLS_f^t	Number of seasonal laborers fired by farmer f at period t		
LT_f^t	Number of temporary laborers working at farm f at period t		
Pr	Profit obtained by the region (€)		

$$Max\ Pr = \sum_{v}\sum_{f}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t}\tilde{p}_{vm}^{t}\cdot QS_{vfm}^{pht} - \sum_{v}\sum_{f}\sum_{p\in P_v} cf_v\cdot NP_{vf}^{p} - \sum_{v}\sum_{f}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t} ch_v\cdot(t-h)\cdot QT_{vfm}^{pht} - \sum_{v}\sum_{f}\sum_{p\in P_v}\sum_{h\in H_v^p}\widetilde{cwa}_v\cdot WAH_{vf}^{ph} - \sum_{v}\sum_{f}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t} ct_{vfm}\cdot QT_{vfm}^{pht} - \sum_{v}\sum_{m}\sum_{t}\widetilde{cud}_{vm}\cdot UD_{vm}^{t} - \sum_{f}\sum_{t}\left(chs\cdot HLS_f^t + cls\cdot LS_f^t + clt\cdot LT_f^t\right) \tag{32}$$

$Subject\ to$:

$$\sum_{v}\sum_{p\in P_v}\frac{NP_{vf}^{p}}{d_v}\le a_f \qquad \forall f \tag{33}$$

$$\frac{NP_{vf}^{p}}{d_v}\ge\ amin_v\cdot YP_{vf}^{p} \qquad \forall v,f,p\in P_v \tag{34}$$

$$\frac{NP_{vf}^{p}}{d_v}\le a_f\cdot YP_{vf}^{p} \qquad \forall v,f,p\in P_v \tag{35}$$

$$NS_{vf}^{t} = \sum_{p\in PS_v^t} NP_{vf}^{p} \qquad \forall v,f,t \tag{36}$$

$$NC_{vf}^{t} = \sum_{p\in PC_v^t} NP_{vf}^{p} \qquad \forall v,f,t \tag{37}$$

$$NK_{vf}^{t} = \sum_{p\in PK_v^t} NP_{vf}^{p} \qquad \forall v,f,t \tag{38}$$

$$\sum_{w} NHW_{vfw}^{ph} = NP_{vf}^{p} \qquad \forall v,f,h,p\in PH_v^h \tag{39}$$

$$\sum_{w}\tilde{y}_{vw}^{ph}\cdot NHW_{vfw}^{ph} = QH_{vf}^{ph} \qquad \forall v,f,p\in P_v,h\in H_v^p \tag{40}$$

$$QH_{vf}^{ph} = \sum_{m}\sum_{h\le t\le h+sl_v^{ph}} QT_{vfm}^{pht} + WAH_{vf}^{ph} \qquad \forall v,f,p\in P_v,h\in H_v^p \tag{41}$$

$$QP_{vf}^{pht} = \sum_{m} QT_{vfm}^{pht} \qquad \forall v,f,p\in P_v,h\in H_v^p,t\ge h \tag{42}$$

$$QT_{vfm}^{pht} = QS_{vfm}^{pht} \qquad \forall v,f,m,p\in P_v,h\in H_v^p,t\ge h \tag{43}$$

$$\sum_{f}\sum_{p\in P_v}\sum_{h\in H_v^p} QS_{vfm}^{pht} + UD_{vm}^{t} = \widetilde{de}_{vm}^{t} \qquad \forall v,m,t \tag{44}$$

$$\sum_{v}\sum_{p=t}\widetilde{tp}_v\cdot NP_{vf}^{p} + \sum_{v}\widetilde{ts}_v\cdot NS_{vf}^{t} + \sum_{v}\widetilde{tc}_v\cdot NC_{vf}^{t} + \sum_{v}\widetilde{tk}_v\cdot NK_{vf}^{t} + \sum_{v}\sum_{p\in P_v}\sum_{w}\sum_{h=t}\widetilde{th}_{vw}\cdot NHW_{vfw}^{ph} + \sum_{v}\sum_{p\in P_v}\sum_{h\in H_v^p}\widetilde{tpa}_v\cdot QP_{vf}^{pht} \le hw\cdot\left(LS_f^t + LT_f^t\right) \quad \forall f,t \tag{45}$$

$$LS_f^t = LS_f^{t-1} + HLS_f^t - FLS_f^t \qquad \forall f,t \tag{46}$$

$$MinLS_f \le LS_f^t \qquad \forall f,t \tag{47}$$

$$\sum_{f} LT_f^t \le MaxLT \qquad \forall t \tag{48}$$

$$\sum_{f} LS_f^t \leq MaxLS \qquad \forall t \tag{49}$$

$$Pr, QH_{vf}^{ph}, QP_{vf}^{pht}, QT_{vfm}^{pht}, QS_{vfm}^{pht}, WAH_{vf}^{ph}, UD_{vm}^{t} \quad CONTINUOUS$$
$$NP_{vf}^{p}, NS_{vf}^{t}, NC_{vf}^{t}, NK_{vf}^{t}, NHW_{vfw}^{ph}, HLS_f^t, LS_f^t, FLS_f^t, LT_f^t \quad INTEGER \tag{50}$$
$$YP_{v_f}^{p} \quad BINARY$$

Constraints (24)-(33) are similar to constraint (2)-(11) of Scenario D, respectively, with the difference of including the index f in order to distinguish among farmers in the centralized model.

Quantities transported coincide with quantities sold for each tomato variety, farmer and time period (34) similar to (20) in the DIS model. This means that not waste can be produced in markets, because it is more economic waste the product immediately after harvest than after being transported. Set of constraints (35) represent the balance equation for the demand of each tomato variety at each market taking into account the supply of all farmers. Through this set of constraints, the unmet demand per variety, market and time period is computed.

Set of constraints (36) ensures that necessary capacity for making all the planting, cultivating, harvesting and packaging activities at each time period do not exceed the capacity of seasonal and temporary workers at each farm for that period. The quantity of seasonal workers fired and hired at each farm and time period is calculated based on the number of seasonal workers in this time period and the period before by set of constraints (37). A minimum number of seasonal workers must work at each farm and period (38). Since the available temporary and seasonal workers are limited for all the region, the sum of temporary and seasonal workers at all farms cannot exceed the availability of each one, respectively (39, 40). Set of constraints (41) defines the nature of the decision variables of the model.

6 Solution Methodology for the Fuzzy Models

In previous section, set of models have been developed to support the crop planning problem in different scenarios. These models consider the following uncertain parameters to be fuzzy due to either lack of knowledge ($\tilde{p}_{vm}^{t}$, $\widetilde{de}_{vm}^{t}$,$\widetilde{deF}_{vm}^{t}$, $\tilde{y}_{vw}^{ph}$, $\widetilde{tp}_{v}$, $\widetilde{ts}_{v}$, $\widetilde{tc}_{v}$, $\widetilde{tk}_{v}$, $\widetilde{th}_{vw}$, $\widetilde{tpa}_{v}$) or vagueness or imprecision ($\widetilde{am}_{v}$, $\widetilde{aM}_{v}$, $\widetilde{cud}_{vm}$, $\widetilde{cwa}_{v}$). As it can be seen in Table 9 the proposed uncertain parameters gather the uncertainty sources in demand and process by means fuzzy numbers in the objective function and constraints, for both technological coefficients and right-hand side (RHS).

All the above scenarios are solved in a deterministic and uncertain context. In the context of possibility theory, several methods exist to models involving coefficients of the objective function and/or the constraints as fuzzy numbers. In solving them it is necessary to answer two questions [41]: a) How to define the feasibility of a decision vector x, when the constraints involve fuzzy numbers and b) How to define the optimality for an objective function with fuzzy coefficients.

Table 9. Fuzzy parameters considered in the MPMs of different Scenarios

Sources of uncertainty	Fuzzy parameters	Fuzzy model element	Formulation
Demand	Selling price for each tomato variety v at market m and period t	Objective coefficients	$\tilde{p}_{vm}^{t}$
	Farmer proportional demand for tomato variety v at market m and period t	RHS	$\widetilde{deF}_{vm}^{t}$
	Demand of the tomato variety v at market m and period t	RHS	$\widetilde{de}_{vm}^{t}$
	Penalty unitary cost for not fulfilling tomato of variety v at market m	Objective coefficients	$\widetilde{cud}_{vm}^{t}$
Process	Quantity of tomatoes obtained from a plant of variety v if planted at period d and harvested at period h following the pattern w (yield)	Technological coefficients	$\tilde{y}_{vw}^{ph}$
	Time needed to plant one tomato plant of variety v	Technological coefficients	$\widetilde{tp}_{v}$
	Time needed per period to stake up one tomato plant of variety v	Technological coefficients	$\tilde{y}_{vw}^{ph}$
	Time needed per period to prune one tomato plant of variety v	Technological coefficients	$\tilde{y}_{vw}^{ph}$
	Time needed per period to apply phytosanitary products on one tomato plant of variety v	Technological coefficients	$\tilde{y}_{vw}^{ph}$
	Time needed to harvest a tomato plant of variety v under pattern w	Technological coefficients	$\tilde{y}_{vw}^{ph}$
	Time needed to pack one kilogram of tomato of variety v	Technological coefficients	$\tilde{y}_{vw}^{ph}$
	Minimum area to be planted per variety v during the horizon at farmer	RHS	$\tilde{y}_{vw}^{ph}$
	Maximum area to be planted per variety v during the horizon at farmer	RHS	$\tilde{y}_{vw}^{ph}$
	Penalty unitary cost for wasting tomato of variety v after harvest	Objective coefficients	$\tilde{y}_{vw}^{ph}$

To answer these questions, we followed a two-step methodology:

1) First, we apply the approach of Jiménez (1996) to transform the fuzzy mixed-integer linear programming models into an equivalent α-parametric crisp model (subsection 6.1). The resulting equivalent α-parametric crisp models for the fuzzy models of each scenario are offered in the Appendix I.
2) Second, we follow the interactive resolution method proposed by [42] for the selection of α to obtain the solution to be implemented (subsection 6.2).

6.1 Formulation of the fuzzy mixed-integer linear programming models as equivalent α-parametric crisp models

In order to show the adopted approach, let us consider the following general linear programming model with fuzzy parameters in the objective function and constraints that can be of type: hand-side "*less than or equal*", "*greater than or equal*" and "*equality*".

$$Max[Z] = \sum_{j=1}^{n} \tilde{c}_j x_j \tag{51}$$

$$subject\ to$$

$$\sum_{j=1}^{n} \tilde{a}_{ij} x_j \geq \tilde{b}_i \qquad i = 1,2,\dots,m1 \tag{52}$$

$$\sum_{j=1}^{n} \tilde{a}_{ij} x_j \leq \tilde{b}_i \qquad i = m1+1, \dots, m2 \tag{53}$$

$$\sum_{j=1}^{n} \tilde{a}_{ij} x_j = \tilde{b}_i \qquad i = m2+1, \dots, m3 \tag{54}$$

$$x_j \geq 0 \qquad j = 1,2, \dots, n \tag{55}$$

where x_j is the jth crisp decision variable; $\tilde{c}_j$ is the fuzzy coefficient of the objective function and j decision variable, $\tilde{a}_{ij}$ is the fuzzy technical coefficient matrix of the i^{th} constraint and the j^{th} decision variable, and $\tilde{b}_i$ is the fuzzy right-hand-side term of the i^{th} constraint.

There are several options of membership functions to describe a fuzzy number $\tilde{z}$. A well-known membership function is the trapezoidal one (Figure 2 (a)) where the fuzzy number is represented by $\tilde{z} = (z_1, z_2, z_3, z_4)$ where $z_1 \leq z_2 \leq z_3 \leq z_4$. Alpha ($\boldsymbol{\alpha}$) means the degree to which the curve progresses toward limits z_2 and z_3. A special case of a trapezoidal fuzzy number is the triangular fuzzy number (TFN) where $z_2 = z_3$ (Figure 2 (b)). In this paper we adopt triangular fuzzy numbers (TFN) (symmetric and asymmetric) to model the epistemic uncertainty in all the fuzzy parameters. Pedrycz [44], states that such membership functions adjust well to cases where the fuzzy value presents modal (typical) behavior with linear distribution along lower and upper bounds. Mula et al. [45] also states that the parameters of a triangular possibility distribution represent the most pessimistic, the most possible and the most optimistic values, which is in concordance with our case.

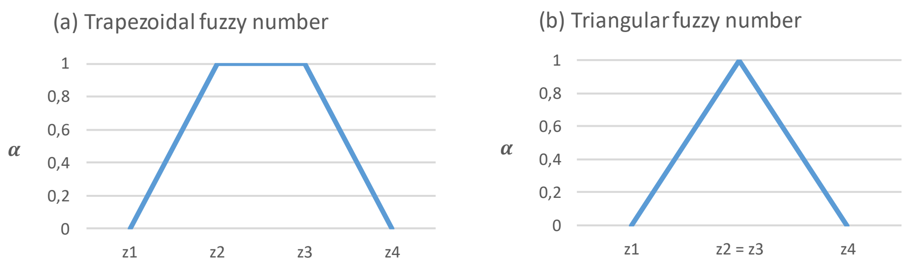

Figure 2. Membership functions to describe a fuzzy number $\tilde{z}$

The expected value of a fuzzy number $\tilde{z}$ ($EV(\tilde{z})$) represents the half point of its expected interval [45], where E_1^z and E_2^z are the lower and upper values of the expected interval, respectively:

$$EV(\tilde{z}) = \frac{E_1^z + E_2^z}{2} \tag{56}$$

If fuzzy number $\tilde{z}$ can be expressed as a trapezoidal membership function as in Figure 2(a) its expected interval and its expected value can be calculated as follows in (48) and (49), respectively, where z_1 and z_4, are the lower and upper limits of the interval, respectively, and z_2 and z_3 represent its intermediate numbers.

$$EI(\tilde{z}) = [E_1^z, E_2^z] = \left[\frac{z_1 + z_2}{2}, \frac{z_3 + z_4}{2}\right] \tag{57}$$

$$EV(\tilde{z}) = \frac{1}{4}\ (z_1 + z_2 + z_3 + z_4) \tag{58}$$

Therefore, the equivalent α-parametric crisp model can be expressed as follows:

$$Max[Z] = \sum_{j=1}^{n} EV(\tilde{c}_j)x_j \tag{59}$$

$subject\ to$

$$\sum_{j=1}^{n}\left[(1-\alpha)E_2^{a_{ij}} + \alpha E_1^{a_{ij}}\right] x_j \geq \alpha E_2^{b_i} + (1-\alpha)E_1^{b_i} \qquad i = 1,2,\dots,m_1 \tag{60}$$

$$\sum_{j=1}^{n}\left[(1-\alpha)E_1^{a_{ij}} + \alpha E_2^{a_{ij}}\right] x_j \leq \alpha E_1^{b_i} + (1-\alpha)E_2^{b_i} \qquad i = m_1+1,\dots,m_2 \tag{61}$$

$$\sum_{j=1}^{n}\left[\left(1-\frac{\alpha}{2}\right)E_1^{a_{ij}} + \frac{\alpha}{2}E_2^{a_{ij}}\right] x_j \leq \frac{\alpha}{2}E_1^{b_i} + \left(1-\frac{\alpha}{2}\right)E_2^{b_i} \qquad i = m_2+1,\dots,m_3 \tag{62}$$

$$\sum_{j=1}^{n}\left[\left(1-\frac{\alpha}{2}\right)E_2^{a_{ij}} + \frac{\alpha}{2}E_1^{a_{ij}}\right] x_j \geq \frac{\alpha}{2}E_2^{b_i} + \left(1-\frac{\alpha}{2}\right)E_1^{b_i} \qquad i = m_2+1,\dots,m_3 \tag{63}$$

$$x_j \geq 0 \qquad j = 1,2,\dots,n \tag{64}$$

To adapt this formulation to the triangular fuzzy numbers, it is only required to make $z_2 = z_3$ in the trapezoidal membership functions. The resulting equivalent crisp models for each scenario obtained after applying this method can be consulted in Appendix A.

6.2 Methodology for selecting the final solution for each scenario under uncertainty

The solution of the above α-parametric crisp model requires to select a feasibility degree of the constraints by means the definition of an α-value. The lower the feasibility degree (α-value) is, the better the objective value becomes but riskier the solution obtained. Therefore, it is necessary to evaluate the solutions under different α-values to find a proper balance for the decision-maker wishes in terms of the objective function and the feasibility degree of the constraints. Several methodologies have been reported in the literature for selecting the α-value [44,46-49] mainly based on an interactive process where the selection of the final value of α, depends on the decision-maker criteria.

Because the selection of the final solution should take into account the three dimensions of sustainability (economic, environmental and social), in this paper, we adopt the interactive resolution method proposed by Peidro et al. [42] in three steps that considers multiple measurable parameters in order to select the final value of α (Figure 3) This interactive resolution method is applied for each scenario and decision-maker in the corresponding scenario. That is, for each MPM, the following procedure should be made in order to select the α-value of the solution to be implemented.

The **first step** consists in solving parametrically for 11 values of α (0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0) the auxiliary crisp mixed-integer linear programming models for each scenario in Appendix A. Each corresponding solution is evaluated according to the three measurable parameters:

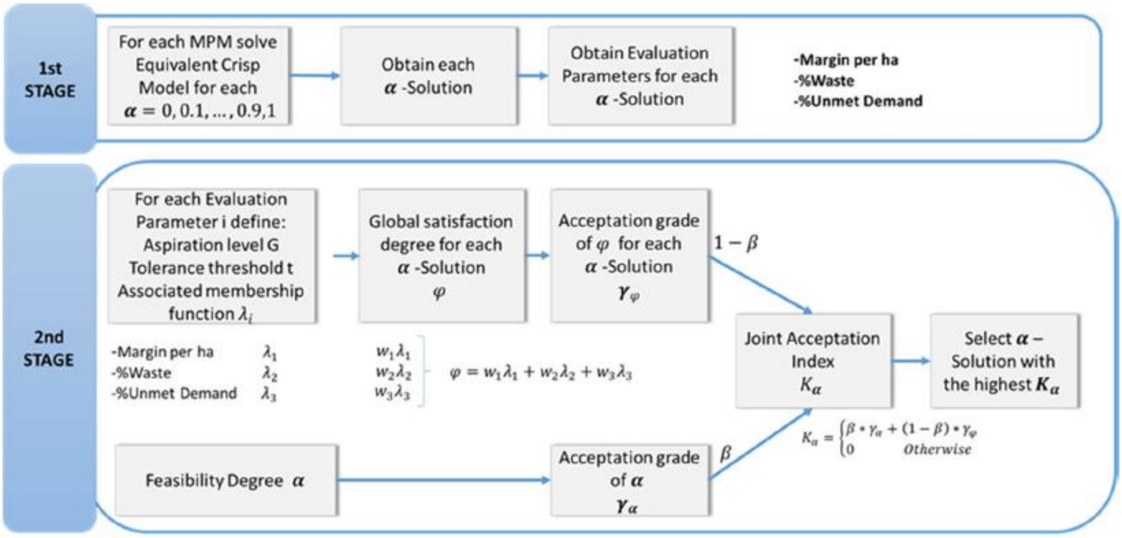

Figure 3. Procedure of Peidro et al. [42] to select the α-value for the final solution.

- **Margin per Hectare**: it is calculated as the incomes per sales minus all the costs, except the penalizations of unmet demand and waste, divided by the farm area.

$$Margin\ per\ ha = \frac{PrF + Waste\ Penalty + Unmet\ Demand\ Penalty}{Total\ Area\ (ha)} \tag{65}$$

- **% Waste**: it is calculated as the percentage of the quantity of waste as regards the whole quantity harvested.

$$\%\ Waste = 100 \cdot \left(\frac{Total\ Waste}{Total\ Quantity\ Harvested}\right) \tag{66}$$

- **% Unmet Demand**: it is calculated as the percentage of the unmet demand of all tomato varieties as regards the global demand.

$$\%\ Unmet\ demand = 100 \cdot \left(\frac{Total\ Unmet\ Demand}{Total\ Demand}\right) \tag{67}$$

The **second step** of the methodology intends to obtain a decision vector that complies with the expectation of the decision-maker as regards two conflicting aspects: the feasibility degree α and a satisfactory value for the three evaluation parameters. In doing so, after seeing the results obtained in the first step, the decision-maker is asked to specify an aspiration level G and its tolerance threshold t for the numerical values obtained by each evaluation parameter.

For the Margin per hectare parameter, that fits with the case "more is better" the goal is expressed by an increasing membership function [41]:

$$\mu_{\tilde{G}}(z) = \begin{cases} 1 & if\ z \geq G \\ \lambda \in [0,1] & increasing\ on\ G - t \leq z \leq G \\ 0 & if\ z \leq G - t \end{cases} \tag{68}$$

On the contrary, for the waste and unmet demand evaluation parameters, that fits with the case "*less is better*" the satisfaction level is expressed by means of a fuzzy set satisfaction level is expressed by means of a fuzzy set $\tilde{G}$ whose membership function is as follows:

$$\mu_{\tilde{G}}(z) = \begin{cases} 1 & if\ z \leq G \\ \lambda \in [0,1] & decreasing\ on\ G \leq z \leq G + t \\ 0 & if\ z \geq G + t \end{cases} \tag{69}$$

We define λ_i (i =1,2,3) as the degree in which the corresponding fuzzy aspiration levels of the above parameters are satisfied by a decision vector. Obviously, the decision-maker wants to obtain a maximum satisfaction degree for all of them. In order to aggregate them we propose the weighted sum. Therefore, the global satisfaction degree of the solution is calculated as: $\varphi = w_1 \cdot \lambda_1 + w_2 \cdot \lambda_2 + w_3 \cdot \lambda_3$ where $w_1 + w_2 + w_3 = 1$.

The **third step** tries to obtain a solution that balance two usually conflicting aspects: the feasibility degree of the solution (α) and the global satisfation degree (φ). To select the final solution two fuzzy sets whose membership functions, represent the decision-maker's acceptation of the feasibility degree, γ_α, and the global satisfaction degree, γ_φ. These two acceptation degrees increase monotonously between the corresponding lower and upper bounds defined by the decision-maker. The recommendation of the final decision is made based on the calculation of a joint acceptation index K by aggregating the two previous acceptation degrees:

$$K_\alpha = \begin{cases} \beta * \gamma_\alpha + (1-\beta) * \gamma_\varphi \; if \; \gamma_\alpha \neq 0 \; and \; \gamma_\varphi \neq 0 \\ 0 \qquad\qquad\qquad\qquad\qquad otherwise \end{cases} \tag{70}$$

7 Computational experiments: Application to an Argentinean tomato supply chain

The computational experiments designed in this section intend to: 1) validate the models proposed for each scenario in a deterministic and uncertain context, 2) analyze their solutions for the whole supply chain and for each farmer in order to assess the impact of different widespread farmers' agricultural practices and collaboration scenarios on different evaluation parameters, 3) compare the behavior of the proposed fuzzy models with their deterministic versions and 4) obtain for each distributed scenario, the discrepancies between the planned results versus the real ones in which the market demands are considered.

7.1 Problem data description

In order to validate the proposed models, data for a realistic tomato supply chain in the region of La Plata (Buenos Aires) integrated by ten farmers and two markets (Central Market of Buenos Aires and Restaurants) is considered. The land area for each farmer and the entire SC, as well as data regarding workers for manual labor, can be consulted in Table 10. The cost for a seasonal worker is 42.5 €/week, for a temporary worker is 69 €/week and for hiring seasonal workers 42.5€.

Table 10. Land area and data of workers per farmer and for the whole SC.

Farmers	1	2	3	4	5	6	7	8	9	10	SC
Land area (ha)	8.9	7.1	6.2	8.5	9.8	10.7	11.6	8	8.5	10.7	90
Seasonal workers (minimum)	4	4	3	4	5	5	6	4	4	5	44
Seasonal workers (maximum)	7	6	5	7	8	9	9	6	8	9	74
Temporary workers (maximum)	2	2	2	2	2	3	3	2	2	3	23

We assume that our planning horizon comprises one year divided into 52 weeks that contemplates a whole planting season. Farmers should decide the allocation of their greenhouses area to three varieties of tomato: round, pear and cherry. The planting year is considered to start in the first week of July (t=1). The planting and harvesting calendar are the same for the three tomato varieties. There are three planting seasons in July (weeks 3 to 5), October (weeks 14 to 18), and January (27 to 31). As it can be observed in Figure 3, the harvesting period comprises several consecutive weeks that are dependent on the week the tomato had been planted.

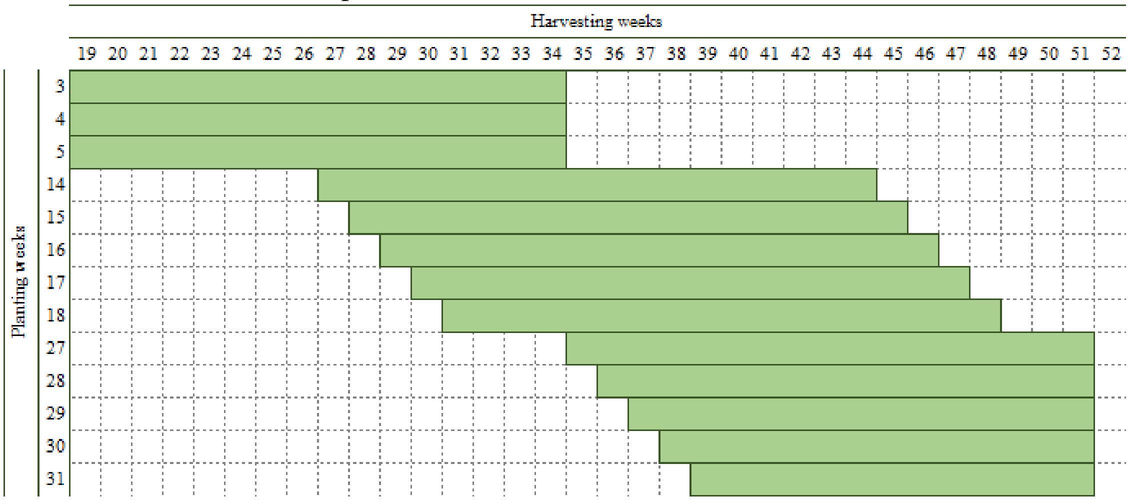

Figure 4. Planting and harvesting calendar for all three tomato varieties.

Data related with operation times per tomato variety during planting, cultivating, harvesting and packaging can be consulted in Table 11. As Ahumada and Villalobos [28] we consider four harvesting patterns: pattern I (harvest every day), pattern II (harvest every two days), pattern III (harvest three times per week) and pattern IV (harvest two times per week). The time to harvest one tomato plant depends on the harvesting pattern (Table 11). The yield per plant of each tomato variety also depends on the harvesting pattern but additionally on the period of planting and harvest (see Appendix B).

Table 11. Cultivating, harvesting and packaging times for each tomato variety.

Tomato variety		Round	Pear	Cherry
Time to plant one plant (min/plant)		0.10909	0.10909	0.12632
Time to stake up one plant (min/plant·week)		0.17455	0.17455	0.20211
Time to prune one plant (min/plant·week)		0.06109	0.06109	0.07074
Time to apply phytosanitary products (min/plant·week)		0.00809	0.00809	0.00937
Time to harvest (min/plant)	Pattern I	0.06818	0.06818	0.15789
	Pattern II	0.06136	0.06136	0.14211
	Pattern III	0.05455	0.05455	0.12632
	Pattern IV	0.04773	0.04773	0.11025
Time to pack tomatoes (min/kg)		0.20000	0.20000	0.20000

Once harvested, the tomato can be stored and later packaged only if it is going to be transported to a market. Inventory costs per week are calculated as the 1% of the maximum price along the year for each tomato variety. The tomato shelf-life once harvested for all varieties is assumed to be one week. If during this time the tomato is not packed and transported, it becomes waste. The penalization for the wasted kilograms is calculated as the 5% of the maximum price for each tomato variety during the year. The penalization for each kilogram of unmet demand is calculated as the 4.5% of the maximum price for each tomato variety and market (Table 12). Cultivation density can also be consulted in Table 12.

Table 12. Relevant costs, penalties and density for each tomato variety.

Tomato variety	Holding cost (€/kg·week)	Planting and cultivating cost (€/plant)	Waste penalties (€/kg)	Cultivation density (plants/ha)	Unmet demand penalties (€/kg)	
					Central market	Restaurants
Round	0.010	0.033	0.052	22,000	0.018	0.047
Pear	0.010	0.033	0.052	22,000	0.022	0.047
Cherry	0.017	0.033	0.092	19,000	0.060	0.083

It is assumed that farmers are physically located in four different regions of La Plata. Farms located at the same region are neighbours and are separated by little distances. Because of that, the transportation costs between farmers and different markets remain the same for the farmers belonging to the same region (Table 13).

Table 13. Transport costs per market and region farmers belong to.

Transport costs (€/ka)			
Region	Farmer	Market	
		Central market	Restaurants
A	1	0.238	0.431
	2	0.238	0.431
B	3	0.283	0.329
	4	0.283	0.329
	5	0.283	0.329
C	6	0.281	0.333
	7	0.281	0.333
D	8	0.169	0.218
	9	0.169	0.218
	10	0.169	0.218

Figure 5 represent the demand and prices per variety of tomato and market. The demand data has been generated by randomly varying the last year supply of the different tomato varieties. Only the demand of harvesting periods has been considered, because the demand for the remaining periods of the year is covered by external supply. Market prices have been obtained from the website of the Central Market of Buenos Aires where prices for end consumers and prices for wholesalers (in this case, restaurants) are published. As it can be observed, the prices for restaurants (retailers) are higher than in Central Market (wholesalers) because the sales in restaurants are more expensive in terms of transport (see Table 13) and order preparation.

Uncertain MPM parameters, are modelled as triangular fuzzy numbers (TFN) represented by $\tilde{b} = (b_1, b_2, b_3)$. For all uncertain parameters, the most possible value (b_2) coincides with the deterministic one and the most pessimistic and optimistic value, except for the selling price, are calculated by decreasing and increasing a fixed percentage of b_2 . This percentage is different for each uncertain parameter and is based on the knowledge of the decision-maker. The fixed percentage for the case time needed to plant, stake up, prune, apply phytosanitary products, harvest tomato plants and pack tomatoes is set to 15%; for the case of the demand to 35%; for the yield of the crops to 30%; for the minimum and maximum areas to be planted to 10% and for waste and unmet demand penalties to 20%.

Figure 5. Demand (kg) and Prices (€/kg) per tomato variety and market.

Finally, the most possible value for the selling prices per tomato variety and time period is defined by the price used in the deterministic context that corresponds to the prices of last year. For defining the most pessimistic vale, the maximum between the minimum price allowed for each tomato variety and the 70% of the most possible value is chosen. The minimum prices can be consulted in Table 14, not being possible to sell tomatoes below them in the corresponding markets. The most optimistic value is obtained by increasing in a 40% the most possible value. In this case, the membership function is not represented with an isosceles triangle. Depending on the period, the triangle will vary.

Table 14. Minimum market prices allowed for each tomato variety.

Tomato variety	Minimum prices (€/kg)	
	Central market	Restaurants
Round	0.13	0.23
Pear	0.22	0.57
Cherry	0.35	1.15

7.2 Experimental design and results

The experimental design (Figure 6) aims to provide an answer to the stated research questions (**RQ**) in Section 1. During the experimental methodology the solutions obtained per farmer in different distributed scenarios under deterministic and uncertain contexts are used to obtain the planned and real evaluation of the whole SC as regards the following evaluation parameters: SC objective function, margin per ha, %waste, %unmet demand and SC unfairness. Under deterministic environment, for each Distributed Scenario, the MPM for each farmer is solved (Figure 6). In order to calculate the above evaluation parameters for the whole SC, an aggregation along farmers is made in the following way:

- SC Objective Function is calculated as the sum of the objective functions of all the SC farmers:

$$Pr = \sum_{f} Pr_f \tag{71}$$

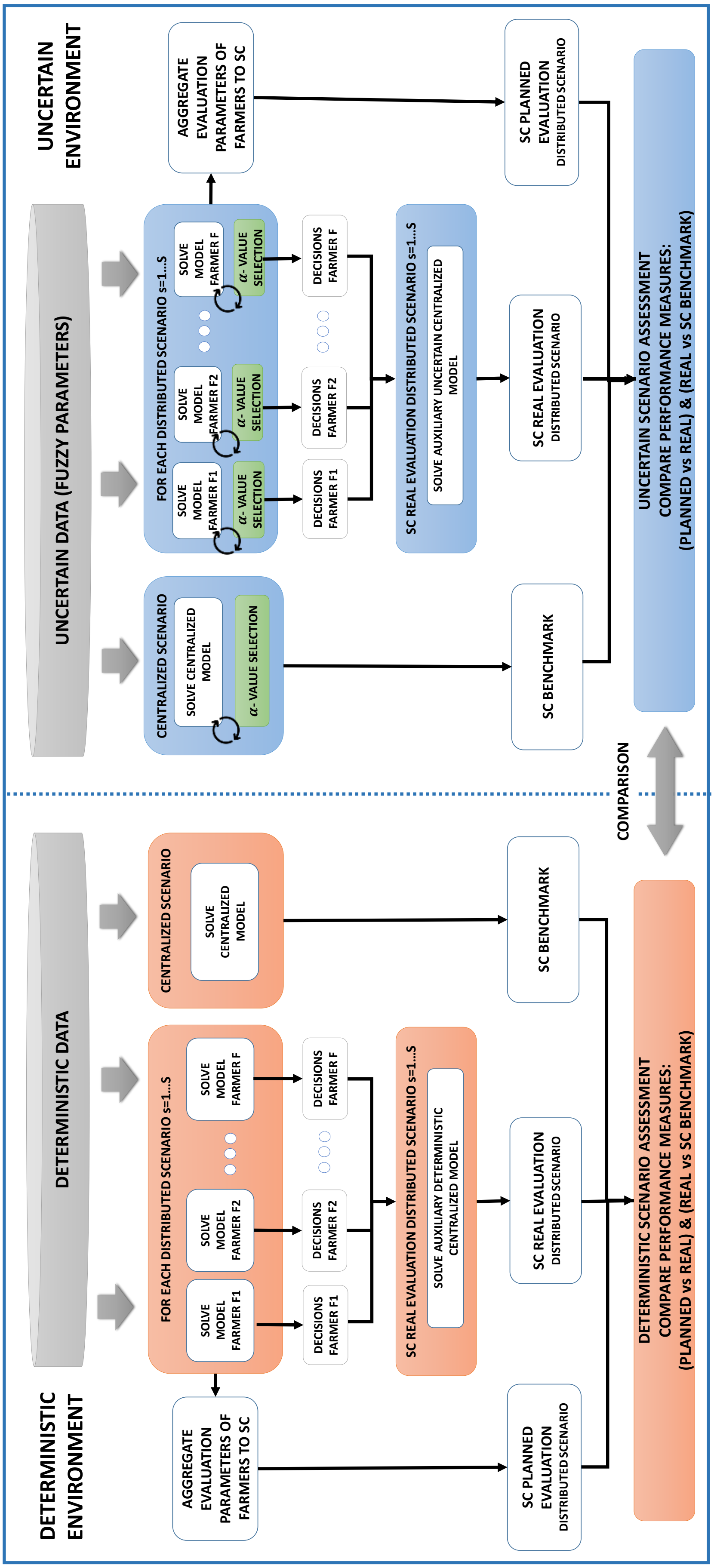

Figure 6. Experimental procedure designed to validate, assess and compare Scenarios in a Deterministic and Uncertain Environment

- SC Margin per ha is calculated as the sum of the gross margin obtained by all SC farmers divided by the sum of all farmers' area (total SC area).

$$SC\ Margin\ per\ ha = \frac{\sum_f Margin_f}{\sum_f a_f} \tag{72}$$

- SC % Wastes is computed as the percentage of the sum of the expired tomato quantities of all farmers as regards the harvested tomatoes by all farmers.

$$SC\ \%\ Wastes = 100 \cdot \frac{\sum_f Wastes_f}{\sum_f Harvest_f} \tag{73}$$

- SC % Unmet Demand is computed as the percentage of the sum of the unmet demand of all farmers as regards the SC total demand.

$$SC\ \%\ Unmet\ Demand = 100 \cdot \frac{\sum_f Unmet\ Demand_f}{SC\ total\ demand} \tag{74}$$

- SC unfairness is an evaluation parameter that tries to assess the disequilibrium in the obtained margin per hectare by the SC farmers. Consequently, unfairness can only be computed when all farmers' solutions are known. Analogously to Stadtler [8] we assume that unfairness results if one member faces an absolute deviation of margin per ha as regards the margin per ha for the SC. The SC unfairness for each scenario is determined by the percentage of the farmers' absolute deviation of margin per ha average as regards the SC margin per ha.

$$Unfairness = 100 \cdot \frac{\sum_f \left(\frac{\left| Margin\ per\ ha_f - SC\ Margin\ per\ ha \right|}{SC\ Margin\ per\ Ha} \right)}{n^{o}\ farmers} \tag{75}$$

where:

$$SC\ Margin\ per\ Ha = \frac{\sum_f Margin_f}{\sum_f a_f} \tag{76}$$

The obtained results are named ***SC Planned Evaluation*** for **Distributed Scenarios**. For Scenario C, SC results extracted from solving the MPM, are directly analyzed. For this Scenario C the only evaluation parameter that requires to be calculated for the whole SC is the unfairness. Because the centralized scenario provides with the optimal solution for the SC objective function, it is considered as the ***SC Benchmark***.

In Distributed Scenarios D, DAf, DAm and DAim, the farmers make decisions without any information about the market demand and decisions made by other farmers. Therefore, the optimal solutions obtained by solving the corresponding MPMs per farmer in each Distributed Scenario, need to be evaluated in order to determine what would happen in a real situation where all the planting and harvesting decisions independently made by farmers are put together in the market to satisfy the market demands. We have named this evaluation ***SC Real Evaluation***.

To calculate the ***SC Real Evaluation***, decisions made by all farmers in each distributed scenario are passed to an **Auxiliary Deterministic Centralized Model** in order to determine the impact of integrating such independent decisions of each farmer in a real situation where market demands are known. To formulate this auxiliary model, the demand assigned to each farmer has been proportional to his/her land area as in the Scenario DIS. Decisions related to the planting, cultivating, harvest of products and labor are given to the auxiliary centralized model as input data. Since tomatoes cannot be wasted at markets, the transport decision remains as a decision variable in the auxiliary centralized model that should decide it based on market demands. Due to the relationship between the transport variable (QT) and quantity packed (QP), wastes (WAH), quantity sold (QS) and unmet demand (UD), all them remain as decision variables in the auxiliary centralized evaluation model. Through the solution of this model, the ***SC Real Evaluation*** parameters are calculated. The ***SC Planned Evaluation*** is compared with the ***SC Real Evaluation***, and the ***SC Real Evaluation*** against the ***SC Benchmark*** (Centralized Scenario C).

The evaluation process for the uncertain context is analogous to the deterministic one, except that it is necessary to apply the methodology of Peidro et al. [42] to select the α-value for each farmer in oder to obtain the final solution as an input to obtained the ***SC Planned Evaluation***. Solutions obtained under both deterministic and uncertain contexts are also compared. Below the description of the results obtained and their comparison is performed.

7.2.1 SC Planned Evaluation per Scenario: Deterministic and uncertain environment

The SC Planned Evaluation is performed per each scenario under deterministic and uncertain contexts, in this last case for each feasibility degree, in terms of: (i) objective function, (ii) margin per hectare, (iii) percentage of wastes, (iv) percentage of unmet demand, and (v) unfairness among farmers (Figure 8). Here we compare the behavior of the proposed fuzzy model under different α-values and also with its deterministic version per scenario with the aim of determining the potential improvements provided by the fuzzy model, which incorporates the uncertainties that may be presented in the fresh tomato SC.

As it can be seen in Figure 7, the SC Planned Evaluation shows a decreasing in the SC objective function and in the SC margin per hectare with an increasing of the feasibility degree (α-value) in all scenarios. This behavior remains for the results for the SC in terms of the percentage of wastes and the percentage of unmet demand since they get worse as the feasibility degree increases. This is because the flexibility given to the constraints where fuzzy parameters exist is bigger when the feasibility degree decreases. It should be noted that for our case study no waste exists in distributed scenarios D, DAf, DAm and DAim although waste could appear if not enough capacity exists to pack all the harvested quantities during their shelf-life. However, as these scenarios don't consider any market demand, unmet demand does not exist in all them. For this reason, wastes and unmet demand appear only for scenarios taking into account market demand (Scenarios DIS and C). It can also be observed that all the fuzzy solutions outperform the deterministic solutions for all scenarios, being the most similar ones when α-value is equal to 1. This situation is logical because the closer the α-value comes to 1, the more similar the triangular fuzzy number is to the deterministic value.

It is remarkable that the unfairness in all the Distributed Scenarios increases very slightly with α, being the increment much more pronounced in the centralized Scenario C. Therefore, it can be said that to consider the uncertainty in fresh tomato SC for the centralized decision making greatly improves the unfairness among farmers.

On the other hand, in the planned situation the distributed scenarios that provide better and worse results are the Scenario D and the Scenario DIS, respectively. In the middle we can found the scenarios with land area limits per variety ordered by decreasing performance of evaluation parameters SC objective function and Waste: DAm, DAf, DAim. Scenario DIS is very near to Scenario C (SC Benchmark). The difference among scenarios for each α-value is very similar but not the same for the Objective Function and Margin per ha, being very different for the remaining evaluation parameters.

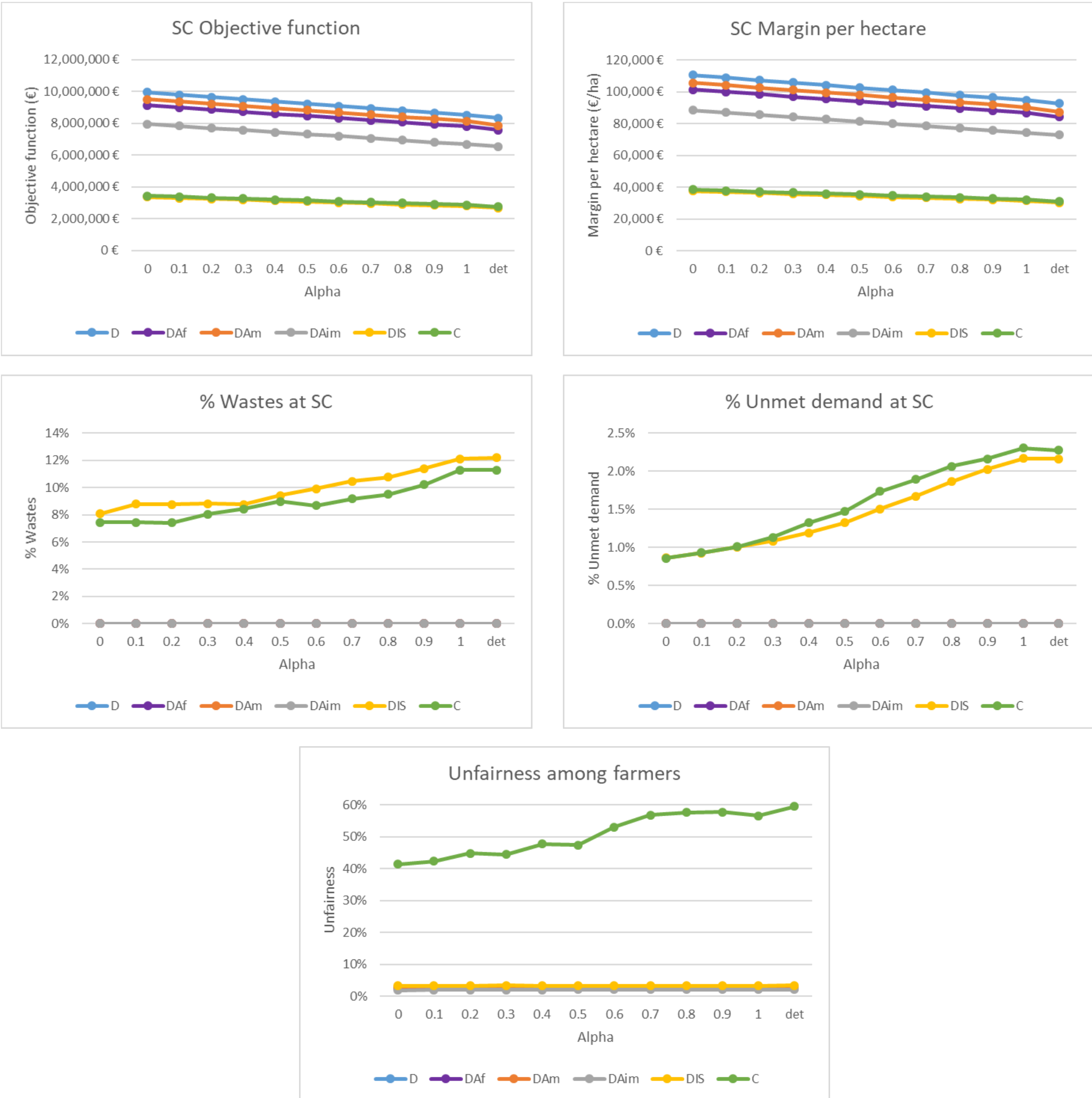

Figure 7. SC Planned Evaluation of the deterministic and uncertain MPM solutions for each Scenario and α-values.

As can be seen in Figure 7 in uncertain environment, once each MPM per farmer is solved for a set of feasibility degrees (α=0, 0.1, 0.2, ..., 1), the decision-maker must choose the specific α-value to derive the final solution. Based on the methodology proposed by Peidro et al. [42] explained in Section 5.2, each α-solution is evaluated in terms of margin per hectare, percentage of wastes and percentage of unmet demand. The decision-maker defines, for these three criteria, the aspiration level (G) and its tolerance threshold (t). In our case, the selection of aspiration levels and tolerance thresholds for each decision-maker in all scenarios have been made in the following way:

- The aspiration level for the margin per hectare is set as the 115% of the margin per hectare obtained for the solution with α = 1 and the tolerance threshold is set by the 15% of the margin per hectare obtained for the solution with α = 1.
- The aspiration level for the percentage of wastes and unmet demand are set as the 80% of values obtained for the solution with α = 1 and the tolerance threshold is set by the 20% of the values obtained for the solution with α =1.

These values are used to determine the satisfaction degree of each evaluation parameter (λ_i, i=1,2,3) for the solution of each Scenario, Farmer and Feasibility degree. Then, a Global satisfaction degree (φ) of the solution is calculated by a weighted sum. The weights for the evaluation parameter margin per hectare, percentage of wastes, and percentage of unmet demand are set to 70%, 15% and 15%, respectively (see an example in Table 15 for Scenario C). Therefore, the Global satisfaction degree $\varphi = 0.7 \cdot \lambda_1 + 0.15 \cdot \lambda_2 + 0{,}15 \cdot \lambda_3$.

As shown in Table 15, the Global satisfaction degree (φ) improves as the feasibility degree (α) decreases. This conflict is solved by representing the decision-maker acceptation of the feasibility degree and the global satisfaction degree. For that, an aspiration level and tolerance threshold are defined by the decision-maker for both indicators.

- The aspiration level and the tolerance threshold for the feasibility degree (α) are set as G = 0.7 and t = 0.3, respectively.
- The aspiration level and the tolerance threshold for the global satisfaction degree (φ) are set as G = 0.7 and t = 0.5, respectively.

A joint acceptation index (K) that helps the decision maker to choose a solution is calculated as the weighted sum of the acceptation of the feasibility degree (γ_α) and the acceptation of the global satisfaction degree (γ_φ) that for our case coincides with the mean value because the same weight (0.5) is given to both. The solution with a highest joint acceptation index (K) is chosen for its implementation.

Table 15. Global satisfaction degree of solutions in Scenario C.

Feasibility degree (α)	Margin per ha	Satisfaction degree: Margin per ha (λ_1)	% Wastes	Satisfaction degree: % Waste (λ_2)	% Unmet demand	Satisfaction degree: % Unmet demand (λ_3)	Global satisfaction degree (φ)
0.0	38,600.79€	1.00	7.43%	1.00	0.86%	1.00	1.00
0.1	37,956.36€	1.00	7.45%	1.00	0.93%	1.00	1.00
0.2	37,310.67€	1.00	7.42%	1.00	1.01%	1.00	1.00
0.3	36,695.60€	0.89	8.04%	1.00	1.13%	1.00	0.93
0.4	36,070.84€	0.77	8.42%	1.00	1.32%	100	0.84
0.5	35,452.12€	0.64	8.97%	1.00	1.47%	1.00	0.75
0.6	34,808.11€	0.50	8.67%	1.00	1.73%	1.00	0.65
0.7	34,189.55€	0.38	9.16%	0.94	1.89%	0.90	0.54
0.8	33,564.84€	0.25	9.49%	0.79	2.06%	0.52	0.37
0.9	32,956.73€	0.12	10.22%	0.47	2.16%	0.31	0.20
1.0	32,357.34€	0.00	11.27%	0.00	2.30%	0.00	0.00

As shown in Table 16, the solution to be implemented in the tomato SC in Scenario C is the one given by the feasibility degree α = 0.7. The same process is repeated for all the distributed Scenarios and farmers where a decision must be made by each farmer. It is remarkable that for the distributed scenarios without information about tomato demand (Scenario D, DAf, Dam and DAim), only the margin per hectare is evaluated to obtain the Global satisfaction degree since neither nor wastes nor unmet demand are produced in any planned solution. From this point on, the chosen solutions will be considered the planned solutions.

Table 16. Joint acceptation index of solutions in Scenario C.

Feasibility degree (α)	Acceptation grade of α (γ_α)	Global satisfaction degree (φ)	Acceptation grade of φ (γ_φ)	Joint acceptation index (K_α)
0.0	38,600.79€	1.00	1.00	0.00
0.1	37,956.36€	1.00	1.00	0.00
0.2	37,310.67€	1.00	1.00	0.00
0.3	36,695.60€	0.93	1.00	0.00
0.4	36,070.84€	0.84	1.00	0.00
0.5	35,452.12€	0.75	1.00	0.67
0.6	34,808.11€	0.65	0.91	0.79
0.7	34,189.55€	0.54	0.68	0.84
0.8	33,564.84€	0.37	0.34	0.67
0.9	32,956.73€	0.20	0.00	0.50
1.0	32,357.34€	0.00	0.00	0.00

7.2.2 SC Planned vs Real Evaluation: comparison for Scenarios in deterministic and uncertain environment

The Section 7.2.1 has shown the SC planned evaluation for all Scenarios. In the following, the results obtained for both the SC planned and SC real evaluations in the deterministic and uncertain contexts for the solutions obtained solving each model with the selected α, are represented (Table 17). The comparison between the SC Real Evaluation and SC Planned Evaluation (Real vs Planned) for the Objective Function and Margin per Hectare parameters are calculated as: 100*(SC Real-SC Planned)/SC Planned. The comparison between the real values and the benchmark (Real vs Benchmark) is calculated as: 100*(SC Real-SC Benchmark)/SC Benchmark.

In terms of the Objective function and the Margin per hectare, results obtained by uncertain MPMs are better than those obtained by the deterministic ones for both, real and planned situations (Table 17). When talking about the planned results, best values are obtained for the Scenario D, followed by Scenario DAm, DAf, DAim and DIS, for both deterministic and uncertain solutions.

However, the values for the objective function and the margin per hectare drastically decrease for the **SC Real Evaluation** for all the distributed scenarios not considering market demands (D, DAf, DAm, DAipm) in uncertain and deterministic contexts. Besides the percentage of worsening is very similar in both contexts.

This is due to the fact that for these scenarios in planned situations, it is assumed that all quantities harvested for every tomato variety are going to be sold because any information about demand market is available. But in the real situation, when planting and harvesting decisions made by each farmer are integrated, the supply exceeds the market demand for some varieties (the most profitable ones) and stays below the market demand for other (the less profitable ones), producing wastes and unmet demand, respectively, in each farmer. Indeed, as it can be seen in Table 20 the discrepancies between the planned and real wastes and unmet demand are important. In case of Scenario DIS planned and real results in terms of the objective function and the margin per hectare are the same because this distributed scenario also has considered market demands in the same way as the auxiliary centralized model (i.e. demands for each farmer are proportional to his/her area).

Table 17. Comparison of evaluation parameters (Objective function and Margin per hectare) for planned and real situations in deterministic and uncertain context.

Context	Scenario	Objective function				Margin per hectare			
		SC Planned (€)	SC Real (€)	Real vs. Planned (%)	Real vs. Benchmark (%)	SC Planned (€)	SC Real (€)	Real vs. Planned (%)	Real vs. Benchmark (%)
Deterministic	D	8,345,629	77,775	- 99.1	- 97.2	92,729	8,144	-91.2	-73.8
	DAf	7,575,755	1,558,267	-79.4	-43.5	84,175	20,084	-76.1	-35.4
	DAm	7,859,709	1,455,119	-81.5	-47.2	87,330	20,911	-76.1	-32.8
	DAim	6,558,188	827,540	-87.4	-70.0	72,869	13,770	-81.1	-55.7
	DIS	2,683,026	2,683,026	0.0	-2.7	30,312	30,312	0.0	-2.5
	C			2,757,388				31,103	
Uncertain	D	8,957,297	143,530	-98.4	-95.3	99,526	9,034	-90.9	-73.6
	DAf	8,203,910	1,615,995	-80.3	-46.9	91,155	22,589	-75.2	-33.9
	DAm	8,550,497	1,572,606	-81.6	-48.3	95,006	22,544	-76.3	-34.1
	DAim	7,069,541	1,002,852	-85.8	-67.0	78,550	15,590	-80.2	-54.4
	DIS	2,966,645	2,966,645	0.0	-2.5	33,400	33,400	0.0	-2.3
	C			3,042,017				34,190	

From the analysis of the SC Real Evaluation versus the SC Benchmark (Scenario C) in the deterministic context, it can be stated that the closest and furthest to the benchmark are the DIS and D scenario, respectively, meanwhile scenarios with maximum and minimum area limits are in the middle, being the DAf and DAm very similar. Indeed, real solutions of DIS scenario are very close to the optimum (-2.7% for objective function and -2.5% for margin per ha) that shows the adequacy of collaboration by means the market demand information sharing. On the contrary, not taking into account market demand and any limits on planting area per variety leads to the worst situation (Scenario D). In the middle, the widespread practice of limiting the minimum and maximum area per crop significantly improves the solution obtained. However, as it can be appreciated, the defined limits for planting areas impact the obtained results to a great extent. So, they need to be carefully defined. The worse result is obtained for the Scenario DAim, that has been assimilated to the usual situation in which farmers decide to plant higher areas for more profitable crops last years that become the least profitable in the current year. The described behaviour maintains also for the uncertain context, but uncertain results always outperform deterministic ones.

As commented before, when analyzing the percentage of wastes and the percentage of unmet demand obtained by each scenario and context (Table 18), it is seen that in Scenario D, DAf, DAm and DAim, neither wastes nor unmet demand is produced in a planned situation because it is assumed that all produced quantities are going to be sold due to the ignorance about market demands. But when the harvested quantities of all tomato varieties for all farmers are considered to satisfy the real market demand, excess and shortage in supply for some periods and varieties exist provoking wastes and unmet demand, respectively.

In real situations, the uncertain solutions not always outperform deterministic solutions as regards the real evaluation parameter %Wastes and %Unmet Demand, being only better for Scenarios D and DAim. In case of Scenario DIS planned and real results in terms of the percentage of wastes and unmet demand are the same, and they are also quite similar to the results obtained for the benchmark.

Finally, the Unfairness among farmers is analyzed. For all distributed scenarios in both deterministic and uncertain context, except for the Scenario DIS, the real unfairness increases in comparison with the planned one, but the difference is very much higher for the deterministic solution. Despite this, the solutions obtained for the distributed scenarios are all very much fairer than those obtained from the centralized scenario. This is caused because of the objective function defined in the Centralized Scenario, since the profit maximization of the entire SC do not balance the profits among farmers.

It is concluded that given the similarity of the objective function, margin per hectare, percentage of wastes and percentage of unmet demand between Scenarios DIS and C, and given the good results in terms of unfairness that Scenario DIS provides, it is a good solution for the supply chain to maintain the independence of the farmers by using a distributed model where information of the markets demand proportional to the farmers' area is included (Scenario DIS).

Table 18. Comparison of evaluation parameters (% Wastes, %Unmet Demand and Unfairness) for planned and real situations in deterministic and uncertain context.

Context	Scenario	% Wastes				% Unmet demand				Unfairness			
		Planned (%)	Real (%)	Real vs. Planned (%)	Real vs. Benchmark (%)	Planned (%)	Real (%)	Real vs. Planned (%)	Real vs. Benchmark (%)	Planned (%)	Real (%)	Real vs. Planned (%)	Real vs. Benchmark (%)
Deterministic	D	0.0	79.0	79.0	67.7	0.0	53.4	53.4	51.1	3.0	6.1	3.1	-53.4
	DAf	0.0	45.7	45.7	34.4	0.0	32.1	32.1	29.8	2.5	4.7	2.2	-54.8
	DAm	0.0	63.4	63.4	52.1	0.0	28.7	28.7	26.4	2.8	10.0	7.2	-49.5
	DAim	0.0	64.7	64.7	53.4	0.0	57.1	57.1	54.8	2.1	4.5	2.4	-55.0
	DIS	12.2	12.2	0.0	0.9	2.2	2.2	0.0	-0.1	3.4	3.4	0.0	-56.1
	C			11.3				2.3				59.5	
Uncertain	D	0.0	78.8	78.8	69.6	0.0	50.5	50.5	48.6	2.9	5.5	2.6	-51.3
	DAf	0.0	63.4	63.4	54.2	0.0	35.3	35.5	33.4	2.4	3.5	1.1	-53.3
	DAm	0.0	66.9	66.9	57.7	0.0	34.2	34.2	32.3	2.6	3.2	0.6	-53.6
	DAim	0.0	63.0	63.0	53.8	0.0	52.9	52.9	51.0	2.1	3.0	0.9	-53.8
	DIS	10.5	10.5	0.0	1.3	1.7	1.7	0.0	-0.2	3.3	3.3	0.0	-53.5
	C			9.2				1.9				56.8	

7.2.3 Experimental results: Computational efficiency

The models corresponding to the different Scenarios in deterministic and uncertain environment as well as the auxiliary evaluation model have been implemented in the MPL® 5.0 modelling language and solved with the Gurobi 8.0.1. Microsoft Access databases were used to store the input data and the obtained values for the decision variables after solving the models. The computer used to solve different scenarios had an Intel® Xeon® CPU E5-2640 v2 with two 2.00 GHz processor, with an installed capacity of 32.0 GB and a 64-bits operating system.

The resolution time for each model execution was limited to 60 min. A relative gap of 0.02% was fixed. This means that the solution search process can stop if a solution is found to be within 0.02% of the best bound before the 60 min have elapsed. Such solution would be the optimal solution to the problem. Table 19 shows for each Scenario the number of executions made, the percentage of optimal solutions found, and the mean time needed to find these optimal solutions. For cases in which an optimal solution has not been found during the limited resolution time (60 min), the relative gap of the obtained solution is displayed.

Table 19. Resolution time and relative gap per Scenario and context.

Context	Scenario	Number of executions	Percentage of optimal solutions	Mean solution time	Mean GAP for non-optimum solutions
Deterministic	D	10	100%	3.5 sec	-
	DAf	10	100%	5.3 sec	-
	DAm	10	100%	6.7 sec	-
	DAim	10	100%	37 sec	-
	DIS	10	100%	1 min 35 sec	-
	C	1	0%	60 min 00 sec	0.0386 %
Uncertain	D	110	100%	5.2 sec	-
	DAf	110	100%	4.9 sec	-
	DAm	110	100%	8.6 sec	-
	DAim	110	100%	1 min 14 sec	-
	DIS	110	100%	4 min 13 sec	-
	C	11	0%	60 min 00 sec	0.0424 %

These results show that optimal solutions have been obtained for all the distributed Scenarios in both, planned and real situations. In case of Scenario C, the optimal solution has not been found in any execution within the resolution time needed. In planned situations, the resolution time for the deterministic models is lower than the resolution time for the uncertain models in all distributed Scenarios (D, DAf, DAm, and DIS). The same occurs to the relative gap of Scenario C, since it is bigger for the uncertain model than for the deterministic one. When jointly analyzing all Scenarios for the planned situation, it seems that the more complex model is the corresponding to the Scenario C, followed by the model designed for Scenario DIS, DAim, DAm and DAf, and finally, the model for Scenario D.

To analyze the computational complexity of the models, the problem size for each Scenario has also been studied (Table 20). The problem size is analyzed in terms of number of continuous, integer, and binary variables, and the number of constraints. As it can be seen the number of decision variables are higher for DIS due to the unmet demand and sales variables and for C because of the integration of all farmers. Finally, the number of constraints increases in the uncertain context. These two aspects could justify the increase in the resolution time for DIS and C and for the uncertain context as regards the deterministic one.

Table 20. Problem size per scenario and context.

Scenario	Total variables	Continuous variables	Integer variables	Binary variables	Constraints	
					Deterministic	Uncertain
D	8,350	5,064	3,247	39	12,731	13,364
DAf	8,350	5,064	3,247	39	17,737	13,370
DAm	8,350	5,064	3,247	39	17,737	13,370
DAim	8,350	5,064	3,247	39	17,737	13,370
DIS	11,194	7,908	3,247	39	33,093	34,038
C	109,132	76,272	32,470	390	325,626	333,828

8 Conclusions and future research lines

To match supply and demand of crops is not an easy task due to the great sources of uncertainty affecting the agricultural sector that mainly impact on the supply, demand and market prices that originates high volume of wastes and unmet demand. This problem is accentuated by the individuality of farmers leading to a distributed decision-making scenario. Although this way of organization is very frequent, the vast majority of the developed MPMs to support the crop planning problem are developed only for one farmer. Besides, in case contemplating several farmers, a centralized decision making is assumed supported by a single MPM without neither any collaboration nor mechanism for ensuring a fair solution among farmers.

In this paper, a novel set of MPMs for the cropping plan problem of fresh tomato supply chain integrated by independent farmers in a deterministic and uncertain context has been developed in several scenarios. Several MPMs in the literature for supporting the crop planning problem for individual farmers do not consider any market demand assuming that all the harvested quantities are going to be sold in the market. As shown in this paper, in the absence of other limitations, this way of making decisions (Scenario D) lead to plant all the land area only with the most profitable crops by all farmers provoking an excessive amount of waste for some crops and high levels of unmet demand for the others when the global production is put in the market. The negative impact of this solution can be measured not only in economic losses for farmers that can see a great decreased in their expected profits, but also in social terms (unmet demand) and environmental (crop wastes, resources losses and unnecessarily cultivated land area).

To mitigate these negative effects and the risk faced by farmers, a widespread custom consists in limiting the maximum and minimum land area planted per crop. This corresponds to Scenarios DAf, DAm and DAim that define the limits based on a fixed, proportional and inversely proportional crop margin percentage of land area allocated to each crop. As shown, the values set for these upper and lower limits highly impact on solutions obtained but, again, surprisingly, no attention has been paid in the literature to fix their value. In these scenarios the planned results also get worse in real situations when integrating production by all farmers against market demand but the negative impact on economic losses, wastes and unmet demand is lower than in the Scenario D.

The best results for the SC in real situations are achieved by the centralized decision-making situation (Scenario C) where market demand is known. Though this scenario gets the optimum SC solution as regards the objective function, it provides the most unfairness solution among farmers. Therefore, unless an only company exists in the SC some mechanism should be introduced to reach a fair solution. Furthermore, in most cases the atomized structure of farmers in some regions make a centralized approach impossible to be implemented.

A collaboration approach that consists in information sharing about the market demand is proposed, respecting the independence among farmers and therefore, the distributed decision-making. This organizational structure can fit in many situations in which some public association advise farmers about what to do (e.g., commerce chamber, regional innovation and technological centres). In this situation the adviser association can know the land area of each farmer and also the forecast market demands calculating a proportional demand to be faced by each farmer based on his/her land area. With this information, farmers make their planting and harvesting decisions. As shown in this paper, this collaboration approach based on information sharing (Scenario DIS), leads to results very closed to the optimal SC solution provided by the centralized MPM (Scenario C) and the best fair solution, encourage farmers to follow it.

Therefore, the concrete way of Scenario DIS for collaboration among producers with minimum information sharing leads to a mutually beneficial cooperation that improve farmers' incomes and their position in the value chain, as well as improve consumers whose demands will be satisfied at more stable prices.

Finally, the obtained results show that the modelling of uncertainty improves the margin per hectare and the unfairness among farmers in all scenarios, meanwhile the waste and the unmet demand do not present a homogeneous behaviour in all scenarios.

Future research lines as regard the MPM models developed can consider the uncertainty in the planting, cultivating and harvesting periods due to weather conditions. The model could be extended to incorporate other crops that can be planted more than once in a season. Finally, the models could be extended to incorporate the processing stage with particular attention paid to the fair distribution of costs, profits and risks among all actors involved in the agri-food value chains in order to improve the position of small farmers.

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Appendix A

In this Appendix, the fuzzy models developed for each scenario in Section 4 are converted into the equivalent α-parametric crisp models by applying the methodology reported in subsection 5.1. Once transformed, the formulation of the complete equivalent crisp models for each scenario are reported.

A.1 Distributed models for each farmer under Scenario D – Equivalent α-parametric crisp model

For deriving the equivalent crisp model for Scenario 1, the objective function (1) and constraints (9) and (12) that contain fuzzy parameters require to be formulated. In the following the equivalent crisp objective function and constraints obtained are presented.

$$\begin{aligned} Max\ PrF = & \sum_v \sum_m \sum_{p \in P_v} \sum_{h \in H_v^p} \sum_t \left(\frac{p_{vm}^{t^1} + p_{vm}^{t^2} + p_{vm}^{t^3} + p_{vm}^{t^4}}{4} \right) \cdot QTF_{vm}^{pht} \\ & - \sum_v \sum_{p \in P_v} cf_v \cdot NPF_v^p - \sum_v \sum_m \sum_{p \in P_v} \sum_{h \in H_v^p} \sum_t ctF_{vm} \cdot QTF_{vm}^{pht} \\ & - \sum_v \sum_m \sum_{p \in P_v} \sum_{h \in H_v^p} \sum_t ch_v \cdot (t-h) \cdot QTF_{vm}^{pht} \\ & - \sum_v \sum_{p \in P_v} \sum_{h \in H_v^p} \left(\frac{cwa_v^1 + cwa_v^2 + cwa_v^3 + cwa_v^4}{4} \right) \cdot WAHF_v^{ph} \\ & - \sum_t (chs \cdot HLSF^t + cls \cdot LSF^t + clt \cdot LTF^t) \end{aligned} \tag{A.1}$$

$$\sum_w \left[\left(1 - \frac{\alpha}{2}\right) \cdot \left(\frac{y_{vw}^{ph^1} + y_{vw}^{ph^2}}{2} \right) + \left(\frac{\alpha}{2}\right) \cdot \left(\frac{y_{vw}^{ph^3} + y_{vw}^{ph^4}}{2} \right) \right] \cdot NHWF_{vw}^{ph} - QHF_v^{ph} \le 0 \quad \forall v, p \in P_v, h \in H_v^p \tag{A.2}$$

$$\sum_w \left[\left(1 - \frac{\alpha}{2}\right) \cdot \left(\frac{y_{vw}^{ph^3} + y_{vw}^{ph^4}}{2} \right) + \left(\frac{\alpha}{2}\right) \cdot \left(\frac{y_{vw}^{ph^1} + y_{vw}^{ph^2}}{2} \right) \right] \cdot NHWF_{vw}^{ph} - QHF_v^{ph} \ge 0 \quad \forall v, p \in P_v, h \in H_v^p \tag{A.3}$$

$$\begin{aligned} & \sum_v \sum_{p=t} \left[(1-\alpha) \cdot \left(\frac{tp_v^1 + tp_v^2}{2} \right) + \alpha \cdot \left(\frac{tp_v^3 + tp_v^4}{2} \right) \right] \cdot NPF_v^p \\ & + \sum_v \left[(1-\alpha) \cdot \left(\frac{ts_v^1 + ts_v^2}{2} \right) + \alpha \cdot \left(\frac{ts_v^3 + ts_v^4}{2} \right) \right] \cdot NSF_v^t \\ & + \sum_v \left[(1-\alpha) \cdot \left(\frac{tc_v^1 + tc_v^2}{2} \right) + \alpha \cdot \left(\frac{tc_v^3 + tc_v^4}{2} \right) \right] \cdot NCF_v^t \\ & + \sum_v \left[(1-\alpha) \cdot \left(\frac{tk_v^1 + tk_v^2}{2} \right) + \alpha \cdot \left(\frac{tk_v^3 + tk_v^4}{2} \right) \right] \cdot NKF_v^t \\ & + \sum_v \sum_w \sum_{p \in P_v} \sum_{h=t} \left[(1-\alpha) \cdot \left(\frac{th_{vw}^1 + th_{vw}^2}{2} \right) + \alpha \cdot \left(\frac{th_{vw}^3 + th_{vw}^4}{2} \right) \right] \\ & \cdot NHWF_{vw}^{ph} \\ & + \sum_v \sum_{p \in P_v} \sum_{h \in H_v^p} \left[(1-\alpha) \cdot \left(\frac{tpa_v^1 + tpa_v^2}{2} \right) + \alpha \cdot \left(\frac{tpa_v^3 + tpa_v^4}{2} \right) \right] \cdot QPF_v^{pht} \\ & \le hw \cdot (LS^t + LT^t) \quad \forall t \end{aligned} \tag{A.4}$$

The final model for Scenario D is:

$Max[PrF]$

$Subject\ to$

(2)-(8), (10), (11), (13-16), (A.2)-(A.4)

A.2 Distributed models for each farmer under Scenarios DAf, DAm and DAim – Equivalent crisp model

The fuzzy models corresponding to scenarios DAf, DAm and DAim differ from the scenario D in only one constraint (17) that present minimum and maximum areas to be planted per crop fuzzy. The equivalent crisp constraints will be formulated as:

$$\sum_{p\in P_v}\frac{NPF_v^p}{d_v}\geq\left[\alpha\cdot\left(\frac{am_v^3+am_v^4}{2}\right)+(1-\alpha)\cdot\left(\frac{am_v^1+am_v^2}{2}\right)\right]\quad\forall v \tag{A.5}$$

$$\sum_{p\in P_v}\frac{NPF_v^p}{d_v}\leq\left[\alpha\cdot\left(\frac{aM_v^1+aM_v^2}{2}\right)+(1-\alpha)\cdot\left(\frac{aM_v^3+aM_v^4}{2}\right)\right]\quad\forall v \tag{A.6}$$

The final model for Scenarios DAf, DAm and Daim is:

$Max[PrF]$

$Subject\ to$

(2)-(8), (10), (11), (13-16), (A.2)-(A.6)

A.3. Distributed models for each farmer under Scenario DIS – Equivalent crisp model

This model differs from the previous ones in that demand per famer and crop is included that allows to compute the imbalance between supply and demand in terms of waste and unmet demand that are penalized in the objective function. Therefore, it is necessary to reformulate the equivalent crisp objective function (A.7). Furthermore, the new constraint (21) includes the fuzzy demand parameter being required to be transformed into the equivalent crisp one (A.8 and A.9).

$$\begin{aligned}PrF=&\sum_{v}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t}\left(\frac{p_{vm}^{t^1}+p_{vm}^{t^2}+p_{vm}^{t^3}+p_{vm}^{t^4}}{4}\right)\cdot QTF_{vm}^{pht}-\sum_{v}\sum_{f}\sum_{p\in P_v}cf_v\cdot NPF_v^p\\&-\sum_{v}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t}ctF_{vm}\cdot QTF_{vm}^{pht}\\&-\sum_{v}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t}ch_v\cdot(t-h)\cdot QTF_{vm}^{pht}\\&-\sum_{t}(chs\cdot HLSF^t+cls\cdot LSF^t+clt\cdot LTF^t)\\&-\sum_{v}\sum_{p\in P_v}\sum_{h\in H_v^p}\left(\frac{cwa_v^1+cwa_v^2+cwa_v^3+cwa_v^4}{4}\right)\cdot WAHF_v^{ph}\\&-\sum_{v}\sum_{m}\sum_{t}\left(\frac{cud_{vm}^1+cud_{vm}^2+cud_{vm}^3+cud_{vm}^4}{4}\right)\cdot UD_{vm}^t\end{aligned} \tag{A.7}$$

$$\sum_{p\in P_v}\sum_{h\in H_v^p}QSF_{vm}^{pht}+UD_{vm}^t\leq\left(\frac{\alpha}{2}\right)\cdot\left(\frac{deF_{vm}^{t^1}+deF_{vm}^{t^2}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{deF_{vm}^{t^3}+deF_{vm}^{t^4}}{2}\right)\quad\forall v,m,t \tag{A.8}$$

$$\sum_{p\in P_v}\sum_{h\in H_v^p}QSF_{vm}^{pht}+UD_{vm}^t\geq\left(\frac{\alpha}{2}\right)\cdot\left(\frac{deF_{vm}^{t^3}+deF_{vm}^{t^4}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{deF_{vm}^{t^1}+deF_{vm}^{t^2}}{2}\right)\quad\forall v,m,t \tag{A.9}$$

The final model for Scenario DIS is:

$Max[PrF]$

$Subject\ to$

(2)-(8), (10), (11), (13-16), (20), (22), (A.2)-(A.4), (A.8)-(A.9)

A.4. Centralized model for Scenario C – Equivalent crisp model

$$Max\ Pr = \sum_{v}\sum_{f}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t}\left(\frac{p_{vm}^{t^1}+p_{vm}^{t^2}+p_{vm}^{t^3}+p_{vm}^{t^4}}{4}\right)\cdot QS_{vfm}^{pht} \tag{A.10}$$
$$-\sum_{v}\sum_{f}\sum_{p\in P_v} cf_v\cdot NP_{vf}^{p} - \sum_{v}\sum_{f}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t} ct_{vfm}\cdot QT_{vfm}^{pht}$$
$$-\sum_{v}\sum_{f}\sum_{m}\sum_{p\in P_v}\sum_{h\in H_v^p}\sum_{t} ch_v\cdot(t-h)\cdot QT_{vfm}^{pht}$$
$$-\sum_{f}\sum_{t}\left(chs\cdot HLS_f^t + cls\cdot LS_f^t + clt\cdot LT_f^t\right)$$
$$-\sum_{v}\sum_{f}\sum_{p\in P_v}\sum_{h\in H_v^p}\left(\frac{cwa_v^1+cwa_v^2+cwa_v^3+cwa_v^4}{4}\right)\cdot WAH_{vf}^{ph}$$
$$-\sum_{v}\sum_{m}\sum_{t}\left(\frac{cud_{vm}^1+cud_{vm}^2+cud_{vm}^3+cud_{vm}^4}{4}\right)\cdot UD_{vm}^{t}$$

$$\sum_{w}\left[\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{y_{vw}^{ph^1}+y_{vw}^{ph^2}}{2}\right)+\left(\frac{\alpha}{2}\right)\cdot\left(\frac{y_{vw}^{ph^3}+y_{vw}^{ph^4}}{2}\right)\right]\cdot NHW_{vfw}^{ph} - QH_{vf}^{ph} \le 0 \quad \forall v,f,p\in P_v,h\in H_v^p \tag{A.11}$$

$$\sum_{w}\left[\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{y_{vw}^{ph^3}+y_{vw}^{ph^4}}{2}\right)+\left(\frac{\alpha}{2}\right)\cdot\left(\frac{y_{vw}^{ph^1}+y_{vw}^{ph^2}}{2}\right)\right]\cdot NHW_{vfw}^{ph} - QH_{vf}^{ph} \ge 0 \quad \forall v,f,p\in P_v,h\in H_v^p \tag{A.12}$$

$$\sum_{f}\sum_{p\in P_v}\sum_{h\in H_v^p} QS_{vfm}^{pht} + UD_{vm}^{t} \le \left(\frac{\alpha}{2}\right)\cdot\left(\frac{de_{vm}^{t^1}+de_{vm}^{t^2}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{de_{vm}^{t^3}+de_{vm}^{t^4}}{2}\right) \quad \forall v,m,t \tag{A.13}$$

$$\sum_{f}\sum_{p\in P_v}\sum_{h\in H_v^p} QS_{vfm}^{pht} + UD_{vm}^{t} \ge \left(\frac{\alpha}{2}\right)\cdot\left(\frac{de_{vm}^{t^3}+de_{vm}^{t^4}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{de_{vm}^{t^1}+de_{vm}^{t^2}}{2}\right) \quad \forall v,m,t \tag{A.14}$$

$$\sum_{v}\sum_{p=t}\left[(1-\alpha)\cdot\left(\frac{tp_v^1+tp_v^2}{2}\right)+\alpha\cdot\left(\frac{tp_v^3+tp_v^4}{2}\right)\right]\cdot NP_{vf}^{p} \tag{A.15}$$
$$+\sum_{v}\left[(1-\alpha)\cdot\left(\frac{ts_v^1+ts_v^2}{2}\right)+\alpha\cdot\left(\frac{ts_v^3+ts_v^4}{2}\right)\right]\cdot NS_{vf}^{t}$$
$$+\sum_{v}\left[(1-\alpha)\cdot\left(\frac{tc_v^1+tc_v^2}{2}\right)+\alpha\cdot\left(\frac{tc_v^3+tc_v^4}{2}\right)\right]\cdot NC_{vf}^{t}$$
$$+\sum_{v}\left[(1-\alpha)\cdot\left(\frac{tk_v^1+tk_v^2}{2}\right)+\alpha\cdot\left(\frac{tk_v^3+tk_v^4}{2}\right)\right]\cdot NK_{vf}^{t}$$
$$+\sum_{v}\sum_{w}\sum_{p\in P_v}\sum_{h=t}\left[(1-\alpha)\cdot\left(\frac{th_{vw}^1+th_{vw}^2}{2}\right)+\alpha\cdot\left(\frac{th_{vw}^3+th_{vw}^4}{2}\right)\right]$$
$$\cdot NHW_{vfw}^{ph}$$
$$+\sum_{v}\sum_{p\in P_v}\sum_{h\in H_v^p}\left[(1-\alpha)\cdot\left(\frac{tpa_v^1+tpa_v^2}{2}\right)+\alpha\cdot\left(\frac{tpa_v^3+tpa_v^4}{2}\right)\right]\cdot QP_{vf}^{pht}$$
$$\le hw\cdot\left(LS_f^t + LT_f^t\right) \quad \forall t$$

The final model for Scenario C is:

$Max[PrF]$

$Subject\ to$

(24)-(30), (32)-(34), (37-41), (A.11)-(A.15)

Appendix B

Suma de y	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51
Redondo																																	
I																																	
3	0,227	0,397	0,397	0,434	0,660	0,660	0,660	0,660	0,552	0,508	0,508	0,508	0,444	0,284	0,284	0,162																	
4	0,227	0,397	0,397	0,434	0,660	0,660	0,660	0,660	0,552	0,508	0,508	0,508	0,444	0,284	0,284	0,162																	
5	0,227	0,397	0,397	0,434	0,660	0,660	0,660	0,660	0,552	0,508	0,508	0,508	0,444	0,284	0,284	0,162																	
14									0,181	0,253	0,253	0,253	0,356	0,613	0,613	0,613	0,549	0,391	0,391	0,391	0,391	0,176	0,140	0,140	0,140	0,060							
15										0,181	0,253	0,253	0,253	0,356	0,613	0,613	0,613	0,549	0,391	0,391	0,391	0,391	0,176	0,140	0,140	0,140	0,060						
16											0,181	0,253	0,253	0,253	0,356	0,613	0,613	0,613	0,549	0,391	0,391	0,391	0,391	0,176	0,140	0,140	0,140	0,060					
17												0,181	0,253	0,253	0,253	0,356	0,613	0,613	0,613	0,549	0,391	0,391	0,391	0,391	0,176	0,140	0,140	0,140	0,060				
18													0,181	0,253	0,253	0,253	0,356	0,613	0,613	0,613	0,549	0,391	0,391	0,391	0,391	0,176	0,140	0,140	0,140	0,060			
27																	0,066	0,230	0,230	0,230	0,230	0,503	0,548	0,548	0,548	0,436	0,352	0,352	0,352	0,329	0,191	0,191	0,191
28																		0,066	0,230	0,230	0,230	0,230	0,503	0,548	0,548	0,548	0,436	0,352	0,352	0,352	0,329	0,191	0,191
29																			0,066	0,230	0,230	0,230	0,230	0,503	0,548	0,548	0,548	0,436	0,352	0,352	0,352	0,329	0,191
30																				0,066	0,230	0,230	0,230	0,230	0,503	0,548	0,548	0,548	0,436	0,352	0,352	0,352	0,329
31																					0,066	0,230	0,230	0,230	0,230	0,503	0,548	0,548	0,548	0,436	0,352	0,352	0,352
II																																	
3	0,204	0,357	0,357	0,391	0,594	0,594	0,594	0,594	0,496	0,457	0,457	0,457	0,400	0,255	0,255	0,146																	
4	0,204	0,357	0,357	0,391	0,594	0,594	0,594	0,594	0,496	0,457	0,457	0,457	0,400	0,255	0,255	0,146																	
5	0,204	0,357	0,357	0,391	0,594	0,594	0,594	0,594	0,496	0,457	0,457	0,457	0,400	0,255	0,255	0,146																	
14									0,163	0,228	0,228	0,228	0,320	0,551	0,551	0,551	0,494	0,352	0,352	0,352	0,352	0,158	0,126	0,126	0,126	0,054							
15										0,163	0,228	0,228	0,228	0,320	0,551	0,551	0,551	0,494	0,352	0,352	0,352	0,352	0,158	0,126	0,126	0,126	0,054						
16											0,163	0,228	0,228	0,228	0,320	0,551	0,551	0,551	0,494	0,352	0,352	0,352	0,352	0,158	0,126	0,126	0,126	0,054					
17												0,163	0,228	0,228	0,228	0,320	0,551	0,551	0,551	0,494	0,352	0,352	0,352	0,352	0,158	0,126	0,126	0,126	0,054				
18													0,163	0,228	0,228	0,228	0,320	0,551	0,551	0,551	0,494	0,352	0,352	0,352	0,352	0,158	0,126	0,126	0,126	0,054			
27																	0,059	0,207	0,207	0,207	0,207	0,453	0,494	0,494	0,494	0,393	0,317	0,317	0,317	0,296	0,172	0,172	0,172
28																		0,059	0,207	0,207	0,207	0,207	0,453	0,494	0,494	0,494	0,393	0,317	0,317	0,317	0,296	0,172	0,172
29																			0,059	0,207	0,207	0,207	0,207	0,453	0,494	0,494	0,494	0,393	0,317	0,317	0,317	0,296	0,172
30																				0,059	0,207	0,207	0,207	0,207	0,453	0,494	0,494	0,494	0,393	0,317	0,317	0,317	0,296
31																					0,059	0,207	0,207	0,207	0,207	0,453	0,494	0,494	0,494	0,393	0,317	0,317	0,317
III																																	
3	0,181	0,317	0,317	0,347	0,528	0,528	0,528	0,528	0,441	0,406	0,406	0,406	0,355	0,227	0,227	0,130																	
4	0,181	0,317	0,317	0,347	0,528	0,528	0,528	0,528	0,441	0,406	0,406	0,406	0,355	0,227	0,227	0,130																	
5	0,181	0,317	0,317	0,347	0,528	0,528	0,528	0,528	0,441	0,406	0,406	0,406	0,355	0,227	0,227	0,130																	
14									0,145	0,202	0,202	0,202	0,285	0,490	0,490	0,490	0,439	0,313	0,313	0,313	0,313	0,141	0,112	0,112	0,112	0,048							
15										0,145	0,202	0,202	0,202	0,285	0,490	0,490	0,490	0,439	0,313	0,313	0,313	0,313	0,141	0,112	0,112	0,112	0,048						
16											0,145	0,202	0,202	0,202	0,285	0,490	0,490	0,490	0,439	0,313	0,313	0,313	0,313	0,141	0,112	0,112	0,112	0,048					
17												0,145	0,202	0,202	0,202	0,285	0,490	0,490	0,490	0,439	0,313	0,313	0,313	0,313	0,141	0,112	0,112	0,112	0,048				
18													0,145	0,202	0,202	0,202	0,285	0,490	0,490	0,490	0,439	0,313	0,313	0,313	0,313	0,141	0,112	0,112	0,112	0,048			
27																	0,053	0,184	0,184	0,184	0,184	0,402	0,439	0,439	0,439	0,349	0,282	0,282	0,282	0,263	0,153	0,153	0,153
28																		0,053	0,184	0,184	0,184	0,184	0,402	0,439	0,439	0,439	0,349	0,282	0,282	0,282	0,263	0,153	0,153
29																			0,053	0,184	0,184	0,184	0,184	0,402	0,439	0,439	0,439	0,349	0,282	0,282	0,282	0,263	0,153
30																				0,053	0,184	0,184	0,184	0,184	0,402	0,439	0,439	0,439	0,349	0,282	0,282	0,282	0,263
31																					0,053	0,184	0,184	0,184	0,184	0,402	0,439	0,439	0,439	0,349	0,282	0,282	0,282
IV																																	
3	0,159	0,278	0,278	0,304	0,462	0,462	0,462	0,462	0,386	0,356	0,356	0,356	0,311	0,198	0,198	0,113																	
4	0,159	0,278	0,278	0,304	0,462	0,462	0,462	0,462	0,386	0,356	0,356	0,356	0,311	0,198	0,198	0,113																	
5	0,159	0,278	0,278	0,304	0,462	0,462	0,462	0,462	0,386	0,356	0,356	0,356	0,311	0,198	0,198	0,113																	
14									0,126	0,177	0,177	0,177	0,249	0,429	0,429	0,429	0,384	0,273	0,273	0,273	0,273	0,123	0,098	0,098	0,098	0,042							
15										0,126	0,177	0,177	0,177	0,249	0,429	0,429	0,429	0,384	0,273	0,273	0,273	0,273	0,123	0,098	0,098	0,098	0,042						
16											0,126	0,177	0,177	0,177	0,249	0,429	0,429	0,429	0,384	0,273	0,273	0,273	0,273	0,123	0,098	0,098	0,098	0,042					
17												0,126	0,177	0,177	0,177	0,249	0,429	0,429	0,429	0,384	0,273	0,273	0,273	0,273	0,123	0,098	0,098	0,098	0,042				
18													0,126	0,177	0,177	0,177	0,249	0,429	0,429	0,429	0,384	0,273	0,273	0,273	0,273	0,123	0,098	0,098	0,098	0,042			
27																	0,046	0,161	0,161	0,161	0,161	0,352	0,384	0,384	0,384	0,305	0,247	0,247	0,247	0,230	0,134	0,134	0,134
28																		0,046	0,161	0,161	0,161	0,161	0,352	0,384	0,384	0,384	0,305	0,247	0,247	0,247	0,230	0,134	0,134
29																			0,046	0,161	0,161	0,161	0,161	0,352	0,384	0,384	0,384	0,305	0,247	0,247	0,247	0,230	0,134
30																				0,046	0,161	0,161	0,161	0,161	0,352	0,384	0,384	0,384	0,305	0,247	0,247	0,247	0,230
31																					0,046	0,161	0,161	0,161	0,161	0,352	0,384	0,384	0,384	0,305	0,247	0,247	0,247

Figure B.1. Yield per plant (kg/plant) of the round tomato depending on the planting date, harvesting date and harvesting pattern.

Suma de y	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
Pera																
I																
3	0,214	0,374	0,374	0,400	0,559	0,559	0,559	0,559	0,490	0,462	0,462	0,462	0,399	0,242	0,242	0,138
4	0,214	0,374	0,374	0,400	0,559	0,559	0,559	0,559	0,490	0,462	0,462	0,462	0,399	0,242	0,242	0,138
5	0,214	0,374	0,374	0,400	0,559	0,559	0,559	0,559	0,490	0,462	0,462	0,462	0,399	0,242	0,242	0,138
14									0,161	0,226	0,226	0,226	0,327	0,580	0,580	0,580
15										0,161	0,226	0,226	0,226	0,327	0,580	0,580
16											0,161	0,226	0,226	0,226	0,327	0,580
17												0,161	0,226	0,226	0,226	0,327
18													0,161	0,226	0,226	0,226
27																
28																
29																
30																
31																
II																
3	0,192	0,336	0,336	0,360	0,503	0,503	0,503	0,503	0,441	0,416	0,416	0,416	0,359	0,218	0,218	0,124
4	0,192	0,336	0,336	0,360	0,503	0,503	0,503	0,503	0,441	0,416	0,416	0,416	0,359	0,218	0,218	0,124
5	0,192	0,336	0,336	0,360	0,503	0,503	0,503	0,503	0,441	0,416	0,416	0,416	0,359	0,218	0,218	0,124
14									0,145	0,203	0,203	0,203	0,294	0,522	0,522	0,522
15										0,145	0,203	0,203	0,203	0,294	0,522	0,522
16											0,145	0,203	0,203	0,203	0,294	0,522
17												0,145	0,203	0,203	0,203	0,294
18													0,145	0,203	0,203	0,203
27																
28																
29																
30																
31																
III																
3	0,171	0,299	0,299	0,320	0,448	0,448	0,448	0,448	0,392	0,370	0,370	0,370	0,319	0,193	0,193	0,111
4	0,171	0,299	0,299	0,320	0,448	0,448	0,448	0,448	0,392	0,370	0,370	0,370	0,319	0,193	0,193	0,111
5	0,171	0,299	0,299	0,320	0,448	0,448	0,448	0,448	0,392	0,370	0,370	0,370	0,319	0,193	0,193	0,111
14									0,129	0,181	0,181	0,181	0,261	0,464	0,464	0,464
15										0,129	0,181	0,181	0,181	0,261	0,464	0,464
16											0,129	0,181	0,181	0,181	0,261	0,464
17												0,129	0,181	0,181	0,181	0,261
18													0,129	0,181	0,181	0,181
27																
28																
29																
30																
31																
IV																
3	0,150	0,262	0,262	0,280	0,392	0,392	0,392	0,392	0,343	0,323	0,323	0,323	0,279	0,169	0,169	0,097
4	0,150	0,262	0,262	0,280	0,392	0,392	0,392	0,392	0,343	0,323	0,323	0,323	0,279	0,169	0,169	0,097
5	0,150	0,262	0,262	0,280	0,392	0,392	0,392	0,392	0,343	0,323	0,323	0,323	0,279	0,169	0,169	0,097
14									0,113	0,158	0,158	0,158	0,229	0,406	0,406	0,406
15										0,113	0,158	0,158	0,158	0,229	0,406	0,406
16											0,113	0,158	0,158	0,158	0,229	0,406
17												0,113	0,158	0,158	0,158	0,229
18													0,113	0,158	0,158	0,158
27																
28																
29																
30																
31																

Suma de y	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51
Pera																	
I																	
3																	
4																	
5																	
14	0,514	0,349	0,349	0,349	0,349	0,160	0,128	0,128	0,128	0,055							
15	0,580	0,514	0,349	0,349	0,349	0,349	0,160	0,128	0,128	0,128	0,055						
16	0,580	0,580	0,514	0,349	0,349	0,349	0,349	0,160	0,128	0,128	0,128	0,055					
17	0,580	0,580	0,580	0,514	0,349	0,349	0,349	0,349	0,160	0,128	0,128	0,128	0,055				
18	0,327	0,580	0,580	0,580	0,514	0,349	0,349	0,349	0,349	0,160	0,128	0,128	0,128	0,055			
27	0,060	0,209	0,209	0,209	0,209	0,486	0,532	0,532	0,532	0,416	0,328	0,328	0,328	0,307	0,181	0,181	0,181
28		0,060	0,209	0,209	0,209	0,209	0,486	0,532	0,532	0,532	0,416	0,328	0,328	0,328	0,307	0,181	0,181
29			0,060	0,209	0,209	0,209	0,209	0,486	0,532	0,532	0,532	0,416	0,328	0,328	0,328	0,307	0,181
30				0,060	0,209	0,209	0,209	0,209	0,486	0,532	0,532	0,532	0,416	0,328	0,328	0,328	0,307
31					0,060	0,209	0,209	0,209	0,209	0,486	0,532	0,532	0,532	0,416	0,328	0,328	0,328
II																	
3																	
4																	
5																	
14	0,462	0,314	0,314	0,314	0,314	0,144	0,116	0,116	0,116	0,050							
15	0,522	0,462	0,314	0,314	0,314	0,314	0,144	0,116	0,116	0,116	0,050						
16	0,522	0,522	0,462	0,314	0,314	0,314	0,314	0,144	0,116	0,116	0,116	0,050					
17	0,522	0,522	0,522	0,462	0,314	0,314	0,314	0,314	0,144	0,116	0,116	0,116	0,050				
18	0,294	0,522	0,522	0,522	0,462	0,314	0,314	0,314	0,314	0,144	0,116	0,116	0,116	0,050			
27	0,054	0,188	0,188	0,188	0,188	0,438	0,479	0,479	0,479	0,374	0,296	0,296	0,296	0,277	0,163	0,163	0,163
28		0,054	0,188	0,188	0,188	0,188	0,438	0,479	0,479	0,479	0,374	0,296	0,296	0,296	0,277	0,163	0,163
29			0,054	0,188	0,188	0,188	0,188	0,438	0,479	0,479	0,479	0,374	0,296	0,296	0,296	0,277	0,163
30				0,054	0,188	0,188	0,188	0,188	0,438	0,479	0,479	0,479	0,374	0,296	0,296	0,296	0,277
31					0,054	0,188	0,188	0,188	0,188	0,438	0,479	0,479	0,479	0,374	0,296	0,296	0,296
III																	
3																	
4																	
5																	
14	0,411	0,279	0,279	0,279	0,279	0,128	0,103	0,103	0,103	0,044							
15	0,464	0,411	0,279	0,279	0,279	0,279	0,128	0,103	0,103	0,103	0,044						
16	0,464	0,464	0,411	0,279	0,279	0,279	0,279	0,128	0,103	0,103	0,103	0,044					
17	0,464	0,464	0,464	0,411	0,279	0,279	0,279	0,279	0,128	0,103	0,103	0,103	0,044				
18	0,261	0,464	0,464	0,464	0,411	0,279	0,279	0,279	0,279	0,128	0,103	0,103	0,103	0,044			
27	0,048	0,168	0,168	0,168	0,168	0,389	0,426	0,426	0,426	0,333	0,263	0,263	0,263	0,246	0,145	0,145	0,145
28		0,048	0,168	0,168	0,168	0,168	0,389	0,426	0,426	0,426	0,333	0,263	0,263	0,263	0,246	0,145	0,145
29			0,048	0,168	0,168	0,168	0,168	0,389	0,426	0,426	0,426	0,333	0,263	0,263	0,263	0,246	0,145
30				0,048	0,168	0,168	0,168	0,168	0,389	0,426	0,426	0,426	0,333	0,263	0,263	0,263	0,246
31					0,048	0,168	0,168	0,168	0,168	0,389	0,426	0,426	0,426	0,333	0,263	0,263	0,263
IV																	
3																	
4																	
5																	
14	0,360	0,244	0,244	0,244	0,244	0,112	0,090	0,090	0,090	0,039							
15	0,406	0,360	0,244	0,244	0,244	0,244	0,112	0,090	0,090	0,090	0,039						
16	0,406	0,406	0,360	0,244	0,244	0,244	0,244	0,112	0,090	0,090	0,090	0,039					
17	0,406	0,406	0,406	0,360	0,244	0,244	0,244	0,244	0,112	0,090	0,090	0,090	0,039				
18	0,229	0,406	0,406	0,406	0,360	0,244	0,244	0,244	0,244	0,112	0,090	0,090	0,090	0,039			
27	0,042	0,147	0,147	0,147	0,147	0,340	0,373	0,373	0,373	0,291	0,230	0,230	0,230	0,215	0,127	0,127	0,127
28		0,042	0,147	0,147	0,147	0,147	0,340	0,373	0,373	0,373	0,291	0,230	0,230	0,230	0,215	0,127	0,127
29			0,042	0,147	0,147	0,147	0,147	0,340	0,373	0,373	0,373	0,291	0,230	0,230	0,230	0,215	0,127
30				0,042	0,147	0,147	0,147	0,147	0,340	0,373	0,373	0,373	0,291	0,230	0,230	0,230	0,215
31					0,042	0,147	0,147	0,147	0,147	0,340	0,373	0,373	0,373	0,291	0,230	0,230	0,230

Figure B.2. Yield per plant (kg/plant) of the pear tomato depending on the planting date, harvesting date and harvesting pattern.

Suma de y	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51
Cherry																																	
I																																	
3	0,098	0,172	0,172	0,175	0,191	0,191	0,191	0,191	0,150	0,133	0,133	0,133	0,150	0,192	0,192	0,109																	
4	0,098	0,172	0,172	0,175	0,191	0,191	0,191	0,191	0,150	0,133	0,133	0,133	0,150	0,192	0,192	0,109																	
5	0,098	0,172	0,172	0,175	0,191	0,191	0,191	0,191	0,150	0,133	0,133	0,133	0,150	0,192	0,192	0,109																	
14									0,081	0,113	0,113	0,113	0,139	0,203	0,203	0,203	0,185	0,143	0,143	0,143	0,143	0,129	0,126	0,126	0,126	0,054							
15										0,081	0,113	0,113	0,113	0,139	0,203	0,203	0,203	0,185	0,143	0,143	0,143	0,143	0,129	0,126	0,126	0,126	0,054						
16											0,081	0,113	0,113	0,113	0,139	0,203	0,203	0,203	0,185	0,143	0,143	0,143	0,143	0,129	0,126	0,126	0,126	0,054					
17												0,081	0,113	0,113	0,113	0,139	0,203	0,203	0,203	0,185	0,143	0,143	0,143	0,143	0,129	0,126	0,126	0,126	0,054				
18													0,081	0,113	0,113	0,113	0,139	0,203	0,203	0,203	0,185	0,143	0,143	0,143	0,143	0,129	0,126	0,126	0,126	0,054			
27																	0,004	0,015	0,015	0,015	0,015	0,153	0,176	0,176	0,176	0,191	0,203	0,203	0,203	0,174			
28																		0,004	0,015	0,015	0,015	0,015	0,153	0,176	0,176	0,176	0,191	0,203	0,203	0,203	0,174		
29																			0,004	0,015	0,015	0,015	0,015	0,153	0,176	0,176	0,176	0,191	0,203	0,203	0,203	0,174	
30																				0,004	0,015	0,015	0,015	0,015	0,153	0,176	0,176	0,176	0,191	0,203	0,203	0,203	0,174
31																					0,004	0,015	0,015	0,015	0,015	0,153	0,176	0,176	0,176	0,191	0,203	0,203	0,203
II																																	
3	0,088	0,155	0,155	0,157	0,172	0,172	0,172	0,172	0,135	0,120	0,120	0,120	0,135	0,172	0,172	0,099																	
4	0,088	0,155	0,155	0,157	0,172	0,172	0,172	0,172	0,135	0,120	0,120	0,120	0,135	0,172	0,172	0,099																	
5	0,088	0,155	0,155	0,157	0,172	0,172	0,172	0,172	0,135	0,120	0,120	0,120	0,135	0,172	0,172	0,099																	
14									0,073	0,102	0,102	0,102	0,125	0,182	0,182	0,182	0,167	0,128	0,128	0,128	0,128	0,116	0,114	0,114	0,114	0,049							
15										0,073	0,102	0,102	0,102	0,125	0,182	0,182	0,182	0,167	0,128	0,128	0,128	0,128	0,116	0,114	0,114	0,114	0,049						
16											0,073	0,102	0,102	0,102	0,125	0,182	0,182	0,182	0,167	0,128	0,128	0,128	0,128	0,116	0,114	0,114	0,114	0,049					
17												0,073	0,102	0,102	0,102	0,125	0,182	0,182	0,182	0,167	0,128	0,128	0,128	0,128	0,116	0,114	0,114	0,114	0,049				
18													0,073	0,102	0,102	0,102	0,125	0,182	0,182	0,182	0,167	0,128	0,128	0,128	0,128	0,116	0,114	0,114	0,114	0,049			
27																	0,004	0,013	0,013	0,013	0,013	0,137	0,158	0,158	0,158	0,172	0,183	0,183	0,183	0,157			
28																		0,004	0,013	0,013	0,013	0,013	0,137	0,158	0,158	0,158	0,172	0,183	0,183	0,183	0,157		
29																			0,004	0,013	0,013	0,013	0,013	0,137	0,158	0,158	0,158	0,172	0,183	0,183	0,183	0,157	
30																				0,004	0,013	0,013	0,013	0,013	0,137	0,158	0,158	0,158	0,172	0,183	0,183	0,183	0,157
31																					0,004	0,013	0,013	0,013	0,013	0,137	0,158	0,158	0,158	0,172	0,183	0,183	0,183
III																																	
3	0,079	0,138	0,138	0,140	0,153	0,153	0,153	0,153	0,120	0,106	0,106	0,106	0,120	0,153	0,153	0,088																	
4	0,079	0,138	0,138	0,140	0,153	0,153	0,153	0,153	0,120	0,106	0,106	0,106	0,120	0,153	0,153	0,088																	
5	0,079	0,138	0,138	0,140	0,153	0,153	0,153	0,153	0,120	0,106	0,106	0,106	0,120	0,153	0,153	0,088																	
14									0,065	0,090	0,090	0,090	0,111	0,162	0,162	0,162	0,148	0,114	0,114	0,114	0,114	0,103	0,101	0,101	0,101	0,043							
15										0,065	0,090	0,090	0,090	0,111	0,162	0,162	0,162	0,148	0,114	0,114	0,114	0,114	0,103	0,101	0,101	0,101	0,043						
16											0,065	0,090	0,090	0,090	0,111	0,162	0,162	0,162	0,148	0,114	0,114	0,114	0,114	0,103	0,101	0,101	0,101	0,043					
17												0,065	0,090	0,090	0,090	0,111	0,162	0,162	0,162	0,148	0,114	0,114	0,114	0,114	0,103	0,101	0,101	0,101	0,043				
18													0,065	0,090	0,090	0,090	0,111	0,162	0,162	0,162	0,148	0,114	0,114	0,114	0,114	0,103	0,101	0,101	0,101	0,043			
27																	0,003	0,012	0,012	0,012	0,012	0,122	0,141	0,141	0,141	0,153	0,162	0,162	0,162	0,139			
28																		0,003	0,012	0,012	0,012	0,012	0,122	0,141	0,141	0,141	0,153	0,162	0,162	0,162	0,139		
29																			0,003	0,012	0,012	0,012	0,012	0,122	0,141	0,141	0,141	0,153	0,162	0,162	0,162	0,139	
30																				0,003	0,012	0,012	0,012	0,012	0,122	0,141	0,141	0,141	0,153	0,162	0,162	0,162	0,139
31																					0,003	0,012	0,012	0,012	0,012	0,122	0,141	0,141	0,141	0,153	0,162	0,162	0,162
IV																																	
3	0,069	0,120	0,120	0,122	0,134	0,134	0,134	0,134	0,105	0,093	0,093	0,093	0,105	0,134	0,134	0,077																	
4	0,069	0,120	0,120	0,122	0,134	0,134	0,134	0,134	0,105	0,093	0,093	0,093	0,105	0,134	0,134	0,077																	
5	0,069	0,120	0,120	0,122	0,134	0,134	0,134	0,134	0,105	0,093	0,093	0,093	0,105	0,134	0,134	0,077																	
14									0,056	0,079	0,079	0,079	0,097	0,142	0,142	0,142	0,130	0,100	0,100	0,100	0,100	0,090	0,089	0,089	0,089	0,038							
15										0,056	0,079	0,079	0,079	0,097	0,142	0,142	0,142	0,130	0,100	0,100	0,100	0,100	0,090	0,089	0,089	0,089	0,038						
16											0,056	0,079	0,079	0,079	0,097	0,142	0,142	0,142	0,130	0,100	0,100	0,100	0,100	0,090	0,089	0,089	0,089	0,038					
17												0,056	0,079	0,079	0,079	0,097	0,142	0,142	0,142	0,130	0,100	0,100	0,100	0,100	0,090	0,089	0,089	0,089	0,038				
18													0,056	0,079	0,079	0,079	0,097	0,142	0,142	0,142	0,130	0,100	0,100	0,100	0,100	0,090	0,089	0,089	0,089	0,038			
27																	0,003	0,010	0,010	0,010	0,010	0,107	0,123	0,123	0,123	0,134	0,142	0,142	0,142	0,122			
28																		0,003	0,010	0,010	0,010	0,010	0,107	0,123	0,123	0,123	0,134	0,142	0,142	0,142	0,122		
29																			0,003	0,010	0,010	0,010	0,010	0,107	0,123	0,123	0,123	0,134	0,142	0,142	0,142	0,122	
30																				0,003	0,010	0,010	0,010	0,010	0,107	0,123	0,123	0,123	0,134	0,142	0,142	0,142	0,122
31																					0,003	0,010	0,010	0,010	0,010	0,107	0,123	0,123	0,123	0,134	0,142	0,142	0,142

Figure B.3. Yield per plant (kg/plant) of the cherry tomato depending on the planting date, harvesting date and harvesting pattern.

Chapter VII:

Conceptual framework for managing uncertainty in a collaborative agri-food supply chain context

Agri-food supply chains are subjected to many sources of uncertainty. If these uncertainties are not managed properly, they can have a negative impact on the agri-food supply chain (AFSC) performance, its customers, and the environment. In this sense, collaboration is proposed as a possible solution to reduce it. For that, a conceptual framework (CF) for managing uncertainty in a collaborative context is proposed. In this context, this paper seeks to answer the following research questions: What are the existing uncertainty sources in the AFSCs? Can collaboration be used to reduce the uncertainty of AFSCs? Which elements can integrate a CF for managing uncertainty in a collaborative AFSC? The CF proposal is applied to the weather source of uncertainty in order to show its applicability.

Keywords: Agri-food supply chains; Collaboration; Uncertainty; Conceptual framework

1 Introduction

The term "agri-food supply chain" (AFSC) has been defined as a set of activities necessary to bring agricultural products "from the farm to the fork" [1–4]. Therefore, both vegetable and animal-based products are produced in and distributed by AFSCs [5].

AFSCs are subjected to many sources of uncertainty. If these sources of uncertainty are not managed properly, not only the AFSC performance may be negatively affected but also the customers service levels and the environment would be also affected. In this sense, collaboration is proposed as a possible solution to reduce this negative impact. For that, a conceptual framework (CF) for managing uncertainty in a collaborative context is proposed. In this context, this paper seeks to answer the research questions (RQ):

RQ1. What are the existing sources of uncertainty in the AFSCs?

RQ2. Can collaboration be used to reduce the uncertainty of AFSCs?

RQ3. Which elements can integrate a CF for managing uncertainty in a collaborative AFSC?

Since horticulture sector has received the least attention in the literature and the production processes of meat and horticulture sectors are extremely different, this paper focuses on the crop-based AFSCs.

Therefore, the main contributions of this paper are the identification of the existing sources of uncertainty in crop-based AFSC, and the proposal of a CF for reducing these uncertainties through the collaboration of the AFSC members. For that, literature search related to collaboration in AFSC is carried out within well-known databases, such as Springer, Elsevier, and many others. To the best of our knowledge there are few papers dealing the collaboration as a tool for reducing uncertainty in AFSCs and, some authors have stated that more research on supply chain collaboration is needed in order to cope uncertainty in the agricultural sector [2,6].

The remainder of this paper is organized as follows. In Section 2, the existing sources of uncertainty in crop-based AFSC are detailed. A reflection of the impact of collaboration over these uncertainties is performed in Section 3. As a result, the CF for managing uncertainty in a collaborative AFSC context is proposed in Section 4. Finally, conclusions are exposed in the last section.

2 Crop-based AFSC sources of uncertainty

Crop-based AFSCs are subjected to many sources of uncertainty which are mainly related to inherent characteristics of the agri-food sector. If these sources of uncertainty are not managed properly, they can have a negative impact on the AFSC performance, its customers, and the environment. However, if the level of uncertainty is reduced, the supply chain performance will be improved. Therefore, the aim of this section is to answer the Research Question: What are the existing sources of uncertainty in the AFSCs?

Supply chains uncertainty commonly refers to situations in which decision-makers have not enough information about objectives to make decisions; have a vague idea of the supply chain and/or its environment; are not able to predict the impact of decisions on supply chain's performance; or lacks effective control actions [7,8].

According to Samson et al. [9], we are in the realm of decision making under uncertainty if it is ignored the probability of occurrence of the possible specific outcomes. In addition, when making a decision under uncertainty, the decision maker may or may not know the different outcomes that can occur [10].

This paper proposed a CF (Figure 1) for the AFSC sources of uncertainty classification. This framework has been based on the CF in van der Vorst [11] where the SC uncertainties are divided into supply, demand, process and planning & control uncertainties. This classification has been extended by adding the sources of uncertainty related to products and to environment. For the purpose of this paper, although the sources of uncertainty are interrelated, we consider it more appropriate to group them into different categories to which they make reference. The categories proposed for the crop-based AFSC sources of uncertainty are product, process, market and, environment.

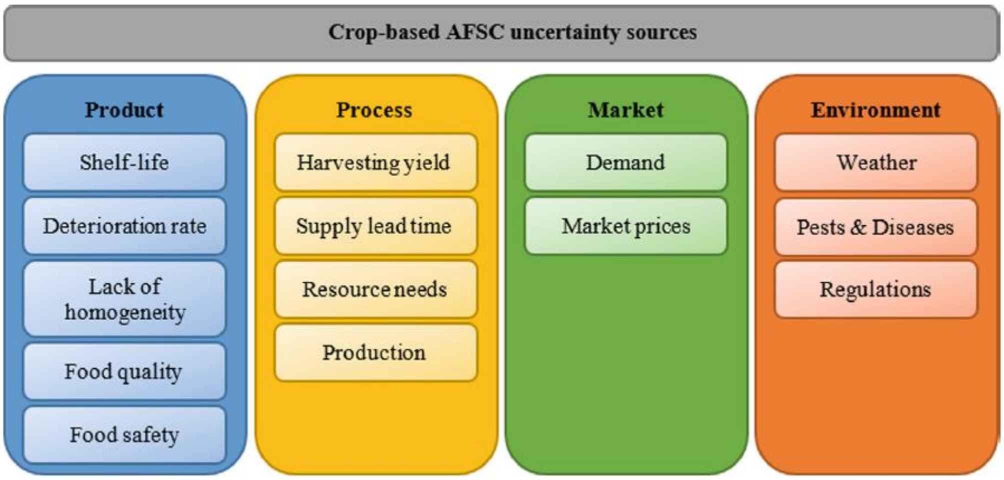


Figure 1. Conceptual framework for the uncertainty sources of crop-based AFSCs

The identified sources of uncertainty related to crop-based AFSC products are:

- Uncertainty on shelf-life. The product shelf-life is the time during which the product losses its tacit initial characteristics becoming a non-value item for customers [12]. Then, the product shelf-life and physical state are not necessarily interrelated since many products deteriorate after the end of their shelf-life. Hence, product shelf-life may reflect its marketable life [13]. As the shelf-life of a product is the period of time during which quality losses do not exceed a tolerated level, the product's time and temperature history must be known; if not, the shelf-life is uncertain [14].
- Uncertainty on deterioration. Deterioration of products is the process where items decay, get damaged or spoiled, being impossible to use them for their original purpose [15]. It can be classified as age-dependent on-going deterioration and age-independent on-going deterioration [13]. Agri-food products are goods subject to age-dependent on-going deterioration. Most authors talk about constant or probabilistic deterioration rates, however, it can be considered as uncertain as the quantity and quality deterioration over time can be unknown.
- Uncertainty on lack of homogeneity of products. Agri-food sector is characterized by the lack of homogeneity of the product, so the products obtained after harvesting differ in some attributes (maturity, color, bacterial level, various size and weights of items…) that are relevant for customers because they require to be served with homogeneous units of the same product [16]. Correct handling of the lack of homogeneity in the product and its inherent uncertainty is important to reduce and avoid inefficiencies of the supply chain and improve customer service level [16].
- Uncertainty on food quality. Food quality is the combination of food features that establishes the customer satisfaction and compliance to legal standards [17]. It usually refers not only to the physical properties of food products, but also to the customer perception of it [18]. Product quality is characterized by properties such as texture, taste, flavor, smell, color, presence of pathogens, toxins or hormones… [17–19]. Some of these attributes can be easy to measure while others are subject

to customer's perception, making its assessment very challenging (e.g., taste) [19]. Then, there is uncertainty in food quality as it is subjective so it cannot be certainly measured.

- Uncertainty on food safety. Food safety generally refers to the prevention of illnesses resulting from the consumption of contaminated food [18]. There is a need to guarantee food safety as the customer's trust and market acceptance depend on it [20]. Since food safety cannot be measured and guaranteed in the final product, it can be considered an uncertain factor.

The uncertainty sources related to crop-based AFSC processes are:

- Uncertainty on harvesting yield. The crops' ripening process and the capability of performing harvesting operations are highly influenced by land and weather conditions, so harvesting yield worsens if part of the crops cannot be collected at the moment of adequate ripeness [21]. Therefore, harvesting yield is usually an uncertain factor in terms of product quantity, quality and harvesting time. This is related to the uncertainty in supply of raw material as the SC stage after harvesting will not know the quantity, quality and time of the supply until it is received.
- Uncertainty on supply lead time. The lead time is the time taken from the beginning of a process to its end. AFSCs are characterized by their long supply lead times as many crops spend from six to nine months since their planting until their harvesting [1,21]. Supply lead time can be considered an uncertain factor as the needed time for crops to grow is generally long, seasonal and, weather and yield dependent [22].
- Uncertainty on resource needs. Resources needed for harvesting, which can be established by the number, capacity and productivity of machines and laborers, are limited [21]. Given the uncertainty on the harvesting quantity, the resource needs cannot be known until the harvest is done.
- Uncertainty on production. Production depends on the raw materials received, as their quantity, quality and characteristics are not known a priori. This uncertainty provokes the need of having alternative recipes in order to produce the same final product [5,11].

The uncertainty sources related to crop-based AFSC markets are:

- Uncertainty on demand. Demand of agri-food products is not only related to product and quantity, but also to the quality and safety requirements of the customer and factors such as remaining shelf-life of the product. Demand uncertainty reflects the uncertainty of customer demand for a product [23]. Natural causes as seasonality and weather as well as promotional activities can cause variability in customer demand, creating uncertainty [1].
- Demand can be dependent of the remaining shelf-life of products, inventory level, time, market trends or price; demand can follow a distribution function or it can be completely unknown [15].
- Uncertainty on market prices. Market prices are volatile and keep changing across the day [24]. The variability of prices in the different stages of supply chains are caused by dynamic factors such as the price of substitute products, inflation, production costs, import, export, customer demands, seasonality, product availability and the supply-demand balance [25].

The uncertainty sources related to crop-based AFSC environment are:

- Uncertainty on weather and land conditions. Weather conditions, such as temperature and precipitation, mainly affect the harvesting yield and activity. The harvesting process is complex as it dispose of limited resources and, it gets even more complex when considering the uncertainty related to weather conditions [21]. Weather and land conditions cannot be known with certainty.
- Uncertainty on pests and diseases. Agri-food products can be contaminated by pests and biotic hazards such as bacteria, viruses and other emerging pathogens [26]. Yield losses can be reduced by protecting the crops from various diseases with pesticides [27]. Pest and disease infestations are random factors that could be controlled by management [28].
- Uncertainty on regulations. The regulatory framework of the agri-food sector, comprised by public and private regulations dealing with food quality and safety, set the diverse requirements for tracking and tracing capabilities [20]. There is uncertainty on the appearance of new, more stringent, regulations.

It is worth mentioning that different relationships exist among the sources of uncertainty described. For instance, uncertainty on weather implicitly originates uncertainty in harvesting yields.

3 Impact of collaboration on crop-based AFSC

Supply chains have been defined as goal-oriented networks in which their partners intensively collaborate with each other towards a common goal [29]. Then, the collaboration on supply chain means that two or more chain members actively and jointly work (spanning the organizations boundaries) for fulfilling and satisfying consumers' needs [2]. With collaboration, stakeholders are able to share their assets and capabilities so they can reduce the uncertainty, share the risk and cost, and serve customers at the right time, quantity, and quality without disregarding the interest of other stakeholders [30].

Collaboration is a powerful tool to improve the AFSCs performance. However, its implementation is complex as existing barriers potentially deteriorate collaboration among companies, e.g. the incompatibility of information exchange systems, the big quantity of enterprises making up a supply chain or the lack of trust between the parties. Despite this, collaboration is becoming more a necessity than an option [2].

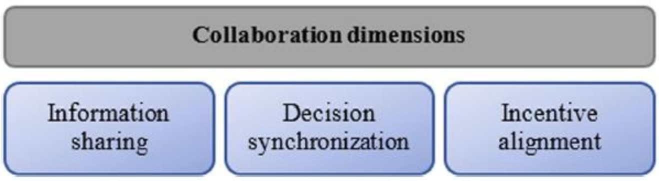


Figure 2. Collaboration dimensions

The collaboration concept can be categorized into three interrelated dimensions (Figure 2): information sharing, decision synchronization, and incentive alignment [31].

These three dimensions represent different levels of collaboration so that for changing from a level of collaboration to a superior one it is necessary to ensure the proper functioning of the previous collaborative levels. Different benefits and risks of collaboration can exist depending on the Supply Chain Activities [2]. According to these authors [30], the information sharing consists in capturing and disseminating timely information that is relevant for decision makers when planning and controlling supply chain operations; the decision synchronization consists in making planning and operational decisions jointly; and, the incentive alignment consists of the degree of sharing costs, risks and benefits between supply chain members.

Then, is it needed the collaboration to reduce the uncertainty on AFSCs? Supply chain collaboration can be necessary for various reasons. Collaboration is needed in AFSC for minimizing its costs, increasing the profits, ensuring the quality, and gaining customers trust [30]. Collaboration is also needed in the agri-food sector as AFSC are competing against other AFSC and single companies are not competing with each other anymore [32]. Another reason for collaborating in AFSC is given by the increased public pressure for transparency, traceability and “due diligence” throughout the AFSC due to the combination of social concern about food safety and the recent food crises [2]. These crises have emphasized the close interdependencies between AFSC actors and their need of cooperation in order to be a competitive AFSC and to ensure the meet of the customers’ requirements related to food quality and safety [20].

However, an additional reason for applying collaboration in AFSC is the huge amount of sources of uncertainty that impact over its performance and which are mainly generated by the lack of information through the AFSC. Uncertainty can be reduced by supply chain collaboration [30,32]. Sharing information reduces uncertainty as decision-makers dispose reliable data to conduct the decision-making process (e.g. if the AFSC members share information about the traceability of the product, the food safety of the product would be guaranteed). Making joint decisions reduces uncertainty as decision-makers of two AFSC stages have all the information to make more appropriate decisions for both parts (e.g. farmers and producers decide jointly when to harvest, then the used capacities of both stakeholders can be optimized). The incentive alignment reduces uncertainty as the motivation to obtain maximum benefits make the stakeholders share high quality information (e.g. stakeholders could establish an equitable distribution of profits between them in order to reduce the share of profits).

Collaboration not only provide benefits, but also risks. The main risks in collaboration are [2]: the risk of failure (loss of the investment made, loss of time, and business plans delay or renouncement); potential interdependence between companies; increasing operational complexity and integration technology.

4 Conceptual framework for uncertainty management through collaboration in AFSCs

In this section a conceptual framework (CF) to manage the inherent uncertainty sources of AFSCs through collaboration is proposed. Then, this CF tries to give and answer to the last research question: What elements can be considered for managing uncertainty by means collaboration in AFSC? The proposed elements for this CF are grouped into four blocks for AFSCs (Figure 3): Sources of uncertainty, Management, Collaboration and Collaboration Impact. In the following, each element is described.

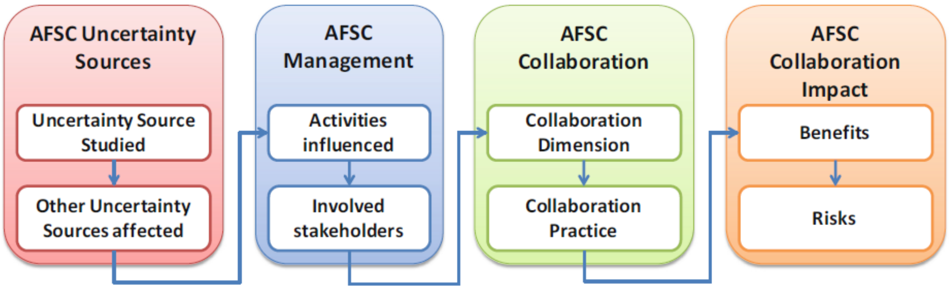


Figure 3. Conceptual framework for managing uncertainty in a collaborative AFSC context

- AFSC Uncertainty Sources: in this block, the sources of uncertainty to be studied in the CF is indicated and the uncertainty sources affected by the studied one are identified.
    - Sources of uncertainty studied: the source of uncertainty to be managed is selected from the CF for the sources of uncertainty of crop-based AFSCs (Section 2).
    - Other Uncertainty Sources affected: Because different sources of uncertainty are not independent, the strongest relationship between the uncertainties studied and the other ones should be identified.
- AFSC Management: in this block, the activities and stakeholders influenced by the studied sources of uncertainty are identified.
    - Management activities influenced by the sources of uncertainty selected and the others affected by it should be determined.
    - Involved stakeholders related to the above activities should be determined with the aim of identifying the possible AFSC members for collaboration: farmers, processors, distributors, retailers and other stakeholders (NGO's, government…) [5].
- AFSC Collaboration: in this block, the collaboration dimensions to be employed to reduce the studied sources of uncertainty and their related practices are identified.
    - Collaboration dimension: the different collaboration dimensions (information sharing, decision synchronization, and incentive alignment) are detailed.
    - Collaboration practices: different collaboration practices can be adopted in order to establish the collaboration between stakeholders. Each collaboration practice will have a different impact on the AFSC.
- Impact on AFSC: the benefits and risks produced by the collaboration practice proposed are identified. For each collaboration practice could be made qualitatively and/or quantitatively:
    - Benefits of each collaboration practice should be detailed (assessed) on the AFSC characteristics and sources of uncertainty.
    - Risks for each collaboration practice should also be taken into account when analyzing the possible collaboration practice to be implemented.

When making the decision of which collaboration dimension to implement for reducing an uncertainty, the CF can be applied to collect information of the benefits, risks and other issues related to each collaboration practice. Although the highest collaboration level could offer more benefits in reducing uncertainty, decision-makers have to make a balance between the level of uncertainty and resources consumption they are ready to assume and the benefits they are obtaining in return. This reason justifies the application of the proposed CF to decide the collaborative practice to implement by collecting the needed information to make an adequate decision.

An example of how to use the proposed CF for identifying the consequences/impact of the information sharing collaboration dimension on the weather uncertainty is illustrated in Table 1. By developing the same table for the two remaining collaboration levels the user would be able to decide which collaboration level is the most appropriate to his case. The objective of this example is not to show the whole decision process, but to illustrate the way to use the CF.

Table 1. Example for the conceptual framework completion

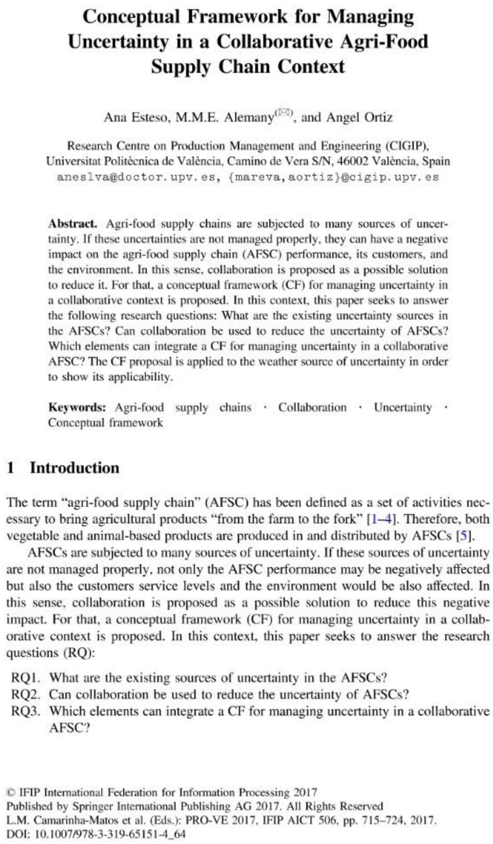
CF Elements	Application
Uncertainty source studied	Weather
Other uncertainty sources affected	Harvesting yield, food quality and indirect effects related with changes in the distribution of pests and diseases
Activities influenced	Planning of harvesting operations (planting and harvesting scheduling, effective resource management among competing crops), Procurement
Involved stakeholders	Seed suppliers, Pesticides suppliers, Farmers and producers
Collaboration dimension	Information sharing
Collaboration practice	Sharing information among involved stakeholders on rainfall, water level in soil, use of pesticides and fertilizers and driving lanes of farm machines
Benefits	Predict the harvesting yield takes an input to multiple process, Optimize the use of pesticides, fertilizers and water
Risks	Technological risks for the necessity of sensors and properly information technologies

5 Conclusions

This paper has identified the existing sources of uncertainty in crop-based AFSC. A CF is proposed where these uncertainties are classified into product, process, market and environment characteristics. If these uncertainties are not managed properly, they can have a negative impact on the AFSC performance. As a solution, collaboration has been proposed as a possible solution to minimize this impact. To conclude, a CF to manage uncertainty in a collaborative AFSC context is designed. After completing this CF, it could be used by researchers and practitioners to determine the best way to reduce the studied uncertainty sources that affect their supply chains.

6 Publication data

Figure 4 shows the first page of the article published in the IFIP Advances in Information and Communication Technology (ISSN: 1868422X).



Conceptual Framework for Managing Uncertainty in a Collaborative Agri-Food Supply Chain Context

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Abstract. Agri-food supply chains are subjected to many sources of uncertainty. If these uncertainties are not managed properly, they can have a negative impact on the agri-food supply chain (AFSC) performance, its customers, and the environment. In this sense, collaboration is proposed as a possible solution to reduce it. For that, a conceptual framework (CF) for managing uncertainty in a collaborative context is proposed. In this context, this paper seeks to answer the following research questions: What are the existing uncertainty sources in the AFSCs? Can collaboration be used to reduce the uncertainty of AFSCs? Which elements can integrate a CF for managing uncertainty in a collaborative AFSC? The CF proposal is applied to the weather source of uncertainty in order to show its applicability.

Keywords: Agri-food supply chains · Collaboration · Uncertainty · Conceptual framework

1 Introduction

The term "agri-food supply chain" (AFSC) has been defined as a set of activities necessary to bring agricultural products "from the farm to the fork" [1–4]. Therefore, both vegetable and animal-based products are produced in and distributed by AFSCs [5].

AFSCs are subjected to many sources of uncertainty. If these sources of uncertainty are not managed properly, not only the AFSC performance may be negatively affected but also the customers service levels and the environment would be also affected. In this sense, collaboration is proposed as a possible solution to reduce this negative impact. For that, a conceptual framework (CF) for managing uncertainty in a collaborative context is proposed. In this context, this paper seeks to answer the research questions (RQ):

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L.M. Camarinha-Matos et al. (Eds.): PRO-VE 2017, IFIP AICT 506, pp. 715–724, 2017.
DOI: 10.1007/978-3-319-65151-4_64

Figure 4. Publication data

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Chapter VIII:

A collaborative model to improve farmers' skill level by investments in an uncertain context

Some small farms are forced to waste a part of their harvests for not reaching the quality standards fixed by consumers. Meanwhile, modern retailers (MR) are interested in selling more quality products to increase their profits. MR could invest in a collaboration program so the small farmers could have access to better technologies and formation to increase the proportion of quality products. Unfortunately, the demand, the quantity of harvest, the proportion of harvest being of quality, and its increase with each investment are uncertain parameters. A fuzzy model considering these uncertainties is proposed to determine the investments that MR should made to maximize the profits of the supply chain in a collaboration context. A method to transform the fuzzy model into an equivalent crisp model and an interactive resolution method are applied.

Keywords: Agri-Food Supply Chain; Farmer Skills; Collaboration; Product Quality; Fuzzy Mathematical Programming.

1 Introduction

Quality standards imposed by end consumers forces some small farmers to throw away big amounts of products. This fact negatively impacts on the environment and the small farmers economies. If the proportion of quality products (QP) obtained in each harvest could be increased, this problem would be eliminated or mitigated. A high level of collaboration is necessary to ensure the quality of the agri-food products [1].

Recent papers propose models to empower small farmers through modern retailers' investments [2-8], but none of them considers the uncertainty of consumers' demand, quantity harvested, proportion of QP obtained from harvest, nor its improvement with each modern retailers' investment. If uncertainty is not considered, models will obtain solutions only applicable to situations in which all the data is known in advance. This paper aims to fill this gap by adapting the model [2] to the uncertain nature of these parameters. Methods to convert the fuzzy model into an equivalent crisp model [9] and a to select the best solution to implement in the AFSC [10] are employed.

The paper is structured as follows. Section 2 describes the problem addressed. Section 3 formulates the fuzzy model. Section 4 explains the methods used to solve the model and to select the solution to be implemented. In Section 5 these methods are applied. Conclusions and future research lines are drawn in Section 6.

2 Problem description

The AFSC is responsible for the production and distribution of vegetables. It is comprised by small farmers (SF), farmer cooperatives (FC), modern retailers (MR), and consumer markets (CM). End consumers require vegetables with a minimum quality standard, however not all vegetables harvested by SF meet these standards. In fact, the quantity of harvest and the proportion of QP obtained in each harvest are uncertain. Once harvest is made, FCs classify the products into QP and non-quality products (NQP). FCs sell QP to MR, which are responsible of the QP distribution to CM. To reduce wastes, NQP are directly sold to CM at a very low price.

To increase the AFSC profits, more demand needs to be covered with QP. For that, MR and SF can establish a collaboration program (CP). In this CP, MR would choose one or more SF and would give them funds with the objective to improve the quality of products. SF should use these funds to acquire new technologies, machineries and/or training. This will increase the proportion of QP to be harvested.

The CP sets three skill levels to which SF can belong according to the proportion of QP obtained in each harvest. When a MR funds one SF, the latter can improve the proportion of QP to be harvested and therefore SF can move up from one skill level to another. However, the improvement of the QP proportion is not known in advance to the fund application. MRs' investments cannot exceed the available budget for the CP.

A fuzzy model for deciding the investments to carry out to maximize the AFSC profits is proposed. The quantity of harvest, the proportion of it being of quality, the improvement of such proportion with each investment, and the demand are uncertain.

3 Fuzzy model formulation

The nomenclature employed to formulate the model is exposed in Table 1, where v refers to vegetables, c to the vegetables quality, i to SF, j to FC, k to MR, m to CM, t to periods of time, and FCi to the set of SFs that belong to a particular FC j. The fuzzy model based on Esteso et al. [2] can be presented as follows:

Table 1. Nomenclature

Parameters	
$\tilde{s}_i^{vt}$	Quantity of vegetable *v* harvested in SF *i* at period *t*
dij_{ij}^{vt}	Cost for distributing one kg of vegetable *v* from SF *i* to FC *j* at period *t*
r_{ij}^{vt}	Cost for producing one kg of vegetable *v* at SF *i* in FC *j* at period *t*
djk_{jk}^{vt}	Cost for distributing one kg of vegetable *v* from FC *j* to MR *k* at period *t*
dkm_{km}^{vt}	Cost for distributing one kg of vegetable *v* from MR *k* to CM *m* at period *t*
djm_{jm}^{vt}	Cost for distributing one kg of vegetable *v* from FC *j* to CM *m* at period *t*
p_{ijm}^{vct}	Price per kg of vegetable *v* with quality *c* from SF *i* through FC *j* in CM *m* at period *t*
pc^{vt}	Penalty cost for wasting or rejecting demand of one kg of vegetable *v* at period *t*
$\tilde{d}_m^{vt}$	Demand of vegetable *v* in CM *m* at period *t*
$\tilde{g}_{ij}$	Proportion of QP to be obtained at SF *i* in FC *j*
$\tilde{\beta}$	Improvement of the QP proportion with one skill level
h_{ij}^t	Cost of increasing one skill level of SF *i* in FC *j* at period *t*
L	Number of skill levels of CP
l_{ij}	Initial skill level of SF *i* at FC *j*
CPB	Budget for CP investments
Decision variables	
q_{ij}^{vct}	Quantity of vegetable *v* with quality *c* transported from SF *i* to FC *j* at period *t*
qm_{ijm}^{vct}	Quantity of vegetable *v* with quality *c* from SF *i* transported from FC *j* to CM *m* at period *t*
w_i^{vt}	Quantity of vegetable *v* wasted in SF *i* at period *t*
SL_{ij}^t	Current skill level for SF *i* in FC *j* at period *t*
qk_{ijk}^{vct}	Quantity of vegetable *v* with quality *c* from SF *i* transported from FC *j* to MR *k* at period *t*
Q_{ijkm}^{vct}	Quantity of vegetable *v* with quality *c* from SF *i* in FC *j* transported from MR *k* to CM *m* at period *t*
rd_m^{vt}	Quantity of vegetable *v* demand rejected in CM *m* at period *t*
F_{ij}^t	Number of skill levels improved in SF *i* in FC *j* at period *t*

$$\begin{aligned}\max Z = {} & \sum_v \sum_c \sum_i \sum_{j\in FC_i} \sum_m \sum_t \left(\sum_k Q_{ijkm}^{vct} + qm_{ijm}^{vct}\right) \cdot p_{ijm}^{vct} \\ & - \sum_v \sum_c \sum_i \sum_{j\in FC_i} \sum_t q_{ij}^{vct} \cdot \left(dij_{ij}^{vt} + r_{ij}^{vt}\right) \\ & - \sum_v \sum_c \sum_i \sum_{j\in FC_i} \sum_k \sum_t qk_{ijk}^{vct} \cdot djk_{jk}^{vt} \\ & - \sum_v \sum_c \sum_i \sum_{j\in FC_i} \sum_m \sum_t qm_{ijm}^{vct} \cdot djm_{jm}^{vt} \\ & - \sum_v \sum_c \sum_i \sum_{j\in FC_i} \sum_k \sum_m \sum_t Q_{ijkm}^{vct} \cdot dkm_{km}^{vt} - \sum_v \sum_t \left(\sum_i w_i^{vt} + \sum_m rd_m^{vt}\right) \\ & \cdot pc^{vt} - \sum_i \sum_{j\in FC_i} \sum_t F_{ij}^t \cdot h_{ij}^t\end{aligned} \quad (1)$$

Subject to:

$$\tilde{s}_i^{vt} = \sum_{j\in FC_i} \sum_c q_{ij}^{vct} + w_i^{vt} \qquad \forall\, i, v, t \quad (2)$$

$$q_{ij}^{vct} \le \tilde{s}_i^{vt} \cdot \left(\tilde{g}_{ij} + \tilde{\beta} \cdot SL_{ij}^t\right) \qquad \forall\, i, j \in FC_i, v, c = 1, t \quad (3)$$

$$q_{ij}^{vct} \le \tilde{s}_i^{vt} \cdot \left(1 - \tilde{g}_{ij} - \tilde{\beta} \cdot SL_{ij}^t\right) \qquad \forall\, i, j \in FC_i, v, c = 2, t \quad (4)$$

$$q_{ij}^{vct} = \sum_k qk_{ijk}^{vct} \qquad \forall\, i, j \in FC_i, v, c = 1, t \quad (5)$$

$$q_{ij}^{vct} = \sum_{m} qm_{ijm}^{vct} \quad \forall\, i, j \in FC_i, v, c = 2, t \tag{6}$$

$$qm_{ijm}^{vct} = 0 \quad \forall\, i, j \in FC_i, v, m, c = 1, t \tag{7}$$

$$qk_{ijk}^{vct} = 0 \quad \forall\, i, j \in FC_i, v, m, c = 2, t \tag{8}$$

$$qk_{ijk}^{vct} = \sum_{m} Q_{ijkm}^{vct} \quad \forall\, i, j \in FC_i, k, v, c, t \tag{9}$$

$$Q_{ijkm}^{vct} \leq qk_{ijk}^{vct} \quad \forall\, i, j \in FC_i, k, m, v, c, t \tag{10}$$

$$\sum_{i} \sum_{j \in FC_i} \sum_{c} \left(qm_{ijm}^{vct} + \sum_{k} Q_{ijkm}^{vct} \right) + rd_m^{vt} = \tilde{d}_m^{vt} \quad \forall\, m, v, t \tag{11}$$

$$\sum_{i} \sum_{j \in FC_i} \sum_{t} F_{ij}^{t} \cdot h_{ij}^{t} \leq CPB \tag{12}$$

$$\left(\tilde{g}_{ij} + \tilde{\beta} \cdot SL_{ij}^{t} \right) \leq 1 \quad \forall\, i, j \in FC_i, t \tag{13}$$

$$SL_{ij}^{t} = l_{ij} + \sum_{t_2=0}^{t} F_{ij}^{t_2} \quad \forall\, i, j \in FC_i, t \tag{14}$$

$$SL_{ij}^{t} = L \quad \forall\, i, j \in FC_i, t \tag{15}$$

$$F_{ij}^{t},\ SL_{ij}^{t} \qquad INTEGER \tag{16}$$

$$q_{ij}^{vct}, qk_{ijk}^{vct}, qm_{ijm}^{vct}, Q_{ijkm}^{vct}, w_i^{vt}, rd_m^{vt} \qquad CONTINUOUS$$

The model aims to maximize the profits obtained by the whole AFSC (1). For that, profits obtained when selling QP or NQP, as well as costs related to production, distribution, penalties for rejecting demand or wasting products, and investments in the collaboration program are considered.

The product balance at SF is set in constraint (2). Constraints (3) and (4) state the distribution of harvested product between QP and NQP respectively. Constraints (5) to (8) define the product flow between FC, MR and CM, ensuring that QP are only distributed through MR and NQP are directly served to CM. Product balance at MR is set in constraints (9) and (10). Quantity of demand being served and/or rejected is determined in constraint (11). Constraint (12) ensures that investments in the CP do not exceed the available budget for that purpose. The inability to obtain more QP than the quantity of harvested products is defined in constraint (13). Current skill level for each SF is calculated in constraint (14) and constraint (15) forces it to be lower than or equal to the maximum skill level of the program. Finally, constraint (16) sets the definition of variables.

4 Solution method

First, the methodology proposed by Jiménez et al. [9] to transform a fuzzy model into an equivalent auxiliary crisp model is employed. The auxiliary MILP crisp model is comprised by the same objective function and constraints that the fuzzy model except for constraints (2-4), (11) and (13) that are replaced by constraints (17-23). We recommend readers to consult original source [9] for more information of this approach.

$$\left[\frac{\alpha}{2} \cdot \left(\frac{s_i^{vt1} + s_i^{vt2}}{2} \right) + \left(1 - \frac{\alpha}{2} \right) \cdot \left(\frac{s_i^{vt2} + s_i^{vt3}}{2} \right) \right] \geq \sum_{j \in FC_i} \sum_{c} q_{ij}^{vct} + w_i^{vt} \quad \forall\, i, v, t \tag{17}$$

$$\left[\frac{\alpha}{2}\cdot\left(\frac{s_i^{vt2}+s_i^{vt3}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{s_i^{vt1}+s_i^{vt2}}{2}\right)\right]\leq\sum_{j\in FC_i}\sum_c q_{ij}^{vct}+w_i^{vt}\qquad\forall\, i,v,t \tag{18}$$

$$\begin{aligned}q_{ij}^{vct}\leq\left[\alpha\cdot\left(\frac{s_i^{vt1}+s_i^{vt2}}{2}\right)+(1-\alpha)\cdot\left(\frac{s_i^{vt2}+s_i^{vt3}}{2}\right)\right]\\ +\left(\left[\alpha\cdot\left(\frac{g_{ij}^1+g_{ij}^2}{2}\right)+(1-\alpha)\cdot\left(\frac{g_{ij}^2+g_{ij}^3}{2}\right)\right]\right.\\ \left.+\left[\alpha\cdot\left(\frac{\beta^1+\beta^2}{2}\right)+(1-\alpha)\cdot\left(\frac{\beta^2+\beta^3}{2}\right)\right]\cdot SL_{ij}^t\right)\qquad\forall\, i,j\in FC_i,v,c=1,t\end{aligned} \tag{19}$$

$$\begin{aligned}q_{ij}^{vct}\leq\left[\alpha\cdot\left(\frac{s_i^{vt1}+s_i^{vt2}}{2}\right)+(1-\alpha)\cdot\left(\frac{s_i^{vt2}+s_i^{vt3}}{2}\right)\right]\\ +\left(1-\left[\alpha\cdot\left(\frac{g_{ij}^1+g_{ij}^2}{2}\right)+(1-\alpha)\cdot\left(\frac{g_{ij}^2+g_{ij}^3}{2}\right)\right]\right.\\ \left.+\left[\alpha\cdot\left(\frac{\beta^1+\beta^2}{2}\right)+(1-\alpha)\cdot\left(\frac{\beta^2+\beta^3}{2}\right)\right]\cdot SL_{ij}^t\right)\qquad\forall\, i,j\in FC_i,v,c=2,t\end{aligned} \tag{20}$$

$$\left[\alpha\cdot\left(\frac{g_{ij}^2+g_{ij}^3}{2}\right)+(1-\alpha)\cdot\left(\frac{g_{ij}^1+g_{ij}^2}{2}\right)\right]+\left[\alpha\cdot\left(\frac{\beta^2+\beta^3}{2}\right)+(1-\alpha)\cdot\left(\frac{\beta^1+\beta^2}{2}\right)\right]\cdot SL_{ij}^t\leq 1\qquad\forall\, i,j\in FC_i,t \tag{21}$$

$$\sum_i\sum_{j\in FC_i}\sum_c\left(qm_{ijm}^{vct}+\sum_k Q_{ijkm}^{vct}\right)+rd_m^{vt}\leq\left[\frac{\alpha}{2}\cdot\left(\frac{d_m^{vt1}+d_m^{vt2}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{d_m^{vt2}+d_m^{vt3}}{2}\right)\right]\qquad\forall\, m,v,t \tag{22}$$

$$\sum_i\sum_{j\in FC_i}\sum_c\left(qm_{ijm}^{vct}+\sum_k Q_{ijkm}^{vct}\right)+rd_m^{vt}\geq\left[\frac{\alpha}{2}\cdot\left(\frac{d_m^{vt2}+d_m^{vt3}}{2}\right)+\left(1-\frac{\alpha}{2}\right)\cdot\left(\frac{d_m^{vt1}+d_m^{vt2}}{2}\right)\right]\qquad\forall\, m,v,t \tag{23}$$

The grade of feasibility for a particular solution is represented by α that is ranged from 0 to 1. All the fuzzy parameters follow triangular membership functions: $\tilde{s}_{ij}^v=\left(s_{ij}^{v1},s_{ij}^{v2},s_{ij}^{v3}\right)$, $\tilde{g}_{ij}=\left(g_{ij}^1,g_{ij}^2,g_{ij}^3\right)$, $\tilde{d}_m^{vt}=(d_m^{vt1},d_m^{vt2},d_m^{vt3})$, $\tilde{\beta}=(\beta^1,\beta^2,\beta^3)$.

To select the final solution to be implemented in the AFSC, an interactive resolution method proposed by Peidro et al. [10] is followed. This method is comprised by three steps: i) to solve the equivalent auxiliary crisp model for different values of α, ii) to determine the satisfaction of decision maker for each α solution, and iii) to select the α solution that better balances its feasibility and the decision maker satisfaction. For more detailed information of this approach, see [10].

5 Implementation and evaluation

The model was implemented in MPL® 5.0.6.114 and solved by using Gurobi™ 7.0.2 Solver. A Microsoft Access Database is used to import input data and save decision variables values. The computer used for solving the model has an Intel® Xeon® CPU E5-2640 v2 with two 2.00GHz processors, with an installed memory RAM of 32.0 GB and a 64-bits operating system.

The instance employed for solving the model is the extracted from [2] for the scenario with 120 periods of time and balanced demand-supply except for the fuzzy parameters. Data for s_i^{vt}, d_m^{vt}, g_{ij}, β in Esteso et al. [2] are used as the central values for the $\tilde{s}_i^{vt}$, $\tilde{d}_m^{vt}$, $\tilde{g}_{ij}$, and $\tilde{\beta}$ membership functions. The lower and upper limits for all functions are obtained by decreasing and increasing the central value by 10%.

The model has been solved for different grades of feasibility α. To evaluate each solution, two parameters have been selected: the total profits obtained by the whole AFSC

(P) and the total quantity of quality products sold (QPS). As a second step, the decision maker specifies the aspiration level G and the tolerance threshold tt that is willing to accept for each evaluation parameter. This information is employed for identifying the membership function (24) that characterizes the satisfaction of the decision maker with each parameter result.

$$\mu_{\tilde{G}}(z) = \begin{cases} 0 & if\ z \leq G - tt \\ \lambda \in [0,1] & if\ G - tt \leq z \leq G \\ 1 & if\ z \geq G \end{cases} \tag{24}$$

In this case, the decision maker indicates that the aspiration level for P is 85,000 € although he would tolerate profits from 75,000 €. Similarly, the decision maker aspirate to sell 360,000 kg of QP although he would accept to sell at least 260,000 kg of QP. Using this data, the satisfaction grade for each parameter (μ_P and μ_{QPS}) are calculated per solution (24). The global satisfaction level Λ for each α solution is determined as a weighted sum of the satisfaction of both evaluation parameters.

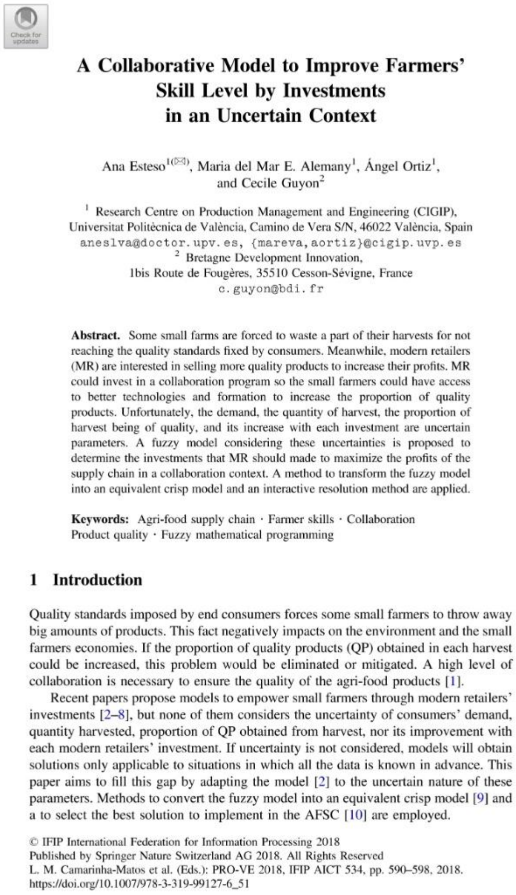
The satisfaction of a solution usually increases as the feasibility of the solution decreases. Thus, the solution that better balances the satisfaction degree and the feasibility degree will be selected for its implementation in the AFSC. To determine such balance, an acceptation index K is calculated for each solution as a weighted sum of the acceptation grade of the feasibility grade γ_α and the acceptation grade of the satisfaction grade γ_Λ. The acceptation grades for α and Λ are also determined by the membership function (24). The decision maker determines that the aspiration level for α is 0.7 although he would tolerate a α from 0.5. Similarly, he will tolerate Λ from 0.2 but sets the aspiration level for the Λ is 0.6. Results of the application of this interactive resolution method [10] are presented in Table 2.

Table 2. Interactive resolution method results.

α	$P(€)$	μ_P	$QPS(kg)$	μ_{QPS}	Λ	γ_α	γ_Λ	K
0.0	87832.02	1.00	359113.23	1.00	1.00	0.00	1.00	0.50
0.1	86829.96	1.00	364062.82	1.00	1.00	0.00	1.00	0.50
0.2	86199.03	1.00	380605.81	1.00	1.00	0.00	1.00	0.50
0.3	84296.07	0.93	365272.20	1.00	0.96	0.00	1.00	0.50
0.4	82688.78	0.77	363798.77	1.00	0.88	0.00	1.00	0.50
0.5	81186.88	0.62	364107.60	1.00	0.81	0.00	1.00	0.50
0.6	**78914.08**	**0.39**	**316925.14**	**0.57**	**0.48**	**0.50**	**0.70**	**0.60**
0.7	75452.38	0.05	276434.09	0.16	0.10	1.00	0.00	0.50
0.8	68686.48	0.00	247245.82	0.00	0.00	1.00	0.00	0.50
0.9	62100.18	0.00	234247.68	0.00	0.00	1.00	0.00	0.50
1.0	55528.60	0.00	228194.37	0.00	0.00	1.00	0.00	0.50

The solution obtained with a grade of feasibility equal to 0.6 will be implemented in the AFSC as it has the most elevated acceptation index. In this solution, the MR invest to improve the quantity of QP in 90% of famers. Some farmers receive just one fund whereas other receive up to three funds. However, only the 67% of the budget for the CP is used. With these investments, the profits of the whole AFSC increases in a one per cent and the 85% of demand is fulfilled with QP. Thus, the presented model let MR know the number of funds to give to maximize the profits of the whole AFSC, and the specific farmers to which funds need to be given.

The solved model counted with 16,441 constraints and 12,000 variables, of which 9,840 were continuous variables and 2,160 were integer variables. The optimal solution has been found for all the α scenarios with an average resolution time of 1.44 seconds.



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A Collaborative Model to Improve Farmers' Skill Level by Investments in an Uncertain Context

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Abstract. Some small farms are forced to waste a part of their harvests for not reaching the quality standards fixed by consumers. Meanwhile, modern retailers (MR) are interested in selling more quality products to increase their profits. MR could invest in a collaboration program so the small farmers could have access to better technologies and formation to increase the proportion of quality products. Unfortunately, the demand, the quantity of harvest, the proportion of harvest being of quality, and its increase with each investment are uncertain parameters. A fuzzy model considering these uncertainties is proposed to determine the investments that MR should made to maximize the profits of the supply chain in a collaboration context. A method to transform the fuzzy model into an equivalent crisp model and an interactive resolution method are applied.

Keywords: Agri-food supply chain · Farmer skills · Collaboration
Product quality · Fuzzy mathematical programming

1 Introduction

Quality standards imposed by end consumers forces some small farmers to throw away big amounts of products. This fact negatively impacts on the environment and the small farmers economies. If the proportion of quality products (QP) obtained in each harvest could be increased, this problem would be eliminated or mitigated. A high level of collaboration is necessary to ensure the quality of the agri-food products [1].

Recent papers propose models to empower small farmers through modern retailers' investments [2–8], but none of them considers the uncertainty of consumers' demand, quantity harvested, proportion of QP obtained from harvest, nor its improvement with each modern retailers' investment. If uncertainty is not considered, models will obtain solutions only applicable to situations in which all the data is known in advance. This paper aims to fill this gap by adapting the model [2] to the uncertain nature of these parameters. Methods to convert the fuzzy model into an equivalent crisp model [9] and a to select the best solution to implement in the AFSC [10] are employed.

L. M. Camarinha-Matos et al. (Eds.): PRO-VE 2018, IFIP AICT 534, pp. 590–598, 2018.
https://doi.org/10.1007/978-3-319-99127-6_51

Figure 1. Publication data.

6 Conclusions

A model for empowering small-farmers through funds obtained by modern retailers' investments is proposed. It is considered that the quantity of harvest, the proportion of QP to be obtained from harvest, the improvement of this proportion through the collaboration program and the demand are uncertain parameters. A method to transform the fuzzy model into an equivalent crisp model [9] and an interactive resolution method [10] to select the solution to implement in the AFSC are employed.

To better represent the real behavior of AFSC, the proposed model could be extended by considering more sources of uncertainty existing in AFSC (e.g. economic data) [11]. In addition, the model could be adjusted to represent some real behaviors of consumers. For example, some consumers may not be willing to buy NQP although there is not enough QP to fulfill their demand. In such cases, some demand can be rejected while some NQP can be wasted. The model could also be extended by considering the perishability aspect of the products causing the loss of a proportion of QP and NQP along the entire AFSC. Finally, more realistic managerial and regulatory factors of AFSC as well as other aspects related with the consumers' behavior could be considered to better adjust the proposed model to real AFSC behavior.

7 Publication data

Figure 1 shows the first page of the article published in the IFIP Advances in Information and Communication Technology (ISSN: 1868422X).

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Chapter IX:

How to support group decision making in horticulture: An approach based on the combination of a centralized mathematical model and a Group Decision Support System

Decision making for farms is a complex task. Farmers have to fix the price of their production, but several parameters have to be taken into account: harvesting, seeds, ground, season etc… This task is even more difficult when a group of farmers must make the decision. Generally, optimization models support the farmers to find no dominated solutions, but the problem remains difficult if they have to agree on one solution. In order to support the farmers for this complex decision we combine two approaches. We firstly generate a set of no dominated solutions thanks to a centralized optimization model. Based on this set of solution we then used a Group Decision Support System called GRUS for choosing the best solution for the group of farmers. The combined approach allows us to determine the best solution for the group in a consensual way. This combination of approaches is very innovative for the Agriculture domain.

Keywords: Centralized Optimization Model, Group Decision Support System, AgriBusiness.

1 Introduction

Fixing the price of farms products is always a hard decision. The real food prices are determined by the food supply-demand balance [1]. The price to be determined is generally function on demand but also on supply [2]. Farmers usually select which crops to plant in function of the expected benefits that will be produced. Nevertheless, if all farmers decide to plant the same crops, this would result in a decrease of the crop's sales price, turning it less profitable. Simultaneously, the supply of less profitable crops would be lower than their demand, resulting in an increase of their final sales price and, therefore, in their conversion into more profitable crops. It is then mandatory to effectively match demand and supply in the agri-food supply chain processes [3]. The remaining question is then, how can farmers decide which crops to cultivate each season to maximize their profits?

It has been proved by Stadtler [4] that one solution to this problem could be to centrally plan the planting and harvest for all the farmers while maximizing the profits of the region. However, this solution could produce inequalities in the profits obtained by farmers, leading to the unwillingness to cooperate.

In this paper, we aim to prove that making decisions for farmers using profitable information can lead to a better global decision. To achieve this objective, we used two technics: one coming from mathematical modelling and one coming from the Group Decision Support Systems. It has been proved by Stadtler [4] it is more favorable to reach an optimal solution for the whole supply chain and then, share it between its members; that implies that the profits obtained by farmers can be maximized and the inequalities between them can be reduced when centrally planning the planting and harvest of crops. A centralized optimal solution is then used in this paper as the best solution for this problem. It will be the benchmark of our study. This information is used in the group decision-making process.

We aim to show how a group engaged in a decision-making problem is influenced by the information that is available. For this purpose, we developed an experimental study. This study is based on the combination of two methodologies. We firstly generated a list of alternatives thanks to mathematical centralized model and then we used a Group Decision Support System. Our main goal is to combine two approaches to generate a satisfactory solution for a group. The paper is organized as follows. In the next section, we describe the related works on the two used technics, i.e. the GDSS and mathematical modeling for used for agriculture or horticulture purpose. The third section we present the used centralized mathematical model. In the fourth section briefly describes the used GDSS called GRoUp Support (GRUS) [5]. In the fifth section we describe the experiment decomposed by three subsections: 1. description of the used scenario, 2. presentation of the obtained alternatives by the centralized mathematical model and 3. description of the second GRUS use. In the sixth section, we analyze the obtained results and we conclude the paper in the last section.

2 Related work

2.1 Group Decision Support Systems for agriculture or horticulture

GDSS are designed to support a group engaged in a decision-making process. There are a lot of study on group creativity and Nunamaker et al. [6] reported a study that is descriptive in nature and designed to generate hypotheses that will form the basis for future research in order to facilitate group creativity. The used application domain is generally business oriented.

Some studies report the design of DSS for agriculture. Recent approaches in building decision support systems (DSS) for agriculture, and more generally for environmental problems, tend to adopt a “systemic” approach [7] focus on design issues faced during the development of a DSS to be used by technicians of the advisory service performing pest management according to an integrated production approach. These last studies report on systems designed for single user and not for a group of decision makers.

Nevertheless, decisions to make are also a question of group of persons in the Agriculture domain. For example, when the products are ready to be sent the supply chain process involves a group of stakeholders: farmers, sellers, transporters, auctions persons. There is a need to develop a process and a support for a group engaged in a decision-making process in agriculture.

2.2 Collaborative planning for agriculture or horticulture

An increasing number of recent research works recognize the necessity of implementing collaboration mechanisms among the members of fruit and vegetable SCs for achieving sustainability [8], increase revenues and customer satisfaction and reduce the negative impact of uncertainty [9]. Simatupang and Sridharan [10] distinguish three interrelated dimensions of collaboration: information sharing, decision synchronization, and incentive alignment. In the context of decision synchronization, we center on collaborative operations planning at the tactical level. Different literature reviews [11,12] conclude the shortage of research addressing collaborative planning issues in the agricultural sector and the scarce number of integrated planning models. When collaborative planning is implemented under a distributed approach, it is necessary to implement coordination mechanisms [13]. Handayati et al. [14] affirm that still, research on coordination-related issues in an agricultural supply chain is in its early development and not cover coordination of the whole supply chain. They state that studies on the coordination of processed fruits and vegetables products have been more widely studied than the coordination of fresh produce.

In their review, Handayati et al. [14] also identify mathematical modelling as one methodology used in agri-food supply chain coordination. One application can be found in the work of Mason and Villalobos [15] who propose a distributed mathematical model for the coordination of perishable crop production among small farmers and a consolidation facility using auction mechanisms. Another example is the research of Esteso et al. [9] where a collaborative mathematical model is proposed to improve farmers’ skill level by investments in an uncertain context.

Handayati et al. [14] conclude in their review that studies on supply chain coordination in agri-food sector with a particular focus on small-scale farmers is very scarce. Besides, Behzadi et al. [16] highlight as a conclusion of their review that although quantitative modeling approaches have been applied to agricultural problems for a long time, adoption of these methods for improving planning decisions in agribusiness supply chains under uncertainty is still limited. Plà et al. [17] identify as new opportunities for operations research in agri-food SC better predictive modelling of the decision-making behavior of actors in the natural resources system, multiple stakeholder decision analysis, optimization in a more complex business environment and multi-criteria decision making. Prima Dania et al. [18] affirm that when dealing with the complexity of agri-food supply chain, sustainability is one of perspectives that can be applied to maintain the competitive strategies in economic, environmental, and social aspects that is called triple bottom line. For that, multi-criteria or multi-objective decision support tools should be developed that take into account the three dimensions of sustainability. Zhu et al. [19] propose hybrid-modelling approaches to cope with the complexity of real-world Sustainable Food SC in order to obtain managerial insights.

It can be drawn as a conclusion that research on coordination issues in agricultural SCs is in its early development. Moreover, research addressing coordination among actors in the same stage specifically at the farmer stage is even more scarce. In view of this, this paper analyses how the multi-criteria group decision-making behavior of small farmers supported by GRUS DSS is affected by the optimal solution knowledge obtained from a mathematical model. Three objectives (criteria) related to the economic, social and environmental categories are considered to achieve the sustainability of the horticulture supply chain coping, therefore, with the so-called triple bottom line. Therefore, with this work we contribute to fill the scarcity of works dealing with multiple stakeholder decision analysis, coordination among small farmers, predictive modelling of their decision-making behavior and application of hybrid modelling approaches to achieve the sustainability in horticulture SCs.

3 Mathematical model for the tomato planning problem

A mixed integer linear programming model has been developed to support the centralized decision making about: the time and quantity of different types of tomato to be planted and harvested by different farmers, the quantity of each type of tomato to be transported from the farmer to each market as well as the unfulfilled demand for each type of tomato and market. The main reason for defining two different decision variables for planting and harvesting quantities stems from the fact that planting and harvesting time periods are different. Therefore, it is important to detail not only how much is harvested but also when it is harvested and put on the market in order to match the market demand at prices as high as possible. Due to the yield of fields in each period is an uncontrollable variable by farmers, it could happen that the quantity ready to be harvested per period was higher than the market demand. In this scenario, the farmer could decide not to harvest all the tomatoes that have matured in order to save additional costs. Based on this, the quantity of each type of tomato wasted at each period in each farm is derived.

The optimum value for the above decision variables in the supply chain will depend on the specific input data and the objectives pursued. As regards the input data, the following information is required: the estimation of the selling price and the market demand for the different types of tomato and for each time period, the yield for each farmer and tomato type, the density of cultivation, the total area available for planting in each farm, the activities to be carried for each type of tomato and the resources consumed, the costs of labor, waste, transporting tomatoes and unfulfilled demand. Feasible dates to plant and harvest each tomato type are also necessary.

When making the above decisions the three dimensions of SC sustainability are taking into account by the definition of three conflicting objectives that give rise to a multi-objective model. These objectives are the following:

- Economic Objective: The first objective consists in maximizing the profits of the whole supply chain calculated as the sales incomes minus the total costs. These costs contemplate those incurred due to tomatoes production in each farm and the distribution from each farm to each market.
- Environmental Objective: The second objective aims at minimizing the total waste along the Supply Chain. The maximum profit does not necessarily imply the minimum waste: a famer can decide to plant a quantity of tomatoes in some specific periods that allow him to sell some quantity of tomatoes in the season with the highest prices. But this decision, that can imply the maximum profit, can also imply more waste because of the uncontrollable yield distribution. Therefore, the profit maximization and the waste minimization can be conflicting objectives. Because the minimization of the food loss and waste is one of the environmental sustainable objectives recognized in several studies and organisms such as FAO [20], we have introduced this objective in our model.
- Social Objective: The third objective tries to minimize the unfulfilled demand along all the Supply Chain covering human requirements and increasing the customer satisfaction.

The decisions made should respect the following constraints. The acreage for each type of tomato should not exceed the available planting area in each farm. It is necessary to ensure that all tomato types are planted in all planting periods. At the same time, it is required that all farmers plant tomatoes at all planting periods to ensure the flow of products. The maximum quantity to be harvested at each period should not be higher than the yield per unit area harvested. It is not possible to transport from each farmer to each market tomato quantities higher than those harvested in the same farm for each time period. The waste in each farm is calculated as the difference between matured tomatoes and those not harvested or transported. The balance equation for calculating the unfulfilled demand for each type of tomato and market is based on the difference between the market demand for each tomato type and the total quantity of this type of tomato transported from all farmers to the market. If more product was transported to markets than the necessary one to fulfil the demand, the exceeding tomatoes were wasted. The quantity of tomatoes that was finally sold could not exceed the supply nor the demand. Constraints are defined to ensure the coherence between the integer and binary variables related to the planting decision.

4 GRoUp Support (GRUS) description

The GRUS (GRoUp Support) system is a Group Decision Support System (GDSS) in the form of a web application developed on the GRAILS framework (an open source platform). GRUS can be used for making collaborative meetings where all participants are connected to the system at the same time or at different time; in the same location (room) or in different locations. GRUS requires an internet connection and provides classical functionalities of multi-user web applications (sign in/sign out, user management, etc.). With GRUS, a user can participate to several meetings at the same time. She/he can facilitate (animate) some of them and only participate as a standard user to other ones.

The GRUS system is based on collaborative tools, the main tools are electronic brainstorming tools, clustering tools, vote tools, multi-criteria tool, etc. A collaborative process in GRUS corresponds to a sequence of collaborative tools. A collaborative meeting requires one facilitator, which can always contribute to the meeting.

A GRUS meeting is composed of two general steps: the meeting creation and the meeting achievement. In the meeting creation step, a user (usually the facilitator) defines the topic of the meeting, the facilitator, the group process, the beginning date and the duration. The facilitator can reuse an existing group process or can define a new one (see Figure 1). In the second step (meeting achievement), the facilitator manages the meeting thanks to a toolbar (see Figure 2). This toolbar is only available in the facilitator interface; other participants do not have it and just follow the group process. With this toolbar, the facilitator can: add/remove participants, go to the next collaborative tool, modify the group process and finish the meeting.

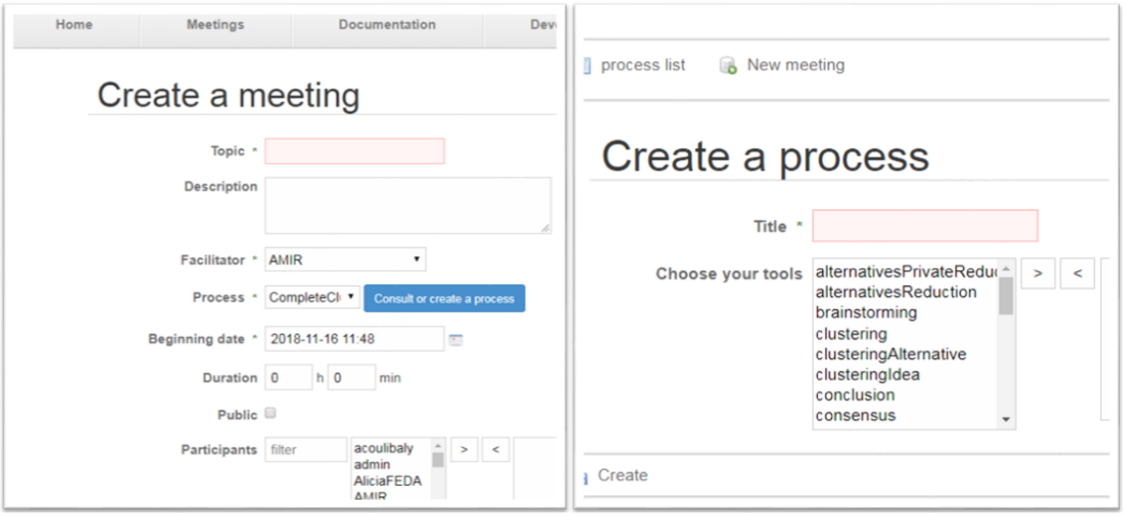


Figure 1. Meeting and process creation

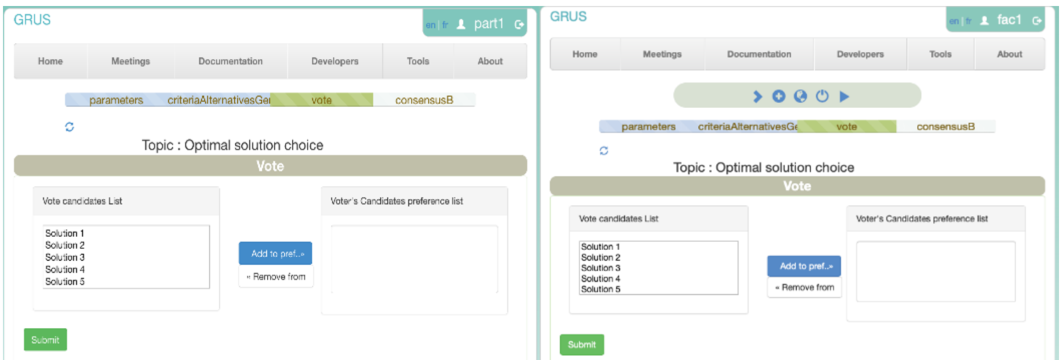


Figure 2. On the left standard participant interface, on the right facilitator interface with the toolbar

5 Experiment

5.1 Scenario/Context

For the decision-making situation under study, we consider five farmers in the region of La Plata, Buenos Aires, Argentina, with an available planting area in hectare (ha) for each farmer of 20, 18, 17, 16 and 15, respectively. Our horizon is one year divided into monthly periods. Three types of tomatoes can be planted during three different months (July, October, and January) that do not depend on the specific type. The harvesting periods are the same for each type but depends on the planting period (Table 1). These planting periods are the usual in the region of La Plata, that is one of the most important areas of tomato in greenhouse for sell in fresh in Argentina.

Table 1. Harvesting periods

	07	08	09	10	11	12	01	02	03	04	05	06
July					X	X	X	X				
October							X	X	X	X		
January									X	X	X	X

During the growth of the plant from the planted date to the harvesting date, different activities need to be made to the plant in order to ensure its correct growth. These activities are called cultural practices. Each variety requires a different number of cultural practices at different time to perform each activity. Besides, one plant of each type of tomato can be harvested different number of times during the harvesting period and requires different time to harvest per plant. Both, the cultural practices and harvest activities, are made by laborers with limited capacity and with contracting costs.

The yield of the plant per month is dependent on the planting date and the type of tomato planted. The yield represents the kilograms (kg) of tomatoes that can be harvested per month from a single plant.

Once harvested the tomatoes are distributed to two different customers: a central market and some restaurants. The cost to transport one kg of tomatoes depends on the origin (farmers) and the destination (type of customer). The demand for each type of tomato is defined based on the month and market.

The price for each type of tomato also depends on the month in which it is sold. In addition, it is considered that sale prices vary in function of the balance between supply and demand. We estimate that prices increase when the total supply from all farmers is lower than demand. Prices decreases when the supply is higher than demand. In cases where some of the demand is not fulfilled because there is not enough supply (demand > supply), the benefit to be obtained is penalized with a cost. The penalization cost is calculated as ½ of the most probable price. Another penalization cost is included for cases in which some product is wasted throughout the supply chain (demand < supply). In its current state, the experiment does not take into account the fact that side payments would be possible to make the generated solution acceptable for all group members.

5.2 Results of the centralized mathematical model

To solve the multi-objective model, we transformed it into a single-objective model by applying the ε-constraint method (21,22). In this method, one of the objectives is selected as the model's objective function, while the other objectives are considered the model's constraints. The right-hand side (RHS) of these constraints are defined by the grid points (ε_i) that are obtained by dividing the objective's ranges of values into as many equal intervals as desired. The ranges of values that each objective modelled as a constraint can assume are determined by a lexicographic optimization proposed by Mavrotas [22].

Following this method, the model is optimized for one objective. Then, the model is optimized for a second objective by constraining the value of the first objective to its optimal value. The same process is made with the third objective by constraining both the first and second objective. When repeating the process for the different combinations of the objectives, a set of solutions is provided. Dominated solutions are discarded and non-dominated solutions are analyzed to identify the best and worst values for each objective. These values define the range of values used to define the grid points. Once the model is run for the different grid points combinations, solutions obtained do not necessarily have to be equally distributed in the objective's values.

For our case study, ten values were defined for the ε_i parameter. The model was implemented using the MPL software 5.0.6.114 and the solver Gurobi 8.0.1. This provide us with ten non-dominated solutions. The detail for each non-dominated solution can be consulted in Table 2 of Appendix A. For each solution, the value of the three objective functions for the entire supply chain and for each farmer are presented. The area of land dedicated to each type of tomato in each farm are also reported. As it can be checked for the solutions reported, the profit, wastes and unfulfilled demand for each farmer varies with solutions and a solution that reports the best objective function for one farmer can be the worst for the other ones. Consequently, it is necessary a complementary procedure to decide which non-dominated solution to implement. This procedure is described in the following section.

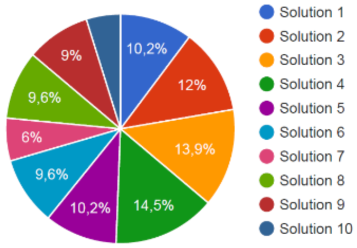
This model could also be used in a distributed way by reducing the number of farmers to one. Obtained non-dominated solutions would not be non-dominated for the whole supply chain but only for the particular farmer.

5.3 GRUS experiment using solutions generated by the centralized model

We used GRUS to rank the 10 generated alternatives. We were five decision makers playing the role of the farmers, including the facilitator as a decision maker. The adopted process was composed by three steps and was the following:

1. Alternatives Generation: The facilitator filled in the system the 10 solutions found thanks to the optimization model.
2. Vote: The five decision makers ranked the 10 solutions according to their own preferences.
3. The system then computes the final ranking for the group using the Borda [23] methodology.

The result is described in the Figure 3.



1. Solution 4: 24 points
2. Solution 3: 23 points
3. Solution 2: 20 points
4. Solutions 1 and 5: 17 points
5. Solutions 6 and 8: 16 points
6. Solution 9: 15 points
7. Solution 7: 10 points
8. Solution 10: 8 points

Figure 3. Result of the Group Ranking.

This result is given for the group of five farmers. The five farmers have the same weight (importance) for this experiment. Nevertheless, we also could choose that the importance of each farmer is linked to the number of hectares, only in Multi-Criteria processes.

We can see that on positions 4 and 5 two alternatives are ex aequo: solutions 1 and 5 for rank 4 and solutions 6 and 8 for rank 5. The best solution for the group is the one for which the five farmers have benefits and the three kinds of tomatoes are planted, that is solution number 4. Nevertheless, we can notice that it is not the solution, which generates the best profit on a global point of view.

This experiment shows that the solution obtained by a centralized optimization model that generates the highest profit, that is the solution 1 in the table of the Appendix A, is not necessarily the best one for the group of agents (humans).

6 Conclusion

In this paper, we combined two approaches in order to generate a good solution for a group of human beings. The application domain is the Agriculture. Planning a strategy of production is a difficult task in the agriculture if several constraints, like for example harvesting, ground to plant, choose the best seed, etc. are taken into account.

First of all, we generated 10 solutions thanks to a centralized optimization model. These solutions are then explained to the group of five farmers. We, in a second step, asked to the five farmers to give their own preferences on these 10 solutions. We finally used a Group Decision Support System, called GRUS, to find the final ranking for the group. This final ranking is based on the preferences given by the stakeholders. Nevertheless, the conclusions of this experiment have some limitations based on the fact the decision makers were researchers and not farmers. We still need to do the same experiment with real farmers and obtain their feedback about the process.

We show in this paper how the GDSS GRUS is helpful to generate a group decision which reduces conflicts in a group (Borda voting procedure) and how it supports to find a consensus. These results are interesting, but we need to conduct more experiments with a decentralized optimization model and compare the obtained non-dominated solutions with the solutions obtained with the GRUS system.

7 Publication data

Figure 4 shows the first page of the article published in Lecture Notes in Business Information Processing (ISSN: 8651348).

How to Support Group Decision Making in Horticulture: An Approach Based on the Combination of a Centralized Mathematical Model and a Group Decision Support System

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Abstract. Decision making for farms is a complex task. Farmers have to fix the price of their production but several parameters have to be taken into account: harvesting, seeds, ground, season etc.… This task is even more difficult when a group of farmers must make the decision. Generally, optimization models support the farmers to find no dominated solutions, but the problem remains difficult if they have to agree on one solution. In order to support the farmers for this complex decision we combine two approaches. We firstly generate a set of no dominated solutions thanks to a centralized optimization model. Based on this set of solution we then used a Group Decision Support System called GRUS for choosing the best solution for the group of farmers. The combined approach allows us to determine the best solution for the group in a consensual way. This combination of approaches is very innovative for the Agriculture domain.

Keywords: Centralized optimization model · Group decision support system · AgriBusiness

1 Introduction

Fixing the price of farms products is always a hard decision. The real food prices are determined by the food supply-demand balance [1]. The price to be determined is generally function on demand but also on supply [2]. Farmers usually select which crops to plant in function of the expected benefits that will be produced. Nevertheless, if all farmers decide to plant the same crops, this would result in a decrease of the crop's sales price, turning it less profitable. Simultaneously, the supply of less profitable crops would be lower than their demand, resulting in an increase of their final sales price and, therefore, in their conversion into more profitable crops. It is then

P. S. A. Freitas et al. (Eds.): EmC-ICDSST 2019, LNBIP 348, pp. 83–94, 2019.
https://doi.org/10.1007/978-3-030-18819-1_7

Figure 4. Publication data

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Appendix A

Table 2. Set of non-dominated optimal solutions for the mathematical programming model

Solution	Profits (€)			Tomato wastes (kg)			Unmet demand	Cherry tomato planting area (ha)			Round tomato planting area (ha)			Pear tomato planting area (ha)		
	SC	Farm		SC	Farm			SC	Farm		SC	Farm		SC	Farm	
1	148.334.625	1	24.758.476	5.316.020	1	998.708	207.317.999	35,9365	1	17,9365	21,6970	1		28,3665	1	2,0635
		2	21.892.373		2				2	18,0000		2			2	
		3	39.408.112		3				3			3	11,6278		3	5,3722
		4	32.890.933		4	4.317.312			4			4	1,5670		4	14,4330
		5	29.384.732		5				5			5	8,5023		5	6,4977
2	148.302.280	1	25.086.408	5.315.998	1	2.115.428	201.749.612	33,6292	1	15,6292	24,0044	1		28,3665	1	4,3708
		2	21.891.207		2				2	18,0000		2			2	
		3	39.407.029		3				3			3	11,6277		3	5,3723
		4	34.825.732		4	3.200.570			4			4	3,3830		4	12,6170
		5	27.091.904		5				5			5	8,9937		5	6,0063
3	148.003.481	1	25.818.920	6.417.520	1	3.958.788	195.841.392	30,4959	1	12,4959	26,0250	1	1,1288	29,4791	1	6,3753
		2	21.889.971		2				2	18,0000		2			2	
		3	39.405.833		3	12			3			3	11,6277		3	5,3723
		4	35.569.237		4	2.458.720			4			4	4,2743		4	11,7257
		5	25.319.522		5				5			5	8,9941		5	6,0059
4	146.849.751	1	26.249.394	11.193.326	1	8.734.549	189.933.239	25,6717	1	7,6717	26,0250	1	1,1293	34,3032	1	11,1989
		2	21.888.734		2				2	18,0000		2			2	
		3	39.404.693		3				3			3	11,6277		3	5,3723
		4	35.568.111		4	2.458.765			4			4	4,2743		4	11,7257
		5	23.738.819		5	12			5			5	8,9937		5	6,0063
5	145.326.260	1	23.810.235	14.017.213	1	11.558.336	184.025.050	21,0899	1	3,0900	26,3350	1	1,4393	38,5751	1	15,4707
		2	21.887.500		2	22			2	17,9999		2			2	
		3	39.403.535		3	10			3			3	11,6277		3	5,3723
		4	35.566.937		4	2.458.822			4			4	4,2743		4	11,7257
		5	24.657.938		5	24			5			5	8,9936		5	6,0064
6	142.518.888	1	23.757.449	11.213.768	1	8.754.980	178.116.854	18,7100	1	0,7100	31,3691	1	6,4735	35,9209	1	12,8165
		2	21.886.261		2				2	18,0000		2			2	
		3	39.402.357		3				3			3	11,6277		3	5,3723
		4	35.565.913		4	2.458.765			4			4	4,2743		4	11,7257
		5	21.906.908		5	23			5			5	8,9936		5	6,0064
7	136.863.913	1	15.839.594	8.410.330	1	4.466.454	172.208.666	14,4576	1		33,0921	1	7,3206	38,4503	1	12,6794
		2	22.373.720		2	1.714.531			2	14,4576		2			2	3,5424
		3	39.401.183		3				3			3	11,6277		3	5,3723
		4	35.435.025		4	2.229.345			4			4	5,1500		4	10,8500
		5	23.814.391		5				5			5	8,9938		5	6,0062
8	146.572.577	1	25.244.207	-	1		204.769.167	37,8087	1	17,6497	26,0250	1		22,1661	1	2,3503
		2	21.891.837		2				2	18,0000		2			2	
		3	39.479.894		3				3			3	11,9768		3	5,0232
		4	34.626.196		4				4	2,1591		4	3,9252		4	9,9157
		5	25.330.443		5				5			5	10,1230		5	4,8770
9	135.083.010	1	22.220.586	-	1		182.724.221	22,8945	1	2,7249	32,5065	1	3,5312	30,5989	1	13,7439
		2	21.887.918		2				2	17,9982		2	0,0016		2	0,0001
		3	39.979.961		3				3			3	7,3755		3	9,6245
		4	34.100.105		4				4	2,1714		4	8,5266		4	5,3020
		5	16.894.441		5				5			5	13,0716		5	1,9284
10	129.129.328	1	15.544.979	25.230.996	1	8.427.387	154.484.078	0,0004	1	0,0003	39,2378	1	8,9728	46,7618	1	11,0269
		2	19.246.325		2	14.995.650			2	0,0001		2	2,8857		2	15,1142
		3	39.397.689		3				3			3	11,6277		3	5,3723
		4	35.193.389		4	1.807.927			4			4	6,7579		4	9,2421
		5	19.746.946		5	32			5			5	8,9937		5	6,0063

Chapter X:

Conclusions and future research lines

This chapter presents the main conclusions of the Thesis. For that, contributions made to Operations Research literature related to operative problems with heterogeneous products in the ceramic sector, strategic problems with perishable products in agri-food sector and planning problems with perishable products in agri-food sector are identified. Understanding that heterogeneous products are those that present lack of homogeneity in subtype and subtype quantity, and perishable products are those that present lack of homogeneity in subtype, subtype quantity and subtype state. In addition, a set of future research lines for these research areas are outlines.

1 Contributions of the Thesis

This Thesis contributes to the Operations Research area, more concretely to the use of Operations Research models to support the decision-making process in the management of supply chains with heterogeneous and perishable products.

In this Thesis, it is understood that heterogeneous products are those that present lack of homogeneity in subtypes and subtype quantities. That means that products with different attributes are obtained from the same inputs and productive process whereas customers require homogeneity for these attributes. In addition, the distribution of production lots into subtypes can be heterogeneous or unbalanced. On the other hand, perishable products are those that present lack of homogeneity in subtypes, subtype quantities and subtype state. That means that, in addition to share their characteristics with heterogeneous products, they include the identification of the state of attributes that characterize each subtype, which can be static or vary along time.

Therefore, the contributions of this Thesis can be classified into three categories according to whether proposals support the decision-making process in: i) operative problems with heterogeneous products in the ceramic sector, ii) strategic problems with perishable products in the agri-food sector, or iii) planning problems with perishable products in the agri-food sector. The specific contributions to each of these categories are outlined in the following subsections. The main novelty of each chapter of this Thesis in addition to the characterization of such chapters are summarized in Table 1. On the other hand, the characteristics contemplated in operations research models included in this Thesis are displayed in Table 2.

1.1 Operative problems with heterogeneous products in the ceramic sector

Along this Thesis, two Operations Research models to support the shortage planning process in the ceramic sector are proposed. First, a multi-objective mathematical programming model to support the shortage planning problem in ceramic sectors is proposed in Chapter II. Then, a system dynamics-based simulation model to support this same process is proposed in Chapter III.

Up to now, existing models to address the shortage planning process with products with lack of homogeneity consider the existence of different homogeneous subtypes without identifying the attributes that characterize such subtypes. These models take into account that customers require the products belonging to the same order line to be homogeneous. This implies the consideration of customer orders with more than one order line, in which the same product can be ordered in different order lines. Quantities of a particular product required in different order lines do not necessarily need to be homogeneous. However, customers can require not only the homogeneity between the units belonging to the same order line, but also the homogeneity between units of products belonging to different order lines in the same order. This may occur when two or more products are going to be assembled together and usually, these products need only to be homogeneous in terms of the gage. This aspect, that has not been previously addressed in literature, has been modeled in Chapter II. For that, it is necessary not only to differentiate between homogeneous subtypes as previously made but also to differentiate between the attributes that characterize them, being it, another contribution proposed in Chapter II.

On the other hand, existing models to support shortage planning problem consider an order can only be delivered to the consumer in case it is complete. It is that all order lines are necessarily fulfilled with homogeneous products. In case one order line cannot be met with homogeneous product, the order would not be served. In addition, some models contemplate the possibility of serving the orders with delay. However, none of analyzed models considers the option of making partial deliveries by serving order lines on different dates, what can help to minimize the quantity of order lines served with delay while ensuring the homogeneity requirements. The proposed models in chapter II and III, takes into consideration both, the possibility of serving orders with delay and the possibility of making partial deliveries of complete order lines. This means that although an order line needs to be completely fulfilled in one period of time, order lines belonging to the same order could be fulfilled on different dates. In addition, on chapter II different policies regarding delivery delays and partial deliveries are analyzed for the shortage planning process. It is found out that the value for the objective function, comprised by the maximization of profits, minimization of partial deliveries and minimization of the number of order lines served with delay, improves in those policies allowing more flexibility in deliveries.

Table 1. Characteristics of Thesis chapters

Ch	Sector	Research type	Decisional level	Decision-maker	Problem	Novelty
II	Ceramic	OR model	Operative	Ceramic tile company	Shortage planning	Consideration of the homogeneity requirement among units from different order lines. Allowance of partial deliveries of order lines. Specification of the attributes that characterize each sublot. New objectives: minimization of order lines served with delay and of partial deliveries of order lines.
III	Ceramic	OR model	Operative	Ceramic tile company	Shortage planning	A simulation model to support the shortage planning problem.
IV	Agri-food	Conceptual framework State of the art	Strategic	-	SC design	Conceptual framework to develop and/or analyze mathematical programming models to design agri-food supply chains considering the specific characteristics and uncertainties inherent to the sector Up to date state of the art of mathematical programming models to design agri-food supply chains.
V	Agri-food	OR model	Strategic Tactical	Supply chain (centralized)	SC design Crop planning Packing planning Distribution planning	Determination of the impact that the products' perishability has on the design of agri-food supply chains. Joint modelling of design, planting, cultivation, harvest, laboring, packing, inventory, transport, operation, wastes and unmet demand decisions, considering the entire supply chain, multiple products, and capacity, perishability and planting constraints.
VI	Agri-food	OR model	Tactical	Supply chain (centralized) Farmer (distributed)	Crop planning Packing planning Distribution planning	To model the planting problem anticipating harvest decisions for a multi-farm fresh tomato SC in a distributed and centralized scenarios considering different collaboration situations. Modelling of novel aspects for the planting problem: harvest patterns, cultivation activities, imbalance between supply and demand, and their impact in unmet demand, inventory, and wastes. Fuzzy modelling of parameters: time required to cultivate, minimum and maximum planted area per crop, yield dependent on harvest patterns, demand, price and unmet demand and waste penalties. To obtain the real performance measures for each farmer and for the whole SC when all the individual planting and harvesting decisions per farmer from the distributed models are integrated to satisfy SC market demands
VII	Agri-food	Conceptual framework	-	-	-	Proposal of a conceptual framework that can be used to reduce the impact of uncertain factors inherent to the agri-food sector on a supply chain by using collaboration mechanisms.
VIII	Agri-food	OR model	Strategic Tactical	Supply chain (centralized)	Investments to improve the quality of products Distribution planning	A mathematical programming model to empower small farmers through funds given by retailers that considers the uncertainty inherent to the agri-food sector.
IX	Agri-food	OR model	Tactical	Farmer (collaborative)	Crop planning Packing planning Distribution planning	A tool comprised by a mathematical programming model and a group decision support system to collaboratively decide among several optimal solutions.

Table 2. Characteristics of OR models comprising this Thesis

Ch.	Modelling	Objectives	Sector's characteristics modelled	Uncertain parameters
II	Multi-objective integer linear programming model	Maximize profits Minimize order lines served with delay Minimize partial deliveries of order lines	Identification of products' gage and color Gage and color homogeneity among units of the same order line Gage homogeneity among units of different order lines Partial deliveries allowed Delayed deliveries allowed	-
III	System dynamic-based simulation model	-	Identification of homogeneous sublots Homogeneity among units of the same order line Partial deliveries allowed Delayed deliveries allowed	-
V	Mixed integer linear programming model	Maximize profits	Perishability of products Minimum freshness of products at markets Entire fresh agri-food supply chain (developed countries): farms, packing plants, warehouses, distribution centers and markets Multiple products Minimum and maximum planting area per crop due to technical reasons	-
VI	Fuzzy mixed integer linear programming model	Maximize profits	Perishability of products Entire fresh agri-food supply chain (developing countries): farms, markets Minimum and maximum planting area per crop due to technical reasons Minimum planting area per crop defined by farmers to diversify risks Consideration of cultivation activities	Yield of plants, time needed to plant, stake up, prune and apply phytosanitary products and harvest plants, time needed packed, selling price, demand, and penalty for wastes and unmet demand
VIII	Fuzzy mixed integer linear programming	Maximize profits	Quality of products Different skill levels per farm, determining the proportion of quality products to be obtained from harvest Investments of retailers to increase the skill level of farmers. Prices dependent on the products' quality	Quantity of vegetable harvested, proportion of products of high quality obtained at harvest, improvement of this proportion of quality products with one investment, and demand
IX	Multi-objective integer linear programming model Group decision support system	Maximize profits Minimize wastes Minimize unmet demand	Variability of prices in function of the demand-supply balance Entire fresh agri-food supply chain (developed countries): farms, cooperatives, retailers, consumer markets Minimum and maximum planting area per crop due to technical reasons Minimum planting area per crop defined by farmers to diversify risks Consideration of cultivation activities	-

Finally, proposal made in Chapter III is the first system dynamics-based simulation model existing to support the shortage planning process in a company with heterogeneous products, and more concretely, a ceramic tile company. This proposal obtains near-optimum results for the shortage planning process considering the homogeneity requirement between units from the same order line with a shorter resolution time than the equivalent mathematical programming models.

1.2 Strategic problems with perishable products in the agri-food sector

The perishability of agri-food products increases the complexity of managing agri-food supply chains. This makes necessary to take into consideration the perishable aspect of products when making mid-time (tactical) and short-time (operational) decisions. However, taking into account perishability in long-term (strategic) decisions can also be critical. This is the case of the supply chain design problem since the definition of the configuration of a supply chains determines the possible future tactical and operational decisions to be made.

Along this Thesis, two chapters are focused on the agri-food supply chain design problem while taking into account the perishability of products. First a conceptual framework to support the development of mathematical programming models to design agri-food supply chains in uncertain contexts was proposed in Chapter III. This conceptual framework stems from the need to consider, not only the perishability of products during the supply chain design, but also the uncertainty inherent to such perishability and to the agri-food sector. This framework can be used as a reference model to characterize the design of agri-food supply chains and their subsequent modelling. The proposed conceptual framework has been then used to perform an up-to-date review of existing Operations Research models to design agri-food supply chains. In this state of the art it was find out that there is a need of models to design agri-food supply chains taking into account: i) the entire supply chain, from farmer to market, ii) multiple products, iii) the integration of planting and harvest decisions, iv) the perishability of products, v) uncertainty on perishability.

Some of these identified gaps have been fulfilled by the mathematical programming model to design agri-food supply chains taking into account the perishability of products proposed in Chapter V. This model designs a supply chain comprised by farmers, packing plants, warehouses, distribution centers and markets, that commercializes more than one perishable product. In addition to design decisions, the model contributes to the literature by integrating tactical decisions such as the planting, cultivation and harvest of crops, laboring, inventory, wastes, packing, operation and distribution. The main contribution of this chapter is the determination of the impact that considering perishability during the agri-food supply chain design process has on the final configuration of the supply chain. Findings point out that the optimum configuration for agri-food supply chains commercializing perishable products with different shelf-life is different in some scenarios, consequently it is demonstrated the relevance of considering the products' perishability during the supply chain design. The model can also be used to design/redesign a partial fresh agri-food supply chain and to plan tactical decisions once the agri-food supply chain is already configured.

1.3 Planning problems with perishable products in the agri-food sector

Along this Thesis, three mathematical programming models to solve planning problems in agri-food supply chains with perishable products have been developed. Proposed models take into account the entire supply chain for two different contexts: fresh agri-food supply chains from developed countries in which multiple intermediaries exist between farms and markets (Chapter VIII), and fresh agri-food supply chains from developing countries in which farmers carry out all activities from planting to distribution of products to markets (Chapter VI and IX). In addition, some characteristics of the agri-food products have been included in all proposals. Perishability of products has been modelled in Chapters VI and IX while Chapter VIII includes the classification of products in function of their quality.

Two chapters of this Thesis (Chapter VI and IX) are focused on the planning of crop planning and also include other planning decisions made along the supply chain such as the distribution or packing of products. These proposals consider the perishability of products by modelling the shelf-life of products. Previous operations research models to plan the planting and harvest of crops do so in a centralized way. This means that one decision-maker takes the decisions related to all members of the supply chain. However, farms usually make these decisions by themselves. This means that there is a misalignment in the way of carrying out the crop planning in literature and reality. In this Thesis, a set of models to plan the planting and harvest of crops under different decision-making scenarios are developed for the tomato case study (Chapter VI). These models are designed for agri-food supply chains comprised by farmers and markets. Optimal results obtained with a centralized model are compared to the obtained for different decentralized models including mechanisms to reach solutions close to the centralized ones. The proposal of these decentralized models is a contribution by itself. In addition, all these models include the consideration of uncertain parameters that have not been previously modelled with fuzzy sets parameters in tomato crop planning literature such as: time needed to plant, cultivate, harvest, yield of plants, demand, prices, and waste and unmet demand penalties. Finally, the results obtained with models are evaluated with an auxiliary model concluding that a collaborative distributed approach can be used to obtain solutions near to the optimum while maintaining the independence of farmers in the decision-making process.

In Chapter IX, another collaborative tool for the crop planning problem is proposed. This tool is comprised by a centralized multi-objective mathematical programming model and a group decision support system. The included mathematical programming model plan the harvest and distribution of products for a set of farms that directly distribute products to markets. This model optimizes three objectives linked to the three-bottom line and by using the ε-constraint method, what allows to obtain multiple optimal solutions to the same problem. A mechanism to contemplate the variation of prices in function of the demand-supply balance has been included in the objective function, being it another contribution to crop planning models. The mathematical programming model is used to centrally decide several crop planning, while the group decision support system is employed to collaboratively choose between the set of optimal solutions obtained with the model. This means that farmers are involved in the decision-making process to choose the solution that benefits them the most, collaboratively obtaining just one crop planning that needs to be implemented by all supply chain members. The combination of the mathematical programming model and group decisions support system is a novel contribution to the agri-food Operations Research area.

Finally, the quality of agri-food products has been modelled in the proposal of Chapter VIII, where a mathematical programming model to plan the commercialization of agri-food products is proposed. In this model, it is considered that the quantity of product belonging to each of the qualities is uncertain as well as other parameter such as the demand and the quantity of product to be harvested. The collaboration is included in the model by considering that modern retailers can invest on farmers in order to improve the quality of products, obtaining more proportion of high-quality products.

2 Future research lines

To conclude this Thesis, four set of future research lines are identified: those related with operative problems with heterogeneous products in the ceramic sector, the ones associated to strategic problems with perishable products in the agri-food sector, those linked to planning problems with perishable products in the agri-food sector, and some related to the Operations Research modelling and resolution tools.

2.1 Operative problems with heterogeneous products in the ceramic sector

Along this Thesis, two homogeneity requirements have been modelled for the shortage planning problem: the homogeneity in all attributes for the units belonging to the same order line, and the homogeneity in gage attribute for the units belonging to different lines of the same order, which represented a novelty in this area. These homogeneity requirements could also be included in future Operations Research models for the order promising process in the ceramic sector, where simpler homogeneity requirements have been modelled until the moment.

In future models to support the order promising or shortage planning processes in the ceramic sector, customers could contemplate different homogeneity requirements in their orders. For example, one customer could require the homogeneity for units belonging to the same order line, while other could require the homogeneity between units from different order lines. For that, customers should define in their orders which order lines should be homogeneous and for which attributes.

Given the uncertain nature of the aspects producing the heterogeneity in ceramic products, a development in the uncertain modelling during the order promising and shortage planning process should be carried out. Apart from modelling the uncertainty in the distribution of a production lot into homogeneous sublots as previously made in literature, the uncertainty in the number of sublots to be obtained from a single production lot, and the uncertainty in the definition of the attributes characterising each of this sublots could be included in future models.

All these improvements in the modelling of homogeneity requirements during the order promising and shortage planning problems could also be used in the development of new simulation models, since only the homogeneity between units from the same order line has been previously modelled in this area.

Simulation models could be developed to prove different reallocation policies during the shortage planning process. This could help decision-makers to determine which reallocating policy better fits with the characteristics of their own ceramic company. The proposed model in Chapter III of this Thesis could be used as an appropriate tool for this objective by adding the policies to be analysed in its modelling. In addition, the model could be extended to adapt it to the real behaviour of ceramic companies by, for example, allowing the consideration of orders with different sizes, or demanding the same product in more than one order belonging to the same order.

2.2 Strategic problems with perishable products in the agri-food sector

The configuration of agri-food supply chains is usually defined by economically optimizing its performance. However, socio-economic aspects of the supply chains sustainability should also be taken into account during the design process. Following with this idea, objectives like the minimization of food wastes and losses generated along the supply chain or the maximization of the freshness of products that are sold at the end market could be jointly included with the economical optimization, as new objectives of Operations Research models developed to support the agri-food supply chain design process.

This Thesis shows that, when designing an agri-food supply chain for a set of products with the same shelf-life, the optimal configuration for the agri-food supply chain configuration is different depending on the shelf-life of products. However, the impact that considering the uncertainty inherent to the perishability of products in the design of agri-food supply chains is to be determined. Moreover, it should be revealed what happens in those supply chains that commercialize products with different shelf-life simultaneously (for example, products with short shelf-life like tomatoes and products with long shelf-life like potatoes) in order to determine if the perishability impacts in the design of this type of supply chains or not.

In addition, new Operations Research models dealing not only with such perishability but also with other aspects characterizing the agri-food products such as their quality, safety and heterogeneity, should also be proposed. These characteristics change over time (for example, the colour, size, flavour of a product, or the remaining shelf-life), what makes necessary to model them in multi-period models in order to reflect the characteristics behaviour. The joint modelling of the uncertainty in these products' characteristics is another gap in the literature that must be filled.

2.3 Planning problems with perishable products in the agri-food sector

Optimization operations research models addressing planning problems in the agri-food sector usually include farming decisions such as the planting, cultivating and harvest of crops. The big majority of models consider that the periods in which planting, cultivating and harvesting activities can be carried out are known. However, these periods are uncertain since they are dependent on environmental conditions which are uncontrollable among other factors.

Farming decisions are usually made by farmers in a distributed way. However, most existing operations research models plan these decisions in a centralized way. In this Thesis, it has been demonstrated that some mechanisms exist to obtain near to optimum centralized solutions with distributed models. Therefore, distributed models could be developed to provide real decision-makers with tools that better fits the real decision-making process in the agri-food sector.

In this new research area, operations research models planning the decisions of the entire supply chain, including both, the flow of fresh and processed products could be developed. In addition, new models should take into consideration crops plants with different cycle life, so that crops that allow more than one planting per year could be considered.

On the other hand, it is important to develop new planning models in which the characteristics of the agri-food products are considered. For example, it is needed to combine the classification of products into homogeneous subtypes and to consider the perishability of units comprising each subtype. The consideration of a different deterioration rate on the perishability of products belonging to the same subtype could be another future contribution to literature. Finally, the transformation of a product from one subtype in another subtype could also be considered. For example, if products are characterised by the size or colour of products, the units compounding each subtype can change over time due to its organoleptic characteristics' transformation during maturation.

2.4 Operations Research modelling and resolution tools

The Operations Research models proposed in this Thesis have been validated for small-medium instances. Most of the experiments have obtained optimum results while others have obtained near-optimum results with small GAPs. These models should be solved for bigger instances in order to determine the time needed to obtain optimal solutions. In cases in which the complexity of the model highly increases with the size of the instance, heuristics should be developed to solve the problems with big instances.

Simulation tools to support the management of ceramic and agri-food supply chains are very scarce. However this type of tools is very useful to determine the efectiveness of different policies on the performance of supply chains. In addition, near-optimum solutions can be obtained in a shorter resolution time than the needed with mathematical programming models. Therefore, new simulation tools could be developed in order to solve strategic, tactical and operational problems in agri-food and ceramic supply chains. A combination of mathematical programming models with simulation tools could be proposed.

Regarding the combination of group decision-support systems and mathematical programming models proposed in Chapter IX, the system could be improved. In this Thesis, a multi-objective mathematical programming model has been used to obtain optimal solutions among which decision makers have to grouply choose with the support of the DSS. In the future, the group DSS could be used in order to determine weights to be assigned to different objectives in a multi-objective optimization model, to define the values for the parameters used in the model, or to define by using the decision-makers expirience the membership functions for uncertain parameters modeled with fuzzy set systems. In this case, decisions made with the DSS would be input data for the optimization model and a single decision to be implemented in the supply chain would be obtained.

New models mixing the deterministic, stochastic and fuzzy nature of parameters could be developed for the agri-food sector where the values for some of the input data can be represented with probabilistic distributions while others are completely unknown. In this case, a methodology to convert a model with stochastic and fuzzy parameters into an equivalent crisp model need to be proposed in order to solve the model. In addition, it would be necessary to determine the best approach to model each of the parameters (deterministic, stochastic, fuzzy).

Appendix A:

Journal authorizations

This appendix contains the authorization from journals where the papers have been published, in order to include such publications as chapters of this Thesis.

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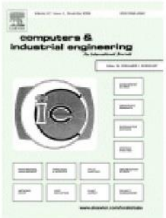

Title: A multi-objective model for inventory and planned production reassignment to committed orders with homogeneity requirements

Author: Ana Esteso,M.M.E. Alemany,Ángel Ortiz,David Peidro

Publication: Computers & Industrial Engineering

Publisher: Elsevier

Date: October 2018

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Figure 1. Copyright authorization from Computers and Industrial Engineering for Chapter II

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Title: Simulation to reallocate supply to committed orders under shortage

Author: Ana Esteso, , Josefa Mula, et al

Publication: International Journal of Production Research

Publisher: Taylor & Francis

Date: Mar 4, 2019

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Figure 2. Copyright authorization from International Journal of Production Research for Chapter III

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Title: Conceptual framework for designing agri-food supply chains under uncertainty by mathematical programming models

Author: Ana Esteso, , M.M.E. Alemany, et al

Publication: International Journal of Production Research

Publisher: Taylor & Francis

Date: Jul 3, 2018

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Author of this Springer Nature content	yes
Title	Operations research models for the management of supply chains of perishable and heterogeneous products in uncertain contexts. Application to the agri-food and ceramic sectors
Institution name	CIGIP, Universitat Politècnica de València, Valencia, Spain
Expected presentation date	Jan 2020
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