TESIS DOCTORAL

MÉTODOS Y MODELOS PARA LA PLANIFICACIÓN DE OPERACIONES EN CADENAS DE SUMINISTRO CARACTERIZADAS POR LA FALTA DE HOMOGENEIDAD EN EL PRODUCTO. APLICACIÓN AL SECTOR CERÁMICO

Presentada por:

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Valencia, Junio de 2016

A mis hijos, Javier y Lucía,

a mi marido, José Ramón,

a toda mi familia.

Métodos y modelos para la planificación de operaciones en cadenas de suministro caracterizadas por la falta de homogeneidad en el producto. Aplicación al sector cerámico.

Presentada por: D.ª María Isabel Mundi Sancho
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Resumen:

La Falta de Homogeneidad en el Producto (FHP) aparece en algunos procesos productivos que incorporan materias primas procedentes directamente de la naturaleza y/o procesos productivos con operaciones que provocan cierta heterogeneidad en las características de los productos obtenidos en relación con ciertos atributos. El resultado es la existencia de varias referencias (subtipos) del mismo producto que son diferentes en algunas características relevantes para los clientes y este aspecto se convierte en un problema cuando los clientes requieren unidades homogéneas en sus pedidos.

Las Cadenas de Suministro (CdS) en los sectores con esta problemática, como el cerámico, maderero, textil, frutícola, o cárnico, entre otros, se ven obligadas a incluir una o varias fases de clasificación a lo largo del proceso productivo cuya localización y criterios de clasificación, dependen de cada sector específico. La clasificación de un mismo ítem en varios subtipos aumenta el número de referencias a manejar y el volumen de información a procesar, lo que complica la gestión del sistema. Además, después de cada etapa de clasificación, la cantidad obtenida de cada subtipo sólo se conoce con posterioridad a su producción lo que introduce un nuevo tipo de incertidumbre inherente a la FHP: la incertidumbre en las cantidades de cada subtipo de los diferentes lotes de producción planificados. Esta incertidumbre supone un problema cuando los pedidos de los clientes deben comprometerse y servirse a partir de unidades homogéneas. El Plan Maestro constituye una de las principales entradas al proceso de comprometer pedidos por lo que, en este caso, es crucial que el Plan Maestro en su definición considere y

anticipe con la mayor exactitud posible las cantidades homogéneas de un mismo producto que estarán disponibles con objeto de servir al cliente no sólo en fecha y cantidad, sino también con la homogeneidad requerida.

En esta Tesis, se plantea como objetivo principal desarrollar métodos y modelos para la planificación maestra de operaciones en las CdS con FHP que traten su incertidumbre inherente asociada. Para conseguirlo, se caracteriza la problemática de la FHP y se identifica su impacto en el proceso de planificación de operaciones. Esta base sirve para el desarrollo de modelos de programación matemática para la planificación maestra de cadenas de suministro con FHP en contextos determinista e incierto. A través de estos modelos se define el tamaño de los lotes de producción considerando su división en cantidades homogéneas así como su incertidumbre asociada con el objetivo de servir la demanda de los clientes con unidades homogéneas. También se propone un sistema de ayuda a la toma de decisiones que facilita el planteamiento de distintos escenarios como un enfoque alternativo al tratamiento de la incertidumbre. Todos los modelos se validan en el sector cerámico. Los resultados obtenidos muestran que el margen bruto y el nivel de servicio al cliente mejoran cuando se contemplan en los modelos de planificación tanto las características debidas a la FHP como su incertidumbre asociada.

Methods and models for operation planning in supply chains characterized by lack of homogeneity in the product. Application to the ceramics sector.

Presented by: D.ª María Isabel Mundi Sancho

Directed by: PhD D.ª María del Mar Alemany Díaz

Abstract:

Lack of Homogeneity in the Product (LHP) appears in some production processes which incorporate raw materials coming directly from nature and/or production processes with operations which cause some heterogeneity in the characteristics of the outputs obtained respect to certain attributes. The result is the existence of several references (subtypes) of the same product which differ in some characteristics relevant to customers and this aspect becomes a problem when customers require homogeneous units in their orders.

Supply Chains (SC) in sectors with this problem, such as ceramic, wood, textiles, fruit or meat, among others, are forced to include one or more classification stages along the production process whose location and classification criteria depend on each specific sector. The classification of the same element in several subtypes increases the number of references and the volume of information to process, complicating management system. In addition, after each classification stage, the quantity of each subtype will only be known after the production is finished which introduces a new type of LHP inherent uncertainty: uncertainty in the quantities of each subtype in different planned lots. This uncertainty is a problem when the customer orders must commit and be served from homogeneous units. The Master Plan is one of the main inputs to the order promising process so that in this case, it is crucial that the Master Plan in its definition, considers and anticipates as accurately as possible the homogeneous quantities of the same product that will be available to serve the customer not only in time and quantity, but also the required homogeneity.

In this thesis, it is proposed as main objective to develop methods and models for master planning of operations in SC with LHP dealing with its inherent uncertainty associated. To achieve this, the problem of LHP is characterized and its impact is identified in the planning process operations. This base serves for the development of mathematical programming models for master planning of SC with LHP in deterministic and uncertain contexts. Through these models the size of the production batch is defined considering their division into homogeneous quantities and the uncertainty associated with the objective of serving the customer demand with homogeneous units. A support system to decision-making that facilitates the proposal of different scenarios as an alternative approach to the treatment of uncertainty is also proposed. All models are validated in the ceramic sector. The results show that the gross margin and the level of customer service improves when taking into account in planning models both characteristics due to the LHP and its associated uncertainty.

Mètodes i models per a la planificació d'operacions en cadenes de subministrament caracteritzades per la falta d'homogeneïtat en el producte. Aplicació al sector ceràmic.

Presentada per: Donya María Isabel Mundi Sancho

Dirigida per: Dra. Donya María del Mar Alemany Díaz

Resum:

La Falta d'Homogeneïtat en el Producte (FHP) apareix en alguns processos productius que incorporen matèries primeres procedents directament de la naturalesa i/o processos productius amb operacions que provoquen certa heterogeneïtat en les característiques dels productes obtinguts en relació amb certs atributs. El resultat és l'existència de diverses referències (subtipus) del mateix producte que són diferents en algunes característiques rellevants als clients i este aspecte es convertix en un problema quan els clients requerixen unitats homogènies en els seus comandes.

Les Cadenes de Subministrament (CdS) en els sectors amb aquesta problemàtica, com el ceràmic, fuster, tèxtil, fruitícola, o càrnic, entre uns altres, es veuen obligades a incloure una o diverses fases de classificació al llarg del procés productiu la localització del qual així com els criteris de classificació, depenen de cada sector específic. La classificació d'un mateix ítem en diversos subtipus augmenta el nombre de referències i el volum d'informació a processar, la qual cosa complica la gestió del sistema. A més, després de cada etapa de classificació, la quantitat de cada subtipus només es coneix amb posterioritat a la seua producció lo que introduïx un nou tipus d'incertesa inherent a la FHP: la incertesa en les quantitats de cada subtipus dels diferents lots de producció planificats. Esta incertesa suposa un problema quan les comandes dels clients han de comprometre's i servir-se a partir d'unitats homogènies. El Pla Mestre constituïx una de les principals entrades al procés de comprometre comandes pel que, en este cas, és crucial que el Pla Mestre en la seua definició considere i anticipe amb la major exactitud possible les quantitats homogènies d'un mateix producte que

estarán disponibles a fi de servir al client no sols en data i quantitat, sinó també amb l'homogeneïtat requerida.

En esta Tesi, es planteja com a objectiu principal desenrotllar mètodes i models per a la planificació mestra d'operacions en les CdS amb FHP que tracten la seua incertesa inherent associada. Per a aconseguir-ho, es caracteritza la problemàtica de la FHP i s'identifica el seu impacte en el procés de planificació d'operacions. Esta base servix per al desenrotllament de models de programació matemàtica per a la planificació mestra de CdS amb FHP en contextos determinista i incert. A través d'estos models es definix la grandària dels lots de producció considerant la seua divisió en quantitats homogènies així com la seua incertesa associada amb l'objectiu de servir la demanda dels clients amb unitats homogènies. També es proposa un sistema d'ajuda a la presa de decisions que facilita el plantejament de distints escenaris com un enfocament alternatiu al tractament de la incertesa. Tots els models es validen en el sector ceràmic. Els resultats obtinguts mostren que el marge brut i el nivell de servici al client milloren quan es contemplen en els models de planificació tant les característiques degudes a la FHP com la seua incertesa associada.

INDICE

CAPÍTULO I:

INTRODUCCIÓN

1. Introducción

El objetivo principal que se persigue en esta Tesis Doctoral es proporcionar métodos y modelos para la planificación maestra de operaciones en las Cadenas de Suministro (CdS) con falta de homogeneidad en el producto (FHP). La tesis se ha desarrollado en el marco del Proyecto de Investigación Nacional "Métodos y modelos para la planificación de operaciones y gestión de pedidos en cadenas de suministro caracterizadas por falta de homogeneidad en el producto (FHP)" (Ref. DPI2011-23597).

La FHP aparece en aquellos procesos productivos que incorporan materias primas procedentes directamente de la naturaleza y/o procesos productivos con operaciones que provocan una heterogeneidad en las características de los productos obtenidos, incluso cuando materiales utilizados son homogéneos. (Alemany et al., 2013). La FHP está presente en industrias como la cerámica, textil, madera, mármol, cuero curtido, marroquinería, hortofrutícola, cárnico, joyería e, incluso, el sector servicios. Las CdS de estos sectores se ven obligadas por un lado, a clasificar el producto final en diferentes subconjuntos homogéneos y por otro lado, a tratar con nuevos tipos de incertidumbre, entre los que destaca la incertidumbre en las cantidades de subconjuntos homogéneos disponibles de un mismo producto en los lotes de producción planificados. Esta incertidumbre supone un problema cuando los pedidos de los clientes deben comprometerse y servirse a partir de unidades homogéneas no pudiendo optar por mezclar cantidades heterogéneas de un mismo producto final.

Tradicionalmente, la solución a la FHP se ha abordado desde una perspectiva puramente tecnológica y no de gestión, siendo muy escasos los trabajos en el ámbito de la Dirección de Operaciones (Roma & Castán, 2009; Alarcón et al., 2011). Sin embargo, una mala gestión de la FHP puede tener efectos muy negativos para la competitividad de las CdS:

1) la existencia de la FHP provoca la atomización del inventario y la aparición de restos de producto a lo largo de la cadena que pueden quedar rápidamente obsoletos para productos con ciclos de vida cortos;
2) la incertidumbre en las cantidades homogéneas que estarán disponibles obliga a fabricar más de lo necesario, incrementando los stocks;
3) el nivel de servicio al cliente puede ser muy deficiente (incluso con unos stocks elevados) si no se dispone de información fiable sobre las cantidades disponibles de producto homogéneo reales y futuras al sistema de comprometer pedidos; y,
4) la incertidumbre inherente a la FHP provoca diferencias entre las cantidades reales homogéneas disponibles y las planificadas, aspecto que, si no se gestiona adecuadamente, puede derivar en el retraso de ciertos pedidos y el incremento de su coste asociado.

Esta investigación se orienta a dar soluciones a la problemática descrita desde una perspectiva de gestión centrándose en uno de sus procesos clave: la planificación maestra de operaciones. Las propuestas realizadas se validan a través de su aplicación a una CdS del sector cerámico. En las empresas de este sector las piezas cerámicas se clasifican al final del proceso productivo en base a los atributos de calidad, tono y calibre. El motivo es que , por motivos funcionales y estéticos, los clientes requieren homogeneidad en las unidades que forman un mismo pavimento o revestimiento cerámico con respecto a los anteriores atributos.

La Tesis está compuesta por seis capítulos de los que cuatro están configurados como artículos. Los dos restantes son el de introducción y un último capítulo con las conclusiones y futuras líneas de investigación. Esta estructura permite que cada capítulo pueda ser leído de forma individual, aunque el trabajo se considere conceptualmente una unidad. Cada artículo se presenta en la misma forma en la que se ha publicado o presentado alguna revista científica. Así, el principal objetivo de este capítulo de introducción, es exponer los objetivos de la Tesis y su conexión con cada uno de los artículos desarrollados, plantear el estado actual de las publicaciones derivadas de este trabajo y, por último, presentar la estructura de la presente investigación.

2. Objetivos de la investigación

Como se ha mencionado anteriormente, el objetivo principal que se persigue en esta investigación es proponer métodos y modelos que proporcionen soluciones en el ámbito de la gestión y, en concreto, para la planificación maestra de operaciones en las CdS con falta de homogeneidad en el producto (FHP).

Para conseguirlo, se establecen los siguientes objetivos específicos:

1. Caracterizar la problemática de la FHP en CdS de diversos sectores e identificar su impacto en el proceso de planificación de operaciones.
2. Desarrollar un modelo conceptual para el proceso de planificación de operaciones considerando las características inherentes a la FHP y su incertidumbre asociada.
3. Elaborar métodos y modelos realistas de ayuda a la toma de decisiones en la planificación de operaciones de CdS con FHP en contexto determinista e incierto.
4. Desarrollar herramientas y sistemas de ayuda a la toma de decisiones para contextos determinista e incierto y comparar ambos enfoques.
5. Validar los resultados de esta Tesis a través de su aplicación a una CdS del sector cerámico.

Para alcanzar estos objetivos propuestos, el primer paso es el análisis de la literatura existente respecto a modelos y métodos para resolver la planificación maestra de operaciones teniendo en cuenta las características particulares que plantea la FHP. Una primera versión muy reducida de este análisis se presenta en el 7th International Conference on Industrial Engineering and Industrial Management- XVII Congreso de Ingeniería de Organización, con el título "**Literature Review of Master Planning Models with Lack of Homogeneity in the Product. Characteristics under Uncertainty Context**". En este trabajo se revisan los modelos de programación matemática en contexto de incertidumbre en sectores con FHP.

Dada la limitada extensión de esta versión, se profundiza y amplia el estudio en un trabajo posterior. Se propone un marco genérico para revisar de manera unificada la literatura sobre modelos de planificación de producción en contexto incierto y con FHP. Este análisis, realizado por sectores, permite identificar similitudes entre ellos con el fin de trasladar soluciones de unos a otros. A partir de esta revisión se plantea el desarrollo de un modelo conceptual agrupando los aspectos considerados hasta el momento en el modelado de la planificación de la producción para sectores con FHP bajo un entorno incierto. El resultado de este trabajo de investigación es demasiado extenso para su publicación en forma de artículo por lo que está en proceso de reducirlo para enviarlo a una revista de prestigio científico. Aún así, aunque no sea una publicación, se ha desarrollado en el mismo formato de artículo que los demás capítulos y es el que se incluye en esta tesis como capítulo II. Con este artículo se abarcan los objetivos específicos 1 y 2, planteando el desarrollo de un modelo conceptual a partir de la revisión bibliográfica.

El objetivo específico 3, que consiste en elaborar métodos y modelos realistas de ayuda a la toma de decisiones en la planificación de operaciones de CdS con FHP en contextos determinista e incierto, se aborda en dos artículos. El contexto determinista se aborda en el artículo: "**The Effect of Modeling Qualities, Tones and Gages in Ceramic Supply Chains' Master Planning**" publicado en 2012 en la revista científica "Informatica Economică", indizada en: Directory of Open Access Journal, Cabell's Directories of Publishing Opportunities, EBSCO, ICAAP, Index Copernicus, Index of Information Systems Journals, Inspec, Open J-Gate, ProQuest Central, RePEc., Ulrich's Periodicals Directory. Además, como preámbulo al artículo y antes de su publicación, surge una ponencia en el XVI Congreso de Ingeniería de Organización en Vigo: "**Managing qualities, tones and gages of Ceramic Supply Chains through Master Planning**".

En cuanto al cumplimiento del objetivo 3, pero bajo contexto incierto, se propone el artículo titulado: “**Fuzzy sets to model master production effectively in Make to Stock companies with lack of homogeneity in the product**” publicado en la revista “Fuzzy Sets and Systems” de reconocido prestigio con un Factor de Impacto JCR de 1,986. En dicho artículo se desarrolla un modelo matemático para la planificación de operaciones con FHP en contexto incierto. Algunas ideas anteriores a la publicación del artículo se presentan en el “Book of proceedings of the 8th International Conference on Industrial Engineering and Industrial Management- XVIII Congreso de Ingeniería de Organización” (2014) con el título “**Mathematical modelling of uncertainty in non-homogeneous lots**”.

En el artículo ”**A Model-Driven Decision Support System for the Master Planning of Ceramic Supply Chains with Non-uniformity of Finished Goods**”, ya publicado en la revista científica "Studies in Informatics and Control” en 2013, con un Factor de Impacto JCR de 0,605 en ese año, se propone y detalla un Sistema de Ayuda a la Toma de Decisiones para la planificación de operaciones en Cadenas de Suministro del sector cerámico caracterizadas por la FHP. Este artículo cubre el objetivo específico 4 ya que desarrolla una herramienta de ayuda a la toma de decisiones en contextos determinista e incierto.

Por último, el objetivo específico 5 que persigue validar los resultados de esta Tesis a través de su aplicación a una Cadena de Suministro del sector cerámico, queda cubierto en los artículos 2, 3 y 4 puesto que en todos los modelos planteados se utilizan datos de este sector para evaluar el comportamiento real.

3. Estructura de la tesis

La presente Tesis Doctoral se ha estructurado como se describe a continuación.

En este capítulo primero, de Introducción, se presentan los objetivos de la tesis conectados con cada uno de los artículos desarrollados y se establece su estructura.

En el capítulo II se analizan los sectores con FHP en el ámbito de métodos y modelos de programación matemática para la planificación maestra de operaciones en contexto incierto teniendo en cuenta las particularidades propias de la FHP. Se propone un marco de análisis común para caracterizar la incertidumbre inherente a la FHP y se analizan los modelos matemáticos de planificación de la producción a través del anterior marco. A partir de esta revisión se plantea un modelo conceptual que sintetiza los resultados del estudio utilizados para modelar la incertidumbre debido a la FHP en la planificación maestra. El modelo conceptual identifica y clasifica los aspectos más relevantes, para modelar de forma conjunta las características de la FHP y su incertidumbre asociada. El resultado conduce al desarrollo del primer artículo: "**Mathematical Models for Production Planning under uncertainty in supply chains with lack of homogeneity in the product: A Review and Conceptual Model**". Los datos del artículo, actualmente en proceso de reducción, son los que aparecen a continuación.

Título:	Mathematical Models for Production Planning under uncertainty in supply chains with lack of homogeneity in the product: A Review and Conceptual Model.
Autores:	Mundi I., Alemany M.M.E., Poler R., Fuertes-Miquel, V. S

El capítulo III se centra en el desarrollo de un modelo de programación matemática para la planificación de operaciones en CdS caracterizadas por la FHP en contexto determinista. El modelo se valida en el sector cerámico donde la FHP se traduce en la división de los lotes de fabricación en sublotes homogéneos del mismo producto terminado que difieren en la calidad, el tono y el calibre. Dicho modelo se publica en el artículo: "**The Effect of Modeling Qualities, Tones and Gages in Ceramic Supply Chains' Master Planning**". Los datos de la publicación aparecen a continuación.

Título:	The Effect of Modeling Qualities, Tones and Gages in Ceramic Supply Chains' Master Planning.
Autores:	Mundi I., Alemany M.M.E., Boza A., Poler R.
Publicación:	*Informatica Economică*, 16 (3), 5.
Año:	2012
Indizada en:	Directory of Open Access Journal, Cabell's Directories of Publishing Opportunities, EBSCO, ICAAP, Index Copernicus, Index of Information Systems Journals, Inspec, Open J-Gate, ProQuest Central, RePEc., Ulrich's Periodicals Directory

En el capítulo IV se desarrolla un modelo para la planificación de operaciones en CdS con FHP bajo incertidumbre utilizando la teoría de los conjuntos difusos. En esta situación, la incertidumbre que aparece por la FHP se debe a que las propiedades de las materias primas son impredecibles y algunos factores productivos son incontrolables. La teoría de los conjuntos difusos es adecuada cuando la incertidumbre se asocia con vaguedad o imprecisión de los datos, y también con la falta de información (Inuiguchi and Ramik, 2000), por lo que en este caso es apropiada para modelar la incertidumbre inherente a la FHP. En el artículo: "**Fuzzy sets to model master production effectively in Make to Stock companies with lack of homogeneity in the product**", se propone un modelo matemático para la planificación de operaciones con FHP donde se modela la incertidumbre en las previsiones de demanda en base al tamaño de los pedidos de los clientes y también en los sublotes homogéneos planificados mediante la teoría de conjuntos difusos. El modelo se valida con datos reales del sector cerámico. Los datos de la publicación son los que aparecen a continuación.

Título:	Fuzzy sets to model master production effectively in Make to Stock companies with lack of homogeneity in the product.
Autores:	Mundi I., Alemany M.M.E., Poler R. Fuertes-Miquel, V. S
Publicación:	*Fuzzy Sets and Systems,* 293, 95–112
Año:	2016
Impact Factor:	1.986 (Correspondiente al año 2014 ya que el del 2015 no se ha publicado todavía)
Categorías:	Computer Science, Theory & Methods (Q1); Mathematics, Applied (Q1); Statistics & Probability (Q1))

El capítulo V propone y detalla un Sistema de Ayuda a la Toma de Decisiones (Decision Support System: DSS) para la planificación de operaciones en CdS del sector cerámico caracterizadas por la FHP. El DSS se basa en el modelo de programación matemática determinista planteado en el capítulo II, en el que se reflejan las características de la FHP. A través del DSS será posible tratar la incertidumbre inherente a la FHP y cualquier otro tipo de incertidumbre por medio de la generación de diferentes escenarios. El DSS se valida con datos del sector cerámico y está publicado con el título: "**A Model-Driven Decision Support System for the Master Planning of Ceramic Supply Chains with non Uniformity of Finished Goods**". Los datos de la publicación aparecen a continuación.

Título:	A Model-Driven Decision Support System for the Master Planning of Ceramic Supply Chains with Non-uniformity of Finished Goods.
Autores:	Mundi I., Alemany M.M.E., Boza A., Poler R.
Publicación:	Studies in Informatics and Control, 22 (2), 153-162.
Año:	2013
Impact Factor:	0.605
Categorías:	Automation & Control Systems (Q4) Operations Research & Management Science (Q4)

En el capítulo VI, se presentan las conclusiones de esta tesis y las futuras líneas de investigación. Por último en el capítulo VII se recoge toda la bibliografía general.

El esquema seguido para el desarrollo de la tesis se refleja a continuación en la Figura 1.1.

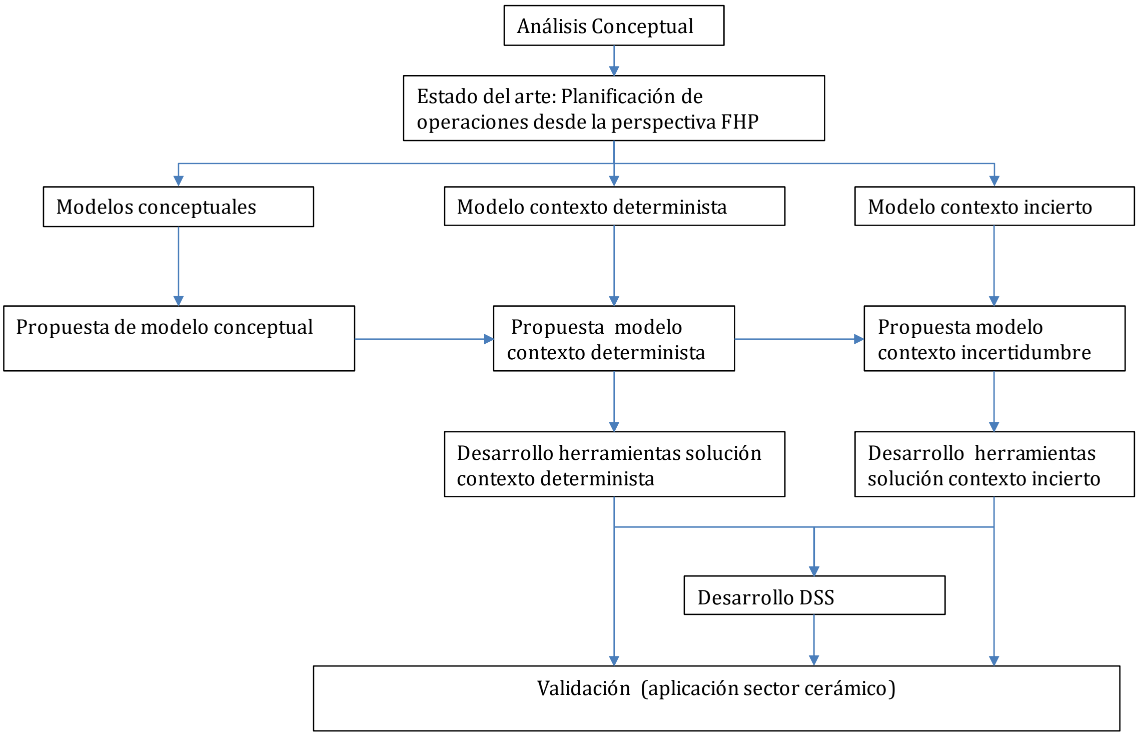

Figura 1.1. Esquema del plan de investigación (Elaboración propia)

La relación del plan de investigación con el desarrollo de los artículos se presenta en la Figura 1.2.

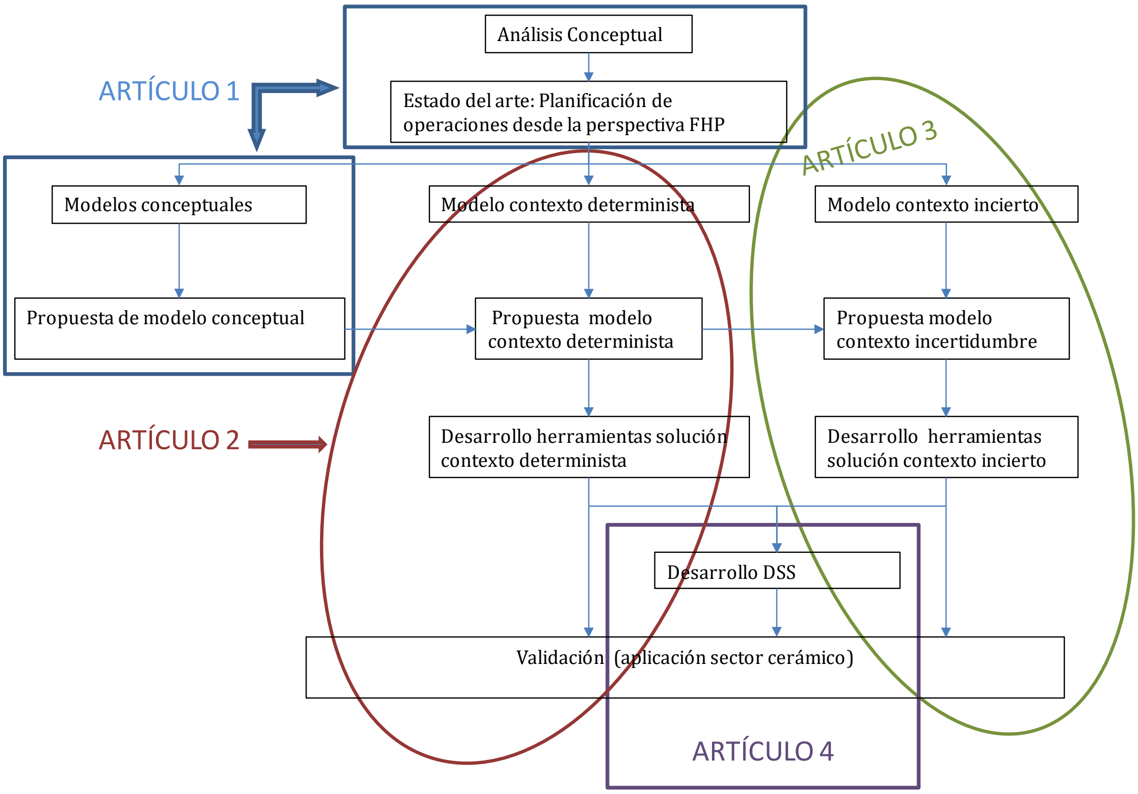

Figura 1.2. Relación del plan de investigación con los artículos desarrollados (Elaboración propia)

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CAPÍTULO II:

MATHEMATICAL MODELS FOR PRODUCTION PLANNING UNDER UNCERTAINTY IN SUPPLY CHAINS WITH LACK OF HOMOGENEITY IN THE PRODUCT: A REVIEW AND CONCEPTUAL MODEL

Abstract. Lack of homogeneity in the product (LHP) appears in some production processes that confer heterogeneity in the characteristics of the products obtained. Supply chains with this issue have to classify the product in different homogeneous subsets, whose quantity is uncertain during the production planning process. This paper proposes a generic framework for reviewing in a unified way the literature about production planning models dealing with LHP uncertainty. This analysis allows the identification of: similarities among sectors to transfer solutions between them and gaps existing in the literature for further research. The results of the review show: 1) sectors affected by LHP inherent uncertainty, 2) the inherent LHP uncertainty types modelled, and 3) the approaches for modelling LHP uncertainty most widely employed. Finally, we suggest a conceptual model reflecting the aspects to be considered when modelling the production planning in sectors with LHP in an uncertain environment.

Keywords: Planning, Optimization, Production, Uncertainty, Mathematical Modelling.

1. Introduction

Production Planning is considered one of the most important processes to balance efficiently supply and demand in terms of quantity and due dates. However, there are some situations where customers additionally require homogeneity among units of their orders. This is the case of companies that incorporate raw materials directly obtained from nature and/or production processes that cause heterogeneity in the characteristics of the items obtained, even when the used materials are homogeneous (Alemany et al., 2013). This lack of homogeneity becomes a problem when customers require homogeneity between units of finished goods as regards certain product attributes because they have to be jointly used, shown, placed or consumed (Alarcón et al., 2011). For example in the agri-food sector, fruits are non-homogeneous in terms of size, weight, colour and quality so their classification is necessary to satisfy commercial retail formats.

Alarcón et al. (2011) define the lack of homogeneity in the product as "*the absence of the homogeneity requested by the customer in the products*". In this paper, the LHP definition above is extended to "the absence of homogeneity in units of the same item at any stage of the transformation process which should be managed in order to meet customer's requirement of homogeneity in finished goods". LHP can appear in raw materials directly obtained from the nature (LHRM), and/or in intermediate products (LHI) due to the LHRM and/or operations which confer heterogeneity upon the items obtained, even when the inputs used are homogeneous. This heterogeneity can be transferred until the finished product, giving rise to lack of homogeneity in the product (LHP). This will be the case, for example, of ceramic pieces which present different qualities, tones and gages. However, there are situations in which LHRM and /or LHI can be eliminated by the appropriate management of the manufacturing process. For these cases, the finished good obtained is homogeneous and therefore there will be not Lack of Homogeneity in the product. For instance, in the petroleum industry there is LHRM, due to raw material composition. But the manufacturing process removes it, so LHP does not exist in the finished good. However, LHRM or LHI appears in this sector so we will consider it in order to assess how LHP characteristics are modelled.

LHP is present in several industries such as mining, ceramic, wood, food or textile. In companies of these sectors the planning process becomes more complex due to the following reasons (Alemany et al., 2013). 1) LHP increases the volume of references to be managed: with the aim of complying with customer requirements, these companies are obliged to include some classification stages for sorting quantities of the same item into homogeneous subsets (subtypes) based on certain attributes that are relevant to the customer. Classifying one same item into several subtypes increases the number of references and the information volume to be processed, which complicates system management. 2) LHP introduces different sources of uncertainty not present in other production planning processes that need to be categorized prior to manage them. For instance, after each classification stage, the quantity of each subtype will only be known subsequent to the production is finished and items are classified. Therefore, these companies will face a new kind of LHP inherent uncertainty: uncertainty in the quantities of each subtype in different lots. 3) Finally, homogeneity requirements of customers introduce new constraints to be taken into account to not worsen the customer service and satisfaction level.

Poor LHP management may have very negative effects on supply chains' (SC) competitiveness: (1) LHP leads to fragmented stocks, which can rapidly become obsolete for products with a short life cycle as they cannot be accumulated to be used in the same order given their heterogeneity; (2) uncertainty in the homogeneous quantities (subtypes) available of finished goods (FGs) entails having to produce more than is necessary, thus increasing stocks; and (3) the customer service level may prove deficient, even with high stock volumes if the subtypes quantities obtained during the production process and defined in the master plan do not match with those required by customers.

To avoid these undesirable effects, the consideration of the LHP characteristics in the production planning process becomes crucial. Production planning is one of the most important SC activities to short-medium term, and it is one of the main inputs to the order promising process. Thus, the master plan should consider LHP characteristics in order to provide reliable information about future available homogeneous quantities to the order promising process to comply with customer homogeneity requirements. The inclusion of LHP characteristics in Production planning leads to modelling LHP uncertainty. SCs with LHP have unique characteristics and sources of uncertainty that differ from those of other SCs. Van der Vorst (2000) defines the inherent sources of uncertainty as those originated by the natural physical characteristics of the SC, and identifies three possible causes:

1. Intrinsic features of products which, in LHP contexts, are caused by the non-homogeneity of the raw materials obtained directly from nature.
2. Technological characteristics of the processes which, in LHP contexts, are characterised by the existence of uncontrollable factors during transformation activities (such as humidity, temperature, etc.) affecting some attributes of the finished goods.

3. Characteristics of logistics actors which refer to customer preferences in some attributes of the finished products and, therefore, into subtypes (e.g. due to the eating habits of the customers).

It can be stated that LHP introduces complex aspects related to materials, transformation activities and characteristics of customer orders. These aspects confer unique characteristics with inherent uncertainty sources to SC with LHP. Although various sectors are affected by LHP and its negative consequences, there is a lack of literature dealing with LHP uncertainty in most of them. This requires analyzing how LHP is modelled at the production planning level in different sectors under a common perspective, with the aim of transferring the valid proposals made in a specific sector to others ones in which LHP characteristics have been treated in minority. We propose a common framework to analyze the literature about mathematical programming models for production planning in an uncertain environment which include some LHP characteristic. This analysis will be summarized later in a conceptual model that can be used as a reference model to practitioners and researchers.

A Conceptual Model is a set of concepts employed to represent or describe an event, object or process and can be based on the integration of different works on the same topic (Meredith, 1993). Several authors use a systematic review of the literature to propose a conceptual model which integrates the most important concepts in different field (Heckmann et al., 2015; Igarashi et al., 2013; Ramasesh and Browning, 2014; Seth et al., 2006). We suggest a conceptual model based on the literature review whose systematic analysis brings together the aspects to consider when modelling the production planning in sectors with LHP in an uncertain environment.

Thus, the main objectives of this paper are to: 1) review and discuss the LHP characteristics handled in Production planning models in a uncertainty context; 2) provide insights to deal with LHP in a unified way; 3) characterize LHP inherent uncertainty through an abstraction of the common LHP uncertain characteristics in different sectors capturing it in a conceptual model; and 4) find existing gaps in the literature for future research.

The rest of the paper is structured as follows: Section 2 exposes the research methodology followed in this paper. Section 3 describes the proposed analysis framework to review the literature. In Section 4, models are classified according to the defined analysis framework by differentiating into sectors. Section 5 suggests a conceptual model based on the analysis of literature. Finally, Section 6 reports the conclusions derived from the obtained results and future research directions.

2. Research methodology

Seuring and Müller (2008) underline that literature reviews are intended to summarize the existing research by identifying patterns which helps to identify the conceptual content of the field (Meredith, 1993) and can contribute to the development of the theory. Following the review methodology successfully used in other papers (Seuring and Müller, 2008; Alfalla-Luque et al., 2012; Igarashi et al., 2013), the first step is to define and delimit the collection of material. The following describes the general aspects (such as publications per year, etc.) and specific aspects or categories to analyze the collected material (based on search terms). Then the papers are classified and analyzed according to the defined categories. We describe collection of material and analyze the general aspects in this section and we analyze the papers from standpoint the specific categories in section 3 by defining an analysis framework.

The search process was carried out in early 2015 (the researched period is 1991-2014), using scientific-technical bibliographic databases, such as Web of Science, Science Direct, IEEE Xplore, Business Premier, Google Academic or Scopus. The search terms refer to the purpose of the review, that is, how LHP characteristics and its inherent uncertainty are integrated in a mathematical model at production planning level in different sectors. Thus, they include four categories relating to: 1) SC planning, 2) uncertainty, 3) LHP characteristics and 4) sectors with LHP.

1. **SC planning**: supply chain planning, master planning, operation planning, production planning and network planning.
2. **Uncertainty**: uncertain, stochastic, probabilistic and fuzzy.
3. **LHP characteristics**: heterogeneity, homogeneity, divergent process, rBOM (reverse bill of materials), classification, sorting, grading, scrap, waste, subtype and quality.
4. **LHP sectors**: ceramic, tile, textile, wood, lumber, marble, tanned hide, fur, leather, horticulture, agricultural, fruit, vegetable, petroleum, oil, steel, food, jewel, meat, furniture.

After excluding unrelated fields and reading the title and abstract, nearly 200 references were selected. In this first filtering step, we ruled out those articles that were focused exclusively on the strategic decision level or scheduling level, and the supply network design. Therefore, the papers selected in the first step were centred on Production planning models in an uncertain context. In a second step, only those references that modelled some LHP characteristics were chosen. As a result, 76 references were elected for this research, which also included some referenced works in the analysed papers that we considered very suitable for this paper.

We use the following category of general classification for the review of relevant literature: distribution of papers per year of publication. The papers reviewed by year are displayed in Figure 2.1. As seen, the amount of published papers increases with time; around 85% of the papers have been published over the last 10 years and nearly 70% of the works, over the last six years. It should be noted that the largest number of publications was located between 2010 and 2012.

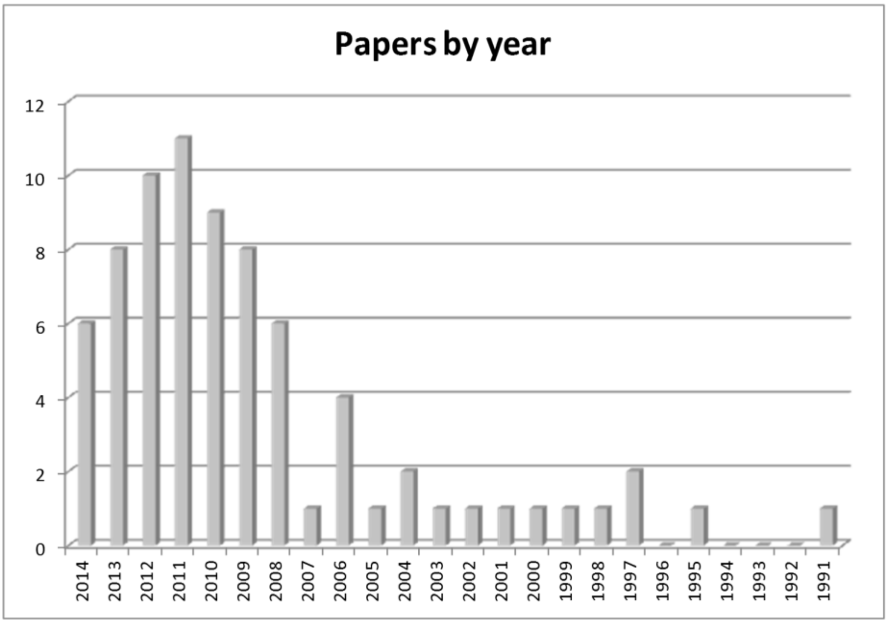

Figure 2.1. Distribution of the papers reviewed by year of publication

3. Analysis Framework

To systematically study the multiple references found in the literature, an analysis framework is proposed (Fig. 2.2) that is based on Mula et al. (2010a) and Peidro et al. (2009), but with some differences in order to reflect the LHP characteristics. Three blocks compose the analysis framework: environment, uncertainty and model. As Mula et al. (2010a), we identify the environment in which the documents analyzed are developed. However, different dimensions for the environment have been considered in our case: sector and LHP characteristics. Then, a new block named uncertainty is proposed to include those environmental characteristics modelled in an uncertainty way ("uncertainty studied") and, more especially, those related with LHP ("LHP uncertainty"). Finally as regards the modelling, and as Peidro et al. (2009), we identify the modelling approach and the uncertainty approach used by the authors. Below, each dimension of the analysis framework is described in more detail.

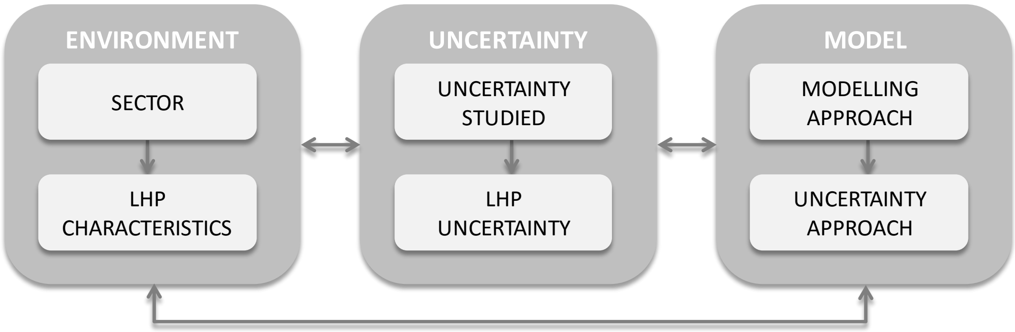

Figure 2.2. Analysis Framework for the literature review of the SC Production Planning models considering LHP inherent uncertainty types

Environment

The way the LHP occurs, depends mainly on the **sector**, **supply chain** and **product**. One of the main contributions of this review is its focus on **sectors** that provide a general framework for the transfer of valid proposals made in a specific sector to others. The analysis of the different selected references is presented by sector in order to clearly show which LHP characteristics appear and have been modelled in each one.

By identifying **LHP characteristics** that appear in each sector, it is possible to determine the most modelled ones in the literature, as well as any existing gaps for future research. In this study, we focus on those **LHP aspects** that are relevant to characterise LHP for planning purposes. Along these lines, the most important LHP aspect that influences the SC Production Planning is the existence of references of the same LHP-item, but with different characteristics (**subtypes**). When customers require that their orders are served with homogeneous units, LHP SCs are obliged to include one or more sorting stages during the production process whose location and classification criteria depend on the specific industry. For each classified item, the **classification attributes** and values that they can take should be identified. These items are sorted into **subtypes**, defined as units of the same LHP-item with the same value of the classification attributes previously defined. For example in the agricultural sector, fruits are classified according to size, colour and quality. Furthermore, subtypes for an item can have the **same or a different economic 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).

The appearance of subtypes increases the volume of information to be managed and adds new constraints and possibilities of serving customer demand, thus increasing the complexity of SC Production Planning. Therefore, the relevant **LHP characteristics** considered to analyse the selected papers are:

- **Number of Subtypes (ST)**: The total number of existing subtypes of each LHP-item depends on the attributes used in the classification stage and their possible values. For instance in the ceramics sector, each piece has to be inspected and classified, and individual models (products) are usually stored in homogeneous subgroups (subtypes) according to quality (aspect), tone (degree of colour) and calibre (thickness) (Alarcón et al., 2011; Davoli et al., 2010). The usual consideration of three quality grades, two tones and three calibres in the same model (finished good) could add up 13 different references. Finally, the number of subtypes that appears in each supplied, produced or distributed quantity can be fixed or variable, depending on the product. For instance in the ceramics sectors, the number and subtypes appearing in each lot is variable.
- **Subtype Quantity (SQ)**: It refers to the quantity obtained of each subtype between lots or in the same lot. Although the final quantity obtained of each subtype can depend on lot size, its proportion can also be fixed or variable.
- **Subtype Value (SV)**: It concerns the economic value or utility given by the buyer for the different subtypes of a LHP-item. Each subtype value can be the same or different. Different values for each subtype usually imply the existence of different qualities and/or amounts of disposable products (scrap with a null value).
- **Subtype State (SS)**: The value of classification attributes of an item in a particular subtype can be dynamic (if changes over time) or static (if not

change over time). For example, in the food sector, products can be perishable; i.e. quality (freshness) decreases over time (decay).

Based on the above definitions, it is important to note that the existence of SQ and/or SV and/or SS implies the existence of ST. However, this classification is needed to identify accurately the LHP uncertainty addressed by each paper as there may be uncertainties in SQ and/or SV and/or SS, but not in ST.

Uncertainty

In the block called "uncertainty", we capture the aspects that have been modelled under uncertainty. We distinguish two dimensions: **uncertainty considered** and **LHP uncertainty**. On the one hand, we name "**Uncertainty considered**" to the uncertainty studied by the authors in their work. If the authors include some LHP characteristic in the "Uncertainty considered", we say that this is "**LHP uncertainty**".

With the aim of analysing how the inherent uncertainties in LHP SCs have been modelled in a structured and precise way, we define "LHP inherent uncertainty types". To characterize them, we consider two dimensions: the uncertainty types and the LHP aspects. Across the board, the types of uncertainty that are considered in the literature are (Peidro et al., 2009; Graves, 2011): a) Supply uncertainty; b) Process uncertainty; and c) Demand uncertainty. The sources of inherent uncertainty in LHP SCs affect four main aspects of relevance for planning purposes, which coincide with the four LHP characteristics of Section 2.1: the number of subtypes (ST), the quantities of each subtype (SQ), the subtype value (SV) and the subtype state (SS). In this paper, we define 12 "**LHP inherent uncertainty types**", which are the result of combining the four LHP characteristics with the three main types of uncertainty (Table 2.1).

Table 2.1. LHP inherent uncertainty types

Uncertainty Types/ LHP Aspects	Supply (Sp)	Process (Pr)	Demand (Dm)
Subtypes (ST)	The number of subtypes of raw materials or components supplied (LHRM) in a specific lot or among lots is uncertain.	The number of subtypes of intermediate (LHI) or finished goods (LHP) is not known with certainty.	The subtypes of finished goods (LHP) required per customers/ markets in their orders are not known with certainty.
Subtype quantity (SQ)	Quantities per subtype of LHRM (in the same lot or among lots) are variable and not known with certainty.	Quantities per subtype of LHI or LHP (in the same lot or among lots) are variable and not known with certainty.	Quantity required for each subtype (LHP) and customer/ market is variable and not known with certainty.
Subtype value (SV)	The value (cost) of supplied subtypes can be equal or different, but it is not known with certainty (cost depends on the availability and demand of LHRM subtypes)	The value (cost) of produced LHI subtypes can be the same or different, but it is not known with certainty (cost depends on demand of LHP subtypes, the process or the final availability of subtypes)	The value (price) of subtypes (LHP) produced in the market can be equal or different but it is not known with certainty.
Subtype state (SS)	The state of the subtype (LHRM) is dynamic and its evolution is not known with certainty (perishability, obsolescence)	The state of the subtype (LHI or LHP) is dynamic and its evolution is not known with certainty (perishability, obsolescence)	The state of the subtype (LHP) is dynamic and its evolution is not known with certainty (perishability, obsolescence)

Therefore, we present the aspects that have been modelled under uncertainty in every paper in the dimension "uncertainty considered". We discuss whether this uncertainty corresponds to some LHP Characteristics. If so, we classify it in one of 12 predefined "**LHP inherent uncertainty types**". This abstraction allows comparison between sectors in a unified language, making it possible to transfer the know-how from one sector to another.

Model

In the "**model**" block, we review **how** the LHP characteristics and LHP inherent uncertainty types have been modelled. The considered **modelling approaches** are based on those of Mula et al. (2010a), but we include simulation models because some reviewed works have used this approach. Hybrid models refer to the papers that combine some of the above approaches with simulation models. The codes provided for each modelling approach are shown in Table 2.2.

Table 2.2. Modelling approach codes

Modelling approach	Code
Linear programming	LP
Non-linear programming	NLP
Multi-objective programming	MOLP
Fuzzy programming	FP
Stochastic programming	SP
Simulation models	SM
Hybrid models	HYB

Finally, the **uncertainty approach** dimension used to introduce uncertainty into the models distinguishes the following proposals to model uncertainty (Lalmazloumian and Wong, 2012):

- Distribution-based approach (**DBA**), where statistical distributions are used to model uncertainty in some parameter.
- Fuzzy-based approach (**FBA**), where uncertain parameters are considered fuzzy numbers.
- Scenario-based approach (**SBA**), in which several discrete scenarios with associated probability levels are used to describe the expected occurrence of particular outcomes.

4. Literature review

In this section, the analysis of the different selected references is presented by sector for the purpose of clearly showing which LHP characteristics appear and have been modelled in each one. Table 2.3 shows the reviewed references by sector.

As observed, the papers dealing with LHP uncertainty in the petroleum sector are the most abundant (22.4%), followed by agri-food sector (21.1%) and remanufacturing sector (19.7%). These three sectors account for over 60% of the references analyzed. Other sectors studied are mining, wood and ceramic. Sectors in which the sample is not representative (one paper) or papers in which the authors present a generic case not making reference to any specific sector are shown separately.

Table 2.3. Distribution of references per sector.

Sector	% papers by sector	Authors
Petroleum	22.4%	Al-Othman et al. (2008); Al-Shammari and Ba-Shammakh (2011); Carneiro et al. (2010); Gupta and Nan (2006); Pitty et al. (2008); Hsieh and Chiang (2001); Chunpeng and Gang (2009); Khor et al. (2008); Pongsakdi et al. (2006); Ravi and Reddy (1998); Ribas et al. (2010); Tarhan et al. (2011); Tong et al. (2012); Wang and Zheng (2010); Zhang et al. (2012); Leiras et al. (2013); Zimberg and Testuri (2006)
Agri-Food	21.1%	Radulescu et al. (2008); Ahumada et al. (2012); Miller et al. (1997); Tan and Çömden (2012); Bohle et al. (2010); Guan and Philpott (2011); Bertrand and Rutten (1999); Hovelaque et al. (2009); Paksoy et al. (2012); Begen and Puterman (2003); Randhawa and Bjarnason (1995); Schutz and Tomasgard (2011); Albornoz et al. (2014); Pauls-Worm et al. (2014); Munhoz and Morabito (2014); Bakhrankova et al. (2014);
Remanufacturing	19.7%	Aras et al. (2004); Benedito and Corominas (2010); Denizel et al. (2010); Dong et al. (2011); Gallo et al. (2009); Poles and Cheong (2009); Shi et al. (2011); Olivetti et al. (2011); Zeballos et al. (2012); Amaro and Barbosa-Povoa (2009); Loomba and Nakashima (2012); Jin et al. (2013); Phuc et al. (2013);Su and Lin (2014); Cai et al. (2014)
Wood	9.2%	Beaudoin et al. (2007); Alem and Morabito (2012); Zanjani et al. (2010a); Zanjani et al. (2010b); Zanjani et al. (2011); Zanjani et al. (2013a); Zanjani et al. (2013b)
Mine	7.9%	Rico-Ramirez et al. (2009); Chakraborty and Chandra (2005); Pendharkar (1997); Pendharkar (2013); Mitra (2009); Kumral (2004)
Ceramic	2.6%	Mundi et al. (2013); Peidro et al. (2012)
Chemical	1.3%	Kannegiesser et al. (2009)
Refinery	1.3%	Rajaram and Karmarkar (2002)
Textile	1.3%	Karabuk (2008)
Film transistor-liquid crystal display (TFT-LCD)	1.3%	Wu et al. (2010)
Semiconductor industry	1.3%	Rastogi et al. (2011)
Steel	1.3%	Rong and Lahdelma (2008)
Biorefinery	1.3%	Osmani and Zhang (2013)
Generic (Agile supply chain)	1.3%	Wang and Zhang (2006)
Generic (Process commonality)	1.3%	Wazed et al. (2011)
Generic (Supply-driven chain)	1.3%	Xiao et al. (2012)
Generic (Endogenous uncertainties)	1.3%	Gupta and Grossmann (2011)
Generic (Quality uncertain)	1.3%	Duenyas and Tsai (2000)
Generic (random yield)	1.3%	Bassok and Akella (1991)

Petroleum sector

Petroleum refinery is one of the most important industries, which comprises many different and complicated processes. Conversion of crude oil into more valuable products involves many processes, each of which is very complex. Crude oil can be blended with a wide range of other crude oils and it can be processed differently depending on the refinery configuration for a given product demand (Gupta and Nan, 2006). Crude oil can be purchased anywhere in the world and it is possible to acquire a broad variety of grades of crude oil (**ST**) in different quantities (**SQ**), which are differentiated according to the following **attributes**: **compositions, yields and characteristics.** Depending on sort of crude oil, refineries produce different **quotas of products** like gasoline, diesel, heating oil, kerosene, liquid gas, as well as bitumen or petrochemical products like ethylene and propylene. On the other hand, the oil market is a global market. The prices for raw materials (crude and semi-finished products) are highly volatile and are strongly driven by the market and its environment, but the local **price** fixing is possible based on its properties (**SV**) (Roitsch and Meyr, 2008). Thus in the petroleum sector, the appearance of subtypes (**ST**) comes about by the occurrence of different crude qualities (in supply and process) due to their compositions or characteristics, which are manifested in different quantities or yields (**SQ**), and which can also take a different value (**SV**).

The reviewed papers relating to the petroleum sector are classified in Table 2.4. As seen in Table 2.4 (column "LHP characteristic"), the only LHP characteristics discussed in the papers are the number of subtypes (**ST**) and subtype quantities (**SQ**) due to the different **compositions** of raw materials (crude oil) or intermediate products, which give rise to different **yields** (SQ) according to the transformation process involved. Although SV may appear, none distinguishes subtypes with different economic values (SV).

With regard to uncertainty in the petroleum sector, Khor (2007) classifies possible uncertainty factors in the planning of a refinery as factors exogenous (external) and endogenous factors (internal). External factors are exerted by outside agents but which impact on the process and include: availabilities of sources of crude oil supply, production demands, economic data on feedstock, intermediates, finished products, utilities and others. Endogenous factors, which arise from lack of a complete knowledge of the process, are properties of components, product/process yields, processing and blending options and machine availabilities. Al-Shammari and Ba-Shammakh (2011) also classify the uncertainty on the basis of the nature of the uncertainty source in the process:

- Model-inherent uncertainty due to inaccurate estimations of model parameters.
- Process-inherent uncertainty due to variations in process parameters.
- External uncertainty such as changes in supply availability, and also on demand and price of product.
- Discrete uncertainty such as equipment availability.

Table 2.4. Classification of the reviewed papers according to the proposed analysis framework (Petroleum).

	Environment		Uncertainty		Model	
Authors	Sector/Product	LHP Characteristic	Uncertainty considered	LHP uncertainty	Modelling approach	Uncertainty approach
Al-Othman et al. (2008)	Petroleum	Refinery throughput and production yields (ST, SQ)	Demands and prices	None	SP	SBA
Al-Shammari and Ba-Shammakh (2011)	Petroleum	Product specifications (ST, SQ)	Demands, supplies, prices, and operations costs	None	LP	SBA
Carneiro et al. (2010)	Petroleum	Composition crude oil supply (ST, SQ)	Crude oil supply, demand, product and oil prices	Sp-SQ	SP	SBA
Gupta and Nan (2006)	Petroleum	Product yields and product properties (ST, SQ)	Product prices	None	NLP	DBA
Hsieh and Chiang (2001)	Petroleum	Composition crude oil (ST, SQ)	Demand, costs	None	LP	FBA
Khor et al. (2008)	Petroleum	Product yields (ST, SQ)	prices of crude oil and saleable Products, product demands, and product yields	Pr-SQ	SP	SBA
Chunpeng and Gang (2009)	Petroleum	Properties raw material (ST, SQ)	Properties RM and demands	Sp-SQ	SP	SBA
Pitty et al. (2008)	Petroleum	Yields (ST, SQ)	Transportation delays, yields, Prices, demands and quality index of customers	Pr-SQ	SM	SBA
Pongsakdi et al. (2006)	Petroleum	Properties of intermediates (ST, SQ)	Demand and product prices	None	LP	SBA
Ravi and Reddy (1998)	Petroleum	Splitting processes (ST, SQ)	Profit Capacity	Pr-SQ	MOLP	FBA
Ribas et al. (2010)	Petroleum	Composition FG (density and viscosity) (ST, SQ)	Crude oil supply, demand, product and oil prices	Pr-SQ	SP	SBA
Tarhan et al. (2011)	Petroleum	Yield of process (ST, SQ)	Initial maximum oil, recoverable oil or gas volume, and water breakthrough time	Pr-SQ	NLP	SBA
Tong et al. (2012)	Petroleum	product yield fluctuation (ST, SQ)	Demand and yields	Pr-SQ	SP	SBA
Wang and Zheng (2010)	Petroleum	Production yields (ST, SQ)	Inventory costs, production yield and inventory level	Pr-SQ	LP	SBA
Zhang et al. (2012)	Petroleum	Sulphur content for the blended oil (ST, SQ)	Delivery delay RM	None	NLP	SBA
Leiras et al. (2013)	Petroleum	Composition FG (ST, SQ)	Demand, oil prices, and product prices	None	SP	SBA
Zimberg and Testuri (2006)	Petroleum	Composition crude oil supply (density and viscosity) (ST, SQ)	Demand of a kind of product (ifo)	Sp-SQ	SP	SBA

As shown in the "Uncertainty considered" column in Table 2.4, most of the reviewed papers analyse external uncertainties: demands and prices. The papers consider external uncertainties in operation costs, delays, inventory costs and inventory levels, to a lesser extent. Internal uncertainties in supply, yields and capacity due to composition of raw materials are also considered.

When comparing the LHP characteristics modelled (the "LHP characteristic" column) with Uncertainty considered by the authors (the "Uncertainty considered" column) in Table 2.4, the only LHP inherent uncertainty types that appear are Sp-SQ and Pr-SQ. The main LHP uncertainty type is Pr-SQ (in 7 of 17 papers); i.e., quantities per subtype (SQ) in the process (Pr) are variable and not known with certainty mainly due to the yield, but it is also due to the splitting process and to specifications of final goods. Three papers deal with Sp-SQ due to composition of raw materials (in 3 of 17 papers). Despite the "uncertainty considered" on demand appearing in some cases, none deals with LHP Inherent Uncertainty on demand because the subtypes are classified in the supply or in the process, not being the final goods differentiated by subtypes. When the LHP characteristic is not considered from the uncertainty point of view, we identified it as "none" in the "LHP uncertainty" column (in 7 of 17 papers). It is noteworthy that although the number of subtypes (ST) appears as a LHP characteristic, it is always considered constant and known with certainty, so it is not considered to be LHP uncertainty.

From the modelling approach perspective (the "modelling approach" column of Table 2.4), the most used modelling approach is Stochastic Programming (SP) (in 8 of 17 papers). Four papers suggest Linear Programming (LP) models and three of them use Non-linear Programming. There is only one paper that employs Simulation Model (SM), and another one that uses Multi-objective programming (MOLP) whose goals are defined by ratios to maximise profit and to minimise capacity. It is noted that none uses Fuzzy Programming (FP).

Furthermore from a point of view of the Uncertainty modelling (the "Uncertainty modelling" column of Table 2.4), the most widely used approach is SBA (Scenario-Based Approach) (in 14 of 17 papers). There are only two papers that use the

Fuzzy-Based Approach (FBA) and only one employs DBA. Of the 10 papers that contemplate LHP uncertainty, nine of them use SBA and only one considers FBA. No paper utilises the DBA.

Agri-food sector

Hovelaque et al. (2009) claim that the design of a specific food supply chain depends on the live nature of the products. Firms find it difficult to forecast their supplies because of the **heterogeneous quality** of raw materials (**ST**) brought about by agronomic and climatic factors. Furthermore, yields are uncertain (**SQ**) as it is very difficult to know the available raw material quantities with certainty before harvests for some (i.e., for seasonal products like potatoes), and the timing and quantity of delivery for other (i.e., milk and meat). Van Wezel et al. (2006) describe the organizational and logistical characteristics in this kind of industry as well as the way in which planning processes are usually organized. Van Donk (2000) highlights that food processing industries process natural materials which vary in **quality** and **composition** (**ST**). Therefore, processes might be uncontrollable in terms of their **yield** (SQ) or **quality of output** (SQ). Moreover, products might easily become obsolete due to limited **shelf lives of food products** (**SS**). Ahumada and Villalobos (2009) distinguish between two main types of SC in the agri-food industry. The first is the fresh agri-foods SC, which are highly **perishable** (**SS**), such as fresh fruits and vegetables, whose shelf life can be measured in days. The second is the for non-perishable agri-foods SC which can be stored for longer periods of time, such as grains, potatoes and nuts, but are perishable if not stored properly. Van Donk (2000) notes, among others, some characteristics of the food processing industry compiled from the literature:

- *Product characteristics*: The nature and source of raw material in the food processing industry often imply **variable quality (ST)**, **supply (SQ) and price** (**SV**) due to unstable yields from farmers. Raw material, semi-manufactured products and end products are **perishable** (**SS**).
- *Production process characteristics*: Processes have a variable yield and processing time. Food industries employ a **splitting process** or **divergent**

product structure (**ST**), especially in the packaging stage. At least one of the processes deals with homogeneous products.

Moreover, the variable quality of the raw material (**ST**) often leads to variations in the quantities used to produce a product (**SQ**). For example, the fat content of raw milk depends on the seasonality or the weight and size of animals which, in turn, depends on the feed provided by farmers. This variability can lead to **recipe variations** in order to keep the **quality** and **characteristics** of the finished product stable. The recipe has to provide certain flexibility in the choice of raw materials and the quantities used. In addition, the available quantities of the raw material can vary significantly over time, which implies that the price of raw materials may also vary (Entrup, 2005). Thus, in the agri-food sector, these characteristics can imply the appearance of subtypes (**ST**) based on their heterogeneous quality and composition of raw materials, variable supply (**SQ**), heterogeneous quality (**SV**) and perishability (**SS**). These features are often ignored or used as "mean" or "most likely" value for production planning (Bohle et al., 2010; Entrup, 2005). Furthermore, it is intended that the stocks stay low to avoid the risk of obsolescence (Entrup, 2005).

The reviewed papers relating to the agri-food sector are provided in Table 2.5. The main LHP characteristic modelled (the “LHP characteristic” column) is **perishability** due to the **quality** and/or **composition of raw materials** (**ST**). Guan and Philpott (2011), Ahumada et al. (2012), Begen and Puterman (2003), Randhawa and Bjarnason (1995), Miller et al. (1997), Pauls-Worm et al. (2014), Bohle et al. (2010), Albornoz et al. (2014) and Bakhrankova et al. (2014) deal with perishability (**SS**). Ahumada et al. (2012), Albornoz et al. (2014) and Bakhrankova et al. (2014) also classify raw materials according to quality based on the different categories established (**ST**), which appears in different quantities (**SQ**). Begen and Puterman (2003) and Randhawa and Bjarnason (1995) also consider composition of raw materials (**SQ**). Furthermore, Schutz and Tomasgard (2011) consider a splitting process (meat) whose yield (SQ) depends on the used rBOM (cutting patterns) and the used recipe. Tan and Çömden (2012) classify raw materials according to quality based on the different categories established (ST), which appears in different quantities (**SQ**). Bertrand and Rutten (1999), Hovelaque et al. (2009) and Munhoz and Morabito (2014) consider variations in recipes (**SQ**) in order to keep the quality and characteristics of the finished product stable. Radulescu et al. (2008) take into account both yields (**SQ**) and value (prices) (**SV**).

Uncertainty sources of the agri-food SC are categorised by Van der Vorst and Beulens (2002) as:

1. Inherent characteristics that cause more or less predictable fluctuations due to specific product and process characteristics, such as perishability, variable harvest (and variable quality) and production yields (and scrap rates).
2. Features that result in potential disturbances of system performance (for example, wrong decision rules applied, inflexible capacities or information delays).
3. Exogenous phenomena that disturb the system such as changes in markets, products, technology, competitors and governmental regulations.

As shown in the "Uncertainty considered" column of Table 2.5, the papers deal the uncertainty demand and prices (exogenous phenomena), quantities, qualities and prices in supply due to variability in raw materials and yields due to product yields (inherent characteristics). Other considered uncertainties are harvest time, packing rate, shortage cost and labour availability, which affect product perishability (inherent characteristics).

When comparing the modelled LHP characteristics (the "LHP characteristic" column) with Uncertainty considered by the authors (the "Uncertainty considered" column in Table 2.5), we identify LHP inherent uncertainty types. They mainly appear in supply and process. Six of the reviewed papers (Ahumada et al., 2012; Tan and Çömden, 2012; Bertrand and Rutten, 1999; Randhawa and Bjarnason, 1995; Albornoz et al., 2014; Munhoz and Morabito, 2014) analyse quantities per subtype in Supply (Sp-SQ) due to quality and composition of raw materials (final goods are not differentiated by subtypes). Only one paper (Miller et al., 1997) deals with perishability in supply from an uncertain standpoint (Sp-SS). Three papers consider LHP Inherent Uncertainty in the process. Radulescu et al. (2008) deal with LHP Uncertainty in the process caused by crop yields (Pr-SQ) and their values (prices) (Pr-SV), while Bohle et al. (2010) and Begen and Puterman (2003) also deal with LHP Uncertainty in the process, but that caused by perishability (Pr-SS). Bohle et al. (2010) consider uncertainty in labour availability to harvest and Begen and Puterman (2003) deal with LHP Inherent Uncertainty in the process caused by perishability (Pr-SS) due to uncertainty in the capacity to process the complete daily catch (fish quality deteriorates with time). It is noteworthy that although the number of subtypes (ST) appears as an LHP characteristic, it is always considered constant and known with certainty, so it is not considered to be LHP uncertainty. The remainder papers do not consider any LHP characteristic from the uncertain standpoint ("none" in the LHP-uncertainty column). Although in some cases "uncertainty considered" appears on demand, none deals with LHP Inherent Uncertainty on demand because final goods are not differentiated by subtypes. It is noteworthy that although the number of subtypes (ST) appears as an LHP characteristic, it is always considered constant and known with certainty, so it is not considered LHP uncertainty.

As seen in Table 2.5 (the “Modelling approach” column), different approaches are adopted, of which Stochastic Programming (SP) (in 7 of 16 papers) is mostly used, followed by Linear programming (LP) (in 4 of 16 papers). There is one paper that employs Fuzzy Programming (FP), another uses Non-linear Programming (NLP) and another work considers Multi-objective programming (MOLP) whose objectives are average loss minimisation, expected return maximisation, financial risk minimisation and loss-return-risk trade-off. Hybrid Models (HYB) are used in two works (2 of 16 papers). These two last papers use Linear programming (LP) and Non-linear Programming (NLP), respectively, in combination with Simulation Models (SM).

Finally from a standpoint Uncertainty modelling (the "Uncertainty approach" column of Table 2.5), most papers use SBA (Scenario-Based Approach). The Distribution-Based Approach (DBA) is only used in three papers, and two others employ the Fuzzy-Based Approach (FBA).

Table 2.5. Classification of the reviewed papers according to the proposed analysis framework (Agri-food sector).

	Environment		Uncertainty		Model	
Authors	Sector/ Product	LHP Characteristic	Uncertainty considered	LHP uncertainty	Modelling approach	Uncertainty approach
Radulescu et al. (2008)	Crops	Yields and market prices (ST, SQ, SV)	Yields and market prices	Pr-SQ Pr-SV	MOLP	DBA
Ahumada et al. (2012)	Fresh products	Quality products, crop yields, perishable product (ST, SQ, SS)	Crop prices and crop yields	Sp-SQ	SP	SBA
Miller et al. (1997)	Tomato	Perishable product (ST, SS)	Harvest time, tomato packing rate, and shortage cost.	Sp-SS	LP	FBA
Tan and Çömden (2012)	Tomato	Yield harvest (ST, SQ)	Yield, demand and harvest	Sp-SQ	NLP	DBA
Bohle et al. (2010)	Wine grape	Quality loss function (ST, SS)	Labour availability	Pr-SS	SP	SBA
Guan and Philpott (2011)	Dairy	Perishable product (ST, SS)	Milk supply	None	SP	SBA
Bertrand and Rutten (1999)	Dairy	Raw materials features in finish goods (ST, SQ)	Demand Raw materials quality	Sp-SQ	SP	SBA
Hovelaque et al. (2009)	Dairy	Raw materials features (ST, SQ)	Product prices	None	HYB	SBA
Begen and Puterman (2003)	Fish	Types, grades, perishability (ST, SQ, SS)	Capacities	Pr-SS	LP	SBA
Randhawa and Bjarnason (1995)	Fish	Composition of raw materials, freshness (ST, SQ, SS)	Quantity and composition of raw materials	Sp-SQ	HYB	SBA
Schutz and Tomasgard (2011)	Meat	Splitting process (ST, SQ)	Demand	None	SP	SBA
Paksoy et al. (2012)	Oil	Waste oil (wax) to recycling (ST, SQ)	Capacities and demands	None	FP	FBA
Albornoz et al. (2014)	Meat	Raw materials quality and perishability (ST, SQ, SS)	Raw materials quality	Sp-SQ	LP	SBA
Bakhrankova et al. (2014)	Fish	Raw materials quality and perishability (ST, SQ, SS)	Market prices and amount of raw material incoming	None	SP	SBA
Pauls-Worm et al. (2014)	Food	Perishability (ST, SS)	Demand	None	SP	DBA
Munhoz and Morabito (2014)	Orange juice	Raw materials features (acidity) (ST, SQ)	Base acidity	Sp-SQ	LP	SBA

Remanufacturing

Remanufacturing sector includes closed-loop SCs, reverse SCs and remanufacturing with component recovery. According to Junior and Filho (2012), remanufacturing is the process that recovers value from used products by replacing components or reprocessing used parts in order to confer the product a like-new condition. Production planning and control activities in remanufacturing can differ vastly from those in traditional manufacturing. Remanufacturing activity brings many challenges to the production and inventory planning problem (Shi et al., 2011). Operational issues in remanufacturing are focused on reverse logistics, testing, sorting, disposition, disassembling, repairing and remanufacturing (Loomba and Nakashima, 2012). In a process environment, French and LaForge (2006) highlight that returned products can be obsolete or have exceeded their shelf-life (**SS**). The most important LHP characteristic in this sector is **quality of returns:** when returns arrive, they are subject to quality inspection and are classified and grouped into several quality grades. The quality of the returns is usually described in terms of different categories as a result of the grading process carried out. For example, it might be assumed that returns are classified into three different grades (good, average and bad) or into two different grades (recovery and disposal). In addition, the different levels of quality defined can involve a distinct cost or value (SV). Thus in the remanufacturing sector, the appearance of subtypes (**ST**) occurs due to the occurrence of different qualities which are evidenced as different amounts (**SQ**) or states (**SS**) which may also have a distinct value (**SV**).

The reviewed papers relating to the remanufacturing sector are classified in Table 2.6. The main LHP characteristics modelled (the "LHP characteristic" column) is **quality of returns** due to the necessary classification of returned items. This classification is based on different categories (**ST**), which appears in different quantities (**SQ**). Olivetti et al. (2011) are the only authors who have classified the raw materials obtained from scrap metal into subtypes (**ST**) based on their composition instead of their quality. Only one paper (Zeballos et al., 2012) distinguishes quality levels of returns with different economic values (**SV**). Although SS may appear, none considers it in the model.

As regards uncertainty, the majority of remanufacturing firms use simple averages to calculate material recovery rates. Nevertheless, the variability in returned product quality remains as a significant problem (Aras et al., 2004). Guide (2000) states that the major complicating characteristics are:

- **Uncertain timing** and **quantity of returns**, because the time and amount of products returned are factors that cannot be controlled by remanufacturers. The product returns process is highly uncertain as far as timing is concerned (when cores which are defined as products not yet remanufactured, are available for remanufacturing) and quantity (how many cores are available). The problem of core acquisition requires core availability to be forecast for planning purposes for both quantities available and timing of availability.
- Uncertainty in the **materials recovered from returned items** reflects that two identical end items returned may yield a very different set of remanufacturable parts. Depending on their condition, parts may be reused in a variety of applications. This uncertainty makes inventory planning and control, and supply more problematic.
- **Disassembly of returned products** because products are disassembled at the part level, assessed in terms of recovery, and acceptable parts are then routed to the necessary operations. Parts that do not meet the minimum remanufacturing standards may be used for spares, or sold for scrap. This disassembly requires a classification stage.
- **Stochastic routings** and **highly variable processing times** for remanufacturing operations due to the uncertain condition of the units returned.

As shown in the "Uncertainty considered" column of Table 2.6, most of the reviewed papers analyse uncertainty in any of the major complicating characteristics indicated by Guide (2000): quantity and quality of returns, arriving times and process time of returns. Likewise, some authors deal with uncertain demand (Aras et al., 2004; Gallo et al., 2009; Shi et al., 2011; Amaro and Barbosa-Povoa, 2009; Loomba and Nakashima, 2012; Jin et al., 2013; Phuc et al., 2013). Only Amaro and Barbosa-Povoa (2009) consider uncertainty in finished goods prices, and only Olivetti et al. (2011) model the uncertainty of raw materials composition (scrap metal), which should be used to generate finished goods with certain quality specifications.

When comparing the “LHP characteristic” column and the "Uncertainty considered” column in Table 2.6, it is possible to identify the LHP uncertainty types modelled in some papers. The only LHP inherent uncertainty type modelled in this sector is **Sp-SQ** (uncertain variability of quantities per subtype in Supply) due to **quality of returns**.

It is worth stressing that although in some papers "uncertainty considered" appears in the process or on demand (i.e., Aras et al., 2004; Amaro and Barbosa-Povoa, 2009; Loomba and Nakashima, 2012), none deals with LHP Inherent Uncertainty because returns are classified in supply (i.e., ST and SQ appears in supply) whereas FG are not classified by subtypes. Moreover, only Zeballos et al. (2012) consider SV as LHP characteristic, but they do not deal with it from a standpoint uncertain. It is noteworthy that although the number of subtypes (ST) appears as an LHP characteristic, it is always considered constant and known with certainty. For this reason Sp-ST does not appear in the “LHP uncertainty” column of Table 2.6. Finally, we found five papers dealing with LHP characteristics, but they do not model them from a point of view uncertain (Amaro and Barbosa-Povoa, 2009; Loomba and Nakashima, 2012; Jin et al., 2013; Su and Lin, 2014; Cai et al., 2014).

The most widely used modelling approach is Stochastic Programming (SP) (in 6 of 15 papers), followed by Non-linear Programming (in 3 of 15 papers). There are two papers which use Simulation Models (SM), two others that suggest Linear Programming (LP) models and two others that use Fuzzy Programming (FP). It should be noted that none uses the Multi-objective programming (MOLP). Furthermore, the most widely used uncertainty approach is SBA, followed by DBA. Two papers use the Fuzzy-Based Approach.

Table 2.6. Classification of the reviewed papers according to the proposed analysis framework (Remanufacturing).

	Environment		Uncertainty		Model	
Authors	Sector/Product	LHP Characteristic	Uncertainty considered	LHP uncertainty	Modelling approach	Uncertainty approach
Aras et al. (2004)	Remanufacturing	Quality of returns (ST, SQ)	Demand, quantity and quality of returns	Sp-SQ	SP	DBA
Benedito and Corominas (2010)	Remanufacturing	Quality of returns (ST, SQ)	Quality and quantity of returns	Sp-SQ	NLP	DBA
Denizel et al. (2010)	Remanufacturing	Quality of returns (ST, SQ)	Quality of returns	Sp-SQ	SP	SBA
Dong et al. (2011)	Remanufacturing	Quality of returns (ST, SQ)	Quality, arriving time, and process time of returns	Sp-SQ	LP	SBA
Gallo et al. (2009)	Remanufacturing	Quality of returns (ST, SQ)	Demand, recovery, assembly, production process Quality of returns	Sp-SQ	SM	SBA
Poles and Cheong (2009)	Remanufacturing	Quality of returns (ST, SQ)	Quantity of returns	Sp-SQ	SM	SBA
Shi et al. (2011)	Remanufacturing	Quality of returns (ST, SQ)	Demand and quality of returns	Sp-SQ	NLP	DBA
Olivetti et al. (2011)	Remanufacturing (Aluminium)	RM composition (ST, SQ)	RM composition	Sp-SQ	NLP	DBA
Zeballos et al. (2012)	Remanufacturing (Glass)	Quality of returns with different economic value (ST, SQ, SV)	Quantity and quality of returns	Sp-SQ	SP	SBA
Amaro and Barbosa-Povoa (2009)	Remanufacturing (Pharmaceutical)	Quality of returns (ST, SQ)	Products' demand and prices	None	LP	SBA
Loomba and Nakashima (2012)	Remanufacturing (Photocopier)	Quality of returns (ST, SQ)	Demand	None	SP	SBA
Jin et al. (2013)	Remanufacturing	Quality of returns (ST, SQ)	Demand	None	SP	DBA
Phuc et al. (2013)	Remanufacturing	Quality of returns (ST, SQ)	Demands, recovery materials, disposal, and reusable products, prices, and costs	Sp-SQ	FP	FBA
Su and Lin (2014)	Remanufacturing	Quality of components of returned products (ST, SQ)	Costs, supplier capacity, lead time	None	FP	FBA
Cai et al. (2014)	Remanufacturing	Quality of returns (ST, SQ)	Prices	None	SP	SBA

Wood sector

According to the analysis conducted by Björheden et al. (2005), timber is a heterogeneous product in terms of quality. The dimensions, species and quality of inbound sawlogs have a decisive impact on the production range. Zanjani et al. (2010a) state that logs are grown under uncertain natural non-homogeneous circumstances with random characteristics (in terms of diameter, number of knots, internal defects, etc.). The natural variable conditions occurring during the growth period of trees make it impossible to anticipate the exact yields of logs. Consequently, due to non-homogeneity in the **characteristics of logs** (**ST**), the **process yields**, that is, the quantities of lumbers that can be produced by each cutting pattern (**SQ**), vary randomly. This means having to sort logs according to some attributes such as diameter class, species, length, taper, etc., which gives rise to the appearance of different subtypes (**ST**) in different quantities (**SQ**). This logs classification can be described in terms of different categories (**ST**) previously established. For example, it might be assumed that they are classified according to their characteristics and their suitability for being manufactured into certain product types, such as softwood lumber, hardwood lumber, pulp, and veneer (Beaudoin et al., 2007).

In this sector however, two aspects must be taken into account: **age classes** and **fibre freshness** (Beaudoin et al., 2007). When fresh fibre is used, common problems associated with log storage are checked, as is development due to drying and sap stains (even if sap stains do not change the structural integrity of the wood, it can severely affect its appearance, resulting in serious loss of value). Variation over age classes (**SV**) is reflected in both the processing cost and the quality of end products (any older fibre used can lower the expected profit margin of the end product). Degree of deterioration (**SS**) may vary according to the season, tree species, the local environment and storage conditions, and may reduce values (**SV**).Thus in the wood sector, subtypes (**ST**) appear given the appearance of different qualities due to log characteristics, which are shown in different amounts (**SQ**) due to uncertainty in process yields, which also presents different values (**SV**) depending on the subtype characteristics that may vary over time, leading to deterioration in quality and value (SS).

The reviewed papers on the wood sector are classified in Table 2.7. The most modelled LHP characteristic (the "LHP characteristic" column) is related to **features of raw materials** (**ST**), mainly due to their non-homogeneity (geometric characteristics, attributes, qualities) that cause randomness in process yield. This classification is based on the different categories established by the authors and leads to different subtypes (**ST**) in distinct quantities (**SQ**). Only one paper (Beaudoin et al., 2007) distinguishes subtype state (**SS**) owing to the age classes and ages of harvested timber (deterioration of wood fibre). Although the existence of **SV** is possible due to the characteristics defined in this sector, it is not addressed by the authors.

In general, uncertainty in the wood sector is due to the non-homogeneous log characteristics, so process yields vary randomly. Another aspect that causes uncertainty is the age class, which can cause uncertainty in supply and process. Uncertainty can also exist due to price variation in the spot market and demand variation in commodity markets.

As shown in the "Uncertainty considered” column of Table 2.7, all the reviewed papers, except one, analyse the process yield. However, Alem and Morabito (2012) deal with uncertainty in production costs and product demands, while Zanjani et al. (2010b) also deal with demand uncertainty. We highlight one paper (Beaudoin et al., 2007) which, apart from considering process yield, takes into account other sources of uncertainty such as standing inventories, stumpage fees, harvesting and transportation costs, storage and milling capacity and customer valuation levels.

When comparing the modelled LHP characteristics (the “LHP characteristic” column) with Uncertainty as considered by the authors (the "Uncertainty considered” column) of Table 2.7, the LHP uncertainty type that appears the most is **Pr-SQ**; i.e., quantities per subtype (SQ) in Process (Pr) are variable and not known with certainty due to **process yield** (in 6 of 7 papers). It is important to stress that one paper (Beaudoin et al., 2007) includes different LHP uncertainties and is the only one that deals with SS. Besides considering Pr-SQ, Beaudoin et al. (2007) consider Sp-SQ due to the classification of raw materials into subtypes, Sp-SS due to age classes and Pr-SS owing to wood fibre deterioration occurring during the process. Although "uncertainty considered" on demand appears in some cases, none deals with it from a view point the LHP Inherent Uncertainty because finished goods are not differentiated by subtypes. Only one paper (Alem and Morabito, 2012) does not contemplate any LHP characteristic from a standpoint uncertain.

The most widely used modelling approach (the "modelling approach" column of Table 2.7) is Stochastic Programming (SP) (6 of 7), and only a paper suggests a Linear Programming (LP) model. None utilises Fuzzy Programming (FP), Non-linear Programming (NLP), Simulation Models (SM) or Multi-objective programming (MOLP). Furthermore from a point of view Uncertainty modelling (the "Uncertainty modelling" column of Table 2.7), all the papers adopt SBA (Scenario-Based Approach).

Table 2.7. Classification of the reviewed papers according to the proposed analysis framework (Wood).

	Environment		Uncertainty		Model	
Authors	Sector/ Product	LHP Characteristic	Uncertainty considered	LHP uncertainty	Modelling approach	Uncertainty approach
Beaudoin et al. (2007)	Wood	Yield end products and yield wood chips, ages of harvested timber, age classes (ST, SQ, SS)	Standing inventories, stumpage fees, harvesting and transportation cost, harvesting, transportation, storage and milling capacity, yield coefficient (end products and wood chips), customer valuation levels	Sp-SQ Sp-SS Pr-SQ Pr-SS	LP	SBA
Alem and Morabito (2012)	Furniture	Process yield (ST, SQ)	Production costs and/or product demands	None	SP	SBA
Zanjani et al. (2010a)	Sawmill	Raw materials attributes (ST, SQ)	Yield of process	Pr-SQ	SP	SBA
Zanjani et al. (2010b)	Sawmill	Raw materials quality (ST, SQ)	Yield of process and product demand	Pr-SQ	SP	SBA
Zanjani et al. (2011)	Sawmill	Raw materials characteristics (ST, SQ)	Yield of process	Pr-SQ	SP	SBA
Zanjani et al. (2013a)	Sawmill	Raw materials characteristics (ST, SQ)	Yield of process	Pr-SQ	SP	SBA
Zanjani et al. (2013b)	Sawmill	raw materials quality and characteristics (ST, SQ)	Yield of process and product demand	Pr-SQ	SP	SBA

Mining sector

The planning and scheduling of mining extractions are a complicated process done in the presence of uncertainties such as the future commodity price and estimated ore grade (Johnson et al., 2010). In general terms, a mine system can be divided into three operations: mining, processing and refining. The raw materials extracted from many mines are sent to the processing units located in the mining area. Then processed materials are transported to the refining unit (Kumral, 2004). Several mines supply the raw materials for processing and **ore properties** and their **quality** varies depending on whether they come from different mines or from different seams (cuts). **Raw ore** from mines is classified according to its **richness** (**ST**) providing different amounts (**SQ**). For example, the quality of iron ore is assessed with regard to iron, silica, alumina, lime contents, among others. Afterwards, it is blended from several sources to obtain the desired level of quality required by the customer. Additionally, given that geological and structural ore body properties, such as seam thicknesses, depths, fault structures and physical characteristics, vary in each mine, **ore prices** and **production costs** can differ from one mine to another (**SV**). Moreover, content fluctuations may cause variations in the quality of the process or the finished product, and high concentration levels of some unwanted materials can lead to environmental pollution. Accordingly, during the production process, there are several stages of classification and can appear different subtypes (ST) with varying amounts (SQ) .Thus in this sector, subtypes (ST) appear because of existence of different ore qualities (in supply, in process and/or finished goods). This causes the appearance of different quantities or yields (SQ) which can also take different values (SV).

The reviewed papers relating to the mining sector are shown in Table 2.8. The most modelled LHP characteristic (the "LHP characteristic" column) is **quality** (**ST**), mainly due to ore composition or ore grade. Items are classified according to different ranks or grades (ST) set by the authors, and different quantities appear per subtype (SQ). None distinguishes subtypes with distinct economic values (SV). Only one paper (Mitra, 2009) considers specific milling process parameters (grindability and sharpness) to classify ore, which leads to different subtype quantities (SQ).

As regards to uncertainty in the mining sector, Rico-Ramirez et al. (2009) classify market uncertainties as exogenous uncertainty and geological risk as endogenous uncertainty. According to Kamrad and Ernst (2001), market uncertainty in this environment is defined as either output price variability or random demand variability, while geological risk is captured by yield uncertainty and is defined as a random multiplier to output quantity. Martinez et al. (2009) explore the main sources of uncertainty that appear during mine planning. Uncertainty on future metal prices arises due to two main factors: lack of exact knowledge of those factors leading to metal supply and demand to increase/decrease; and the practices that producers or consumers carry out when faced with powerful speculative and political motives. Geology and ore distribution in a mineral deposit are estimated from the information deriving from exploration drilling samples. Since the information obtained from the samples is not representative of the entire ore deposit, the geology of the ore deposit is one of the most critical sources of technical uncertainty in a mining operation.

As shown in the "Uncertainty considered" column of Table 2.8, all the reviewed papers analyse technical uncertainty, that is, the uncertainty that arises due to the composition or quality of the mineral. Only one paper (Chakraborty and Chandra, 2005) deals with the input cost of raw coal from a viewpoint uncertain, but it is known for each material.

When comparing the modelled LHP characteristics (the "LHP characteristic" column) with Uncertainty considered by the authors (the "Uncertainty considered" column of Table 2.8), we identify the LHP inherent uncertainty types (the "LHP Uncertainty" column). The main LHP inherent uncertainty type that mostly appears is Sp-SQ (in 4 of 6 papers); i.e., the quantities per subtype (SQ) in Supply (Sp) are variable and not known with certainty due to ore quality. One of them (Mitra, 2009) deals with LHP Inherent Uncertainty in the process that causes subtype quantities (Pr-SQ) to appear because specific milling process parameters (grindability and sharpness) are used to classify ore. The last one (Pendharkar, 1997) considers LHP Inherent Uncertainty on Demand also caused by subtype quantities (Dm-SQ) that appear due to the quality for a given attribute set by each market. It is noteworthy that despite the number of subtypes (ST) appearing as an LHP characteristic, it is always considered constant and known with certainty, so it does not appear as LHP uncertainty.

From a point of view of modelling approach (the "modelling approach" column of table 2.8), different approaches are used. The most widely employed modelling approaches are Stochastic Programming (SP) (2 of 6) and Fuzzy Programming (FP)

(2 of 6). One paper suggests a Linear Programming (LP) model and other one considers Non-linear Programming (NLP). It is noted that none uses Simulation Models (SM) or Multi-objective programming (MOLP). Furthermore from the Uncertainty modelling point of view (the "Uncertainty modelling" column of Table 2.8), the most widely adopted approach is FBA (Fuzzy-Based Approach). Only one paper mentions using SBA and other one adopts DBA.

Table 2.8. Classification of the reviewed papers according to the proposed analysis framework (Mining).

	Environment		Uncertainty		Model	
Authors	Sector/ Product	LHP Characteristic	Uncertainty considered	LHP uncertainty	Modelling approach	Uncertainty approach
Rico-Ramirez et al. (2009)	Ore	Ore quality (ST, SQ)	Ore quality	Sp-SQ	SP	SBA
Chakraborty and Chandra (2005)	Coal	Quality: raw coal grades (ST, SQ)	Composition RM (%Ash), yield (input- output), cost RM	Sp-SQ	FP	FBA
Pendharkar (1997)	Coal	Qualities (ST, SQ)	Level of quality and profitability	Dm-SQ	LP	FBA
Pendharkar (2013)	Coal	Coal quality (ST, SQ)	Profit and coal quality	Sp-SQ	FP	FBA
Mitra (2009)	Grinding	Grindability Sharpness (ST, SQ)	Grindability indices Sharpness indices	Pr-SQ	NLP	FBA
Kumral (2004)	Iron	Ore content (ST, SQ)	Ore content	Sp-SQ	SP	DBA

Ceramic sector

Normally, ceramic pavings and coverings are placed and presented together, so their appearance needs to be homogeneous. However due to raw material heterogeneity (clay), some components (frits and enables) and uncontrollable factors in the process (temperature, humidity and pressure), units of the same model in the same lot which differ in aspect (quality), tone (colour) and gage (thickness) (**ST**). Different subtypes of one model should not be mixed to serve the same customer order (Alemany et al., 2013). The number of subtypes and their quantity can vary from one lot to another (**SQ**). Furthermore, ceramic tiles of different qualities are sold at different prices (**SV**).

As regards the modelled LHP characteristics (Table 2.9, the "LHP characteristic" column) in this sector, Peidro et al. (2012) model only finished goods of first quality and scrap (ST, SQ), and Mundi et al. (2013) model the appearance of homogeneous subsets of first quality (ST, SQ) in lots, but none distinguishes subtypes with different economic values (SV).

Regarding uncertainty in the ceramic sector, and as shown in the "Uncertainty considered" column of Table 2.9, Peidro et al. (2012) analyse uncertainty in the gross margin, idle time and backorder quantities, while Mundi et al. (2013) do it in the appearance of homogeneous subsets. Thus when considering the "LHP uncertainty" column of Table 2.9, only one paper (Mundi et al., 2013) deals with LHP inherent uncertainty in process, because it analyses uncertainty in the number of subtypes that appear in the process (Pr-ST) and considers that quantities per subtype are variable and uncertain (Pr-SQ). Peidro et al. (2012) do not consider the LHP characteristic from a standpoint uncertain.

From a point of view the modelling approach (the "modelling approach" column of Table 2.9), Mundi et al. (2013) suggest a Linear Programming (LP) model, whereas Peidro et al. (2012) use Fuzzy Programming (FP). Furthermore from the Uncertainty modelling perspective (the "Uncertainty modelling" column of Table 2.9), Mundi et al. (2013) use SBA (Scenario-Based Approach) and Peidro et al. (2012) employ the Fuzzy-Based Approach (FBA) to model uncertainties.

Table 2.9. Classification of the reviewed papers according to the proposed analysis framework (Ceramics)

	Environment		Uncertainty		Model	
Authors	Sector/Product	LHP Characteristic	Uncertainty considered	LHP uncertainty	Modelling approach	Uncertainty approach
Mundi et al. (2013)	Ceramic	Homogeneous subsets (ST, SQ)	Homogeneous subsets	Pr-ST Pr-SQ	LP	SBA
Peidro et al. (2012)	Ceramic	First quality finished goods (ST, SQ)	Gross margin, idle time, backorder quantities	None	FP	FBA

Others

LHP characteristics have been taken into account in other sectors like textile, chemicals, and so on, although we only found an unrepresentative sample. We also reviewed some papers in which the authors did not address any specific sector. We include in Table 2.10 all these papers examined.

Table 2.10. Classification of the reviewed papers according to the proposed analysis framework (Other sectors).

	Environment		Uncertainty		Model	
Authors	Sector/Product	LHP Characteristic	Uncertainty considered	LHP uncertainty	Modelling approach	Uncertainty approach
Kannegiesser et al. (2009)	Chemical	Raw material consumption and price ranges (ST, SQ, SV)	Prices and quantities of finished goods and raw materials	Sp-SQ Sp-SV Dm-SQ Dm-SV	LP	SBA
Rajaram and Karmarkar (2002)	Refinery	Production yields (ST, SQ)	Production yields	Pr-SQ	SP	DBA
Karabuk (2008)	Textile	Yarn end products (sku) (ST, SQ)	Demand	None	SP	SBA
Wu et al. (2010)	Film transistor-liquid crystal display (TFT-LCD)	Quality grades in assemblies and finished goods (ST, SQ)	Price and demand of finished goods	None	SP	SBA
Rastogi et al. (2011)	Semiconductor industry	Sort stage and test stage yield (ST, SQ)	Demand	None	SP	SBA
Rong and Lahdelma (2008)	Steel	Raw materials composition (ST, SQ)	Raw materials composition and final product composition	Sp-ST Sp-SQ	FP	FBA
Duenyas and Tsai (2000)	Generic	Quality FG, quality yields (ST, SQ)	Quality FG, demand, production times, quality yields	Dm-SQ	SP	DBA
Gupta and Grossmann (2011)	Generic	Yields (ST, SQ)	Yields	Pr-SQ	SP	SBA
Wang and Zhang (2006)	Generic (Agile supply chain)	Internal quality and assembled quality (ST, SQ)	Due date	None	FP	FBA
Bassok and Akella (1991)	Generic	Raw materials quality (ST, SQ)	Demand, raw materials quality and arrival time	Sp-SQ	NLP	DBA
Wazed et al. (2011)	Generic (Process commonality)	Defective items (ST, SQ)	Quality and breakdown	Pr-SQ	LP	SBA
Osmani and Zhang (2013)	Biorefinery	Crops' yields (ST, SQ)	Demand, sale price and switchgrass yield	Sp-SQ	SP	SBA
Xiao et al. (2012)	Generic (Supply-driven chain)	Imperfect quality (quality disturbances of users, suppliers, manufacturers and distributors) (ST, SQ)	Imperfect quality (quality disturbances of users, suppliers, manufacturers and distributors)	Sp-SQ Pr-SQ Dm-SQ	HYB	FBA

In the paper of Kannegiesser et al. (2009) on the chemical industry (chemical commodities like polymers), commodities are the standard chemicals characterised by sales and supply volatility in volume and value. The characteristics of this SC are analogous to the petroleum sector in terms of the increasing and volatile prices of crude oil-dependent raw materials. Thus subtypes (**ST**) appear by the existence of different oil qualities due to their compositions or characteristics, giving place to different quantities or yields (**SQ**), which may have different values (**SV**). The LHP characteristics discussed in this work that appear are subtypes (**ST**) with different quantities per subtype (**SQ**) due to variable raw material consumption rates and different economic values (**SV**) as a result of the scaling prices of raw materials and demand. As shown in the "Uncertainty considered" column of Table 2.10, the paper considers uncertainty in sales prices for commodities and procurement prices for raw materials. Thus when we look at the "LHP uncertainty" column of Table 2.10, the LHP inherent uncertainty types that appear are **Sp-SQ** and **Sp-SV** owing to variable raw material consumption rates with different economic values in supply and **Dm-SQ** and **Dm-SV** because the quantity required per subtype and market is variable and not known with certainty, and the price of these subtypes on the market can be equal or differ, but it is not known with certainty. Finally, Kannegiesser et al. (2009) use a Linear Programming model (LP) and SBA (Scenario-Based Approach).

Rajaram and Karmarkar (2002) consider a refinery industry of wheat- and starch-based products, such as glucose, sorbitol, dextrose and gluten, which are utilised as components in the food processing, cosmetics, pharmaceuticals, textiles and specialty chemicals industries. As the production in these industries varies due to uncertainty in the yield of the chemical reactions employed in these processes, the characteristics of this SC are analogous to the petroleum sector already studied. Thus, subtypes (**ST**) appear by the different qualities of raw materials as result of their compositions or characteristics, giving place to different quantities or yields (**SQ**) which may take different values (**SV**). The LHP characteristic in the paper is the appearance of subtypes (ST) with different quantities per subtype (SQ) due to the inherent randomness in yield. The paper considers uncertainty in production yields, so LHP uncertainty (the "LHP uncertainty" column of Table 2.10) occurs in the process (Pr-SQ). From the modelling approach perspective (the "modelling approach" column of Table 2.10), Rajaram and Karmarkar (2002) use Stochastic Programming (SP) and they adopt DBA (Distribution-Based Approach) from a viewpoint Uncertainty modelling (the "Uncertainty modelling" column of Table 2.10).

Karabuk (2008) deals with the textile sector. Yarn is manufactured by blending, combing, carding, roving and spinning natural and manmade fibres. After spinning, yarn is classified according to its thickness, which is measured as yarn count (**ST**). Therefore a final yarn product is identified by its blend type and count number (sku). This identification results in the appearance of different amounts per subtype (**SQ**). Despite this paper considers uncertainty on demand, no LHP characteristic is contemplated from a point of view uncertain. Stochastic Programming (SP) is chosen as the modelling approach (the "modelling approach column" of Table 2.10) and the SBA (Scenario-Based Approach) is taken as the uncertainty modelling.

Wu et al. (2010) study the production and transportation in the film transistor-liquid crystal display (TFT-LCD) industry. One of the characteristics of this industry is classification of assembly products and finished goods into quality grades (**ST**, **SQ**), which may take different economic values (**SV**). The quality grades of TFT-LCD products result from production process yields. However, the paper examines uncertainty in price and demand of finished goods, so the LHP characteristic is not considered from a point of view uncertain. The modelling approach (the "modelling approach" column of Table 2.10) utilised is Stochastic Programming (SP), while the uncertainty modelling used (the "Uncertainty modelling" column of Table 2.10) is SBA.

Rastogi et al. (2011) undertake their research in the semiconductor industry. The typical semiconductor supply network configuration consists of layers for wafer fab, sort, assembly, test and demand centres. There are two stages where classification is performed. These stages (sort and test) can lead to subtypes (ST) due to yield (SQ). The modelled LHP characteristics are yield of sort stage and yield of test stage (ST, SQ). However, they consider only uncertainty on demand of finished goods, and no LHP characteristic is modelled uncertainly. The modelling approach (the "modelling approach" column of Table 2.10) used is Stochastic Programming (SP) and SBA is chosen for uncertainty modelling.

Rong and Lahdelma (2008) conduct their research in the steel industry. The raw materials employed in the steel industry come scrap metal. They are divided into several standard types and are classified into different subtypes based on chemical contents (**ST**), among others, which give rise to different amounts (**SQ**). The modelled “LHP characteristic” is raw materials composition and the “Uncertainty considered” occurs in raw materials composition and finished goods composition. Thus LHP uncertainty (the “LHP uncertainty” column of Table 2.10) occurs in the number of subtypes in supply (Sp-ST) because they are not always the same materials and in the quantities by subtype in supply (Sp-SQ) due to such quantities are variable and not known with certainty. Fuzzy Programming (FP) and the Fuzzy-Based Approach (FBA) are chosen for uncertainty modelling.

Duenyas and Tsai (2000) consider a manufacturing system in which the quality of the end product is uncertain. Product is graded at several quality levels after production (**ST**), giving rise to different quantities (**SQ**). They assume stochastic demand per quality level, stochastic production time and random quality yields as "uncertainty considered". So LHP Inherent Uncertainty occurs in quantities by subtype on demand (**Dm-SQ**) due to quantities per subtype are variable and not known with certainty. They use Stochastic Programming (SP) from a point of view the modelling approach, and the Distribution-Based Approach (DBA) to model uncertainties from the Uncertainty modelling perspective.

Gupta and Grossmann (2011) present a generic model that contemplates endogenous uncertainty in yields. The endogenous uncertainty is represented by a parameter associated with the "source" of endogenous uncertainty. These parameters represent intrinsic properties of the source (**ST**, **SQ**). Thus, these authors consider LHP Inherent Uncertainty in quantities per subtype in Process (**Pr-SQ**). They use Stochastic Programming (SP) as the modelling approach and the Scenario-Based Approach (SBA) from the Uncertainty modelling perspective.

Wang and Zhang (2006) consider a generic agile SC by taking into account the internal quality and assembly quality in the model. This leads to the appearance of subtypes (**ST**, **SQ**), but these authors consider that due date is uncertain, so the LHP characteristic is not contemplated from a standpoint uncertain ("none" in the LHP-uncertainty column). Furthermore in modelling approach terms, they employ

Fuzzy Programming (FP) and adopt the Fuzzy-Based Approach (FBA) as Uncertainty modelling.

Bassok and Akella (1991) consider an aggregate production planning problem in a manufacturing facility with a critical raw material. The arrival process for raw material is stochastic and only a fraction of the material supplied is defect free. This produces the appearance of subtypes (ST, SQ). Besides the arrival time, demand and raw materials quality are considered uncertain. Thus, seeing column "LHP uncertainty" in Table 2.10, LHP Inherent Uncertainty occurs in quantities by subtype in supply (Sp-SQ) due to quantities per subtype are variable and not known with certainty. On the other hand, from a point of view of modelling approach, they use Non Linear Programming (NLP) and from a standpoint of Uncertainty modelling, they use the DBA to model uncertainties.

Wazed et al. (2011) develop mathematical models for multiproduct and multistage production under quality and breakdown uncertainties. In manufacturing systems, a given proportion of products become defective due to poor production quality and material defects. Subsequently defective products are scrapped if they are not re-workable, or are not cost-effective to do so. This fact can lead to the appearance of subtypes (**ST**) that are classified into ranges to give rise to different amounts (**SQ**) during the process (**Pr-SQ**) (the "LHP uncertainty" column of Table 2.10). Moreover, this paper uses Linear Programming (LP) as the modelling approach and the Scenario-Based Approach (SBA) from the Uncertainty modelling perspective.

Osmani and Zhang (2013) consider a refinery of switchgrass to obtain biocombustible. As the production in these industries varies due to uncertainty in the yield of crops, thus, subtypes (ST) appear as a result of raw material yield. The LHP characteristic in the paper is the appearance of subtypes (**ST**) with different quantities per subtype (**SQ**) due to the randomness in yield of crops. The paper considers uncertainty on demand, sale price and switchgrass yield, so LHP uncertainty (the "LHP uncertainty" column of Table 2.10) occurs in the supply (**Sp-SQ**). From the modelling approach perspective (the "modelling approach" column of Table 2.10), Osmani and Zhang (2013) use Stochastic Programming (SP) and they adopt SBA (Scenario-Based Approach) from a viewpoint Uncertainty modelling (the "Uncertainty modelling" column of Table 2.10).

Finally, Xiao et al. (2012) propose a generic model for the supply-driven chain where quality disturbances (**ST**) occur in every SC node giving place to the occurrence of quantities per subtype (**SQ**). The imperfect quality along the supply-driven chain is modelled according to a function called quality disturbance, which is variable and not known. "Uncertainty considered" is an imperfect quality in every SC node (users, suppliers, manufacturers and distributors), so LHP Inherent Uncertainty occurs in quantities per subtype in supply (**Sp-SQ**), in process (**Pr-SQ**) and on demand (**Dm-SQ**). From a viewpoint modelling approach, this paper uses a hybrid model (HYB) by combining Non-linear Programming and simulation. For uncertainty modelling, the authors employ the Fuzzy-Based Approach (FBA) to model uncertainties.

<u>*Comparative analysis*</u>

All reviewed papers develop a model of production planning in an uncertain environment and all of them deal with some LHP characteristic in the model. But the 72.4% consider some LHP characteristic uncertain, while the remaining 27.6% deal with other parameters in an uncertain way. Table 2.11 offers a classification of the reviewed papers according to the LHP uncertainty types defined by the authors. The most modelled LHP uncertainty aspect by far is **Subtype Quantity** (SQ) in 53 papers, but some authors deal with two types of uncertainty or more, which accounts for 84%. The issues covered by the authors in this category are due to **yields**, **quality** issues, **RM composition** and **FG specifications**. Five papers consider the **Subtype State** (SS) (8%), due to **perishability**, three papers deal with **Subtype Value** (SV) (5%) by means of **price**, and only two papers specifically consider **number of Subtypes** (ST) (3%), owing to **RM composition** and **qualities**.

We can state that the most LHP features addressed in an uncertainty context are quantities per subtype in raw materials and components (Sp-SQ) and quantities per subtype in intermediate products and finished goods (Pr-SQ), while the remaining LHP inherent uncertainty types are very scarcely or not addressed under uncertainty.

Table 2.11. Classification of the reviewed papers according to LHP inherent uncertainty types.

Uncertainty Types/ LHP Uncertainty Aspects	Supply (Sp)	Process (Pr)	Demand (Dm)
Subtypes (ST)	Rong and Lahdelma (2008)	Mundi et al. (2013)	
Subtype quantity (SQ)	Ahumada et al. (2012) Tan and Çömden (2012) Bertrand and Rutten (1999) Randhawa and Bjarnason (1995) Bassok and Akella (1991) Rico-Ramirez et al. (2009) Chakraborty and Chandra (2005) Kumral (2004) Carneiro et al. (2010) Chunpeng and Gang (2009) Zimberg and Testuri (2006) Aras et al. (2004) Benedito and Corominas (2010) Denizel et al. (2010) Dong et al. (2011) Gallo et al. (2009) Poles and Cheong (2009) Shi et al. (2011) Olivetti et al. (2011) Munhoz and Morabito (2014) Osmani and Zhang (2013) Albornoz et al. (2014) Pendharkar (2013) Phuc et al. (2013) Zeballos et al. (2012) Rong and Lahdelma (2008) Xiao et al. (2012) Kannegiesser et al. (2009) Beaudoin et al. (2007)	Mundi et al. (2013) Rajaram and Karmarkar (2002) Gupta and Grossmann (2011) Wazed et al. (2011) Mitra (2009) Khor et al. (2008) Pitty et al. (2008) Ribas et al. (2010) Tarhan et al. (2011) Tong et al. (2012) Wang and Zheng (2010) Zanjani et al. (2010a) Zanjani et al. (2010b) Zanjani et al. (2011) Zanjani et al. (2013a) Zanjani et al. (2013b) Radulescu et al. (2008) Ravi and Reddy (1998) Xiao et al. (2012) Beaudoin et al. (2007)	Duenyas and Tsai (2000) Pendharkart (1997) Kannegiesser et al. (2009) Xiao et al. (2012)
Subtype value (SV)	Kannegiesser et al. (2009)	Radulescu et al. (2008)	Kannegiesser et al. (2009)
Subtype state (SS)	Miller et al. (1997) Beaudoin et al. (2007)	Bohle et al. (2010) Beaudoin et al. (2007) Begen and Puterman (2003)	

The most widely employed modelling approach is Stochastic programming (47.4%) and the most used approach to model uncertainty is by far the Scenario-Based Approach (65%). In fact, this is the combination of the most widely used modelling approaches (30 of 76), which represents 39.5%. The distribution of the reviewed papers according to modelling approach and to uncertainty modelling is detailed in Table 2.12. This proportion is similar considering only works with LHP uncertainty.

Table 2.12. Distribution of the reviewed papers according to modelling approach and uncertainty modelling.

Modelling approach/ Uncertainty approach	LP	MOLP	NLP	SP	FP	SM	HYB	TOTAL	TOTAL (%)
SBA	12		2	30		3	2	49	65%
DBA		1	6	6				13	17%
FBA	3	1	1		8		1	14	18%
TOTAL	15	2	9	36	8	3	3		
TOTAL (%)	19.7%	2.6%	11.8%	47.4%	10.5%	3.9%	3.9%		

Stochastic Programming and the Scenario-Based Approach are used more for modelling purposes. This modelling purpose usually considers that one or more parameter, such as yields or qualities, are described by a set of discrete scenarios.

As shown, the MOLP approach has been used very little for LHP modelling. Yet other objectives relating to profits or costs in terms of minimisation of undesirable stocks or dynamic subtype state, such as quality function loss, should be taken into account for certain situations. However, the SP and SBA approaches have two main drawbacks: they can be computationally inefficient and, very often, the distributions deriving from recorded past evidence are not always available or reliable (Mula et al., 2010b). Therefore whenever statistical data are unreliable, or are not even available, stochastic models may not be the best choice (Wang and Shu, 2005). The Fuzzy Set Theory and the Possibility Theory may be an alternative, and are simpler and less data-demanding than the Probability Theory to deal with SC uncertainties (Dubois et al., 2003; Peidro et al., 2010). Fuzzy programming is proposed to handle these imprecise and/or unavailable data to help make decisions. However, very few authors consider this approach.

The conceptual model based on the literature review and analysis is described next.

5. Conceptual model

Meredith (1993) defines a Conceptual Model as a set of concepts employed to represent or describe an event, object or process. It can be a description, a taxonomy or an inductive reflection. Our Conceptual Model (Fig. 2.3) is based on an inductive reflection which integrates a number of different works on the same topic and summarizes the common elements. We pose a conceptual model from an exhaustive literature review which synthesizes existing research. This conceptual model arises from the theoretical foundations discussed in the literature review and brings together the aspects which have been considered so far when modelling the production planning in sectors with LHP in an uncertain environment. The model can be used by practitioners as a tool to identify common characteristics with other conducted researches. This allows to identify similarities between sectors and to transfer solutions from one sector to another. Thus, the purpose of the model is twofold. First, it summarizes the results of research by sector on modelling the uncertainty due to the lack of homogeneity in the product in the production planning, identifying and combining the most important aspects in a model which allows use it as a tool to identify the most advisable model. Second, researchers can use it as a framework to identify gaps in order to direct future research.

The model is divided into three parts (Fig. 2.3). The first part (SECTOR) includes sectors where some LHP uncertain characteristics are contemplated for planning purposes. These are: Petroleum, agri-food, remanufacturing, wood, mining, ceramic, chemical industry, refinery and steel. There are some papers that are not described in any sector but consider some LHP uncertain feature in the generic model (quality, yield).

In the second part (LHP UNCERTAINTY), the LHP characteristics that are modelled uncertainly are grouped according to the kind of subtype which they cause. That is, LHP characteristics that are taken into account in papers are: composition RM, specification FG, quality, yield, perishability and price. These LHP features belong to some group of the defined subtypes. Specifically, the number of subtypes is considered variable in a case where the RM composition is heterogeneous and another when the quality is not homogeneous. The cases which appear under the heading Subtype State (SS) are due to the existence of uncertainty in the perishability of items. The uncertainty of economic value of the different subtypes is due to price of RM or FG. Finally, most treated inherent uncertainty is caused by the variability in quality, performance, composition RM and/or specification FG. These LHP characteristics are grouped under the name of Subtype Quantity (SQ). The relations (arrows) which connect the part one and the part two in the model, identify the kind of subtype taken into account in each sector.

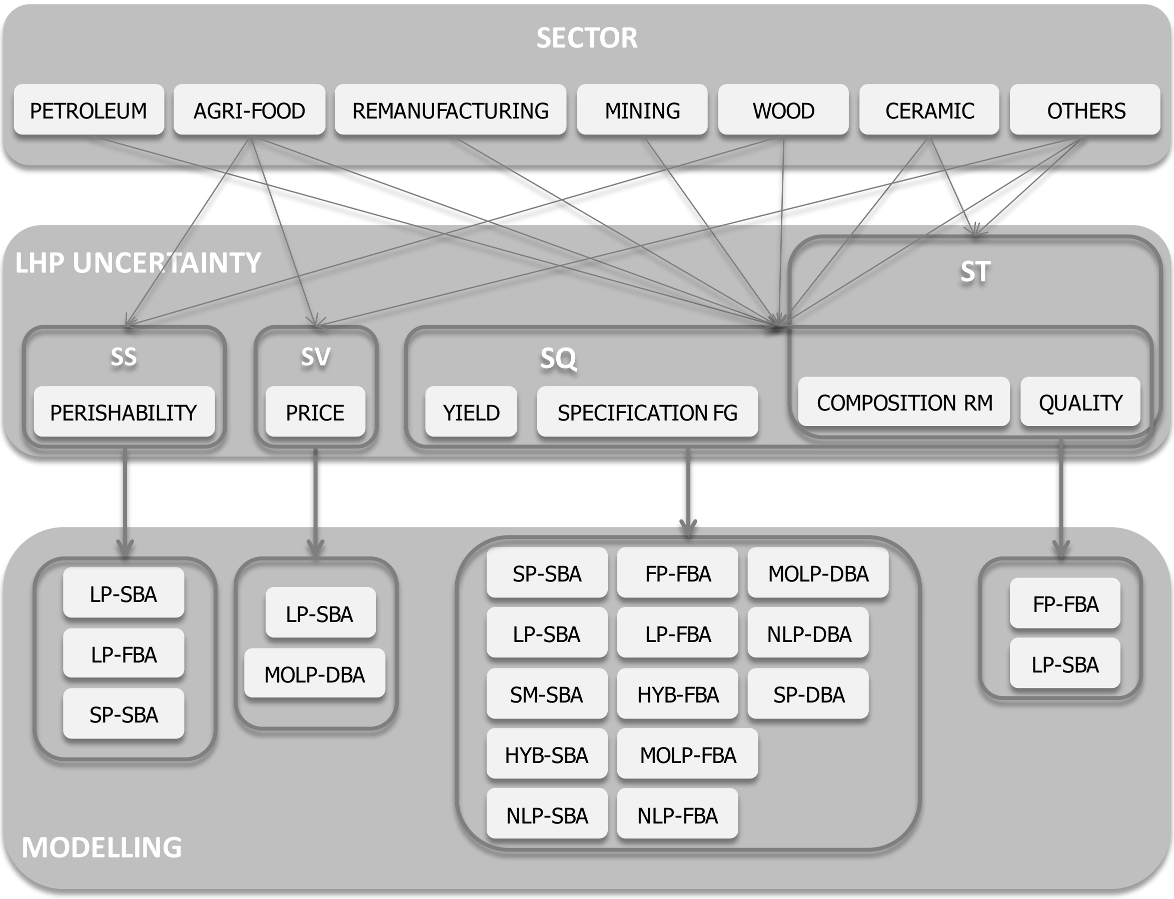

Figure 2.3. Conceptual model

In the third part (MODELLING), we sort the approaches used by the papers analyzed. That is, we link what modelling approach is used to pose each LHP characteristic and what approach is used to solve their inherent uncertainty. We establish the relationship between LHP UNCERTAINTY (Part Two) and

MODELLING (Part Three) indicating the approaches used to model each LHP uncertainty. This enables to identify the most appropriate model to use as a pattern.

6. Conclusions and future research

The management system becomes more difficult in the presence of LHP, increasing not only the information volume but also the uncertainty in the system. Dealing with LHP improperly can lead to very negative effects as regards stocks, customer service level and SC efficiency. Production Planning plays a crucial role in this task and becomes vital for accomplishing with customer requests in terms of ordered quantities, due dates and homogeneity specifications. Although LHP is present in several sectors, the incorporation of LHP uncertainty characteristics in Production planning is very scarce for some of them. These last could take profit from the know-how in other sectors if a common framework is available.

Along these lines, this work proposes an analysis framework which characterises the LHP inherent uncertainty according to three dimensions: environment (sector and LHP characteristic), uncertainty and modelling approaches. Then, research papers have been reviewed based on the previous analysis framework with the aim of knowing how LHP uncertainty is handled in Production planning models for different sectors. Conclusions drawn from this study assert that: (1) there are some sectors that consider LHP inherent uncertainty in the planning process, such as agri-food and remanufacturing, however, in other sectors very affected by LHP, the existing literature is scarce (mining, wood, ceramic) or inexistent (textile, jewel or leather); (2) the most considered LHP uncertainty aspect is the Subtype Quantity (SQ), mainly in supply whilst the other aspects (ST, SS, SV) are addressed very little or nothing; (3) the most widely modelling approach employed is Stochastic programming and the most used approach to model uncertainty is the Scenario-Based Approach. In fact this is the combination of the most widely used modelling approaches. Next, the paper offers a conceptualization of a pattern, based on the literature review, which synthesises the results of study for modelling the uncertainty due to the lack of homogeneity in the product in the production planning. The conceptual model identifies and ranks the most important aspects, to jointly model the LHP characteristics and their inherent uncertainty.

Therefore, it can be concluded that current production planning models do not provide complete adequate decision support for the uncertainty modelling of LHP characteristics. As already mentioned, production planning is one of the most important SC activities in the medium-short term, and it is one of the main inputs to the order promising process. Based on master plan quantities and committed customer orders, the so-called Available-To-Promise (ATP) quantities are derived. ATP quantities are then used for the quantity and due date setting of customer orders. The master plan should anticipate LHP features in order to provide with reliable information about future available homogeneous quantities for the order promising process, complying with customer homogeneity requirements.

Based on this review, we point out gaps in the literature and suggest future research: (1) there are very few works that pose models to address the LHP uncertainty on demand. Therefore, there is a need for optimization models and approaches of solution in this field; (2) there are very few works dealing with three of the four main aspects of relevance for planning purposes: the number of subtypes (ST), the subtype value (SV) and the subtype state (SS); (3) very few authors consider fuzzy programming to handle imprecise and/or unavailable data to help make decisions. However, this approach may be a good alternative to the LHP uncertainty; (4) It is possible the identification of similarities among sectors being possible to transfer solutions from some sectors to other ones.

Existing research tends to oversimplify the real problem which can lead to short-term conflict, when the planned amounts assumed homogeneous become real and the customer needs cannot be achieved due to discrepancies in the homogeneity requirements. This gap provides an opportunity to do new research as regards reference models, modelling and solution techniques to properly handle LHP inherent uncertainty types. This new research field will allow the development of more realistic models that can significantly improve the Production planning practice.

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CAPÍTULO III:

THE EFFECT OF MODELING QUALITIES, TONES AND GAGES IN CERAMIC SUPPLY CHAINS MASTER PLANNING

Abstract. Ceramic production processes are characterized by providing quantities of the same finished goods that differ in qualities, tones and gages. This aspect becomes a problem for ceramic supply chains (SCs) that should promise and serve customer orders with homogeneous quantities of the same finished good. In this paper a mathematical programming model for the centralized master planning of ceramic SC is proposed. Inputs to the master plan include demand forecasts in terms of customer order classes based on their order size and splitting percentages of a lot into homogeneous sub-lots. Then, the master plan defines the size and loading of lots to production lines and their distribution with the aim of maximizing the number of customer orders fulfilled with homogeneous quantities in the most efficient manner for the SC. Finally, the effect of modeling qualities, tones and gages in master planning is assessed.

Keywords: Ceramic Supply Chains, Mathematical Programming Model, Qualities, Tones, Gages, Lack of Homogeneity in the Product.

1. Introduction

Lack of Homogeneity in the Product (LHP) appears in those productive processes which include raw materials that directly originate from nature and/or production processes with operations which confer heterogeneity to the characteristics of the outputs obtained, even when the inputs used are homogeneous. LHP appears in certain industries like ceramics, textile, wood, marble, tanned hides and leather goods, and it becomes a problem when the customer needs to be served with homogeneous units of one same product [1]. These companies are obliged to include a classification stage [2] whose localization in the production process depends on each industry. This is true to the extent that the various homogeneous quantities available of one same product are known only after finalizing each classification stage, and not beforehand. The classification criterion used differs from one industry to another [1]. For instance, in the furniture sector, color and grain sorting of furniture parts is an important manufacturing step where color uniformity has an impact on the value of final products [3]. In the horticulture sector, important criteria for sorting and grading fresh fruit are size, weight, ripeness, damages, color, shape and firmness [4].

LHP in ceramic supply chains (SCs) implies the existence of units of the same finished good (FG) in the same lot that differ in the aspect (quality), tone (color) and gage (thickness) [1,5] that should not be mixed to serve the same customer order. The usual consideration of three qualities, two tones and three gages causes the existence of thirteen different subtypes of the same model (FG). This fact increases the volume of information and makes the system management more complex. Additionally, the customers from this type of companies tend to request quantities of different FGs in one same order, and they also require that the units of one same FG in the order are homogeneous. This is because ceramic pavings and coverings must normally be placed and presented together, so their appearance needs to be homogeneous.

However, the real homogeneous quantities of each subtype in a FG lot will not be known until their production was finished. Not to know the homogeneous quantities available of the same FG to be promised to customers proves to be a problem when customers' orders have to be committed, reserved and served from homogeneous units available derived from the planned production. Furthermore, not to accomplish with this homogeneity requirement can lead to returns, product and company image deterioration, decreasing customer satisfaction and even lost of customers.

The order promising process (OPP) plays a crucial role in customer requirements satisfaction [6] and, therefore, in properly managing the special LHP characteristics. The OPP refers to the set of business activities that are triggered to provide a response to customer order requests [7]. This process requires information about available-to-promise (ATP) quantities, i. e. the stocks on hand or projected inflows of items stocked at the customer order decoupling point (already in transit or planned by the master plan) that has not yet been allocated to specific orders and thus can be promised to customers in the future. Because one of the main inputs to the OPP is the master plan, the objective of this paper is to define a master plan that anticipate LHP features and can provide this process with reliable information about future available homogeneous quantities.

The paper is structured as follows. Section 2 describes the problem under consideration. Section 3 presents the mixed integer linear programming model proposed for the centralized master planning of ceramic SCs that explicitly takes into account LHP. Section 4 reports the methodology followed for the model validation. In this section a comparison between results obtained from master planning in ceramic SC with and without LHP is made. Finally, Section 5 states the conclusions derived from the obtained results and future research lines.

2. Problem Characteristics

In this paper, we consider the master planning problem for replenishment, production, and distribution in ceramic tiles SCs with LHP. The characteristics of the problem under study are the same as in [8] but with relevant differences introduced by the LHP consideration. In the following paragraphs the main features of the problem addressed are describe, highlighting those novel aspects introduced by LHP consideration.

These ceramic SCs are assumed to be multi-item, multi-supplier, multi-facility, multi-type and multi-level distribution centers. For the problem under consideration, it is assumed that the possibilities of flow between the nodes of the various stages (arcs), as well as the parts, components, raw materials (RMs), and FGs that might circulate through them, have been considered beforehand. The existence of several production plants situated in various geographical locations is also assumed. These production plants are supplied with various RMs provided by different suppliers with a limited supply capacity. This represents the total capacity of the supplier assigned to the SC under study because it is assumed that RM suppliers may supply production plants belonging to other SCs. Each production plant has one or several production lines (processors in parallel) with a limited capacity. Different FGs can be processed by each production line. There are FGs with high added values that are manufactured only in production plants; others may be partly subcontracted, while some may be totally subcontracted to external suppliers (normally products with a low added value). FGs are grouped into product families for production and commercial reasons. A product family is defined as a group of FGs of identical use (flooring or coverings), format (size), grout (white or red), and whose preparation on production lines is similar. This is done to minimize setup times and costs. Changeovers from one product family to the next incur setup costs owing to the time spent in changing, for instance, moulds. Lines may not be standardized, in which case each product family can be processed according to specific facilities with the appropriate technical features. Therefore, not all production lines are capable of processing all the product families, although the product families that may be processed on each line are known. Given the important setup times between product families on production lines, production within a minimum number of consecutive time periods should be carried out whenever a production line is set up for a specific product family (minimum run length). Item setups among the products belonging to the same product family also exist. Because of technological factors involved in the production process itself, when a certain product is manufactured on a specific line, it should be produced in an equal or greater amount than the minimum lot size. This is partly because a certain defects occur during the production process, and only a percentage of the manufactured items may be sold as first quality FG. Furthermore, in this paper, it is assumed that for first quality quantities of the same FG different tones and gages can appear in the same lot. That is, the LHP real characteristic is taking into account in the master plan.

In the majority of the production planning models developed at the tactical level, the capacities at each stage are aggregated and setup changes are not explicitly considered. However, if at this level the setup times involve an important consumption capacity and have been completely ignored this may lead to an overestimation of the real capacity availability which, in turn, may lead to unfeasible events during the subsequent disaggregation of tactical plans. Considerable savings may also be achieved through optimum lot-sizing decisions. However, accounting for setup times at the tactical level would mean simultaneously including decisions about the allocation and lot sizing of production. This problem is known as the capacitated lot-sizing and loading problem (CLSLP) [9]. Given the lengthy setup times involved in the manufacturing of ceramic floorings and coverings, these setup times need to be considered at the tactical level. This work also aims to solve this problem within the CLSLP framework.

The distribution of several FGs (multi-item) from production plants to end customers is carried out in various stages (multi-level) by different types of distribution centers (multi-type), such as central warehouses, logistic centers and shops. Neither manufactured nor subcontracted FGs can be stored in manufacturing plants. So they are sent to the first distribution level, which is made up of a number of central warehouses with a limited storage capacity. Outgoing FGs from central warehouses are designed to not only cover the demand of certain end customers (for instance, independent distributors that do not belong to the firm, construction firms, etc.), but to also supply logistics centers. Logistics centers, unlike warehouses, do not have the required storage capacity and only supply FGs to shops that have been previously assigned to them. Finally, shops, which do not have storage capacity, attend to end customers' demands. Although this type of SC attempts to achieve a maximum customer service level, backorders are permitted in both central warehouses and shops. However, backorders quantities are limited to a certain demand percentage to ensure the accomplishment of an objective customer service level defined by the SC. This is a usual situation in the ceramic tile sector, given its limited production flexibility owing to setup costs and times.

In short, the characteristics of the problem under study are the same as in [8] but with relevant differences introduced by the LHP consideration summarized in the following. As in [8] the master plan considers the CLSLP to reflect the fact that production lots of the same product processed in different production lines present a high probability of not being homogeneous. Furthermore, the splitting of each lot into homogeneous sublots of the same FG is also incorporated to reflect the LHP characteristics: different tones and gages for the first quality items. The sizing of lots is made in such a way that an integer number of customer order classes can be served from homogeneous quantities of each sublot. To this end, different customer order classes are defined according to their size.

At the master plan level, demand forecasts are usually expressed in aggregate manner without taking into account customer classes. Customer classes definition (also known as customer segmentation) has been traditionally used in the field of the so called “allocation planning”. The allocation planning follows a push strategy (based on forecasts), as the master plan, but it is carried out after the master plan and before the OPP. The allocation planning has been used for SC operating under a supply constrained mode where not all customer demand can be fulfilled and should answer on-line to customer requirements based on the first-come-first-served policy. Yet in shortage situations where demand is higher than ATP quantities, single-order processing entails the risk of promising scarce availabilities to the wrong customers; e.g., to less important customers or to customers with smaller profit margins. Allocation planning promises to be a way to improve real-time single-order processing by reserving shares of the ATP, the so-called “quotas” or “allocated ATP”, for important customers in the mid-term and by afterward promising orders in relation to these allocated quotas in the short term [10]. In doing so, a classification is defined that is used to segment and prioritize customer orders. The defined classes could be either flat or they could form a hierarchy [11]. Examples of different customer classes’ definition can be found in [12], [10], [13], [14].

Therefore, the consideration of customer classes for sizing lots and defining demand forecasts jointly with the splitting of lots into homogeneous sub-lots constitute the most relevant aspects that differentiate the model for master plan proposed in this paper from that proposed by Alemany et al. [8] and other models for SC master plan. The next section describes the mixed integer programming model proposed to solve the described problem.

3. Modeling Lack of Homogeneity in the Product in Ceramic Supply Chains through Master Planning

The following mixed integer linear programming model (MP-CSC-LHP) is proposed to solve the master planning problem described above. The model MP-RDSINC proposed by Alemany et al. [8] is considered as the starting point to formulate the present model but properly modified in order to reflect the LHP characteristics cited previously.

Tables 3.1 to 3.4, respectively, describe the indices, sets of indices, model parameters and decision variables of the MP-CSC-LHP, respectively. Those model elements that differ from the MP-RDSINC are written in *italics*.

Table 3.1. Indices

i	Finished goods (i= 1, ..., I)	q	Logistics centers (q= 1, ..., Q)
f	Product families (f= 1, ..., F)	w	Shops (w= 1, ..., W)
c	Raw materials and components (c= 1, ..., C)	r	Suppliers of raw materials and components (r= 1,... ,R)
p	Production plants (p= 1, ..., P)	k	*Customer order classes (k= 1, ..., K)*
a	Warehouses (a= 1, ..., A)	t	Periods of time (t= 1, ..., T)

Table 3.2. Set of Indices

$Il(l)$	Set of FGs that can be manufactured on manufacturing line l
$Fl(l)$	Set of product families that can be manufactured on manufacturing line l
$If(f)$	Set of FGs that belong to product family f
$Ip(p)$	Set of FGs that can be produced in production plant p
$Ia(a)$	Set of FGs that can be stored in warehouse a
$Ic(c)$	Set of FGs of that RM c form part
$Iq(q)$	Set of FGs that can be sent to logistic center q
$Iw(w)$	Set of FGs that can be sent to shop w
$Lf(f)$	Set of manufacturing lines that may produce product family f
$Lp(p)$	Set of manufacturing lines that belong to production plant p
$Pa(a)$	Set of production plants that can send FGs to warehouse a
$Aq(q)$	Set of warehouses that can supply logistic center q
$Rc(c)$	Set of suppliers that can supply RM c
$Rp(p)$	Set of suppliers of RMs that can supply production plant p
$Cr(r)$	Set of RMs that can be supplied by supplier r
$Qa(a)$	Set of logistics centers that can be supplied by warehouse a
$Wq(q)$	Set of shops that can be supplied by logistic center q
$Qw(w)$	Set of logistics centers capable of supplying shop w
$Ap(p)$	Set of warehouses that can be supplied by production plant p

Table 3.3. Model Parameters

ca_{crt}	Capacity (units) of supplying RM *c* of supplier *r* in period *t*
$costtp_{crp}$	Purchase and transport cost of one unit of RM *c* from supplier *r* to production plant *p*
caf_{lpt}	Production capacity available (time) of production line *l* at plant *p* during time period *t*
cm_i	Loss ratio of FG *i* (percentage of faulty m2 obtained of the production process)
cq_i	Percentage of m^2 that can be sold of product *i* as first quality
$costp_{ilp}$	Cost of producing one m^2 of FG *i* on production line *l* of production plant *p*
$costsetupf_{flp}$	Setup costs for product family *f* on production line *l* of production plant *p*
$costsetup_{ilp}$	Setup costs for FG *i* on production line *l* of production plant *p*
$tfab_{ilp}$	Time to process one m^2 of FG *i* on production line *l* of production plant *p*
$tsetup_{flp}$	Setup time for product family *f* on production line *l* of production plant *p*
$tsetupi_{ilp}$	Setup time for article *i* on production line *l* of production plant *p*
lmi_{ilp}	Minimum lot size (m^2) of FG *i* on production line *l* of production plant *p*
tmf_{flp}	Minimum run length (expressed as multiples of the time period used) of product family *f* on production line *l* of production plant *p*
v_{ic}	Units of RM *c* needed to produce one m^2 of FG *i*
ssc_{cp}	Safety stock of RM *c* in production plant *p*
ssa_{ia}	Safety stock (m^2) of FG *i* at warehouse *a*
$capal_a$	Storage capacity (m^2) in warehouse *a*
$costtak_{ipak}$	*Unitary transport cost of FG i from production plant p to warehouse for customer order class k*
$costtclk_{iaqk}$	*Unitary transport cost of FG i from warehouse a to logistic centre q for customer order class k*
$costinak_{iak}$	*Unitary holding cost of FG i of customer order class k in the warehouse a in a period*
$costdifak_{iak}$	*Unitary backorder cost of FG i for customer order class k in warehouse a in a period*
pak_{iak}	*Sales value of FG i in warehouse a for customer order class k*
$\alpha 1_k$	*Maximum backorder quantity permitted by customer order class k in a period in warehouses expressed as a percentage of the demand of that period*
$costtwk_{iqwk}$	*Unitary transport cost of FG i from logistics centre q to shop w for customer order class k*
$costdifwk_{iwk}$	*Unitary backorder cost of FG i of customer order class k in a time period at shop w*
pwk_{iwk}	*Sales price of FG i in shop w for customer order class k*
$\alpha 2_k$	*Maximum backorder quantity permitted in a period by customer order class k in shops expressed as a percentage of the demand of that period*
$M1, M2$	*Very large integers*
$ordq_{ik}$	*Average size of the order of FG i of customer order class k*
dw_{iwkt}	*Forecast of demand of FG i at the warehouse a of customer order class k in period t*
da_{iakt}	*Forecast of demand of FG i in shop w of customer order class k in period t*
$\beta 1_{ilp}$	*Percentage of a batch of FG i produced on the line l of the plant p at any period which can be considered as the first homogeneous sub- batch of product i*
$\beta 2_{ilp}$	*Percentage of a batch of FG i produced on the line l of the plant p at any period which can be considered as the second homogeneous sub- batch of product i*
$\beta 3_{ilp}$	*Percentage of a batch of FG i produced on the line l of the plant p at any period that can be considered as the third homogeneous sub- batch of product i*

Table 3.4. Decision Variables

CTP_{crpt}	Amount of RM c to be purchased and transported from supplier r to production plant p in period t
INC_{cpt}	Inventory of the RM c at plant p at the end of period t
MPF_{flpt}	Amount of product family f manufactured on production line l of production plant p in period t
MP_{ilpt}	Amount of FG i manufactured on production line l of production plant p in period t
X_{ilpt}	Binary variable with a value of 1 if FG i is manufactured on production line l of production plant p in time period t, and with a value of 0 otherwise
Y_{flpt}	Binary variable with a value of 1 if product family f is manufactured on production line l of production plant p in time period t, and with a value 0 otherwise
ZI_{ilpt}	Binary variable with a value of 1 if a setup takes place of product i on production line l of production plant p in time period t, and with a value of 0 otherwise
ZF_{flpt}	Binary variable with a value of 1 if a setup takes place of product family f on production line l of production plant p in time period t, and with a value of 0 otherwise
$CTAK_{ipakt}$	*Amount of FG i to be transported from production plant p to warehouse a for customer order class k in time period t*
$INVNAK_{iakt}$	*Inventory of FG i in warehouse a for customer order class k in period t*
$VENAK_{iakt}$	*Amount of FG i sold in warehouse a to customer order class k during period t*
$DIFAK_{iakt}$	*Backorder quantity of FG i of customer order class k in warehouse a during period t*
$CTCLK_{iaqkt}$	*Amount of FG i of customer order class k transported from warehouse a to logistics centre q in period t*
$CTTWK_{iqwkt}$	*Amount of FG i of customer order class k transported from logistics centre q to shop w in period t*
$VENWK_{iwkt}$	*Amount of FG i of customer order class k sold in shop w during period t*
$DIFWK_{iwkt}$	*Backorder quantity of FG i of customer order class k in shop w during time period t*
NKL_{ilpkt}	*Number of orders of FG i from customer order class k which can be served from the lot of the FG i to be produced on line l of the plant p in period t*
NKL1ilpkt	*Number of orders of FG i from customer order class k which can be served from the first homogeneous sub-lot of the FG i to be produced on line l of the plant p in period t*
NKL2ilpkt	*Number of orders of FG i from customer order class k which can be served from the second homogeneous sub-lot of the FG i to be produced on line l of the plant p in period t*
NKL3ilpkt	*Number of orders of FG i from customer order class k which can be served from the third homogeneus sub-lot of the FG i to be produced on line l of the plant p in period t*
NKPipkt	*Number of orders of FG i from customer order class k which can be served from lots of the article i to be produced on all lines of the plant p in period t*

Objective Function:

$$
\begin{aligned}
& Máx \sum_t \sum_i \sum_k \left\{ \sum_a pak_{iak} * VENAK_{iakt} + \sum_w pwk_{iwk} * VENWK_{iwkt} \right\} - \\
& - \sum_t \sum_p \sum_{r \in Rp(p)} \sum_{c \in Cr(r)} costtp_{crp} * CTP_{crpt} - \sum_t \sum_p \sum_{l \in Lp(p)} \sum_{i \in Il(l)} costp_{ilp} * MP_{ilpt} - \\
& - \sum_t \sum_p \sum_{l \in Lp(p)} \sum_{f \in Fl(l)} costsetup_{flp} * ZF_{flpt} - \sum_t \sum_p \sum_{l \in Lp(p)} \sum_{i \in Il(l)} costsetupi_{ilp} * ZI_{ilpt} - \\
& - \sum_t \sum_a \sum_{p \in Pa(a)} \sum_{i \in Ip(p)} \sum_k costtak_{ipak} * CTAK_{ipakt} - \sum_t \sum_a \sum_{i \in Ia(a)} \sum_k costinak_{iak} * INVNAK_{iakt} - \\
& - \sum_t \sum_a \sum_{i \in Ia(a)} \sum_k costdifak_{iak} * DIFAK_{iakt} - \sum_t \sum_a \sum_{q \in Qa(a)} \sum_{i \in Iq(q)} \sum_k costtclk_{iaqk} * CTCLK_{iaqkt} - \\
& - \sum_t \sum_q \sum_{w \in Wq(q)} \sum_{i \in Iw(w)} costtwk_{iqwk} * CTTWK_{iqwkt} - \sum_t \sum_w \sum_{i \in Iw(w)} \sum_k costdifwk_{iwk} * DIFWK_{iwkt}
\end{aligned}
\tag{1}
$$

Constraints:

$$INC_{cpt} = INC_{cpt\ \ 1} + \sum_{r \in Rc(c)} CTP_{crpt} - \sum_{i \in Ic(c)} \left(v_{ic} * \sum_{l \in Lp(p)} MP_{ilpt} \right) \quad \forall c,p,t \tag{2}$$

$$INC_{cpt} \geq ssc_{cp} \quad \forall c,p,t \tag{3}$$

$$\sum_{p} CTP_{crpt} \leq ca_{crt} \quad \forall c,p,t \tag{4}$$

$$\sum_{f \in Fl(l)} tsetupf_{flp} * ZF_{flpt} + \sum_{i \in Il(l)} \left(tsetupi_{ilp} * ZI_{ilpt} + tfab_{ilp} * MP_{ilpt} \right) \leq caf_{lpt} \quad \forall p, l \in Lp(p), t \tag{5}$$

$$MPF_{flpt} = \sum_{i \in If(f)} MP_{ilpt} \quad \forall p, l \in Lp(p), f \in Fl(l), t \tag{6}$$

$$MP_{ilpt} \geq lmi_{ilp} * X_{ilpt} \quad \forall p, l \in Lp(p), i \in Il(l), t \tag{7}$$

$$MP_{ilpt} \leq M1 * X_{ilpt} \quad \forall p, l \in Lp(p), i \in Il(l), t \tag{8}$$

$$MPF_{flpt} \leq M2 * Y_{flpt} \quad \forall p, l \in Lp(p), f \in Fl(l), t \tag{9}$$

$$ZI_{ilpt} \geq X_{ilpt} - X_{ilpt\ \ 1} \quad \forall p, l \in Lp(p), i \in Il(l), t \tag{10}$$

$$\sum_{i} ZI_{ilpt} \geq \sum_{i} X_{ilpt} - 1 \quad \forall p, l \in Lp(p), t \tag{11}$$

$$ZF_{flpt} \geq Y_{flpt} - Y_{flpt\ \ 1} \quad \forall p, l \in Lp(p), f \in Fl(l), t \tag{12}$$

$$\sum_{f} ZF_{flpt} \geq \sum_{f} Y_{flpt} - 1 \quad \forall p, l \in Lp(p), t \tag{13}$$

$$\sum_{t=t'}^{t'+tmf_{flp}\ \ 1} ZF_{flpt} \leq 1 \quad \forall p, l \in Lp(p), f \in Fl(l), t' = 1, \ldots, T \quad tmf_{flp} + 1 \tag{14}$$

$$(1 - cm_i) * cq_i * \beta 1_{ilp} * MP_{ilpt} = \sum_{k} NKL1_{ilpkt} * ordq_{ik} \quad \forall p, \forall l \in Lp(p), i \in Ip(p), t \tag{15}$$

$$(1 - cm_i) * cq_i * \beta 2_{ilp} * MP_{ilpt} = \sum_{k} NKL2_{ilpkt} * ordq_{ik} \quad \forall p, \forall l \in Lp(p), i \in Ip(p), t \tag{16}$$

$$(1 - cm_i) * cq_i * \beta 3_{ilp} * MP_{ilpt} = \sum_{k} NKL3_{ilpkt} * ordq_{ik} \quad \forall p, \forall l \in Lp(p), i \in Ip(p), t \tag{17}$$

$$NKL_{ilpkt} = NKL1_{ilpkt} + NKL2_{ilpkt} + NKL3_{ilpkt} \quad \forall p, i \in Ip(p), \forall l \in Lp(p), \forall k, \forall t \tag{18}$$

$$NKP_{ipkt} = \sum_{l \in Lp(p)} NKL_{ilpkt} \quad \forall p, i \in Ip(p), \forall k, \forall t \tag{19}$$

$$NKP_{ipkt} * ordq_{ik} = \sum_{a \in Ap(p)} CTAK_{ipakt} \quad \forall p, i \in Ip(p), \forall k, \forall t \tag{20}$$

$$INVNAK_{iakt} = INVNAK_{iakt-1} + \sum_{p \in Pa(a)} CTAK_{ipakt} - VEANK_{iakt} - \sum_{q \in Qa(a)} CTCLK_{iaqkt} \ \forall i \in Ia(a), a, k, t \tag{21}$$

$$VENAK_{iakt} + DIFAK_{iakt} - DIFAK_{iakt\ \ 1} = da_{iakt} \ \forall i \in Ia(a), a, k, t \tag{22}$$

$$DIFAK_{iakt} \leq \alpha 1_k \, da_{iakt} \quad \forall i \in Ia(a), a, k, t \tag{23}$$

$$\sum_{k} INVNAK_{iakt} \geq ssa_{ia} \quad \forall a, i \in Ia(a), t \tag{24}$$

$$\sum_{i \in Ia(a)} \sum_{k} INVNAK_{iakt} \leq capal_a \quad \forall a, t \tag{25}$$

$$\sum_{a \in Aq(q)} CTCLK_{iaqkt} = \sum_{w \in Wq(q)} CTTWK_{iqwkt} \quad \forall q, i \in Iq(q), k, t \tag{26}$$

$$\sum_{q \in Qw(w)} CTTWK_{iqwkt} = VENWK_{iwkt} \quad \forall w, i \in Iw(w), k, t \tag{27}$$

$$VENWK_{iwkt} + DIFWK_{iwkt} - DIFWK_{iwkt\ \ 1} = dw_{iwkt} \quad \forall i \in I(w), w, k, t \tag{28}$$

$$DIFWK_{iwkt} \leq \alpha 2_k \, dw_{iwkt} \quad \forall i \in I(w), w, k, t \tag{29}$$

$$
\begin{array}{c}
MPF_{flpt}, MP_{ilpt}, CTP_{crpt}, INC_{cpt}, CTAK_{ipakt}, INVNAK_{iakt}, CTCLK_{iaqkt}, CTTWK_{iqwkt} \geq 0 \\
VENAK_{iakt}, VENWK_{iwkt}, DIFAK_{iakt}, DIFWK_{iwkt} \geq 0 \\
NKL_{ilpkt}, NKP_{ipkt}, NKL1_{ilpkt}, NKL2_{ilpkt}, NKL3_{ilpkt} \geq 0 \; y\, enteras \\
and \quad X_{ilpt}, Y_{flpt}, ZF_{flpt}, ZI_{ilpt} \in \{0,1\} \\
\forall f \in F, \forall i \in I, \forall c \in C, \forall l \in L, \forall p \in P, \forall a \in A, \forall q \in Q, \forall w \in W, \forall r \in R, \forall k \in K, \forall t \in T
\end{array}
\qquad (30)
$$

For being concise, in this section only the MP-CSC-LHP functions that differ from the MP-RDSINC are described. For more details, the reader is referred to [8]. The objective function (1) expresses the gross margin maximization over the time periods that have been computed by subtracting total costs from total revenues. In this model, selling prices and other costs including the backlog costs can be defined for each customer class allowing reflect their relative priority.

Constraints (2) to (14) coincide with those of the MP-RDSINC and make reference to suppliers and productive limitations related to capacity and setup. Constraints (15)-(17) reflect the splitting of a specific lot into three homogeneous sub-lots of first quality ($\beta 1_{ilp} + \beta 2_{ilp} + \beta 3_{ilp} = 1$). The number of sub-lots considered in each lot can be easily adapted to other number different from three. Through these constraints the sizing of lots is decided based on the number of orders from different customer order classes that can be served from each homogeneous sub-lot.

Customer order classes are defined based on the customer order size (i.e, the m^2 ordered). Constraint (18) calculates for each time period, customer class and FG the total number of orders of a specific customer class that can be served from a certain lot by summing up the corresponding number of orders served by each homogeneous sub-lot of this lot. Constraint (19) derives the number of each customer order class that is possible to serve from the planned production of a specific plant. Through constraints (15-19), the production is adjusted not to the aggregate demand forecast as traditionally, but to different customer orders classes.

Furthermore, in contrast to the MP-RDSINC, the distributed, stocked and sold quantities downstream the production plants are expressed in terms of the customer class whose demand will be satisfied through them, being possible to discriminate the importance of each order class. Constraint (20) calculates the quantity of each FG to be transported from each production plant to each warehouse for each customer class based on the order number of each customer class that is satisfied by each production plant and the mean order size. Constraint (21) represents the inventory balance equation at warehouses for each finished good, customer class and time period. As backorders are permitted in both central warehouses and shops, sales may not coincide with the demand for a given time period. Backorder quantities in warehouses for each customer class are calculated using constraint (22). Constraint (23) limits these backorder quantities per customer class in each period in terms of a percentage of the demand of each time period. Constraint (24) forces to maintain a total inventory quantity higher or equal to the safety stock in warehouses. Constraint (25) is the limitation in the warehouses' capacity that is assumed to be shared by all the FG and customer order classes.

Constraint (26) represents the inflows and outflows of FGs and customer order classes through each logistic center. Because it is not possible to maintain inventory in shops, constraint (27) ensures that the total input quantity of a FG for a specific customer class from warehouses to shops coincides with the quantity sold in shops. As backorders are permitted in both central warehouses and shops, sales may not coincide with the demand for a given time period. Constraints (28) and (29) are similar to constraints (22) and (23), respectively, but referred to shops instead of warehouses. The model also contemplates non-negativity constraints and the definition of variables (30).

4. Model Validation: Assessing the Impact of LHP Modeling

The MP-CSC-LHP model has been implemented in MPL (V4.11) and solved with CPLEX 6.6.0. With the aim of comparing the performance of the model with and without LHP modeling, the input data for validation has been mainly extracted for the paper of Alemany et al. [8] that do not consider LHP: MP-RDSINC.

However, some additional parameters have been necessary for the model considering LHP (MP-CSC-LHP). These parameters have been defined maintaining the coherence of the data used by the two models. With this input data the MP-CSC-LHP and the MP-RDSINC have been solved. Results show that MP-RDSINC obtains a greater gross margin than the MP-CSC-LHP mainly due to the lower production costs of the former. This is due to the fact that the MP-RDSINC should produce a lower quantity than the MP-CSC-LHP for satisfying the aggregate demand (Table 3.5).

This result can lead to the wrong conclusion that the MP-RDSINC outperforms the MP-CSC-LHP. This is not true because the MP-RDSINC does not take into account the homogeneity requirement for customer orders. Due to the fact that MP-RDSINC considers all the units of the same lot homogeneous and considers the demand forecasts in an aggregate manner, this model can allow serve the same customer order with quantities of the same FG manufactured in the different lots, thus not guaranteeing the homogeneity in orders.

To obtain results from both models that were really comparable, the lots obtained by the MP-RDSINC model solution (value of decision variable MP_{ilpt}) was transferred as an input data (mp_{ilpt}) to the MP-CSC-LHP computing the new gross margin obtained (MP-RDSINC-LHP). Because the sizing of lots derived from MP-RDSINC were made without considering the customer order size, it may occur that it was impossible to serve an integer number of different customer order classes from the lots of MP-RDSINC leaving some units of lots without being possible to assign them to a specific customer class, and, therefore, obtaining unfeasible solutions. To avoid obtaining unfeasible solutions, the constraints (15-17) have been relax from "=" to "≥" . These new constraints (31-33) allow homogeneous sub-lots defined by the MP-RDSINC (MP_{ilpt}, now mp_{ilpt}) being equal or greater than the sum of an integer number of customer order classes. The difference between the left and the right hand side of the constraints cause the appearance of fragmented stocks (rests) that cannot be assigned to any customer because of the impossibility of accumulating them due to their heterogeneity.

$$(1-cm_i)*cq_i*\beta 1_{ilp}*mp_{ilpt} \geq \sum_k NKL1_{ilpkt}*ordq_{ik} \quad \forall p, \forall l \in Lp(p), i \in Ip(p), t \tag{31}$$

$$(1-cm_i)*cq_i*\beta 2_{ilp}*mp_{ilpt} \geq \sum_k NKL2_{ilpkt}*ordq_{ik} \quad \forall p, \forall l \in Lp(p), i \in Ip(p), t \tag{32}$$

$$(1-cm_i)*cq_i*\beta 3_{ilp}*mp_{ilpt} \geq \sum_k NKL3_{ilpkt}*ordq_{ik} \quad \forall p, \forall l \in Lp(p), i \in Ip(p), t \tag{33}$$

A comparison of the results obtained for the different models are shown in Table 3.5.

Table 3.5. Comparison of results from MP-RDSINC, MP-CSC-LHP and MP-RDSINC-LHP

	MP-RDSINC	MP-CSC-LHP	MP-RDSINC-LHP
Incomes	1.008.539,55	1.008.539,55	1.003.116,65
Supply costs	208.465,58	216.835,92	208.465,58
Production costs	381.918,37	397.034,01	381.918,37
Inventory costs	9.313,91	11.397,90	9.387,50
Setup costs	7.584,24	9.676,45	7.584,24
Transport costs	42.642,71	42.775,75	42.269,60
Backorder costs	0	0	94.500,00
Total costs	649.924,81	677.720,03	744.125,29
Gross margin	358.614,74	330.819,52	258.991,36

As expected, the new value of the gross margin for the MP-RDSINC-LHP was lower than the MP-CSC-LHP because a lower number of customer orders were able to be served with homogeneous quantities by the lots initially defined by the MP-RDSINC (see backorder costs for MP-RDSINC-FHP). It can also be observed an increment of the inventory holding costs of the MP-RDSINC-LHP with respect to those of the MP-RDSINC, due to the fact that the rests of lots that cannot be used to complete a customer order are maintained in inventory. On the other hand, transport costs of the MP-RDSINC model are lower than those of the MP-RDSINC-LHP because a lower number of customer orders are served and, therefore, a lower quantity needs to be transported from the warehouses to shops.

5. Conclusions

Poor LHP management may have very negative effects on SC's competitiveness: (a) LHP leads to fragmented stocks, which can rapidly become obsolete for products with a short life cycle as they cannot be accumulated to be used in the same order given their heterogeneity; (b) uncertainty in the homogeneous quantities available of FGs entails having to produce more than is necessary, thus increasing stocks; and (c) the customer service level may prove deficient, even with high stock volumes, if the order-promising system is not supplied with reliable information about the real and future homogeneous quantities available of a product.

When faced with this situation, there are two clearly different ways to act: technology and management. Research into the technological field focuses mainly on automating the classification process of the FG into different homogeneous subtypes because, to date, eliminating the heterogeneity of the input material or that caused by the production process itself appears to be unachievable. From the management viewpoint, LHP introduces a new requirement in customer's orders that should be served not only on time and with the right quantity, as usual, but also with the adequate homogeneity degree. The OPP plays a crucial role in customer requirements satisfaction and, therefore, in properly managing the special LHP characteristics. But in turn, one of the main inputs to this process is the master plan. Therefore, in this paper a mathematical programming model to solve the master planning problem for replenishment, production, and distribution in ceramic tiles SCs with LHP has been proposed. The result is a master plan that anticipates LHP features in sizing lots and distributing produced quantities along SC and, additionally, provides the OPP with reliable information about future homogeneous quantities available.

The MP-RDSINC model proposed by Alemany et al. [8] has been considered as the starting point to formulate the present model but properly modified in order to reflect the LHP characteristics. Traditionally, the master plan defines the quantities that should be available per product and time period for achieving the aggregate demand forecasts, without specifying the productive resources. In LHP environments the productive process and/or the input materials originates units of the same FG that are not homogeneous regarding some attribute required by the customer. For these cases, it is recommendable to define the master plan in such a way that the future available homogeneous quantities in the production lots can be anticipated as much as possible. To achieve this objective, it could be necessary to define the master plan with a higher level of detail.

Along these lines, because in ceramic sector lots of the same FG manufactured in different production lines and time periods present a high probability of not being homogeneous, it has been necessary to define the quantities to be produced not only for each FG and time period but also specifying the productive resource (production line). This aspect has led to solve the CLSLP. Another novel aspect has been the consideration of splitting one lot into different homogeneous sub-lots. Finally, to model the homogeneity requirement of customer orders, the sizing of lots is made in such a way that an integer number of customer order classes can be served from homogeneous quantities of each sub-lot. To this end, different customer order classes have been defined according to their size and the demand forecasts are expressed in terms of these customer order classes and not in terms of aggregate demand as usual.

The impact of modeling qualities, tones and gages has been assessed by comparing results obtained from the model with LHP (MP-CSC-LHP) and without LHP (MP-RDSINC). Results show that profits and customer service level is higher when considering LHP because lots are sizing to serve an integer number of customer order classes. This aspect also leads to a reduction of the rests of stocks of the same FG along the SC that cannot be assigned to any customer because they cannot be joined due to the lack of homogeneity. Additionally, the obtained information at the master plan level about the homogeneous sub-lots of each FG can be used to calculate the homogeneous ATP quantities, improving the OPP.

Future work will be focused on the following research lines. The first one implies the consideration of uncertainty in the splitting of lots into homogeneous sub-lots as well as in the demand forecasts based on customer classes. The second one implies an analysis of the LHP under an information system's perspective because LHP implies the existence of several references of the same FG. Therefore, this aspect jointly with other ones should be taking into account when designing and building information systems that can provide the right information to the proposed model under a decision-making perspective [15]. Finally, the LHP modeling and its inherent uncertainty increases the complexity of the problem, converting LHP productive systems in large-scale complex systems [16]. As a consequence, another research line will be the development of sustainable decision support systems to help decision-makers in such complex situations [17].

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CAPÍTULO IV:

FUZZY SETS TO MODEL MASTER PRODUCTION EFFECTIVELY IN MAKE TO STOCK COMPANIES WITH LACK OF HOMOGENEITY IN THE PRODUCT

Abstract: Supply chains (SCs) with Lack of Homogeneity in the Product (LHP) present inherent sources of uncertainty due to the heterogeneity of raw materials and uncontrollable productive factors. LHP SCs are characterized by producing units of the same finished goods that are not homogeneous. However, the exact quantity of each one in a production lot will only be known when it is produced. These SCs must classify finished goods into subtypes according to customer requirements. In this paper, a fuzzy mathematical programming model is proposed. To match homogeneity customer requirements with the sizing of production lots, the proposed master plan considers two main aspects: 1) forecast demand is expressed in terms of number of orders with a similar order size; 2) LHP is modeled by considering that each production lot is split into several homogeneous sub-lots. Then uncertainty is considered by means of fuzzy sets in order sizes and homogeneous sub-lots quantities. The fuzzy model is evaluated by emulating real conditions and is compared with the equivalent deterministic one to assess its robustness. The results demonstrate that the fuzzy approach outperforms the deterministic one and that it is more effective for handling real situations when LHP is present.

Key words: master planning, make to stock, fuzzy mathematical programming, lack of homogeneity in the product, fuzzy sets, uncertainty modeling.

1. Introduction

One of the most important objectives of companies is the fulfillment of customer requirements. Traditionally, customer requirements have been expressed in terms of quantities, due dates and quality levels. However, there are situations in which customers request homogeneity among ordered units of finished goods (FG) with respect to certain attributes because they have to be used, shown, placed or consumed jointly [1]. The customer may need homogeneity among components of a product, such as diamonds on a bracelet or among units of the same product, for example ceramic tiles on the floor. Lack of Homogeneity in the Product (LHP) appears in production processes which include raw materials that directly originate from nature and/or production processes with operations that give the heterogeneity of the characteristics of the outputs obtained, even when the inputs used are homogeneous [2]. Alarcón et al. [1] define Lack of Homogeneity in the

Product (LHP) as the absence of the homogeneity requested by the customer in the products.

Companies with LHP should include one classification stage or several during their productive process to sort units of the same item in a lot into homogeneous subsets (subtypes) based on attributes that are relevant to customer requirements. The classification criteria of an FG into subtypes depend on each sector. Indeed, LHP in lots appears in very different sectors in several ways. For instance, in fruit supply chains there are several classification (sorting and grading) stages located at different points during the productive process which aim to eliminate waste and to classify fruits into several qualities based on different attributes. The main attributes for sorting and grading fresh fruit are size, weight, ripeness, damage, color, shape and firmness. In the ceramic sector, LHP is due to the non uniformity of raw materials (clays) and some components (frits and enamels), along with some uncontrollable productive variables. As customers require homogeneity in units of the same ceramic wall or tile, these companies locate one classification stage at the end of the process. In this stage, ceramic pieces are classified based on the following attributes: quality, tone and gage. In short, the total number of existing subtypes of each LHP-item depends on the attributes used in the classification stage and their possible values. Historical data can provide the number of subtypes obtained, but in other cases this number can be *a priori* unknown.

These LHP characteristics complicate system management in different ways: 1) the customer homogeneity requirement introduces new constraints to be accomplished, which complicates the identification of not only the optimal solution, but also of a feasible one; 2) the existence of several subtypes of the same item increases the number of references and the volume of information to be processed; 3) after each classification stage, the quantity of each subtype in production lots will be known only after production has finished and FGs have been classified. Therefore, companies with LHP face a new kind of uncertainty:

uncertainty in the homogeneous quantities of each subtype that will be available in the planned production lots.

The master plan (MP) definition plays a crucial role in balance demand and supply at the tactical level. The MP determines the inventory levels at the customer order decoupling point (CODP), which links planned production with specific customer orders [3]. Traditionally, the homogeneous subsets (sub-lots) from classified items are not normally taken into account at the MP level. However, LHP SCs have to serve customers not only the right quantities and on due dates, but also in the requested homogeneity terms. In this context, it is essential that the homogeneous quantities manufactured should complete a whole FGs order size efficiently. To fulfill this objective, the MP should anticipate these homogeneous quantities as much as possible in order to better size production batches and improve the customer service level. Moreover, order size becomes a very important LHP factor because the larger the customer order size, the harder it is to meet the homogeneity requirement among all its units. For these reasons, it is worthwhile defining the forecasted customer demand in terms of the expected order number of a specific customer class. Each customer order class is characterized to request a similar order quantity (order size) of a FG. This represents another differentiated aspect because demand forecasts at the MP level are usually expressed in an aggregate manner by product families or FGs [4].

In this paper, modeling LHP uncertainty in lots and customer order size by fuzzy sets is proposed. The Fuzzy Set Theory provides a means to represent uncertainties and is a marvelous tool for modeling the kind of uncertainty that is associated with vagueness, imprecision, and/or lack of information on a particular element of the problem at hand [5]. For LHP contexts, the unpredictable characteristics of raw materials and/or the existence of uncontrollable productive factors make knowledge of the homogeneous quantities of each subtype available in future planned lots imprecise. Furthermore, it is sometimes not feasible or is very costly to measure them reliably. In these cases, the use of Fuzzy Sets is appropriate. As described in section 3, it is necessary to apply the Fuzzy Theory to dependent technological coefficients when modeling this type of LHP uncertainty. Up to our knowledge, the uncertainty modeling by Fuzzy Sets has been limited to independent fuzzy coefficients. Therefore, this aspect constitutes another contribution of this paper.

Thus, the main objectives of this paper are summarized as follows:

(i) Introducing a novel fuzzy mathematical programming model for master planning companies with LHP and,
(ii) Assessing the impact of LHP uncertain modeling by applying it to a ceramic company and analyzing its behavior under realistic conditions.

The rest of this paper is structured as follows. Section 2 reviews the literature related to mathematical modeling for LHP SC master planning under uncertainty. Section 3 proposes the novel fuzzy mathematical programming model for the master planning of LHP companies and its solution methodology. In Section 4, the model is validated under real conditions for a ceramic company. Finally, Section 5 presents the conclusions and future research.

2. Background literature

In the decision making related to SC planning, all the necessary information is not always available [6]. A general definition of uncertainty is provided by Galbraith [7], who states that the difference lies between the amount of information required to perform a task and the information actually possessed. Many authors classify sources of uncertainty into three groups [6,8,9]: demand, process and supply. Yet a variety of uncertainty factors affect distinct organizations in different ways. In fact, SCs with LHP have unique characteristics with inherent sources of uncertainty that have a great impact on the customer service level. SCs with LHP are forced to face a new kind of uncertainty [2,10], LHP inherent uncertainty, because the quantity of each subtype in lots is known only after production has finished and items have been classified.

Most SC planning researches model uncertainties with probability distributions, which are usually predicted from historical data [11]. Mula et al. [12] propose different approaches to cope with various forms of uncertainty. A conclusion of their research is that the stochastic approach is the most widely used to model uncertainty in SCs. LHP inherent uncertainty affects several sectors in different ways. LHP appears in papers that deal with different sectors, although the authors do not exactly name it LHP. For instance, subtypes are often identified with units of the same product with different qualities. Many authors propose handling such LHP uncertainty through stochastic models by considering different scenarios. In the petroleum sector, these are: Carneiro et al. [13] consider the composition of intermediate products as uncertain parameters; Luo and Rong [14] define that properties for components are uncertain parameters with continuous probability distribution; Ribas et al. [15] deal with density and viscosity as uncertain parameters. In the remanufacturing sector, Aras et al. [16], Denizel et al. [17] and Zeballos et al. [18] consider that returned products are categorized in relation to their quality. In the mining sector, Rico-Ramirez et al. [19] define the quality of ore by an uncertain parameter and pose different scenarios for the analysis. Other works in the literature on LHP uncertainty that have used stochastic models are Ahumada et al. [20] in the agricultural sector, Osmani et al. [21] in a biorefinery industry, and Zanjani et al. in the wood sector with several works [22,23,24]. They deal with uncertainty in coefficients of yield. Some authors as Albornoz et al. [25] and Munhoz and Morabito [26] in the food sector, suggest LP models and take into account the uncertainty due to quality and composition of raw materials by considering different scenarios.

However, the stochastic programming approach has two main drawbacks: it can be computationally inefficient and, very often, the probability distributions deriving from past evidence are not always available or reliable [27]. Inuiguchi and Ramik [5] compare fuzzy mathematical programming approaches to stochastic programming ones, and note that solving a fuzzy mathematical programming problem can be easier than a stochastic programming problem. Therefore whenever statistical data are unreliable, or are not even available, stochastic models might not be the best choice. The Fuzzy Set Theory and the Possibility Theory may be simpler and less data-demanding alternatives than the Probability Theory to deal with SC uncertainties [28,29]. Despite its advantages, very few authors consider Fuzzy approach to deal with LHP uncertainty. In the mining industry, Chakraborty et al [30] consider grades of coal as fuzzy parameters and Pendharkart [31,32] deal with different quality levels in two works. [30] deal with optimal planning for blending raw coal of different grades to satisfy the requirements of end users who have desired specifications. They consider three fuzzy objectives in conflict: the permitted amount of ash percentage in wash coal; the desired yield of wash coal; the maximum input cost of raw coal. However, the degree of achievement depends on the permissible ranges of the input raw coal according to the decision maker's choice. Pendharkart [31] considers two fuzzy measures: acceptable level of profit (objective function) and acceptable level of quality (upper quality bound: maximum sulfur limit). Pendharkart [32] bases this work on [31] but using simpler fuzzy membership functions than [31]. Rong and Lahdelma [33] propose a model which poses raw materials composition as fuzzy parameters in the steel sector. They consider uncertainty in element concentrations for different scrap types. The uncertainty of the element concentrations for scrap causes the element concentration in the product to deviate from the product standard. The product standard specifies lower and upper limits for each alloying element concentration. None of these three works considers classifications or divisions of lots into different subtypes, but the exact opposite; materials with a different quality or composition are blended to obtain FGs with certain specifications. Miller et al. [34] and Ghasemy et al. [35] contemplate perishable products. [34] consider the costs of objective function to be fuzzy, including cost of waste due to delays in harvesting tomatoes, and these authors use Zimmermann's approach [36] to resolve. [35] propose a model in a fuzzy environment by integrating production planning and pricing policy for short life cycle products (perishable products). They consider the objective function, unit costs and capacity and storage levels to be fuzzy. They also consider the salvage value of products to be fuzzy parameters. Phuc et al. [37] deal with uncertainty in remanufacturing sector by considering several parameters as uncertain: demands, recovery materials, disposal, and reusable products, prices, and costs. Then, a method is proposed to solve the possibilistic model that can be easily applied to various types of fuzzy numbers, either linear or nonlinear ones. In all cases mentioned above, the technological coefficients are independent.

From the literature review, only two papers deal with uncertainty in the ceramic sector. Peidro et al. [38] consider three fuzzy objectives in conflict in their mathematical model, but do not refer to LHP inherent uncertainty. Mundi et al. [10] proposed a deterministic mathematical programming model embedded into a Decision Support System. The LHP in production lots is also modeled through dependent coefficients, but LHP uncertainty is managed through the DSS functionalities that help to define, solve and analyze different scenarios based on selected uncertain parameters.

Thus from the literature review it can be stated that, to our knowledge, there are no studies on fuzzy mathematical programming models for the MP of LHP companies with dependent fuzzy parameters. The need for modeling uncertainty among interdependent coefficients derives from representing homogeneous sub-lots by means of production lot fractions. The sum of these fractions should equal one; i.e.: the sum of homogeneous sub-lots equals the entire lot. Furthermore, we propose a novel way of modeling demand uncertainty by considering customer classes based on their mean order size. The next section presents the mathematical formulation of the fuzzy model.

3. Fuzzy master planning model for LHP manufacturing contexts (FMP-LHP)

In this paper, the capacitated MP problem of companies with parallel resources working under a Make-To-Stock in an LHP context is considered. First, the problem characteristics under study are presented. Second, the formulation of the fuzzy model is described. Finally, the solution methodology is detailed.

3.1. Problem description

In this research work, LHP uncertainty modeling for MP in the production stage is addressed. A simplification of the problem, as stated in [4], is taken as a basis for this research. Unlike the problem studied in [4], neither the multi-supplier in the replenishment stage nor multi-level distribution centers is/are considered. The reason is because we are interested in the effects of inherent LHP uncertainty modeling in the production stage to be always connected with customer demand. Therefore, given the aim to eliminate any other factors that can distort the results when assessing the LHP uncertainty impact, the SC physical scope diminishes and only the production and sales stages are considered.

Other main features of the problem under study in the production stage are:

- There are different parallel resources (production lines) with limited capacity.
- Different FGs can be processed by each production line.
- Item setup changes are explicitly considered because setup times involve major capacity consumption.
- Units of the same FG with different attributes (subtypes) appear in each lot.
- Therefore, splitting each manufactured lot into homogeneous sub-lots of the same FG is incorporated to reflect the LHP characteristics.

As regards the demand stage, it is worth stressing that LHP becomes a managerial problem because of customers' homogeneity requirements. Therefore, LHP introduces a new customized aspect into the order proposals: the homogeneity type required among ordered products.

- Customers require homogeneity among units of the same FG without specifying the subtype; i.e. the only LHP constraint is that all the units of each FG in the order are homogeneous, and the subtype from which the order is completed is not relevant.

The way to model customer demand depends primarily on the model purpose. For planning purposes, demand is usually expressed as forecasts of product families or FGs. Yet when modeling LHP in production lots at the planning level, the homogeneity requirement in demand should be incorporated in some way in order to better size lots in each productive resource. Note that order size becomes a very relevant LHP factor because the larger the order size is, the more difficult it is to meet the uniformity requirements among all its units. For this reason, herein:

- Customer order classes are defined based on their size.
- Forecast demand is expressed in terms of the expected number of orders for each customer order class.
- Backorders are permitted.

Therefore during the process of linking demand with supply, which is the MP definition, the following considerations are taken into account:

- Sizing of lots for each production line is done so that an integer number of customer order classes can be served from the homogeneous quantities of each sub-lot.
- In order to ensure the homogeneity required by customers, it is not allowed to serve the same customer order class by mixing quantities from different homogeneous sub-lots.
- Two parameters are considered to be uncertain: the percentage of a specific lot that can be considered homogeneous ($\tilde{\beta}_{\beta ilt}$); the size of each customer order class ($\tilde{ord}q_{ik}$).

3.2. FMP-LHP Model formulation

In this section, the fuzzy model formulation to support MP in LHP contexts, dubbed as FMP-LHP, is described. The indices (Table 4.1), sets of indices (Table 4.2), model parameters (Table 4.3) and decision variables (Table 4.4) are presented below. As seen in Table 4.3, fuzzy parameters include a tilde "~". If these parameters are considered deterministic, solving the following model can provide the deterministic solution.

Table 4.1. Indices

i	Finished goods (i= 1, …, I)
l	Production lines (l= 1, …, L)
k	Customer order classes (k= 1, …, K)
t	Periods of time (t= 1, …, T)
β	Homogeneous sub-lot of a subtype in a lot (β= 1, …, B)

Table 4.2. Sets of indices

Il(l)	Set of FGs that can be manufactured on manufacturing line *l*
Li(i)	Set of manufacturing lines that can produce FG*i*

Table 4.3. Parameters (fuzzy parameters are shown with a tilde "~"):

cap_{lt}	Production capacity available (time) of production line l during time period t
cp_{il}	Production costs for one unit of FG i on production line l
$csetup_{il}$	Setup costs for FG i on production line l
tpr_{il}	Time to process one unit of FG i on production line l
$tsetup_{il}$	Setup time for article i on production line l
ch_i	Unitary holding cost of FG i during a period
cbl_{ik}	Unitary backorder cost of FG I for customer order class k during a period
p_{ik}	Sales value of FG i for customer order class k
M_i	Very large integer defined for each FG i
$o\tilde{r}dq_{ik}$	Average size of customer order class k of FG i
nk_{ikt}	Forecast number of orders of FG I of customer class k during period t
d_{ikt}	Forecast demand of FG i of customer class k during period t
$\tilde{B}_{\beta ilt}$	Fraction of each planned lot that can be considered homogeneous. Through these coefficients, the splitting of lots into homogeneous sub-lots is modeled, which depend on the FG, the production line and the time period. These coefficients are not independent because their total sum should equal $1(\sum_{\beta}\tilde{B}_{\beta ilt}=1)$.

Table 4.4. Decision variables

MP_{ilt}	Total amount of FG i manufactured on production line l during period t
$MPBeta_{ilt}$	Amount of homogeneous sub-lot β of FG i produced on production line l during period t
Z_{ilt}	Binary variable with a value of 1 if a setup of product i takes place on production line l during time period t, and with a value of 0 otherwise
INV_{ilt}	Inventory of FG i derived from production line l during period t
$INVBeta_{ilt}$	Inventory of homogeneous sub-lot β of FG i from production line l during period t
VEK_{ikt}	Quantity of FG i sold to customer class k during period t
BLK_{ikt}	Backorder quantity of FG i to customer class k from period t to period t +1
$NKVB_{ikt}$	Total number of backorders from customer class k of FG i from period t to period t +1
$VEKBeta_{\beta ilkt}$	Amount of homogeneous sub-lot β of FG i produced on production line l and sold to customer class k during period t
$NKVEK_{ikt}$	Total number of orders of FG i sold to customer class k during period t
$NKVEKBeta_{\beta ilkt}$	Total number of orders of FG i which derive from homogeneous sub-lot β of FG i produced on production line l and sold to customer class k during period t
$NKLBeta_{\beta ilkt}$	Number of orders of FG i belonging to customer class k that can be served from homogeneous sub-lot β of FG i to be produced on production line l during period t

The FMP-LHP Model is formulated as follows:

Objective Function

$$Max[z] = \sum_{i,k,t} p_{ik} * VEK_{ikt} - \sum_{i,l,t} csetup_{il} * Z_{ilt} - \sum_{i,l,t} cp_{il} * MP_{ilt} - \sum_{i,t} ch_i * INV_{it} - \sum_{i,k,t} cbl_{ik} * BLK_{ikt} \quad (1)$$

Subject to

$$\sum_{i \in Il(l)} (tsetup_{il} * Z_{il} + tpr_{il} * MP_{ilt}) \leq cap_{lt} \quad \forall l, t \quad (2)$$

$$MP_{ilt} \leq M_i * Z_{ilt} \quad \forall l, i \in Il(l), t \quad (3)$$

$$Z_{ilt} \leq MP_{ilt} \quad \forall l, i \in Il(l), t \quad (4)$$

$$MPBeta_{\beta ilt} = \tilde{B}_{\beta ilt} * MP_{ilt} \quad \forall \beta, l, i \in Il(l), t \quad (5)$$

$$MPBeta_{\beta ilt} = \sum_k NKLBeta_{\beta ilkt} * o\tilde{r}dq_{ik} \quad \forall \beta, l, i \in Il(l), t \quad (6)$$

$$INVBeta_{\beta ilt} = INVBeta_{\beta ilt-1} + MPBeta_{\beta ilt} - \sum_k VEKBeta_{\beta ilkt} \quad \forall \beta, l, i \in Il(l), t \quad (7)$$

$$INV_{ilt} = \sum_\beta INVBeta_{\beta ilt} \quad \forall l, i \in Il(l), t \quad (8)$$

$$VEK_{ikt} = \sum_\beta \sum_{l \in Li(i)} VEKBeta_{\beta ilkt} \quad \forall i, k, t \quad (9)$$

$$VEK_{ikt} = d_{ikt} + BLK_{ikt-1} - BLK_{ikt} \quad \forall i, k, t \quad (10)$$

$$NKVEK_{ikt} = nk_{ikt} + NKVB_{ikt-1} - NKVB_{ikt} \quad \forall i, k, t \quad (11)$$

$$\sum_t NKLBeta_{\beta ilkt} \leq \sum_t nk_{ikt} \quad \forall \beta, i, k, t \quad (12)$$

$$NKVEKBeta_{\beta ilkt} \leq NKLBeta_{\beta ilkt=0} + \sum_{t' \leq t} NKLBeta_{\beta ilkt} \quad \forall \beta, i, l, k, t \quad (13)$$

$$d_{ikt} = nk_{ikt} * o\tilde{r}dq_{ik} \quad \forall i, k, t \quad (14)$$

$$VEK_{ikt} = NKVEK_{ikt} * o\tilde{r}dq_{ik} \quad \forall i, k, t \quad (15)$$

$$BLK_{ikt} = NKVB_{ikt} * o\tilde{r}dq_{ik} \quad \forall i, k, t \quad (16)$$

$$VEKBeta_{\beta ilkt} = NKVEKBeta_{\beta ilkt} * o\tilde{r}dq_{ik} \quad \forall \beta, i, l, k, t \quad (17)$$

$MP_{ilt}, MPBeta_{\beta ilt}, VEK_{ikt}, VEKBeta_{\beta ilkt}, BLK_{ikt}, INV_{ilt}, INVBeta_{ilt} \geq 0$

$$NKVEK_{ikt}, NKVEKBeta_{\beta ilkt}, NKVB_{ikt}, NKLBeta_{\beta ilkt} \geq 0 \text{ and integers} \qquad \forall\, \beta, i, l, k, t \tag{18}$$

$Z_{ilt} \in \{0,1\}$

The objective function (1) expresses the profit on the horizon considered by subtracting total costs from total revenues. Total revenue is calculated as the income produced by sales. Total costs include the setup, production, storage and backorder costs of FGs.

Constraint (2) ensures that the capacity required for the setup of the products produced during each time period, and the processing of the lots allocated to each line, do not exceed the available capacity on each production line at each time period. Constraint (3) guarantees that only a certain amount of an article can be manufactured on one line, provided that the production of this product has been assigned to this line. Constraint (4) means that the setup is not conducted if production is not allocated to the production line.

The homogeneous sub-lots in each lot is given by index β. Constraint (5) reflects the splitting of a specific lot into homogeneous sub-lots and calculates every homogeneous sub-lot derived from a batch produced on a production line during a period by the corresponding fraction $\tilde{B}_{\beta ilt}$. As it can be observed, different combinations of $\tilde{B}_{\beta ilt}$ will provide the same division of a lot into homogeneous sub-lots. For instance the $\tilde{B}_{\beta ilt}$ fractions (0.2,0.1,0.7) of a lot are equivalent to either (0.7,0.2,0.1) or (0.1,0.7,0.2). This is because all these combinations represent the same situation: a lot divided into three homogeneous sub-lots in the proportions 10%, 20% and 70% of the original lot size. Therefore, the order in which the proportions of the beta coefficients are set is indistinct because all the possibilities reflect the same situation and, therefore, provide the same set of customer orders to be served. The underlying reason is that the proposed model assumes that customers do not specify the subtype in their orders and only require to be served with homogeneous units, regardless of the homogeneous sub-lot which they come from. Constraint (6) ensures that each homogeneous sub-lot must exactly cover an integer number from a combination of different customer orders classes. Through this constraint, the lots in the MP are sized in such a way that an integer number of orders from different customer order classes can be served from each homogeneous sub-lot. Constraint (5), along with constraint (6), represents the core constraints of the LHP problem being considered.

Constraint (7) represents the inventory balance equation for each FG from subtype β by production line and time period. Constraint (8) calculates the total inventory of each FG manufactured on production line l at the end of a time period by summing the inventory of each subtype. Constraint (9) calculates the total amount of FG I sold to customer class k by summing all the amounts sold of the same FG and customer class, but from the different homogeneous sub-lots for all the production lines.

As backorders are permitted, sales may not coincide with demand for a given time period. The backorder quantities for each customer class are calculated using constraint (10). Constraint (11) is the same as constraint (10), but in terms of the integer number of orders instead of quantities.

Constraint (12) reflects that the number of orders that can be served from all the homogeneous sub-lots cannot exceed the estimated number of forecast orders. Constraint (13) ensures that the number of orders sold cannot exceed the number of orders that can be served from the quantities produced of each homogeneous sub-lot during previous periods, including those derived from the initial stock quantities.

Through Constraint (14), the relationship between the demand forecast, the number of orders and their average size appears per customer order class and time period. Constraint (15) calculates the number of orders from each customer class k based on the total amount to be sold and the mean order size of the corresponding customer class. Constraint (16) is analogous to constraint (15), but refers to backorders.

Constraint (17) represents the link between the amount of each homogeneous sub-lot of each product sold to each customer class with the number of orders and the size of the order.

The model also contemplates non negativity constraints and the definition of variables (18).

3.3. Solution methodology of the FMP-LHP Model

Having formulated, the fuzzy model FMP-LHP is needed to proceed to its resolution. In the possibility theory context, there are different approaches to model the coefficients of the objective function and/or the constraints as fuzzy numbers [45,46,47]. In this paper, we adopt the approach by Jiménez et al. [47]. This approach is computationally efficient to solve an LP problem because it preserves its linearity and applies the robustness, among other properties, to justify ranking methods. The authors propose a method for solving linear programming models where all the coefficients are, in general, fuzzy numbers, whose possibility distribution is given by trapezoidal fuzzy numbers. This previous research defines an approach to transform the original model with fuzzy coefficients on the left-right hand side of the constraints into an equivalent crisp model. In this paper however, additional constraints to this equivalent crisp model should be added to manage the dependency among the fuzzy beta coefficients ($\tilde{B}_{\beta ilt}$). We have no knowledge of any research work that models uncertainty in dependent technological coefficients which is, therefore, one of the contributions of this paper.

The fuzzy coefficients of the equivalent crisp model are represented as alpha-parametric values, which can vary in a predefined interval based on the alpha parameter. The value of the alpha parameter belongs to the interval [0, 1]. Low alpha values represent high levels of uncertainty, and vice versa, and modeling the alpha equals 1, which is completely deterministic behavior. [47] also propose an interactive solution method to select the most suitable alpha value, which is also adopted in the present research.

Given a linear programming problem with fuzzy parameters in Constraints (19),

$$Min[z] = c^t x$$
$$s.a.\ x \in N(\tilde{A}, \tilde{b}) = \{x \in R^n \,/\, \tilde{a}_{ij} x \geq \tilde{b}_i, \qquad \forall\, i = 1, \dots n,\ x \geq 0 \tag{19}$$

the uncertain and/or imprecise nature of the parameters of the problem led us to compare fuzzy numbers. By applying the approach described by [47], we can transform the fuzzy linear programming model into the crisp equivalent parametric linear programming problem.

If fuzzy number ã presents a trapezoidal membership function, its expected interval can be calculated as expressed in (20), where a_1 and a_4, represent the lower and upper limits of the interval, respectively, and a_2 and a_3 represent its intermediate numbers. It is represented by: a = [a_1, a_2, a_3, a_4]. In the particular case of $a_2 = a_3$, the membership function of the fuzzy number becomes triangular:

$$EI(\tilde{a}) = [E_1^a, E_2^a] = \left[\frac{a_1 + a_2}{2}, \frac{a_3 + a_4}{2}\right] \tag{20}$$

Thus, if a constraint is a less than, or equal, type constraint, it can be transformed into the equivalent crisp constraint (21).

$$[(1-\alpha)E_1^a + \alpha E_2^a]x \leq \alpha E_1^b + (1-\alpha)E_2^b \qquad \alpha \in [0,1] \tag{21}$$

If the constraint is a more than, or equal, type constraint, this can be transformed into the equivalent crisp constraint (22).

$$[(1-\alpha)E_2^a + \alpha E_1^a]x \geq \alpha E_2^b + (1-\alpha)E_1^b \qquad \alpha \in [0,1] \tag{22}$$

Finally, if constraint is an equal type constraint, it can be transformed into two equivalent crisp Constraints (23) and (24):

$$\left[\left(1-\frac{\alpha}{2}\right)E_1^a + \frac{\alpha}{2}E_2^a\right]x \leq \frac{\alpha}{2}E_1^b + \left(1-\frac{\alpha}{2}\right)E_2^b \qquad \alpha \in [0,1] \tag{23}$$

$$\left[\left(1-\frac{\alpha}{2}\right)E_2^a + \frac{\alpha}{2}E_1^a\right]x \geq \frac{\alpha}{2}E_2^b + \left(1-\frac{\alpha}{2}\right)E_1^b \qquad \alpha \in [0,1] \tag{24}$$

where $\alpha \in [0,1]$ is the degree of feasibility of decision x.

Consequently, by applying this approach to the defined model and considering the uncertain parameters defined by $\tilde{ordq}_{ik}$= ($ordq^1_{ik}$, $ordq^2_{ik}$, $ordq^3_{ik}$, $ordq^4_{ik}$) and $\tilde{B}_{\beta ilt}$= ($B^1_{\beta ilt}$, $B^2_{\beta ilt}$, $B^3_{\beta ilt}$, $B^4_{\beta ilt}$), we obtain an auxiliary crisp mixed-integer linear programming model:

Objective Function

$$Max[z] = \sum_{i,k,t} p_{ik} * VEK_{ikt} - \sum_{i,l,t} cp_{ilt} * MP_{ilt} - \sum_{i,l,t} csetup_{ilt} * Z_{ilt} - \sum_{i,t} ch_i * INV_{it} - \sum_{i,k,t} cbl_{ik} * BLK_{ikt} \quad (1)$$

Subject to

$$\sum_{i \in Il(l)} (tsetup_{il} * Z_{il} + tpr_{il} * MP_{ilt}) \leq cap_{lt} \forall l, t \quad (2)$$

$$MP_{ilt} \leq M_i * Z_{ilt} \forall l, i \in Il(l), t \quad (3)$$

$$Z_{ilt} \leq MP_{ilt} \forall l, i \in Il(l), t \quad (4)$$

$$MPBeta_{\beta ilt} \geq \left[\frac{\alpha}{2}\left(\frac{B^3_{\beta ilt}+B^4_{\beta ilt}}{2}\right) + \left(1-\frac{\alpha}{2}\right)\left(\frac{B^1_{\beta ilt}+B^2_{\beta ilt}}{2}\right)\right] * MP_{ilt} \forall \beta, l, i \in Il(l), t \quad (5a)$$

$$MPBeta_{\beta ilt} \leq \left[\frac{\alpha}{2}\left(\frac{B^1_{\beta ilt}+B^2_{\beta ilt}}{2}\right) + \left(1-\frac{\alpha}{2}\right)\left(\frac{B^3_{\beta ilt}+B^4_{\beta ilt}}{2}\right)\right] * MP_{ilt} \forall \beta, l, i \in Il(l), t \quad (5b)$$

$$MPBeta_{\beta ilt} \geq \sum_k NKLBeta_{\beta ilkt} * \left[\left(1-\frac{\alpha}{2}\right)\left(\frac{ordq^1_{ik}+ordq^2_{ik}}{2}\right) + \frac{\alpha}{2}\left(\frac{ordq^3_{ik}+ordq^4_{ik}}{2}\right)\right] \forall \beta, l, i \in Il(l), t \quad (6a)$$

$$MPBeta_{\beta ilt} \leq \sum_k NKLBeta_{\beta ilkt} * \left[\left(1-\frac{\alpha}{2}\right)\left(\frac{ordq^3_{ik}+ordq^4_{ik}}{2}\right) + \frac{\alpha}{2}\left(\frac{ordq^1_{ik}+ordq^2_{ik}}{2}\right)\right] \forall \beta, l, i \in Il(l), t \quad (6b)$$

$$INVBeta_{\beta ilt} = INVBeta_{\beta ilt-1} + MPBeta_{\beta ilt} - \sum_k VEKBeta_{\beta ilkt} \qquad \forall \beta, l, i \in Il(l), t \quad (7)$$

$$INV_{ilt} = \sum_\beta INVBeta_{\beta ilt} \qquad \forall l, i \in Il(l), t \quad (8)$$

$$VEK_{ikt} = \sum_\beta \sum_{l \in Li(i)} VEKBeta_{\beta ilkt} \qquad \forall i, k, t \quad (9)$$

$$VEK_{ikt} = d_{ikt} + BLK_{ikt-1} - BLK_{ikt} \qquad \forall i, k, t \quad (10)$$

$$NKVEK_{ikt} = nk_{ikt} + NKVB_{ikt-1} - NKVB_{ikt} \qquad \forall i, k, t \quad (11)$$

$$\sum_t NKLBeta_{\beta ilkt} \leq \sum_t nk_{ikt} \qquad \forall \beta, i, k, t \quad (12)$$

$$NKVEKBeta_{\beta ilkt} \leq NKLBeta_{\beta ilkt=0} + \sum_{t' \leq t} NKLBeta_{\beta ilkt} \qquad \forall\, \beta, i, l, k, t \qquad (13)$$

$$d_{ikt} \geq nk_{ikt} * \left[\left(1-\frac{\alpha}{2}\right)\left(\frac{ordq_{ik}^{1}+ordq_{ik}^{2}}{2}\right)+\frac{\alpha}{2}\left(\frac{ordq_{ik}^{3}+ordq_{ik}^{4}}{2}\right)\right] \qquad \forall\, i, k, t \qquad (14a)$$

$$d_{ikt} \leq nk_{ikt} * \left[\left(1-\frac{\alpha}{2}\right)\left(\frac{ordq_{ik}^{3}+ordq_{ik}^{4}}{2}\right)+\frac{\alpha}{2}\left(\frac{ordq_{ik}^{1}+ordq_{ik}^{2}}{2}\right)\right] \qquad \forall\, i, k, t \qquad (14b)$$

$$VEK_{ikt} \geq NKVEK_{ikt} * \left[\left(1-\frac{\alpha}{2}\right)\left(\frac{ordq_{ik}^{1}+ordq_{ik}^{2}}{2}\right)+\frac{\alpha}{2}\left(\frac{ordq_{ik}^{3}+ordq_{ik}^{4}}{2}\right)\right] \qquad \forall\, i, k, t \qquad (15a)$$

$$VEK_{ikt} \leq NKVEK_{ikt} * \left[\left(1-\frac{\alpha}{2}\right)\left(\frac{ordq_{ik}^{3}+ordq_{ik}^{4}}{2}\right)+\frac{\alpha}{2}\left(\frac{ordq_{ik}^{1}+ordq_{ik}^{2}}{2}\right)\right] \qquad \forall\, i, k, t \qquad (15b)$$

$$BLK_{ikt} \geq NKVB_{ikt} * \left[\left(1-\frac{\alpha}{2}\right)\left(\frac{ordq_{ik}^{1}+ordq_{ik}^{2}}{2}\right)+\frac{\alpha}{2}\left(\frac{ordq_{ik}^{3}+ordq_{ik}^{4}}{2}\right)\right] \qquad \forall\, i, k, t \qquad (16a)$$

$$BLK_{ikt} \leq NKVB_{ikt} * \left[\left(1-\frac{\alpha}{2}\right)\left(\frac{ordq_{ik}^{3}+ordq_{ik}^{4}}{2}\right)+\frac{\alpha}{2}\left(\frac{ordq_{ik}^{1}+ordq_{ik}^{2}}{2}\right)\right] \qquad \forall\, i, k, t \qquad (16b)$$

$$VEKBeta_{\beta ilkt} \geq NKVEKBeta_{\beta ilkt} * \left[\left(1-\frac{\alpha}{2}\right)\left(\frac{ordq_{ik}^{1}+ordq_{ik}^{2}}{2}\right)+\frac{\alpha}{2}\left(\frac{ordq_{ik}^{3}+ordq_{ik}^{4}}{2}\right)\right] \qquad \forall\, \beta, i, k, t \qquad (17a)$$

$$VEKBeta_{\beta ilkt} \leq NKVEKBeta_{\beta ilkt} * \left[\left(1-\frac{\alpha}{2}\right)\left(\frac{ordq_{ik}^{3}+ordq_{ik}^{4}}{2}\right)+\frac{\alpha}{2}\left(\frac{ordq_{ik}^{1}+ordq_{ik}^{2}}{2}\right)\right] \qquad \forall\, \beta, i, l, k, t \qquad (17b)$$

$$MP_{ilt}, MPBeta_{\beta ilt}, VEK_{ikt}, VEKBeta_{\beta ilkt}, BLK_{ikt}, INV_{ilt}, INVBeta_{ilt} \geq 0$$

$$NKVEK_{ikt}, NKVEKBeta_{\beta ilkt}, NKVB_{ikt}, NKLBeta_{\beta ilkt} \geq 0 \text{ } y \text{ } enteras \qquad \forall\, \beta, i, l, k, t \qquad (18)$$

$$Z_{ilt} \in \{0,1\}$$

In this paper, it is assumed that the expected values of the fuzzy beta coefficients and the fuzzy size of each customer order class can be represented by either a trapezoidal function or a triangular one by making $B^2_{\beta ilt} = B^3_{\beta ilt}$ and $ordq^2_{ik} = ordq^3_{ik}$, respectively. For instance, if it is assumed that three homogeneous sub-lots are obtained (B=3) in proportions of 0.7, 0.2 and 0.1 for each lot. These beta values, are considered the central values and a triangular fuzzy number can be generated for each beta within the +/- 50% range from the central value. In this way, the three resulting fuzzy numbers would be $\tilde{B}_{1ilt}$= (0.35-0.7-1.05), $\tilde{B}_{2ilt}$= (0.1-0.2-0.3) and $\tilde{B}_{3ilt}$= (0.05-0.1-0.15). Beta coefficients are represented by membership functions and do not take a unique value. Then, they are adjusted so their sum will be equal to one by means of constraints (29) as it is explained below. Similarly, a triangular fuzzy number can originate for each size order customer class within the range +/- 20% from the central value. In case the number of homogeneous sub-lots was *a priori* unknown, the model remains valid if its maximum number (B) was known. It is enough to equal the B parameter to this maximum number and define the variation range of each beta width enough to include the zero value. This makes possible some of the beta values become zero that is equivalent to modify the number of homogeneous sub-lots.

A novel aspect when modeling LHP uncertainty by fuzzy beta coefficients consists in ensuring that they all sum up to 1 because they represent the fraction of an MP lot. Therefore, the sum of the homogeneous sub-lots should equal the corresponding MP lot. The most evident way is to model this aspect by adding one constraint to ensure that the sum of the beta coefficients equals 1. However, when beta coefficients are considered fuzzy, they are represented by membership functions and do not, therefore, take a unique value.

In order to adjust the fuzzy beta coefficients, we add new constraints (29), which ensure that the sum of the sub-lots always equals the original lot that they come from. These constraints (29) derive from summing constraints (5) through beta.

$$\mathrm{MPBeta}_{\beta ilt} = \widetilde{\mathrm{B}}_{\beta ilt} * \mathrm{MP}_{ilt} \qquad \forall \beta, l, i \in \mathrm{Il}(l), t \tag{5}$$

$$\textstyle\sum_{\beta} \mathrm{MPBeta}_{\beta ilt} \quad = \sum_{\beta} \widetilde{\mathrm{B}}_{\beta ilt} * \mathrm{MP}_{ilt} \qquad \forall l, i \in \mathrm{Il}(l), t \tag{26}$$

Because the total amount of FG i manufactured on production line l during period t (MP_{ilt}) does not depend on beta, it is possible to rewrite (26) as (27):

$$\textstyle\sum_{\beta} \widetilde{\mathrm{B}}_{\beta ilt} * \mathrm{MP}_{ilt} \quad = \left[\sum_{\beta} \widetilde{\mathrm{B}}_{\beta ilt}\right] * \mathrm{MP}_{ilt} \qquad \forall l, i \in \mathrm{Il}(l), t \tag{27}$$

Furthemore the sum of all betas in a lot should be equal to one (28), even though each one is uncertain.

$$\sum_{\beta} \widetilde{B}_{\beta ilt} = 1 \qquad \forall l, i \in Il(l), t \qquad (28)$$

Then, it is possible to derive the equation (29) that ensures that the sum of the sub-lots in a lot always equals its original lot, that it is equivalent to oblige that the sum of all betas of a lot should be equal to 1.

$$MP_{ilt} = \sum_{\beta} MPBeta_{\beta ilt} \qquad \forall\, l, i \in Il(l), t \qquad (29)$$

The above equivalent crisp model of FMP-LHP, including this constraint (29), is an alpha-parametric model. Therefore, it is necessary to choose the alpha value that provides the decision maker (DM) with a balanced solution between the degree of feasibility and the degree of satisfaction. For this purpose, the proposed model is solved parametrically to obtain the values of the decision variables and the objective function for each degree of feasibility α (α Є [0,1]). The result is a fuzzy set and the master planner has to decide what degree of feasibility is more adequate to obtain a crisp solution by considering that the bigger the feasibility degree is, the worse the objective value is. We adopt the method resolution proposed by Jiménez et al. [47] because of its computational efficiency, and also for the easiness of practical implementation. [47] propose a resolution method for a linear programming problem with fuzzy parameters, which helps make a decision interactively with the DM. These authors build a fuzzy subset in the decision space whose membership function represents the balance between feasibility degree of constraints, given by α, and the satisfaction degree of the goal. Thus, the DM may require a lower satisfaction return for better viability.

4. FMP-LHP Model validation

The objective of this section is to validate the formulation of the FMP-LHP model and to assess the performance of the fuzzy approach as compared to the deterministic one. Therefore, our aim was to assess whether FMP-LHP can be a useful tool for improving the decision-making process in MP given the existence of the LHP inherent uncertainty in production lots. To go about this, the deterministic model has also been solved to compare the behavior of the proposed fuzzy model with it in order to determine the improvements that the fuzzy MP model can provide. The formulation of the deterministic model coincides for that of the FMP-LHP model, where the fuzzy coefficients are deterministic (Section 3.1). The deterministic model can also be obtained by making alpha=1 in the formulation of the equivalent crisp FMP-LHP model.

Data used to validate the FMP-LHP model are based on a Spanish ceramic company obtained from [4] and conveniently adapted to the particular case under study. The model's planning horizon is assumed to be of six weeks which is usual in the ceramic sector. For our case, three FGs (i_1 to i_3) and six production lines (l_1 to l_6) are considered. It is assumed that all FGs may be processed by all production lines. It is usual in the ceramic sector that production lines work on a two-shift basis of 8 hours per shift (80 hours/week). For this case, the available capacity per production line and time period (cap_{ilt}) is considered to be of 37 hours/week that represents only a percentage of the real capacity (80 hours/week) because only part of the real demand for the time horizon is considered. It is assumed that three homogeneous sub-lots (B=3) are obtained for all lots and FGs in fractions ($B_{\beta ilt}$) of 0.7, 0.2 and 0.1. Once a lot is produced it is classified into the different homogeneous sub-lots and stored to serve incoming customer orders. The inventory holding cost per FG and time period (ch_i) is set to 0.16 €/m^2 for i_1, 0.14 €/m^2 for i_2 and 0.1 €/m^2 for i_3. Initial inventories have been set to 350 m^2 for i_1 from the first homogeneous sub-lot, 100 m^2 for i_2 from the second homogeneous sub-lot and 10 m^2 for i_3 from the third homogeneous sub-lot. A backorder cost (cbl_{ik}) of 10% of the FG selling price has been also contemplated. Table 4.5 shows the remaining the production data of each FG.

Table 4.5. Production data of Finish Goods (FGs)

		Production lines					
FGs		l_1	l_2	l_3	l_4	l_5	l_6
i_1	$csetup_{il}$ (€)	459.43	459.43	459.43	459.43	459.43	459.43
	$tsetup_{il}$ (h)	4	4	4	4	4	4
	cp_{il} (€/m^2)	5.76	5.76	5.76	5.76	5.76	5.76
	tpr_{il}(h/m^2)	0.021	0.019	0.019	0.021	0.019	0.019
i_2	$csetup_{il}$ (€)	351.16	351.16	351.16	351.16	351.16	351.16
	$tsetup_{il}$ (h)	4	4	4	4	4	4
	cp_{il} (€/m^2)	5.28	5.28	5.28	5.28	5.28	5.28
	tpr_{il}(h/m^2)	0.015	0.017	0.017	0.017	0.015	0.015
i_3	$csetup_{il}$ (€)	322.29	322.29	322.29	322.29	322.29	322.29
	$tsetup_{il}$ (h)	4	4	4	4	4	4
	cp_{il} (€/m^2)	4.8	4.8	4.8	4.8	4.8	4.8
	tpr_{il}(h/m^2)	0.014	0.012	0.014	0.014	0.012	0.014

As it can be observed in Table 4.6, four customer classes (k1 to k4) have been defined for each FG that correspond with different mean order sizes ($ordq_{ik}$). The selling price of each FG has been set to be the same irrespectively of the customer class, although the model allows discriminate the prices based on the customer class. The forecast demand per FG, customer order class and time period can be also consulted in Table 4.6.

The fuzzy and deterministic models were implemented by the MPL Maximal Software. The input data and the model solution values were processed with the Microsoft Access database (2007). The experiment was run on an Intel core 2 quad processor, 2.5 GHz with 4GB RAM. The solver used for both the deterministic and the fuzzy model was Gurobi 5.5. Solver parameters and options were set as those specified by default in Gurobi 5.5 having only limited the solution time to 1200 seconds. Table 4.7 compares the computational efficiency of the proposed fuzzy model with the deterministic one. The "fuzzy" column shows the mean values for the different models generated with various feasibility degrees (α Є [0,1]). As it can be observed, the fuzzy model presents the same number of variables but a higher number of constraints than the deterministic one. This is due to the method for ranking the fuzzy numbers applied which duplicates the equality type constraints because these are transformed into two equivalent constraints for the fuzzy model. On the other hand, the fuzzy model provides a mean GAP lower than the deterministic one for the same solution time limit.

Table 4.6. Commercial data of Finish Goods (FGs)

FGs	*Customer classes*	p_{ik}(€/m^2)	$ordq_{ik}$(m^2)	*Forecast demand per periods*(m^2)					
				t_1	t_2	t_3	t_4	t_5	t_6
i_1	*k1*	17.86	10	160			260		50
	k2	17.86	50	750	900	150	700		
	k3	17.86	150		750	1050			
	k4	17.86	500	9500	7500	500	2500		
i_2	*k1*	15.74	10	200		70		60	90
	k2	15.74	75	1200	150	300		1275	225
	k3	15.74	200		400	600	3800	1800	3800
	k4	15.74	500		1500	4000	5000	10000	
i_3	*k1*	11.65	10	130		60	330		
	k2	11.65	100	400	1300	100			1700
	k3	11.65	250			1750	8400	3500	1750
	k4	11.65	500	3000				1500	1500

Table 4.7. Solution characteristics

	Deterministic	Fuzzy
Iterations	4657654	6174893
Constraints	7206	10662
Variables	6522	6522
Integers	4140	4140
Non zero elements	34488	44892
Density (%)	0.07	0.06
CPU time (sec.)	1200	1200
GAP (%)	5.3	4.1

The results obtained of deterministic and uncertain model are shown in Table 4.8.

As it can be observed in Table 4.8, the fuzzy model generally obtains better results than the deterministic one. As seen in Fig. 5.1, the fuzzy model for the different feasibility degrees obtains gross margins that are better than the deterministic model.

According to [47], the DM should choose the alpha value so that the equilibrium between the feasibility degree of the constraints and satisfaction degree of the goal is achieved. In this case, the best solution is obtained for α = 0.7. The obtained solution when α is replaced with 0.7 is named Z_f^{pl}, which is used to compare the results obtained by deterministic model Z_d^{pl} when performing MP.

Table 4.8. Results of the uncertain model for each degree of feasibility α and deterministic model

Feasibility grade	Incomes	Production Cost	Set Up Cost	Inventory Cost	Backorder Cost	Total Cost	Objective value
0	1157734.63	397449.5	14306.6	900.3	26598.8	439255.3	718479.4
0.1	1160745.73	398619.4	13847.2	1192.6	31609.5	445268.6	715477.1
0.2	1158097.99	398619.4	13847.2	1285.8	36749.9	450502.3	707595.7
0.3	1164353.73	400231.2	13738.9	1202.3	50087.1	465259.6	699094.2
0.4	1161996.29	400231.2	13738.9	1319.0	55664.1	470953.2	691043.0
0.5	1154345.16	398864.7	13738.9	1444.0	57622.8	471670.4	682674.8
0.6	1155822.27	402662.7	13710.0	1780.7	63330.8	481484.3	674338.0
0.7	1147863.99	401172.7	13710.0	1897.2	66528.9	483308.9	664555.1
0.8	1141140.85	398702.2	14412.4	2017.7	69774.0	484906.2	656234.6
0.9	1123924.36	392755.5	14383.5	2045.9	82763.3	491948.3	631976.1
1	1105873.00	388656.0	13710.0	2851.5	89905.4	495122.9	610750.1
Deterministic	1105873.00	388656.0	13710.0	2851.5	89905.4	495122.9	610750.1

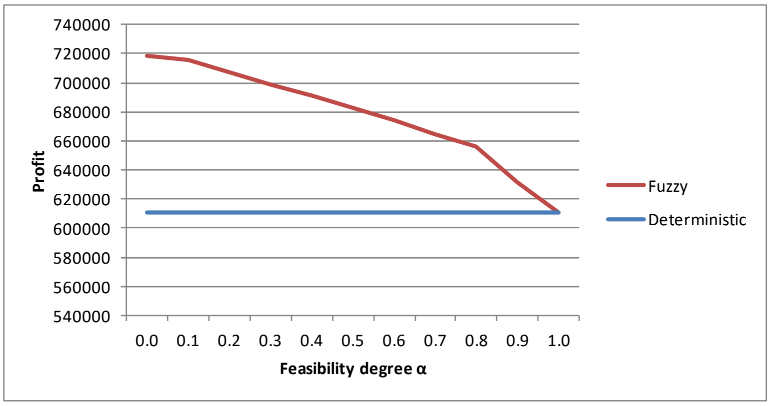

Figure 4.1. Profit according to the feasibility degree.

Table 4.8 and Figure 4.1 show that in a planned situation, the FMP-LHP model performs better than the deterministic one. However, as we are interested in knowing the behavior of each model under real conditions, we must answer these two questions:

1. What are the real profits and customer service level once the production lots are manufactured and classified into homogeneous sub-lots, and the real demand of each customer order is known?
2. What is the difference between the real and planned situation for profits and customer service level; i.e. what about model robustness?

To answer these two questions, the methodology of Figure 4.2 was followed. The deterministic and fuzzy model solutions provide us with the total amount of each FG to be manufactured on each production line and time period for both, the deterministic and the uncertain contexts, respectively. For solving both models, the uncertain parameters, $B_{\beta ilt}$ and $ordq_{ik}$, have been estimated for future periods of the planning horizon either through mean values (deterministic model) or through triangular fuzzy numbers (fuzzy model). Since time spends, the future periods will become the present ones and then, the real value of homogeneous sublots ($B_{\beta ilt}$) and the real size of each customer order will be known ($ordq_{ik}$). At that moment, it will be possible to check how many customer orders from those previously defined by the fuzzy and the deterministic model can be really served with the real homogeneous sub-lots, i.e. the real performance of the deterministic and fuzzy solutions can be assessed.

To simulate these real situations, projections of beta parameters ($B_{\beta ilt}$) for each MP lot and for each customer order size ($ordq_{ik}$) inside their membership functions were produced. That is, based on the planned percentages of homogeneous sub-lots ($B_{\beta ilt}$) and the average size of the planned orders for each customer class ($ordq_{ik}$), 120 scenarios were generated using random numbers. The range of variation was 50% for $B_{\beta ilt}$, and 20% for the $ordq_{ik}$ parameters. Each scenario can be understood as a possible real situation where the real size of homogeneous sub-lots for each lot of the MP and the real order size for each customer order classes are known.

Then, to assess the real profits and customer service level for each scenario and master plan, a new version of the deterministic model (Auxiliary Model) is developed. The Auxiliary Model considers the sizing of lots (MP_{ilt}) not as decision variables but as an input parameter (mp_{ilt}) provided by the solution of the deterministic and fuzzy model (5').

$$MPBeta_{\beta ilt} = \tilde{B}_{\beta ilt} * mp_{ilt} \qquad \forall \beta, l, i \in Il(l), t \qquad (5')$$

As it can be observed, different values of $B_{\beta ilt}$ obtained for each projection of a real situation (scenario), originate different size of homogeneous sub-lots $\mathrm{MPBeta}_{\beta ilt}$ that can alter the number of customer order classes that can be served. For this reason, constraint (6) of the Auxiliary Model is relaxed from "=" to "≥" (6') to ensure a feasible solution, because in a real situation, it cannot be possible to serve an integer number of customer orders due to the inherent LHP uncertainty.

$$MPBeta_{\beta ilt} \geq \sum_k NKLBeta_{\beta ilkt} * \tilde{ordq}_{ik} \qquad \forall \beta, l, i \in Il(l), t \qquad (6')$$

The real projected values of $B_{\beta ilt}$ and $ordq_{ik}$ for each of the 120 scenarios along with the MP_{ilt} values derived from either the FMP-LHP model with α = 0.7 or the deterministic model were used as input for the Auxiliary Model that calculates the number of each customer order class ($NKLBeta_{\beta ilkt}$) really served from a specific

MP_{ilt}. Under these conditions, we obtain the objective function value after considering the planned production in the deterministic case for every generated scenario, whose mean value is represented by Z_d^r, as well as the objective function value considering the uncertain environment for every generated scenario, whose mean value is Z_f^r.

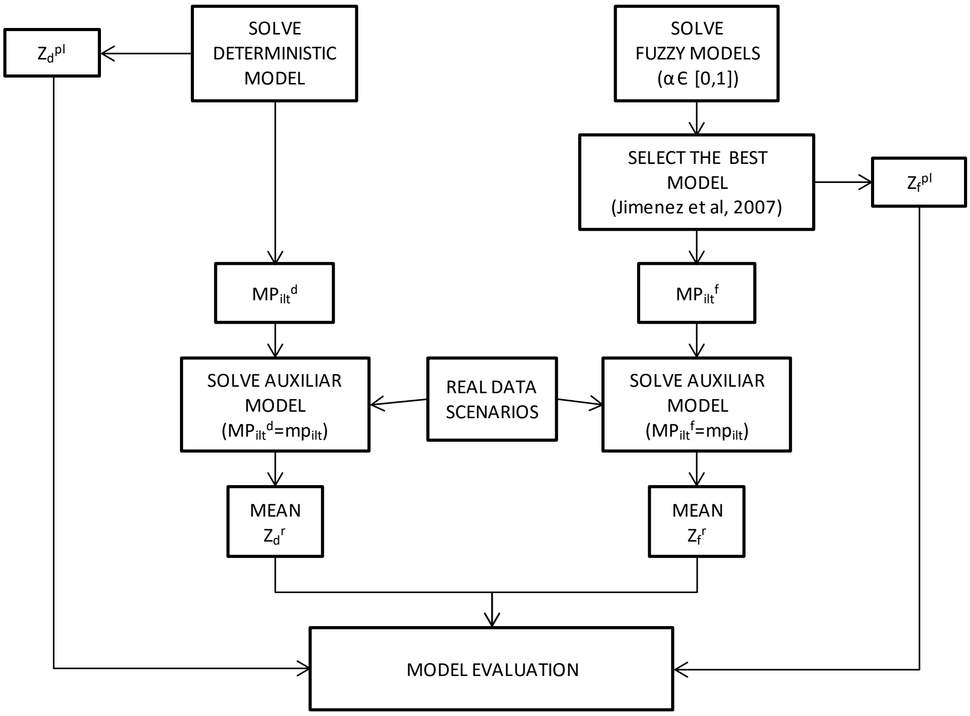

Figure 4.2. Experimentation Methodology

Table 4.7 provides the answer to the two previous questions. The Dif Fuzzy *vs.* Det (30) performance measure gives the improvement percentage of the fuzzy model as compared to the deterministic one in both planned and real situations as regards profits.

$$\text{Dif Fuzzy } vs. \text{ Det } (\%) = \frac{Z_f - Z_d}{Z_d} * 100 \qquad (30)$$

In Table 4.9 we can observe that, in a planned situation, the fuzzy model with alpha=0.7 obtains 8.1% more profits than the deterministic model. However, we are more interested in calculating the real profits when the lots specified by the fuzzy or the deterministic model in the MP will be finally produced and classified in the corresponding homogeneous sub-lots. The definitive size of each homogeneous sub-lot will be equivalent to a particular realization of the beta fuzzy parameters (scenario). Furthermore, in a real situation, the order sizes for each customer order will also be known. With all this information, it will be possible to assess the definitive number of customer orders served and, consequently, the real profits achieved. As it can be observed in Table 4.9, the real profit diminishes as compared with the planned profit for both the fuzzy (-0.9%) and the deterministic (-1.7%) model.

As the worsening in profit for real situations is more pronounced for the deterministic model (-1.7%) than for the fuzzy one (-0.9%), the difference between the profits obtained by both models becomes wider for real situations (8.9%) than for the planned one (8.1%). Therefore, if the master plan obtained by the fuzzy model is implemented, the profits obtained are, on average, 8.9% higher than the profits for the deterministic one.

A difference in the real profits of 8.9 % is far from negligible for any company that desires to work under lean principles. Indeed, the improvement of 8.9% provided by the fuzzy model is aligned with other applications of fuzzy models reported in the literature: 7.8% in Peidro et al. [27], 9.7% in Mula et al. [48] and 5.5% in Phuc et al. [43] in costs, among others.

To answer the question about the robustness of the solutions provided by both models, the performance "Difference Planned *vs.* Real" indicator (31) is calculated. It is necessary to highlight that method for ranking fuzzy numbers was used because it preserves its linearity and applies the robustness, among other properties (see [47]). A solution is considered to be robust when the influence of data changes in the system's results is small. In our particular case, a solution will be robust when discrepancies between planned and real betas as well as planned and real customer order sizes originate small differences between the planned and real values of the profits. As observed in Table 4.9, the real mean value of the profits achieved is lower than the planned one for both the deterministic and fuzzy models, which indicates that the real performance of solutions is worse than expected. However, the percentage of worsening, calculated according to (31), is higher for the deterministic model (1.7%) than for the fuzzy one (0.9%). Both values are quite small meaning that both models are quite robust as regards profits. However the percentage of worsening is almost twice for the deterministic model as compared with the fuzzy one. This means that the real objective value comes closer to the planned one in the fuzzy model and this last model is, therefore, more robust for our experimental design.

$$\text{Difference Planned } vs. \text{ Real } (\%) = \frac{z^r - z^{pl}}{z^{pl}} * 100 \qquad (31)$$

Table 4.9. Results of the objective value of the deterministic and uncertain models for planned and real scenarios

	Planned parameters (Z^{pl})	Average of real parameters (Z^r)	% Difference Planned *vs.* Real
Fuzzy(Z_f)	664555.1	658816.4	-0.9%
Deterministic(Z_d)	610750.1	600126.0	-1.7%
% Dif Fuzzy *vs.* Det	8.1%	8.9%	

The behavior of the deterministic and fuzzy models as regards the customer service level (32) for both the real and planned situations is shown in Table 4.10.

$$\text{Customer Service Level } (\%) = \frac{\text{Total Demand} - \text{Total Backorders}}{\text{Total Demand}} * 100 \qquad (32)$$

Similarly to profits, the results are better for the fuzzy model as compared to the deterministic one because the customer service level in the fuzzy model is higher than for the deterministic model in both cases: planned (1.9%) and real (5.1%). The percentage of improvement achieved by the fuzzy model over the customer service level can be considered relevant if it is compared with others reported in the literature: 0.5% for Peidro et al. [27] and 0.05% for Mula et al. [48]. As it can be observed, the improvement obtained by the fuzzy model in terms of the customer service level is lower than in terms of profits. Furthermore, as before, the difference between both models as regards service level increases for the real case (1.9% vs 5.1%).

As in the case of profits, the percentages of customer service level achieved in the real scenarios are lower than in the planned one for both the deterministic and fuzzy models, indicating that the real performance of solutions, as regards customer service level, is worse than expected. However, the difference between planned and real situations in the deterministic model (-9.6%) is worse than in the fuzzy model (-6.5%) which can be said to be more robust than the deterministic one. The worsening percentage is higher for the customer service level than for the profits for both, the deterministic and fuzzy model, meaning that both models provide solutions more robust in terms of profits than in terms of customer service level.

Table 4.10. Results of the customer service level of the deterministic and uncertain models for planned and real scenarios

	Planned parameters	Average of real parameters	Difference Planned *vs.* Real
Fuzzy	83.8%	77.3%	-6.5%
Deterministic	81.9%	72.2%	-9.6%
DifFuzzy *vs.* Det	1.9%	5.1%	

All these results demonstrate the advantage of a fuzzy approach for master planning in a SC with LHP in an uncertain environment because the fuzzy model provides higher profits and customer service level. Furthermore, it is better able to adapt to changes in planning because it is more robust. Therefore, for all these reasons, the utilization of the fuzzy model against the deterministic one is justified.

5. Conclusions and future research lines

LHP complicates system management in several ways, and LHP inherent uncertainty in production lots is one of the characteristic LHPs with the greatest impact on the company's profits and its customer service level. The MP plays a crucial role in efficiently accomplishing customer requests in terms of ordered quantities and homogeneity specifications. In this paper, a novel mathematical model for the master planning of companies with LHP working according to an MTS strategy is developed. To deal with LHP inherent uncertainty, the fuzziness in the fraction of each homogeneous sub-lot in the MP lots and the mean customer order size has been considered. The sizing of lots for each production line is made in such a way that an integer number of customer order classes can be served from the homogeneous quantities of each sub-lot. This aspect prevents a solution from mixing quantities from different lots to serve a customer order, thus ensuring the homogeneity required by customers.

The evaluation of the obtained results under planned and real conditions has demonstrated the outperformance of the fuzzy approach as compared to the deterministic one for profits, customer service level and robustness.

Finally, the inclusion of other LHP uncertainty factors not considered in FMP-LHP, such as shelf life, can be considered in future research lines.

Acknowledgments

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CAPÍTULO V:

A MODEL-DRIVEN DECISION SUPPORT SYSTEM FOR THE MASTER PLANNING OF CERAMIC SUPPLY CHAINS WITH NON UNIFORMITY OF FINISHED GOODS

Abstract: In this paper, a Model-Driven Decision Support System (DSS) for the Master Planning of ceramic Supply Chains characterized by producing units of the same finished good in a specific lot that differ in the aspect (quality), tone (colour) and/or gage (thickness) is proposed. The DSS is based on a mathematical programming model reflecting these non-uniformity characteristics. Through the different DSS functionalities, Decision Makers can generate different scenarios through changing any data. Optimal solution of each scenario can be evaluated for robustness under other scenarios. The Decision Maker can compare different solutions and finally choose the most satisfactory one for being implemented. To demonstrate the validity of the DSS, a realistic example is described through the generation of different scenarios based on the degree of finished goods uniformity in lots.

Keywords: Model-Driven Decision Support System, Master Planning, Ceramic Supply Chains, Lack of Uniformity

1. Introduction[1]

Supply chains (SCs) operations planning is a complicated task due to the existence of a huge number of decisions, constraints, objectives (sometimes conflictive), possible alternatives to be evaluated and the presence of uncertainties. For the case of ceramic SCs, this planning task becomes even more complex due to the appearance of the so called Lack of Homogeneity in the Product (LHP) [1].

LHP in ceramic SCs implies the existence of units of the same finished good (FG) in the same lot that differ in the aspect (quality), tone (color) and/or gage (thickness) [1,2] that should not be mixed to serve the same customer order. The usual consideration of three qualities, two tones and three gages causes the existence of thirteen different subtypes of the same FG. This fact increases the volume of information and makes the ceramic system management more complex.

[1] Complementary versions of this paper were presented in the “6th International Conference on Industrial Engineering and Industrial Management”, Vigo, July 2012, with the title “Managing qualities, tones and gages of Ceramic Supply Chains through Master Planning” and published in Informatica Economică, vol. 16, no. 3, pp.5-18, (2012) with the title “The Effect of Modeling Qualities, Tones and Gages in Ceramic Supply Chains’ Master Planning”. The current paper provides significant additional content including a Decision Support System and additional results from different solution scenarios dealing with LHP uncertainty.

Additionally, the customers from this type of companies tend to request quantities of different FGs in one same order, and they also require that the units of one same FG in the order are homogeneous.

LHP systems should face with a new kind of uncertainty [3]: the uncertainty in the future homogeneous quantities in production lots. Due to the inherent LHP uncertainty, the real homogeneous quantities of each subtype in a FG lot will not be known until their production was finished. Not knowing the homogeneous quantities available of the same FG to be promised to customers proves to be a problem when customers' orders have to be committed, reserved and served from homogeneous units available derived from the planned production. Furthermore, not accomplishing with this homogeneity requirement can lead to returns, product and company image deterioration, decreasing customer satisfaction and even lost of customers.

The order promising process (OPP) plays a crucial role in customer requirements satisfaction [3] and, also, in properly managing the special LHP characteristics. The OPP refers to the set of business activities that are triggered to provide a response to customer order requests [4]. This process requires information about available-to-promise (ATP) quantities, i. e. the stocks on hand or projected inflows of items stocked at the customer order decoupling point (already in transit or planned by the master plan) that has not yet been allocated to specific orders and thus can be promised to customers in the future. Because the master plan is a fundamental input to the OPP, one of the objectives and contributions of this paper is to define a master plan that considers LHP features and can provide this process with reliable information about future available homogeneous quantities.

Up to our knowledge there is no DSS that takes into account LHP features. Therefore, in this paper, we propose model-driven Decision Support System (DSS) for the operations planning of ceramic supply chains with diversity in qualities, tones and gages. Model-driven DSS are designed so a user can manipulate model parameters to examine the sensitivity of outputs or to conduct a more ad hoc "what if?" analysis [5]. Thus, DSS functionalities are designed to allow the definition of several scenarios by changing input data, generating, evaluating and comparing different solutions through a series of interactive steps. Hence, dealing with assumptions is one of the main DSS roles [6]. Another important advantage of the DSS is that the Decision-Maker (DM) does not require understanding the complexities of the mathematical modeling, reducing the gap between theoretical contributions by researchers and the expectations of managers responsible for implementing the plans [7].

The system under our study can be considered as a Large Complex System (LSS). Filip and Leiviskä [8] indicate that LSS are characterized by their high dimensions (large number of variables), constraints in the information structure and the presence of uncertainties. The complexity of systems designed nowadays is mainly defined by the fact that computational power alone does not suffice to overcome all difficulties encountered in analyzing, planning and decision-making in presence of uncertainties. Thus, when human intervention is necessary, DSSs can represent a solution. These systems can help the decision-maker to overcome his/her limits and constraints he/she may face when approaching decision problems that count in the organization [9] and this is the objective of the DSS proposed in this paper.

The rest of the paper is structured as follows. Section 2 describes the problem under consideration and reviews the more closely related literature. Section 3 presents the mixed integer linear programming model proposed for the centralized master planning of ceramic SCs that explicitly takes into account LHP. Section 4 describes the DSS architecture. Section 5 shows the functionalities and practicability of the DSS through its application to a ceramic SC by means of realistic case. Finally, section 6 states the conclusions derived from the obtained results and future research lines.

2. Problem Description

In this paper, we consider the master planning problem for replenishment, production, and distribution in ceramic tiles SCs with LHP. These ceramic SCs are assumed to be multi-item, multi-supplier, multi-facility, multi-type and multi-level distribution centers. The characteristics of the problem under study are the same as in [10] but with relevant differences introduced by the LHP consideration [11] summarized in the following paragraph (Figure 5.1). As in [10] the Master Plan considers the Capacitated Lot-Sizing and Loading Problem with the aim of modeling the capacity consumption due to the high setup times among FGs and the fact that production lots of the same FG processed in different production lines present a high probability of not being homogeneous.

Furthermore, the splitting of each lot into homogeneous sub-lots of the same FG is also incorporated to reflect the LHP characteristics in a more realistic manner: different tones and gages for the first quality items. The sizing of lots for each production line is made in such a way that an integer number of customer order classes can be served from homogeneous quantities of each sub-lot. This aspect prevents a solution mixing quantities from different lots to serve a customer order, ensuring the homogeneity required by customers. To this end, different customer order classes are defined according to their size (Figure 5.1).

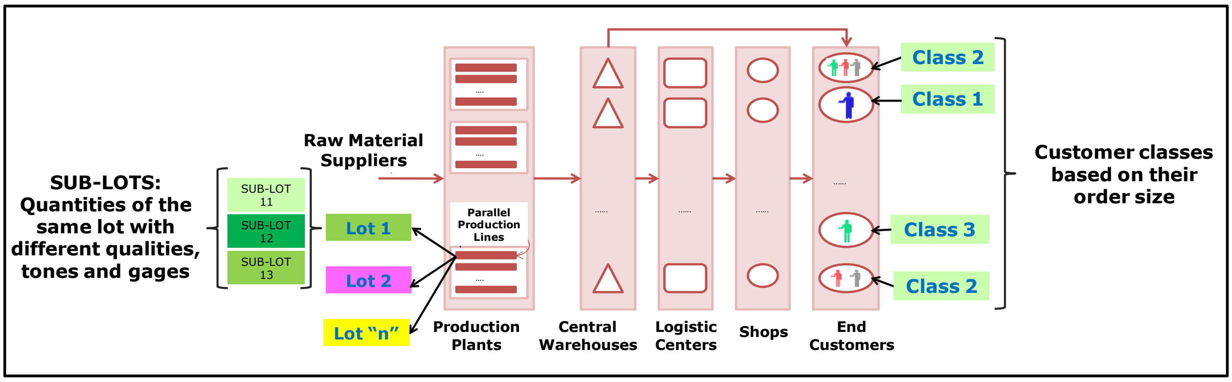

Figure 5.1. Main characteristics of Ceramic Supply Chains with LHP

At the Master Plan level, demand forecasts are usually expressed in an aggregate manner without taking into account customer classes. Customer classes definition (also known as customer segmentation) has been traditionally used in the field of the so called "allocation planning". The allocation planning follows a push strategy (based on forecasts), as the master plan, but it is carried out after the master plan and before the OPP. The allocation planning has been used for improving the OPP results in shortage situations where demand is higher than supply quantities and the policy of promising orders in a first-come-first–served (FCFS) mode, entails the risk of promising scarce availabilities to the wrong customers; e.g., to less important customers or to customers with smaller profit margins [12]. During the allocation planning a classification scheme is defined that is used to segment and prioritize customer orders. For LHP contexts the homogeneous quantities manufactured should complete a whole FG's order size. For this reason, the classification attribute for defining customer classes is the order size.

Therefore, the consideration of customer classes for sizing lots and defining demand forecasts jointly with the splitting of lots into homogeneous sub-lots constitute the most relevant aspects that differentiate the model for master plan proposed in this paper from that proposed by Alemany et al. [10] and other models for SC master plan. The next section describes the mixed integer linear programming (MILP) model proposed to solve the described problem that constitutes the base for the DSS.

3. The MILP Model for Master Planning of LHP Ceramic SCs

To solve the ceramic SC master planning problem a mixed integer linear programming model (MP-CSC-LHP-1) is proposed. The model MP-RDSINC proposed by Alemany et al. [10] is considered as the starting point to formulate the present model but properly modified in order to reflect the LHP characteristics cited previously. The nomenclature (the indices, sets of indices, model parameters and decision variables) of the MP-CSC-LHP-1 model can be consulted on Tables 1 to 4, respectively, in [11]. The mathematical formulation is presented in Annex. Those model elements that differ from the MP-RDSINC are written in *italics*.

For being concise, in this section only the MP-CSC-LHP functions that differ from the MP-RDSINC are described. For more details, the reader is referred to [10, 11]. The objective function (1) expresses the gross margin maximization over the time periods that have been computed by subtracting total costs from total sales revenues. In this model, selling prices and other costs including the backlog costs can be defined for each customer class allowing reflect their relative priority.

Constraints (2) to (14) coincide with those of the MP-RDSINC and make reference to suppliers and productive limitations related to capacity and setup. Constraints (15)-(17) reflect the splitting of a specific lot into three homogeneous sub-lots of first quality ($\beta 1_{ilp}$+ $\beta 2_{ilp}$+ $\beta 3_{ilp}$=1). The number of sub-lots considered in each lot can be easily adapted to other number different from three. Through these constraints the sizing of lots is decided based on the number of orders from different customer order classes that can be served from each homogeneous sub-lot.

Customer order classes are defined based on the customer order size (i.e, the m^2 ordered). Constraint (18) calculates for each time period, customer class and FG the total number of orders of a specific customer class that can be served from a certain lot by summing up the corresponding number of orders served by each homogeneous sub-lot of this lot. Constraint (19) derives the number of each customer order class that is possible to serve from the planned production of a specific plant. Through constraints (15-19), the production is adjusted not to the aggregate demand forecast as traditionally, but to different customer orders classes.

Furthermore, in contrast to the MP-RDSINC, the distributed, stocked and sold quantities downstream the production plants are expressed in terms of the customer class whose demand will be satisfied through them, being possible to discriminate the importance of each order class. Constraint (20) calculates the quantity of each FG to be transported from each production plant to each warehouse for each customer class based on the order number of each customer class that is satisfied by each production plant and the mean order size. Constraint (21) represents the inventory balance equation at warehouses for each finished good, customer class and time period. As backorders are permitted in both central warehouses and shops, sales may not coincide with the demand for a given time period. Backorder quantities in warehouses for each customer class are calculated using constraint (22). Constraint (23) limits these backorder quantities per customer class in each period in terms of a percentage of the demand of each time period. Constraint (24) forces to maintain a total inventory quantity higher or equal to the safety stock in warehouses. Constraint (25) is the limitation in the warehouses' capacity that is assumed to be shared by all the FG and customer order classes.

Constraint (26) represents the inflows and outflows of FGs and customer order classes through each logistic centre. Because it is not possible to maintain inventory in shops, constraint (27) ensures that the total input quantity of a FG for a specific customer class from warehouses to shops coincides with the quantity sold in shops. As backorders are permitted in both central warehouses and shops, sales may not coincide with the demand for a given time period. Constraints (28) and (29) are similar to constraints (22) and (23), respectively, but referred to shops instead of warehouses. The model also contemplates non-negativity constraints and the definition of variables (30).

4. The Model-Driven DSS

The proposed Model-Driven DSS for the master planning of ceramic supply chains with LHP (DSS-LHP-CSC) meets the necessary requirements for DSS pointed out by Power and Sharda [5]:

- It uses different quantitative models. The DSS developed is based on the previous described model (MP-CSC-LHP-1) and another one (MP-CSC-LHP-2) defined to implement the different DSS functionalities.
- The designed model-driven DSS allows users manipulate model parameters through defining different scenarios in order to examine the sensitivity of outputs or to conduct a more ad hoc "what if?" analysis.
- It is accessible to a non-technical specialist in mathematical models.
- It is designed to be used in a repetitive decision: the operations planning of ceramic supply chain is a period-driven decision.

The DSS-LHP-CSC architecture follows the generic dialog-data-modeling architecture proposed by Sprage [13]. The DSS building blocks include dialog, modeling and data components (Figure 5.2).

- **Dialog components:**
  - The *user interface* as the interaction point with the decision-maker. It is a combined graphical and tabular interface designed for providing a friendly interaction with the DSS.
  - The *user functionalities* to provide the necessary interaction with the database and the models. The main DSS functionalities are: definition of scenarios, solve scenarios, robustness evaluation and compare solutions.

- **Modeling components:**
  - *Models*. The models are the main component in a Model Driven DSS. Two models (MPM-CSC-LHP-1 and MPM-CSC-LHP-2) have been defined to support user functionalities.
  - *Solver*. The Model Base Management System requires a solver found optimal solutions to the different models.
- **Data components**:
  - *Data Base Management System (DBMS).* It is in charge of the creation, access and update of data.
  - *Data*. It is the collection of interrelated data organized to be use in the decision process. It includes Analytical Data as data required in the decision process, and Decision Data as information obtained in the decision process through the models' resolution.

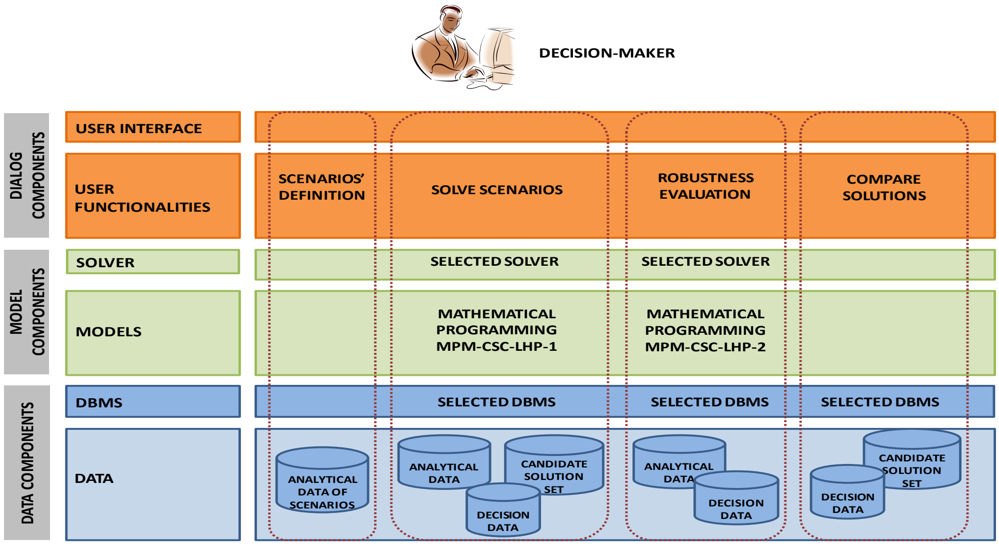

Figure 5.2. DSS-LHP-CSC Architecture

Java v7 and the ECLIPSE platform have been used for developing the dialog components. MPL v4.2 has been selected to translate the mathematical programming models to a readable-machine format. GUROBI solver has been chosen due to the contrasted quality of solutions obtained. DB in Access has been used to store the corresponding data.

5. Description of DSS-LHP-CSC functionalities: an illustration of a ceramic case

We propose a DSS-LHP-CSC with a variety of functionalities that makes possible the DM to deal with assumptions in a friendly way. The DM could choose among different interactive options with the DSS and combine them in order to choose the final solution. During the process of finding the most satisfactory or optimal solution, the DM has the possibility of adding or removing solutions to the candidate solution set. The candidate solution set contains those solutions to the problem that are satisfactory and/or interesting for the DM and therefore, are candidate to be the finally chosen for being implemented.

With the aim of demonstrating the utility of the proposed DSS, an illustrative case has been developed which uses data derived from a real ceramic SC. The data for the case presented is the same used in [11] but with some modifications in order to illustrate the DSS functionalities that are described in the following.

Scenarios' Definition: this functionality (Figure 5.3) allows the DM to retrieve the necessary input data for obtaining the master plan through loading the corresponding data base (DB). The DM can define different scenarios retrieving data from different databases (Add DB). New scenarios can be also defined by means of copying and modifying one or more input data from a selected DB. The possible data to change is that regarding the objective function coefficients (profit/costs) and/or technological coefficients and/or right-hand-side coefficients (times and capacities, demand, homogeneity parameters). The new scenarios can be saved in the set of scenarios. The DM can use this functionality for generating different situations for making "what-if" analysis as well as dealing with uncertainty in the data. The selected scenarios by the DM among those generated will be solved in the next functionality (Select to Solve).

Because one of the distinguishing features of the proposed model is the LHP consideration, the proposed ceramic case tries showing how the DM can manage the inherent LHP uncertainty. For doing so, the DM will define different scenarios based on the value of beta parameters ($\beta 1_{ilp}$, $\beta 2_{ilp}$, $\beta 3_{ilp}$). For the illustrative example (Figure 5.3), three scenarios have been defined using the beta coefficients. For the case under study, all three scenarios have been selected to solve. All scenarios assume that lots processed in different production lines and/or period of time are not homogeneous, but the degree of non uniformity in the units of the same production lot differs depending on the scenario:

- **Optimistic scenario** ($\beta 1_{ilp}=1$, $\beta 2_{ilp}=0$, $\beta 3_{ilp}=0$): This scenario assumes low heterogeneity, only one beta different from zero, meaning that units of the same production lot are all homogeneous.
- **Probable scenario** ($\beta 1_{ilp}=0.2$, $\beta 2_{ilp}=0.8$, $\beta 3_{ilp}=0$): This scenario assumes a medium heterogeneity, two betas different from zero, meaning that a production lot is divided into two homogeneous sub-lots.

- **Pessimistic scenario** (*$\beta 1_{ilp}$=0.1, $\beta 2_{ilp}$=0.4, $\beta 3_{ilp}$=0.5*): This scenario assumes high heterogeneity, three betas different from 0, meaning that a production lot is divided into three homogeneous sub-lots.

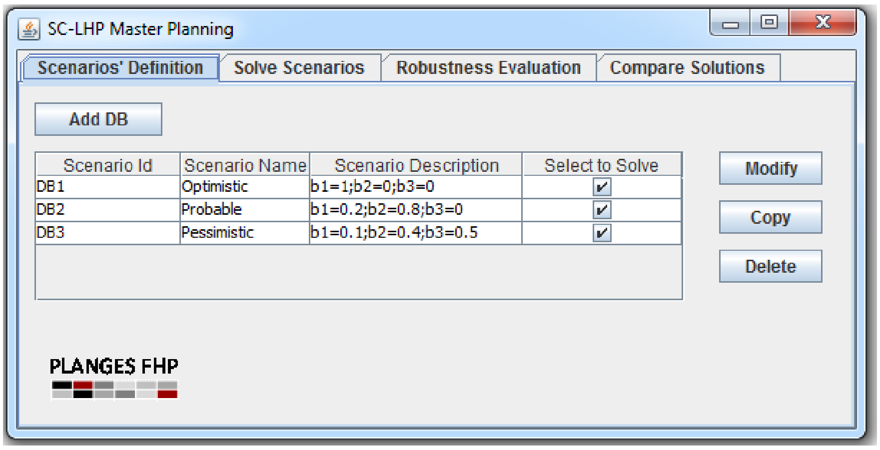

Figure 5.3. Definition of Scenarios

Solve scenarios: the selected scenarios in the previous functionality will be entered as input data for the MPM-CSC-LHP-1 that will be solved for each one of them. The DSS provides the value of the Objective Function of each solution and the gap for each set of data (scenario). The DM can make a deeper analysis of a selected solution through the "Detailed Solution" option. This detailed analysis allows the DM either view the value of the different components of the objective function (sales revenue, supply costs, production costs, setup costs, transportation costs, holding costs and backorder costs) and/or the decision variables. As a result of this analysis the DM can eliminate solutions (Remove Solution) or select those satisfactory solutions to be incorporated to the candidate solution set (Save Solution).

For the example under consideration the optimal solution for the three scenarios appears in Figure 5.4. As it can be seen, the optimal solution to the optimistic scenario presents the maximum gross margin. After analyzing them, the DM can add interesting solutions to the candidate solution set. For the illustrative example, all the optimal solutions for each scenario have been selected to be added to the candidate solution set.

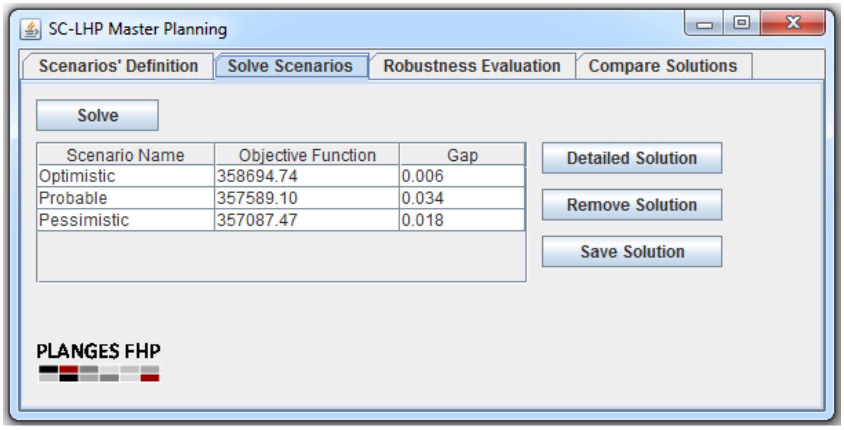

Figure 5.4. Resolution of Scenarios

Robustness Evaluation: It is important to highlight that the objective function value of the solution of each scenario would only be achieved if the solution implemented occurs in the corresponding scenario. Therefore, the DM should be interested in evaluating the behavior of the solutions generated in a specific scenario under other scenarios. For this, the DM should specify the solutions to be evaluated and the corresponding scenarios ("Select Solutions and Scenarios" option) (Figure 5.5). This functionality allows the DM to evaluate the robustness of the main decisions generated under a specific scenario when other situations occur.

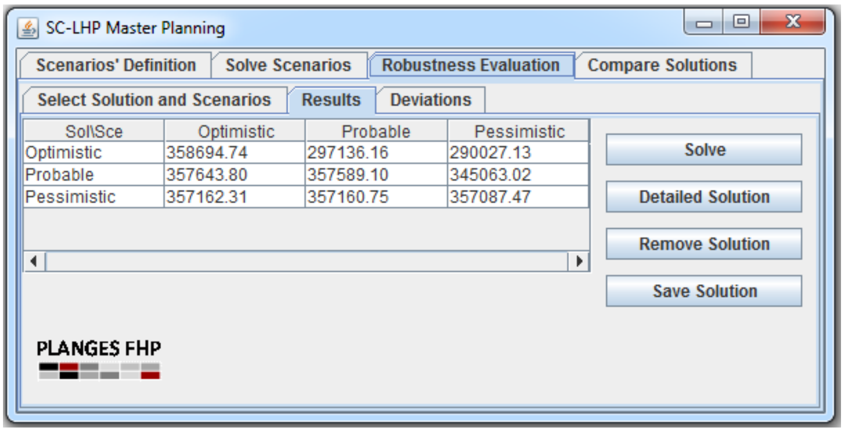

Figure 5.5. Robustness Evaluation of solutions under different scenarios

In this case, our main decision is MP_{ilpt} (amount of FG i manufactured on production line l of production plant p in period t). Thus, a new version of the previously used MPM-CSC-LHP-1 model has been defined (named MPM-CSC-LHP-

2). This new model version considers the previous decision variable (MP_{ilpt}) as a model parameter (mp_{ilpt}) and simultaneously replaced the constraints (15-17) of the MPM-CSC-LHP-1 by the constraints (31-33). The original constraints (15-17) are relaxed from "=" to " ≥ " with the aim of ensuring a feasible solution, because with the specified mp_{ilpt} obtained under a specific scenario (solution of the MPM-CSC-LHP-1) it will possible not to serve an integer number of customer orders under other scenarios.

$$(1-cm_i)*cq_i*\beta 1_{ilp}*mp_{ilpt} \geq \sum_k NKL1_{ilpkt}*ordq_{ik} \quad \forall p,\forall l \in Lp(p), i \in Ip(p), t \tag{31}$$

$$(1-cm_i)*cq_i*\beta 2_{ilp}*mp_{ilpt} \geq \sum_k NKL2_{ilpkt}*ordq_{ik} \quad \forall p,\forall l \in Lp(p), i \in Ip(p), t \tag{32}$$

$$(1-cm_i)*cq_i*\beta 3_{ilp}*mp_{ilpt} \geq \sum_k NKL3_{ilpkt}*ordq_{ik} \quad \forall p,\forall l \in Lp(p), i \in Ip(p), t \tag{33}$$

Through the "Solve" button of the Results Option (Figure 5.5), the execution of the new model MPM-CSC-LHP-2 is made for all selected solutions under the corresponding scenarios, providing the DM with the value of the objective function of a specific solution under other scenarios.

For the example under consideration, optimistic solution obtained as the optimal resolution of the model MPM-CSC-LHP-1 under the optimistic scenario is used to answer the following question: What happens if the DM implements the MP_{ilpt} optimal solution obtained from the optimistic scenario (mp_{ilpt}), but finally the probable or pessimistic scenario occurs? This question can be made for all solutions in the candidate solution list under all scenarios. Figure 5.5 provides the answer to this question for our case. The diagonal of the matrix, in this case, corresponds for the optimal solution under the corresponding scenario. The "Detailed Solution" option allows the objective terms analysis of solutions for each scenario. For our case, this study reveals that differences in the gross margin are mainly due to the backorder costs. Backorders exist for the optimistic solution in probable and pessimistic scenarios. Backorders also exist for the probable solution in pessimistic scenario. Finally, there are no backorders for the pessimistic solution under any scenario. From this analysis we can state that to consider the LHP in lots diminishes the gross margin (diagonal of the table in Figure 5.5), but provide more robust solutions under any scenario. For this analysis the DM can remove or save the solution for the candidate solution set.

Before doing so, the DM has the possibility of comparing (Figure 5.6) the chosen solutions under different scenarios in relative terms ("Calculate Deviations"), providing for each solution its deviation related to the best solution for this scenario. The DSS also calculates for each solution the minimum, medium and maximum deviation for all scenarios. Based on this information the DM can remove or save solutions from the candidate solution set.

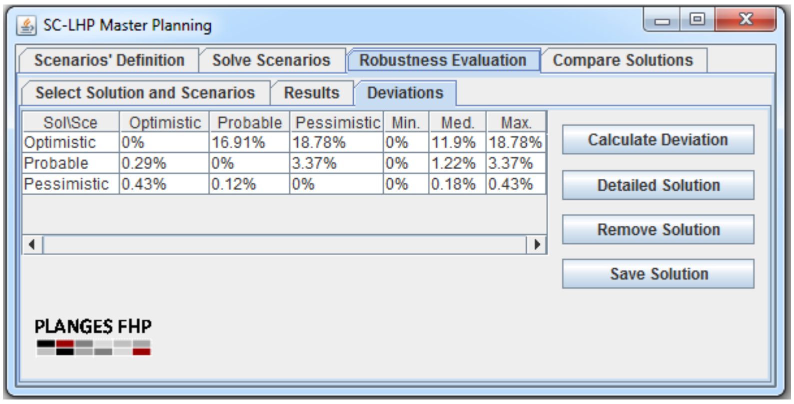

Figure 5.6. Relative performance of solutions under different scenarios

Compare solutions. By means functionalities 2 and 3, the DM can save and remove solutions from the candidate solution set. Through this functionality, at any moment of the decision process, the DM can select two different solutions from the candidate solution set and comparing them in terms of the global objective function or its components as well as in terms of the decision variables. As a result of this DSS functionality, the DM can remove some solutions from the candidate solution set. Finally, the DM should choose one solution of the candidate solution set as final solution, that is, as the final master plan to be implemented.

6. Conclusions and Future Research

This paper presents a mathematical programming model for the master planning of ceramic SCs characterized by LHP. Obtaining a satisfactory master plan in LHP industries involves dealing with a large number of variables and constraints in the information structure and the presence of uncertainties. Indeed, in LHP contexts appears a new source of inherent uncertainty: uncertainty in the quantities of homogeneous subsets of the same product available in planned production batches.

To facilitate the use of the mathematical programming model for practicing managers without the necessary mathematical knowledge, a model-driven DSS have been proposed. The DSS functional features are quite user-friendly and allow the DM to generate, analyze and compare different solutions. The DSS scenario definition capability constitutes a powerful tool to make what-if analysis, analyze the sensitivity of different operational and cost parameters and to deal with uncertainty in any input data of the model. The DSS utility have been shown by an illustrative realistic example of a ceramic SC where the definition of scenarios have been made based on the beta coefficients for representing the inherent LHP uncertainty. Furthermore, the DSS could be easily implemented in APS systems, reducing the gap of mathematical modeling power and its use by enterprises.

Future research lines include the consideration of a distributed and collaborative supply chain master planning process [14] among different SC's members. For this case, it could be very useful a DSS with a front-end web allowing reduce technological barriers and made it easier and less costly decision making for users in geographically distributed locations [15]. Furthermore, it will be very interesting to develop a web service that allows the company to do not be in charge of the solver and even of the model. This is because through this web service, the company could subcontract the necessary model modifications to fit it to their requirements.

The last future research line will be the integration of the proposed DSS with other order promising DSS for LHP contexts with the aim of providing reliable information about future uncommitted available homogeneous quantities (ATP-LHP). For those customer orders that cannot be committed with ATP-LHP quantities it would be interesting to evaluate the possibility of defining new production lots using the uncommitted capacity (CTP) modifying, therefore, the initial master plan. These new research lines will allow a more flexible DSS to adapt the production to customer requirements and to face with discrepancies between plans and reality due to the inherent LHP uncertainty.

Acknowledgements

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CAPÍTULO VI:

CONCLUSIONES

1. Introducción

En este capítulo se exponen las principales conclusiones de la investigación realizada, exponiendo las aportaciones más relevantes. Así mismo, se proponen las líneas futuras de investigación que surgen a partir del trabajo realizado en esta Tesis.

2. Conclusiones

Las CdS afectadas por la FHP presentan una serie de características particulares que en caso de no ser tratadas adecuadamente pueden tener un efecto muy negativo para su competitividad. En este tipo de CdS no sólo es necesario servir a los clientes en la cantidad y fecha solicitada, sino también en los términos de homogeneidad requeridos por los clientes. En este contexto, el proceso de comprometer pedidos se perfila como uno de los procesos fundamentales para gestionar adecuadamente la FHP. Puesto que una de las entradas fundamentales al proceso de comprometer pedidos es el plan maestro, éste pasa a ser un elemento fundamental en este tipo de CdS, que además debe tratar con todas las fuentes de incertidumbre inherente a la FHP.

Aunque la FHP se hace evidente en diversos sectores, como el cerámico, textil, maderero, de piel curtida o agrícola entre otros, el capítulo II muestra la ausencia de un cuerpo de investigación común para gestionar de manera adecuada la FHP. De hecho, el estudio de los modelos de programación matemática, muestra que no en todos los sectores se incorporan las características de la FHP y su incertidumbre asociada en la planificación maestra. Por tanto, se hace necesario disponer de un marco común que permita identificar aquellas características FHP comunes a diferentes sectores y cómo han sido modeladas en el mismo sector o en otros donde aparece, con objeto de trasvasar el conocimiento sobre métodos y modelos entre ellos. En este sentido, en el Capítulo II se propone un marco para caracterizar la incertidumbre inherente a la FHP en base al cual se analizan los modelos de programación matemática existentes en la literatura para la planificación maestra en diversos sectores con FHP, con objeto de determinar la intensidad con la que han sido abordados los diferentes tipos de incertidumbre inherentes a la FHP y las técnicas empleadas para ello. Por lo que las principales aportaciones de esta revisión son: 1) su enfoque por sectores, 2) la propuesta de un marco común para analizar las características de la FHP en los modelos de planificación maestra en contexto de incertidumbre, 3) la abstracción de las características de la FHP comunes en diferentes sectores agrupadas en un modelo conceptual y 4) la identificación de vacíos existentes en la literatura que pueden servir como base para la investigación futura. A partir de este análisis se pueden extraer algunas conclusiones importantes:

- Hay algunos sectores en los que la literatura existente tiene en cuenta la incertidumbre inherente a la FHP (por ejemplo, agroalimentario y remanufactura), sin embargo, en otros sectores muy afectados por la existencia de la FHP, la literatura existente es escasa (minería, madera, cerámica) o inexistente (textil, joyería o cuero).
- El tipo de incertidumbre inherente a la FHP más modelado en la literatura es la cantidad incierta de cada subtipo, en el mismo lote o entre lotes y, principalmente en el aprovisionamiento, mientras que otros aspectos, relativos al valor o al estado dinámico del subtipo (aspecto perecedero), se abordan minoritariamente o son inexistentes (aspecto perecedero en la demanda).
- El método de modelado más ampliamente utilizado es la programación estocástica y el análisis de la incertidumbre se realiza mediante un enfoque basado en escenarios.

En el capítulo III se plantea un modelo determinista de programación matemática para resolver el problema de la planificación maestra en una CdS de pavimentos y revestimientos cerámicos con FHP y fabricación contra stock. Así, la principal contribución de este artículo consiste en que para hacer coincidir al máximo los requerimientos de homogeneidad de los clientes con el dimensionado de los lotes de producción, el plan maestro considera dos aspectos novedosos: 1) puesto que uno de los aspectos más importantes a la hora de cumplir con la demanda de los clientes con unidades homogéneas es el tamaño de los pedidos, el modelado del plan maestro considera diferentes clases de clientes en función del tamaño medio de sus pedidos; 2) la previsión de la demanda de un ítem no se trata de manera agregada por producto y periodo temporal, como es habitual, sino que se expresa en términos del número de pedidos de diferente tamaño; y 3) la FHP se modela considerando que cada lote de producción se divide en varios sublotes homogéneos. Los resultados demuestran que con esta aproximación, se consigue dimensionar los lotes en el plan maestro para servir un mayor número de pedidos con unidades homogéneas lo que supone que, tanto el margen bruto como el nivel de servicio al cliente son superiores cuando se modela la FHP en la planificación maestra.

Sin embargo, para dimensionar los lotes de producción de manera que se maximice el número de pedidos que se podrán servir con cantidades homogéneas no sólo es necesario considerar la subdivisión de éstos en sublotes homogéneos y el tamaño medio de los pedidos de los clientes, sino también su incertidumbre asociada. En el capítulo IV se pretende dar respuesta a estos dos aspectos a través de la propuesta de un modelo de programación matemática basado en la Teoría de Conjuntos Difusos. Esta visión demuestra su validez cuando la incertidumbre se asocia con vaguedad o imprecisión de los datos, y también con la falta de información (Inuiguchi and Ramik, 2000). Es por ello que en este caso se justifica su utilización para modelar la incertidumbre inherente a la FHP, sin embargo, el enfoque difuso solo se utiliza en un 18% de los modelos de planificación maestra según se revela en la revisión bibliográfica. El modelo se valida con datos reales del sector cerámico. La principal contribución de este capítulo está en la aplicación de la teoría de los conjuntos difusos a coeficientes tecnológicos dependientes. En concreto, los coeficientes que reflejan las fracciones de un lote en sublotes homogéneos en función de los atributos de clasificación. Así, un lote de producción se divide en diferentes fracciones o sub-lotes homogéneos que son inciertos, sin embargo, la suma de todos ellos sigue siendo el lote producido, siendo esta relación lo que provoca que se trate de coeficientes tecnológicos dependientes, por lo que es necesario considerar esta condición en el modelo. La evaluación de los resultados obtenidos en condiciones previstas y reales ha demostrado la efectividad del enfoque difuso en comparación con el determinista, tanto en la calidad de las soluciones obtenidas (margen bruto y el nivel de servicio al cliente) como en la robustez de las mismas (diferencias entre lo planificado y la realidad).

La obtención de un plan maestro satisfactorio en CdS con FHP implica manejar un gran número de variables y restricciones en la estructura de la información y la presencia de incertidumbres. Para facilitar el uso del modelo de programación matemática cuando los usuarios que toman las decisiones no tienen el conocimiento matemático necesario, en el capítulo V se ha propuesto un Sistema de Ayuda a la Toma de Decisiones (DSS) basado en el modelo de programación matemática definido en el capítulo III, que permita generar, analizar y comparar diferentes soluciones mediante la definición de escenarios. La novedad de este artículo radica en la definición de un DSS para la planificación maestra en CdS con FHP de modo que el usuario, aún sin conocimientos de programación matemática, pueda considerar la incertidumbre en la planificación maestra y obtener soluciones óptimas. El tratamiento de la incertidumbre se realiza a través de la definición de escenarios en base a la modificación de cualquier parámetro de entrada al modelo por parte del usuario, lo que permite el tratamiento de la incertidumbre en cualquiera de ellos. Además, las soluciones de cada escenario se evalúan en el resto de escenarios a través de un modelo auxiliar. Esta evaluación permite conocer cuáles serían los resultados si la solución óptima de un escenario se implementara y, finalmente, en la realidad se produjera otro escenario diferente. El usuario puede guardar y comparar el resultado de diferentes soluciones satisfactorias para finalmente, elegir la más adecuada según su criterio. La utilidad del DSS se ha demostrado con un ejemplo realista de una CdS cerámica donde la definición de escenarios se ha realizado en base a la incertidumbre en las fracciones o sub-lotes homogéneos en los que se divide el lote de producción.

Una vez mostradas las conclusiones más relevantes de la investigación realizada, a continuación se proponen las principales líneas de investigación que surgen derivadas de este trabajo científico.

3. Futuras líneas de investigación

La investigación existente simplifica el problema real lo que no asegura que, el plan maestro definido en entornos con FHP permita servir al cliente con la homogeneidad requerida. Este aspecto ofrece la oportunidad de desarrollar nuevas investigaciones en cuanto a modelos de referencia y técnicas de solución para gestionar adecuadamente la incertidumbre inherente a la FHP. Una de las principales fuentes para definir futuras líneas de investigación, proviene de los vacíos detectados en la revisión de la literatura efectuada en el capítulo II. En base a este capítulo se definen las siguientes líneas de investigación futura desde diferentes perspectivas:

- Desde el punto de vista sectorial, se identifican diversos sectores donde la FHP está claramente presente y en los que, sin embargo, la investigación en el campo de la planificación maestra es muy escasa o inexistente: cerámico, maderero, peletero, textil, joyería y minería. Por tanto, estos sectores representan casos potenciales de estudio.
- Desde el punto de vista del modelado de tipos de incertidumbre inherentes a la FHP, se detecta una escasez de modelos y enfoques que consideren el tipo de incertidumbre relacionada con el valor del subtipo (precio, coste) y el estado dinámico del subtipo (vida útil). Por tanto, el modelado de estos tipos de incertidumbre inherente a la FHP representan futuras líneas de investigación, especialmente en el sector agroalimentario.
- Desde el punto de vista de enfoques para modelar la incertidumbre inherente a la FHP, muy pocos autores consideran la programación difusa para manejar datos imprecisos y/o no disponibles, sin embargo, este enfoque puede ser una buena alternativa a la incertidumbre en la FHP. Por tanto, una futura línea de investigación podría ser la implementación de

diversas técnicas de modelado de la incertidumbre para los diversos tipos de FHP y su comparación con objeto de establecer la más idónea en cada situación.

La última línea de investigación futura propuesta es la integración del DSS propuesto para evaluar distintas soluciones del plan maestro con otro sistema DSS para el proceso de comprometer pedidos (Order Promising Process: OPP) en contextos con FHP con el objetivo de proporcionar información fiable sobre las futuras cantidades homogéneas disponibles no comprometidas. Para aquellos pedidos de los clientes que no pueden ser comprometidos con las cantidades disponibles, sería interesante evaluar la posibilidad de definir nuevos lotes de producción utilizando la capacidad disponible sin comprometer y, modificando, por tanto, el plan maestro. Esta línea de investigación permitirá un DSS más flexible que adapte la producción a las exigencias de los clientes y haga frente a las discrepancias entre lo planificado y lo real debidas a la incertidumbre inherente a la FHP.

CAPÍTULO VII:

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