Models and algorithms for the optimisation of replenishment, production and distribution plans in industrial enterprises

PhD Thesis

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Abstract

Optimisation in manufacturing companies is especially important, due to the large investments they make, as sometimes these investments do not obtain the expected return because the profit margins of products are very tight. Therefore, companies seek to maximise the use of productive and financial resources by minimising lost time and, at the same time, improving process flows while meeting market needs.

The planning process is a critical activity for companies. This task involves great challenges due to market changes, alterations in production processes within the company and in the supply chain, and changes in legislation, among others.

Planning of replenishment, production and distribution plays a critical role in the performance of manufacturing companies because ineffective planning of suppliers, production processes and distribution systems contributes to higher product costs, longer lead times and less profits. Effective planning is a complex process that encompasses a wide range of activities to ensure that equipment, materials and human resources are available in the right time and the right place.

Motivated by the complexity of planning in manufacturing companies, this thesis studies and develops quantitative tools to help planners in the replenishment, production and delivery planning processes. From this perspective, realistic models and efficient methods are proposed to support decision making in industrial companies, mainly in small- and medium-sized enterprises (SMEs).

The contributions of this thesis represent a scientific breakthrough based on a comprehensive literature review about replenishment, production and distribution planning that helps to understand the main models and algorithms used to solve these plans, and highlights trends and future research directions. It also provides a holistic framework to characterise models and algorithms by focusing on production planning, scheduling and sequencing. This thesis also proposes a decision support tool for selecting an algorithm or solution method to solve concrete replenishment, production and distribution planning problems according to their complexity, which allows planners to not duplicate efforts modelling or programming solution techniques. Finally, new state-of-the-art mathematical models and solution approaches are developed, such as matheuristic algorithms, which combine mathematical programming and metaheuristic techniques.

The new models and algorithms comprise improvements in computational performance terms, and include realistic features of real-world problems faced by manufacturing companies. The mathematical models have been validated with a case of an important company in the automotive sector in Spain, which allowed to evaluate the practical relevance of these novel models using large instances, similarly to those existing in the company under study. In addition, the matheuristic algorithms have been tested using free and open-source tools. This also helps to contribute to the practice of operations research, and provides insight into how to deploy these solution methods and the computational time and gap performance that can be obtained by using free or open-source software.

Resumen

La optimización en las empresas manufactureras es especialmente importante, debido a las grandes inversiones que realizan, ya que a veces estas inversiones no obtienen el rendimiento esperado porque los márgenes de beneficio de los productos son muy ajustados. Por ello, las empresas tratan de maximizar el uso de los recursos productivos y financieros minimizando el tiempo perdido y, al mismo tiempo, mejorando los flujos de los procesos y satisfaciendo las necesidades del mercado.

El proceso de planificación es una actividad crítica para las empresas. Esta tarea implica grandes retos debido a los cambios del mercado, las alteraciones en los procesos de producción dentro de la empresa y en la cadena de suministro, y los cambios en la legislación, entre otros.

La planificación del aprovisionamiento, la producción y la distribución desempeña un papel fundamental en el rendimiento de las empresas manufactureras, ya que una planificación ineficaz de los proveedores, los procesos de producción y los sistemas de distribución contribuye a aumentar los costes de los productos, a alargar los plazos de entrega y a reducir los beneficios. La planificación eficaz es un proceso complejo que abarca una amplia gama de actividades para garantizar que los equipos, los materiales y los recursos humanos estén disponibles en el momento y el lugar adecuados.

Motivados por la complejidad de la planificación en las empresas manufactureras, esta tesis estudia y desarrolla herramientas cuantitativas para ayudar a los planificadores en los procesos de la planificación del aprovisionamiento, producción y distribución. Desde esta perspectiva, se proponen modelos realistas y métodos eficientes para apoyar la toma de decisiones en las empresas industriales, principalmente en las pequeñas y medianas empresas (PYMES).

Las aportaciones de esta tesis suponen un avance científico basado en una exhaustiva revisión bibliográfica sobre la planificación del aprovisionamiento, la producción y la distribución que ayuda a comprender los principales modelos y algoritmos utilizados para resolver estos planes, y pone en relieve las tendencias y las futuras direcciones de investigación. También proporciona un marco holístico para caracterizar los modelos y algoritmos centrándose en la planificación de la producción, la programación y la secuenciación. Esta tesis también propone una herramienta de apoyo a la decisión para seleccionar un algoritmo o método de solución para resolver problemas concretos de la planificación del aprovisionamiento, producción y distribución en función de su complejidad, lo que permite a

los planificadores no duplicar esfuerzos de modelización o programación de técnicas de solución. Por último, se desarrollan nuevos modelos matemáticos y enfoques de solución de última generación, como los algoritmos matheurísticos, que combinan la programación matemática y las técnicas metaheurísticas.

Los nuevos modelos y algoritmos comprenden mejoras en términos de rendimiento computacional, e incluyen características realistas de los problemas del mundo real a los que se enfrentan las empresas de fabricación. Los modelos matemáticos han sido validados con un caso de una importante empresa del sector de la automoción en España, lo que ha permitido evaluar la relevancia práctica de estos novedosos modelos utilizando instancias de gran tamaño, similares a las existentes en la empresa objeto de estudio. Además, los algoritmos matheurísticos han sido probados utilizando herramientas libres y de código abierto. Esto también contribuye a la práctica de la investigación operativa, y proporciona una visión de cómo desplegar estos métodos de solución y el tiempo de cálculo y rendimiento de la brecha que se puede obtener mediante el uso de software libre o de código abierto.

Resum

L'optimització a les empreses manufactureres és especialment important, a causa de les grans inversions que realitzen, ja que de vegades aquestes inversions no obtenen el rendiment esperat perquè els marges de benefici dels productes són molt ajustats. Per això, les empreses intenten maximitzar l'ús dels recursos productius i financers minimitzant el temps perdut i, alhora, millorant els fluxos dels processos i satisfent les necessitats del mercat.

El procés de planificació és una activitat crítica per a les empreses. Aquesta tasca implica grans reptes a causa dels canvis del mercat, les alteracions en els processos de producció dins de l'empresa i la cadena de subministrament, i els canvis en la legislació, entre altres.

La planificació de l'aprovisionament, la producció i la distribució té un paper fonamental en el rendiment de les empreses manufactureres, ja que una planificació ineficaç dels proveïdors, els processos de producció i els sistemes de distribució contribueix a augmentar els costos dels productes, allargar els terminis de lliurament i reduir els beneficis. La planificació eficaç és un procés complex que abasta una àmplia gamma d'activitats per garantir que els equips, els materials i els recursos humans estiguen disponibles al moment i al lloc adequats.

Motivats per la complexitat de la planificació a les empreses manufactureres, aquesta tesi estudia i desenvolupa eines quantitatives per ajudar als planificadors en els processos de la planificació de l'aprovisionament, producció i distribució. Des d'aquesta perspectiva, es proposen models realistes i mètodes eficients per donar suport a la presa de decisions a les empreses industrials, principalment a les petites i mitjanes empreses (PIMES).

Les aportacions d'aquesta tesi suposen un avenç científic basat en una exhaustiva revisió bibliogràfica sobre la planificació de l'aprovisionament, la producció i la distribució que ajuda a comprendre els principals models i algorismes utilitzats per resoldre aquests plans, i posa de relleu les tendències i les futures direccions de recerca. També proporciona un marc holístic per caracteritzar els models i algorismes centrant-se en la planificació de la producció, la programació i la seqüenciació. Aquesta tesi també proposa una eina de suport a la decisió per seleccionar un algorisme o mètode de solució per resoldre problemes concrets de la planificació de l'aprovisionament, producció i distribució en funció de la seua complexitat, cosa que permet als planificadors no duplicar esforços de modelització o programació de tècniques de solució. Finalment, es desenvolupen nous models matemàtics i enfocaments de solució d'última generació, com ara els

algoritmes matheurístics, que combinen la programació matemàtica i les tècniques metaheurístiques.

Els nous models i algoritmes comprenen millores en termes de rendiment computacional, i inclouen característiques realistes dels problemes del món real a què s'enfronten les empreses de fabricació. Els models matemàtics han estat validats amb un cas d'una important empresa del sector de l'automoció a Espanya, cosa que ha permés avaluar la rellevància pràctica d'aquests nous models utilitzant instàncies grans, similars a les existents a l'empresa objecte d'estudi. A més, els algorismes matheurístics han estat provats utilitzant eines lliures i de codi obert. Això també contribueix a la pràctica de la investigació operativa, i proporciona una visió de com desplegar aquests mètodes de solució i el temps de càlcul i rendiment de la bretxa que es pot obtindre mitjançant l'ús de programari lliure o de codi obert.

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Chapter 1

Introduction

Abstract:

This chapter presents an overview of the research conducted in this thesis, starting with the description of the different types of plans, including replenishment, production and distribution, followed by a description of the problem statement and motivation. Subsequently, research questions are raised and the objectives pursued by this research are defined. The research methodology is shown, which begins with theoretical construction to the development of systems. Finally, the structure in which this thesis is organised is presented and corresponds to the research papers presented or published in different scientific journals.

1.1 Planning in Supply Chain Management

Supply chain planning deals with the organisation and coordination of processes, and seeks to respond to demand, replenishment, production and distribution at the required time and place and in the right quantity. Planning provides support for decision making because companies make a large number of decisions that need to be continuously addressed. These decisions range from replenishment, resource utilisation for production and distribution of finished products to sales planning [1].

The Supply Chain Operations Reference (SCOR) model [2] describes the different planning schemes, which can be organised according to distinct modules [3], as shown in Figure 1.1.

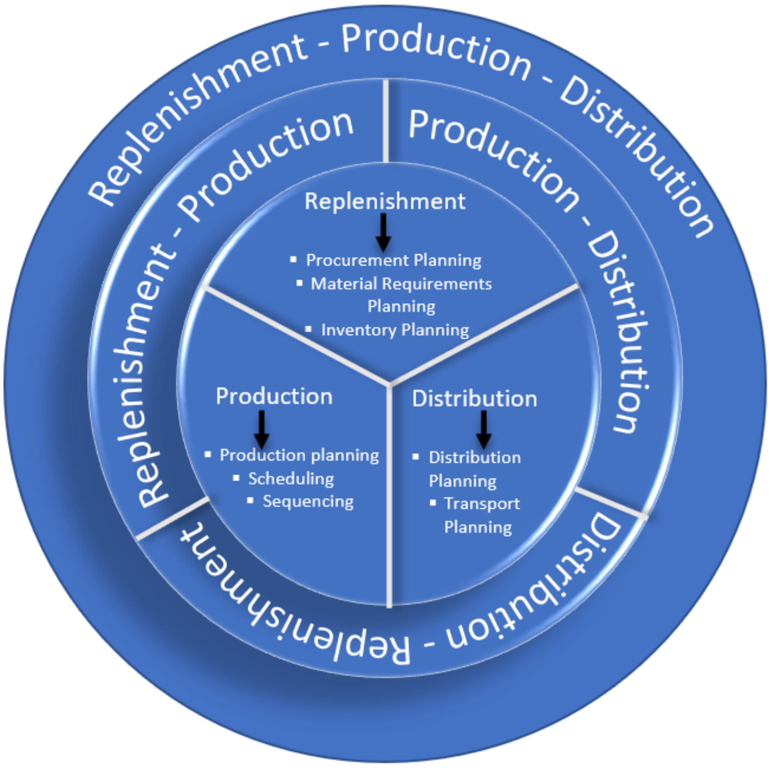

Figure 1.1. Classification of plans (based on: the SCOR model [2] and Andres et al. [3]).

According to SCOR [2], supply chain planning consists of three main schemes, which are replenishment, production and distribution, all of which are governed by demand, or its forecast, in a planning horizon. Within the replenishment scheme, we find the following modules:

- Procurement planning: it focuses on the process of identifying, compiling purchasing needs, procurement schedules, as well as identifying and selecting suppliers for the procurement of a variety of goods [4].
- Inventory Planning: it aims to minimise the total storage cost and to reduce the costs of keeping products in stock. It is responsible for the design of policies and procedures for inventory storage and includes raw materials, components and final products. In addition, it is responsible for inventory replenishment by the acquisition of raw materials or finished products. This plan helps to sufficient quantity of items to produce or sell to exist [5, 6].
- Material requirements planning: it focuses on determining in detail the right quantity at the right time of the materials, components and subassemblies needed to produce a final product, and plans their production or purchase based on a planning horizon [7].

The modules within the production scheme are detailed below:

- Production planning: it is responsible for determining the required level of production, inventory and manpower according to a planning horizon from actual or planned demand [3].
- Production scheduling: it establishes the resource utilisation schedule, i.e. it is a matter of assigning specific start and end times for resource allocation with capacity constraints, precedence and compliance dates being relevant to this plan [3, 8].
- Production sequencing: it specifies the order in which resources are used in a shared workstation [8, 9].

With the distribution scheme, there are the following modules:

- Distribution Planning: it determines the flow of goods between the customers or centres of a distribution network. In this plan, the best alternatives for distribution are evaluated, an analysis of the logistic flows (demographic characteristics and travel patterns), and even the design of a network, are carried out [10].

- Transport planning: it is in charge of establishing truck loads by respecting the design of trucks, in addition to the routing of vehicles, and seeking to respect delivery times, legal restrictions for drivers and ecological legislation [1].

The different above-described planning modules can share information and provide feedback to one another. To do so, there are several architectures that have the main advantage of sharing data within an integrated module and not only independent databases that can cause redundancies. Integrated and collaborative modules are detailed below:

- Replenishment and production planning: it takes care of acquiring items or services to turn them into finished products based on demand [4].
- Production planning and distribution planning: it determines the quantity of production and distribution of each item in a planning horizon. This type of plan generally depends on capacity and delivery times [10].
- Inventory planning and distribution planning: it involves the routing of vehicles and inventory management where inventory allocation and short-term transport are determined, i.e., it deals with the distribution of a product from a facility to customers. The aim of this plan is no customer shortages. So it determines how much to deliver, the customer to deliver to and routes, by seeking to minimise distribution costs [11, 12].
- Replenishment, production and distribution planning. This approach type is characterised by the collaboration between plans, ranging from procurement of materials by calculating requirements to the transformation of these materials into finished products, to meet expected or actual demand and, finally, to be delivered to individual customers or a distribution network by calculating vehicle capacity and possible delivery routes [3].

1.2 Problem statement and motivation

Over the years, the business world has faced different types of crises of economic, social and health kinds. One of the biggest exponents of the economic crisis that the business world faced was the Great Economic Recession that hit European countries hard between 2008 and 2013 [13]. Now the outbreak of COVID-19 has once again tested companies' resilience. According to BBC World's online publication "Coronavirus and the economy: three key differences in the Great

Recession of 2008" [14], the current crisis caused by the pandemic and the consequences of the virus could be comparable for some countries to the 2008 global financial crisis. The common features between the Great Recession and the pandemic were the great uncertainty that it generated, uncertainty that was marked by economic recovery and employment.

Some of the problems faced by production companies in different crises were caused by uncertainty, and by the speed with which they had to adapt to new working conditions and respond to new market demands. For example, with the COVID-19 crisis, textile companies had to change their production and start processing textiles for protective masks, clothing for medical staff, among others. In response to this new demand, textile companies faced the problem of not only planning deliveries and shipments, but also changes in production processes and operations. All this made such tasks challenges because they had to generate optimal production plans that minimised downtime, and they had to plan how much and when to produce.

Other companies like beverage and non-essential food supply companies, e.g. carbonated soft drinks, faced limited space in their warehouses for finished products, raw materials and components, as well as changes in their shipments because borders were closed by some countries [15]. In some cases delivering raw materials and components on time became a very difficult task. This meant that companies had to react quickly and plan their sales, which resulted in downtime due to not receiving components to be able to produce and not knowing how to respond to change.

Meat product companies also had to overcome new challenges because they had to introduce new operations into the production cycle related to personnel hygiene, such as workers' additional hand washing, antiseptic treatment and taking body temperature before they started a working day. In addition, they had to reduce the number of people on a shift and change from a 2-shift mode to a 3-shift mode. They also had to introduce an additional cleaning operation of production and processing plants with disinfectant. All this meant that many companies could not plan in such a way to not reduce production volumes.

According to Myro [16], the manufacturing industry in Spain was affected by the pandemic as it had a knock-on effect on other productive activities, especially the most directly affected ones: hotels, leisure and restaurants, as well as transport, commerce and construction. The most affected goods were consumer durables and capital goods. The same author estimates that the automotive industry in April 2020 suffered a year-on-year decline of 98.7%, components, parts and accessories (88%), and bodywork and trailers (62.5%). Furniture, jewellery and games and toys recorded falls of more than 70%, as did footwear and clothing, followed closely by textile finishing. Metal industries contracted nearly 50%, slightly more than construction materials, while machinery industries saw their output fall by nearly 40%. In chemical and food industries, the drop in production was not as high, except for artificial fibres and plastics for the former, or bakery products, pasta and beverages for the latter, which fell by more than 20%. However, Spain and other European Union (EU) countries could obtain funding from the Recovery Plan proposed by the European Commission. According to Torres and Férnandez [17], forecasts are still subject to a very high degree of uncertainty and, therefore, to a much higher than usual margin of error; not only because of the possibility of new restrictions on certain economic activities, but also because of the great uncertainty regarding the behaviour of certain macroeconomic variables in such an unusual situation. For example, one can only make more or less well-founded, assumptions about the level of precautionary savings, which will be a key determinant of the extent of recovery in consumption.

Many manufacturing companies in both the pandemic and the Great Recession did not have the arrangements to adapt quickly to new working conditions and change their sourcing, production and distribution plans while optimising their costs. Adaptability, flexibility and rapid response to change are the basis for success in today's global economy. Today the success of most companies, especially small- and medium-sized enterprises (SMEs), is linked to the efficiency of their production processes. The importance of optimising company processes has led researchers and governments to look for methods to help companies to improve and optimise their production processes.

1.2.1 Planning optimization

The task of optimally utilising all available resources and efficiently planning replenishment, production and distribution has become a key element for many manufacturing companies. In this context, situations like changes in the production process, the emergence of new labour resource constraints, delays from supplier components replenishment, and changes in deliveries and shipments, lead many companies to make mistakes in their decision-making processes due to lack of efficient mathematical tools to support planning process optimisation. Nowadays combinatorial optimisation problems constantly arise and in many forms in not only the manufacturing sector, but also in different economic and social sectors. This is because there are lots of services driven by optimisation algorithms; for example, public transport, delivery services, shift scheduling in hospitals, amongst others. These algorithms allow to better use available resources and guarantee a service level [18].

In a more general context, decision support systems continue to be very popular in industrial engineering thanks to their ability to help decision makers manage their resources despite various imposed replenishment, manufacturing and delivery constraints. However, manufacturing systems are complex because they connect many technical and human resources. These systems often seek greater efficiency and, as a result, new strategies are developed. Presently, such systems must be able to adapt quickly to market needs.

In summary, one of the most effective methods for solving materials replenishment, production and delivery planning problems are automated systems based on mathematical optimisation methods (finding the minimum and maximum of the objective function) [19]. There are many reported applications and events that document the success and importance of this research area. Optimisation is about minimising cost, time, distance or risk, and about maximising quality, satisfaction, profit, among others. Finding the best solution for certain optimisation problems of scientific or industrial importance often results in computational representations that are of intractable complexity.

This is why particular interest is shown in heuristic, metaheuristic and matheuristic algorithms in the optimisation field, which serve as intelligent strategies to design or improve general optimising procedures for solving complex problems with excellent performance.

According to this reality, more and more researchers are striving to study and develop systems and techniques given the fact that most combinatorial optimisation problems are NP-Hard, and there is no deterministic polynomial-time algorithm for such intractable problem. This scenario means that some algorithms cannot finish in practical computational times once the problem size has become too large. In practice, finding optimal solutions for these problems remains a research topic, and searching for solutions that are superior in quality to previously known best solutions is extremely valuable.

The use of approximation algorithms is the main alternative to solve this kind of problems because it allows a solution close to the optimal one in reasonable computational times to be obtained. The application of algorithms to optimisation problems has been very important in recent decades. Its main advantage is flexibility in the problems to be solved and the robustness of the provided solutions because this allows algorithms to be applied to a wide range of problems.

This causes combined or hybrid techniques to start to become successful in view of the fact that choosing an appropriate combination of algorithms can be key to achieve better performance in a solution [20]. Hence a combination of algorithms can provide sufficiently good solutions in practical computational times [21].

In fields like computer science, artificial intelligence and operations research, many of these problems have been addressed for some years now without them interacting much. However in recent years, due to the fourth industrial revolution (Industry 4.0)[22], these groups have joined forces and started to look at the progress that all these areas can make by seeking to develop optimisation techniques that are faster, robuster and easier to maintain.

In this context, the central focus of this thesis lies in the need to develop tools to improve the use of available resources, avoid waste and improve the sustainability of services in companies. Therefore, this thesis is framed in the secondary or industrial sector of the economy. Hence, this thesis is framed in the secondary or industrial sector of the economy. This sector is the cornerstone for a country's economic growth, for which various optimisation methods are researched in depth by placing emphasis on resolution methods, and on developing strategies for certain classes of NP-Hard combinatorial optimisation problems. Given the aim to design and implement new models and algorithms from the base created by European project C2NET (Cloud Collaborative Manufacturing Networks) [23], the intention is to examine the combination of various methods, such as metaheuristic or heuristic methods, to make the best of the characteristics of each technique type to obtain a flexible and easy-to-use system for companies.

1.3 Research Questions and Objectives

The current environment in which companies operate is highly competitive, and generally changes rapidly. So, companies must design, manufacture and distribute their products at the same speed, while being efficient and reducing costs at the same time. This leads companies to seek to continuously improve their operations.

Companies' economic performance is linked with technological research and innovation. Both these aspects are of decisive importance today because we are facing a new technological revolution of unusual magnitude that is driven by advances in digitalisation and the need for a firm and large-scale fight for environmental sustainability. Computer systems, mathematical models and algorithms for decision-making support are tools now available to companies that aim to improve their performance, which turns the use of this technology into a competitive advantage.

Mathematical models make a representation of a system or a real problem by means of mathematical equations, these equations try to represent the components of the system and the solution of these equations serve to predict the changes in the system or the changes that can undergo in time [24]. There are different types of methods to solve different types of mathematical models, such as optimiser, heuristic, metaheuristic and matheuristic algorithms.

By considering the importance of providing advanced models and algorithms that allow SMEs to achieve the integral optimisation of their production assets, and respond more quickly and efficiently to the market, the following research questions are posed to support the design of models and algorithms oriented to solve real-world replenishment, production and distribution plans efficiently; that is, in adequate computational times with high-quality solutions. With the eagerness to integrate the objective of this research, the following general research question (GRQ) is posed:

GRQ: *What suitable approach could efficiently solve replenishment, production and distribution planning, which are computationally difficult to solve by exact solvers?*

The following research questions (RQ) derive from this general research question:

RQ1. How can replenishment, production and distribution planning problems and solution methods be categorised?

RQ2. How can the most suitable algorithm or solution method be selected to solve replenishment, production and distribution planning according to its complexity?

RQ3. What new algorithms should be developed to solve real replenishment, production and distribution planning problems?

In order to answer the research questions, the general research objective (GRO) is defined:

GRO. *Design and implement new models and algorithms for the calculation of replenishment, production and distribution plans in industrial companies.*

From the GRO, the following specific objectives (O) can be derived:

O1. Propose a taxonomy to categorise the optimisation problems for replenishment, production and distribution plans.

O2. Propose a framework to evaluate the different types of models and algorithms that can solve the identified replenishment, production and distribution planning problems.

O3. Develop a decision support tool to properly select an algorithm or solution method for a replenishment, production and distribution planning problem.

O4. Develop and implement new models and algorithms to solve real-world problems

O5. Validate the applicability of the developed models and algorithms by applying them to real cases.

1.4 Research Methodology

To answer the research questions, and to fulfil the stated objectives, a multimethod approach that combines quantitative and qualitative research is adopted, which is incorporated into an overall methodological framework based on the multimethod approach proposed by Nunamaker et al. [25]. The selected research methodology consists of four stages: (i) observation; (ii) theory building; (iii) experimentation; (iv) systems development (see Figure 1.2).

This methodology was used to achieve the proposed objectives and, additionally, this approach was used in the development of each of the chapters of this doctoral thesis. The main characteristic of this methodology is that it has a scheme that can be used sequentially, and each stage can be feedback to the other stages. Figure 1.2 shows how each stage is used for each of the objectives of the doctoral thesis. The following subsections describe each of the stages and how they have been used to achieve the objectives.

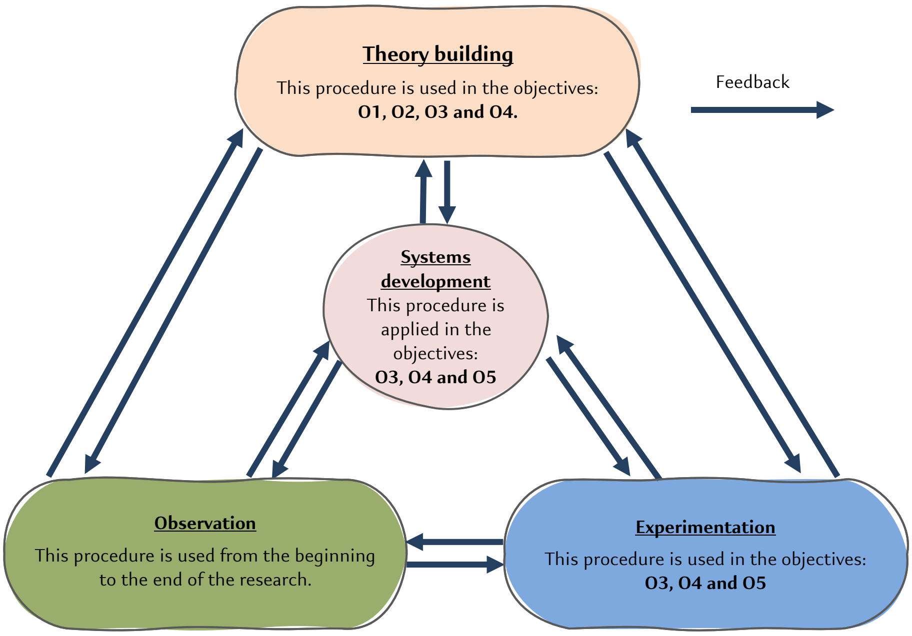

Figure 1.2. Research Methodology proposed by Nunamaker et al. [25] and analogously with the research objectives.

1.4.1 Observation

According to the methodological approach proposed by Nunamaker et al. [25], *Observation* is used to inquire about the topic under study. By exploring the study field, this approach helps to create generalisations or hypotheses that must be demonstrated by the research. Observation in this research is used to meet all the set objectives. The aim of this stage is to study the mathematical models proposed in the literature to represent replenishment, production and distribution planning problems and their characteristics, and to investigate the used solution methods and to study the relation between models and algorithms. The observation stage provides the thesis with an overview of the entire spectrum of methods used in planning problems.

1.4.2 Theoretical construction

This research methodology stage develops concepts, conceptual frameworks and mathematical models [25].

This stage tackles objectives *O1, O2, O3* and *O4*. Based on the results obtained from the analysis of the planning problems, and after gaining an overview of the whole spectrum of models and algorithms used in planning problems, a taxonomy for classifying optimization problems and a holistic framework for evaluating the different types of models and algorithms are proposed. The taxonomy and the holistic framework allowed defining the most relevant classification dimensions of planning problems with which this thesis intends to provide new insights into the characteristics of problems.

After defining the different dimensions, and knowing that the literature details many resolution methods for optimisation problems, a decision support tool is generated to put these resolution methods to best use. Here the aim is to seek to develop a methodology to select an algorithm or resolution method given a portfolio of algorithms. In this way, the users who use the decision support tool will obtain a ranking of algorithms or solution methods that can be used to solve replenishment, production and delivery planning problems from different complexities. This will help to avoid having to duplicate efforts in generating or programming different algorithms and then evaluating their solutions.

Following this stage, different mathematical formulations are generated with which to seek to capture companies' needs. For this purpose, solutions are given to problems with a combined replenishment and production planning approach and with a combined replenishment and distribution planning approach. In this way, we respond to the existing research gaps in the literature. To validate our formulations, a real case of a company in the automotive sector is used with which attempts are made to perceive how the company under study can achieve cost reduction, which is an important test to validate models. Finally, knowing the computational difficulty of the planning problems that are generally presented as NP-hard or Np-complete, and considering that the most advanced solvers have difficulties in generating good quality solutions for different mathematical models, the aim is to develop matheuristics algorithms for different planning problems, such as the sequencing problem and the combined production and distribution approach, and to use free and open-source solvers because they can be useful for companies that do not wish to incur costs associated with licences.

1.4.3 Experimentation

In this stage, experiments or computational simulations, laboratory or field tests can be carried out. Experimentation is used to validate theories. The experimental stage is guided by the theoretical basis and facilitated by the development of systems, and this stage can help to refine theories, models or simulations [25].

This approach is used in objectives *O3, O4 and O5*, which validate the mathematical models and matheuristics algorithms using large datasets similar to those used by companies. In doing so, we aim to validate our formulations while seeking to obtain high-quality solutions in acceptable resolution times. The proposed models are evaluated in a real-world problem, and realistic instances are also created to assess the industrial relevance of the proposed matheuristics algorithms.

1.4.4 System Development

In this stage, systems are designed, the architecture of systems is built, and prototypes are created. Here theoretical knowledge is adapted with technological advances, and the viability of concepts is demonstrated by creating prototypes. The difficulties in this stage mean that concepts or theories are raised again or modified. The success of this stage represents the development of a product and technological transfer to companies; that is to say, the success of the theories, concepts and models raised in the previous stages [25]. This approach is used for the *O3, O4 and O5* in which a set of data generators is developed (see under [26–28]), along with programmes containing the algorithms and methodology for selecting algorithms.

1.5 Research Outline

The chapters of this thesis comprise a set of selected scientific articles that answer the research questions posed in previous sections and are aligned with the previously defined objectives. An overview of the main aspects addressed in the articles is detailed below.

Chapter 1 provides an overview of the research work conducted in this thesis. This chapter outlines the motivation and the problem statement, in addition to formulating the research questions, objectives and the research methodology employed.

Chapter 2 presents an analysis of the different models and algorithms for optimising replenishment, production and distribution plans in the supply chain based on the latest literature reviews in this field. It provides an overview of models and algorithms used to solve different types of problems encountered in the supply chain. This review presents a starting point for the selection of models and algorithms to solve these types of supply chain problems and discusses several lines of future research. This chapter aims to answer *RQ1* by generating a taxonomy to categorize and analyse the different types of plans to meet *O1*

Chapter 3 provides a holistic conceptual framework for production scheme. It includes production planning, scheduling and sequencing. The proposed conceptual framework answers *RQ1* and fulfils *O2* by studying the different levels of aggregation. and disaggregation of plans, modelling approaches to represent different types of plans and their characteristics, solution approaches with adopted algorithms, application areas, levels of intra- and interenterprise integration, dataset sizes used to validate models and algorithms, development tools and the quality of solutions obtained in relation to the problem data size.

Chapter 4 provides a decision support tool for algorithm selection by a fuzzy TOPSIS approach to help decision makers to choose the best algorithm to solve replenishment, production and delivery planning problems in manufacturing companies. This tool contributes to solving *RQ2*, since the selection of an algorithm in an attempt to solve an optimisation problem is a difficult task. In replenishment, production and distribution planning problems, different methods and techniques with many characteristics are applied. Hence the difficult problem of knowing which algorithm is suitable for a planning problem arises. The main contribution of this chapter to fulfil Objective 3 is to provide a tool to select a solving method, which can range from a solver (commercial or free) to different types of heuristic, metaheuristic and matheuristic algorithms.

Chapter 5 provides a mixed integer linear programming (MILP) model for the lot-sizing/scheduling problem for the manufacture of automotive plastic components. A second-tier supplier in the automotive supply chain is studied. The second-tier supplier produces plastics for automobiles. These plastics are produced in moulds that are assembled on flexible injection moulding machines in parallel. To cover *O4* on the development of new models for real problems, the novelty of this model lies in the fact that it considers the arrival of materials as raw material for the injection of parts into the moulds, and the utilisation of raw materials and the availability of containers for the packaging of finished products. In addition, moulds can only be assembled during specific time periods according to the amount of available labour during each period. The usefulness of this model is demonstrated with randomly generated instances fulfilling *O5*, thus answering *RQ3*.

Chapter 6 responds to *RQ3* and addresses Objectives 4 and 5 by proposing a mixed integer linear programming model to address the production lot-sizing and delivery decisions of a containers fleet in a production system. The model is approached in the automotive supply chain from the second-tier supplier perspective. The model determines the number of cardboard containers that the second-tier supplier should use when production exceeds the number of available reusable containers required to deliver components from the second- to the first-tier supplier. As the second-tier supplier has a storage space constraint, it has to limit production to the warehouse size, but always in line with the first-tier supplier's demand plan. In addition, the second-tier supplier is limited in terms of the number of empty reusable containers that the first-tier supplier delivers to the second-tier supplier, which are used to package and deliver the injected plastic components. The filled reusable containers are delivered to the first-tier supplier in accordance with the demand plan for plastic components.

Chapter 7 focuses on developing a new efficient matheuristic to solve the machine scheduling and sequencing problem. This chapter fulfils Objectives 4 and 5 and solves *RQ3*. From a mathematical point of view, this problem is classified as NP-hard. The matheuristic algorithm is proposed for the job-shop problem by combining a genetic algorithm with a disjunctive mathematical model, and the open-source solver Coin-OR Branch & Cut is used. The matheuristic algorithm, in which an optimal model and a metaheuristic algorithm interoperate, provides efficient solutions to be found and reduces the computation time by using an open-source optimisation solver combined with a genetic algorithm.

Chapter 8 presents a matheuristic approach to solve the combined production and distribution planning problem. Given the complexity of this problem, the combination of a genetic algorithm and a mixed integer linear programming model is proposed. The matheuristic algorithm was tested using the open-source solver Coin-OR Branch & Cut. The computational results revealed that the presented matheuristic algorithm can be used to solve real-size problems. Objectives 4 and 5 are met in this chapter and RQ3 is answered.

Finally, **Chapter 9** summarises the contributions of this thesis and the most important results obtained and offers directions for future research.

An outline summarizing the relationship between the research questions, the objectives and the chapters of the thesis is shown in Figure 1.3

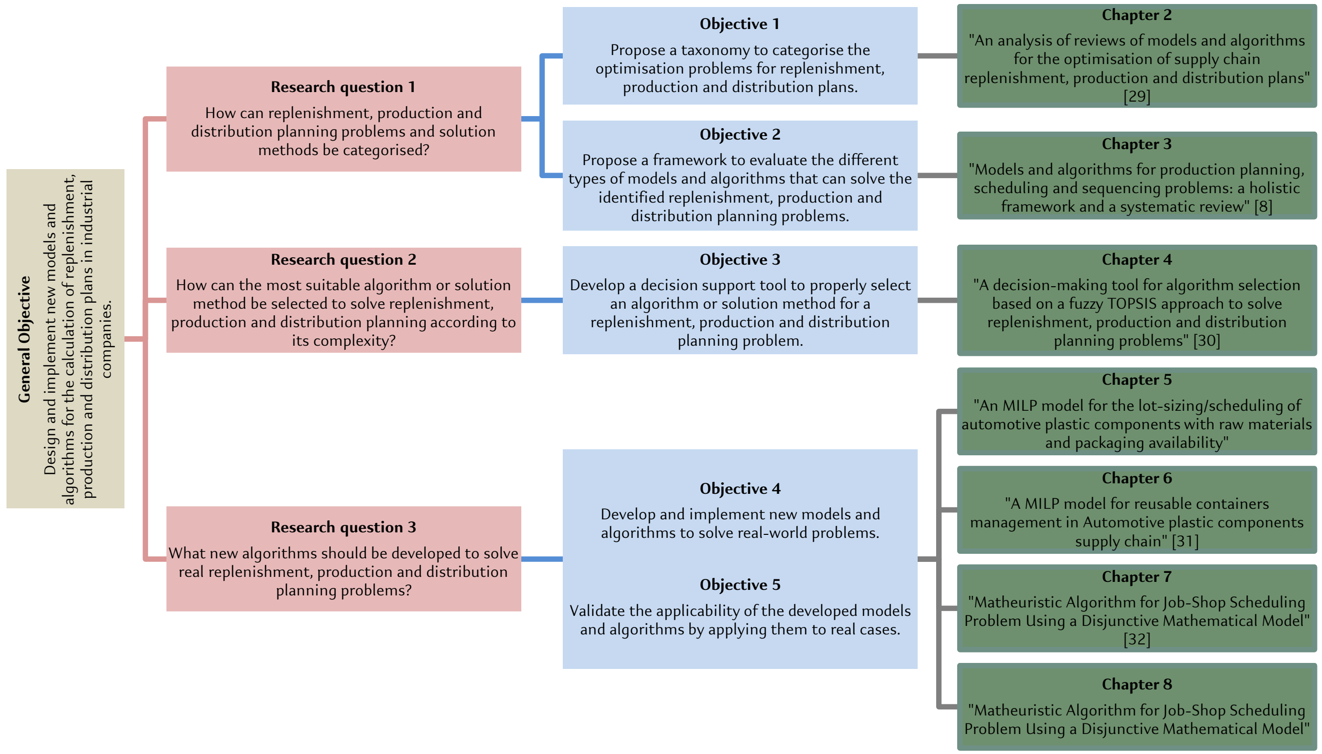

Figure 1.3. Research questions, objectives and structure of this thesis.

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Chapter 2

An analysis of reviews of models and algorithms for the optimisation of supply chain replenishment, production and distribution plans.

Guzmán, E, R Poler, and B Andres. 2020. "*Un Análisis de Revisiones de Modelos y Algoritmos Para La Optimización de Planes de Aprovisionamiento, Producción y Distribución de La Cadena de Suministro*." Dirección y Organización 70: 28–52. https://doi.org/https://doi.org/10.37610/dyo.v0i70.567.

Abstract:

This section provides an analysis of the different models and algorithms for the optimisation of sourcing, production and delivery plans in the supply chain based on the latest literature reviews in this field. It aims to provide researchers with a starting point to select models and algorithms to solve this type of problems in the supply chain and to present several future research lines.

2.1 Introduction

Since 1982, when Keith Oliver, a consultant at Boaz Allen Hamilton, introduced the term "supply chain management" during an interview for the *Financial Times* [1], different models and methods for supply chain design and management have been published in various studies, which are generally of the primary type (original research), while others of the secondary type (literature reviews) and tertiary studies (analyses of literature reviews) are scarce. In their review article on the closed-loop supply chain, Kazemi et al. [2] mention that, due to the volume of constantly appearing publications and their growth in recent years, it is difficult to maintain a broad overview of the study area, which makes the contribution of secondary or tertiary studies that help to synthesise and structure each research study necessary.

This article provides a tertiary study to conduct a systematic analysis of literature reviews on models and algorithms for the optimisation of procurement, production and distribution plans in the supply chain. It proposes useful guidelines for the research and development of new models and algorithms in these areas. The following research questions were posed for this study:

RQ1: What are the perspectives or approaches proposed in the literature on the supply chain?

RQ2: What is the current status of research into the optimisation of procurement, production and distribution plans?

RQ3: What are the most relevant reviews in the optimising procurement, production and distribution plans context in the supply chain?

RQ4: How can procurement, production and distribution plans be conceptualised?

RQ5: How can the quantitative methods used in the optimisation of procurement, production and distribution plans be conceptualised?

RQ6: What quantitative methods have been used in the literature for procurement, production and distribution plans?

RQ7: What future research lines can be proposed based on existing reviews and what research areas can be targeted for future studies?

To answer these research questions, a systematic analysis of literature reviews that focus on supply chain planning problems was conducted. It evaluated 168 articles and 17 were selected for their in-depth analysis. The selection criteria were based mainly on the reviews that had analysed mathematical models or quantitative methods, and had used a methodological process in the review. The found research works generally suggest review approaches, such as systematic, narrative and meta-analysis. However, this study focuses on systematic reviews to facilitate comparisons of the quantitative methods used in the different supply chain approaches. In addition, the SCOR model is employed to classify the analyses produced by the selected articles.

This analysis aims to concisely summarise the type of planning addressed in the reviewed articles, and the models and methods followed to solve not only optimisation problems, but also algorithms and approaches. This research also aims to identify gaps and opportunities to propose future research directions in the supply chain operations planning field.

This article is organised as follows: Section 2.2 shows the approaches or perspectives studied in the literature and their definition. Section 2.3 explains the methodology followed in the systematic analysis. Section 2.4 presents the research findings. Section 2.5 shows the observations, perspectives and orientations given by researchers. Finally, Section 2.6 presents the conclusions and directions for future research.

2.2 Perspectives from reviews.

The supply chain concept has been described by several authors, who express similar features in their definitions. In turn these definitions are adapted to the analysis or research field. One definition that aptly summarises the term is that by Ivanov and Sokolov [3]: a supply chain: *"is a network of organizations, flows and processes wherein a number of various enterprises (suppliers, manufacturers, distributors and retailers) collaborate (cooperate and coordinate) along the entire value chain to acquire raw materials, to convert these raw materials into specified final products, and to deliver these final products to customers"*.

It is important to highlight the approaches or perspectives on supply chains and the direction that researchers are currently taking. Table 2.1 describes the supply chain research areas found in the literature. The definitions of these terms are intended to answer RQ1.

Table 2.1. Perspectives on supply chain analyses.

Perspective	Definition
Supply Chain Management	Supply chain management is the management of material, information and financial flows through the supply chain. It includes the coordination and collaboration of processes and activities across different functions, such as marketing, sales, production, product design, procurement, logistics, finance and information technology in the supply chain [4].

Table 2.1. Continued. Perspectives on supply chain analyses.

Perspective	Definition
Supply Chain under Uncertainty	Supply chains that address uncertainty express how uncertainty propagates up and down and influences their performance. Uncertainty affects demand volumes and supply capacities that are subject to economic instability and market fluctuations in addition to other endogenous and exogenous factors [5].
Closed-loop Supply Chain Management	A closed-loop supply chain can be seen as the traditional supply chain supplemented with reverse operations for recovered products that are reprocessed and eventually re-enter the supply chain. Closed-loop supply chain management describes the design, control and operation of a system to maximise value creation throughout the product's entire life cycle with a dynamic recovery of value from different types and volumes of returns over time [6].
Sustainable Supply Chain Management	Sustainable supply chain management is an extension of the traditional supply chain management concept, and it adds economic, environmental and social/ethical aspects by taking into account the requirements of customers and other stakeholders [7, 8].
Supply Chain Risk Management	Supply chain risk management is a multidisciplinary area where research and practice are based on at least three domains: supply chain management, enterprise risk management (identification, assessment, mitigation, response), and crisis management [4, 9].
Green Supply Chain Management	It is the integration of environmental thinking into supply chain management, including product design, material selection and sourcing, manufacturing processes, delivery of the final product to consumers, and end-of-life management [10].
Supply Chain Resilience	it addresses a supply chain's adaptive capacity to reduce the likelihood of facing sudden disruptions, resisting the propagation of disruptions while maintaining control over structures and functions, and recovering and responding through immediate and effective reactive plans to transcend the disruption and to restore the supply chain to a robust state of operations [11].

2.3 Methodology

The literature review forms part of the basic research structure. The objective of this study is to systematically analyse the reviews carried out on supply chains by taking into account the relation with the applied approach by identifying its key elements and the types of methods studied to date. This section provides an answer to RQ2.

In order to fulfil this objective, we follow the methodology proposed by Seuring and Müller [12] and Seuring and Gold [13], in which four steps are established to carry out a systematic review: 1) collection of material; 2) descriptive analysis; 3) selection of categories; 4) evaluation of the material.

2.3.1 Collection

The scope of the study starts with the selection of databases, and SCOPUS and Web of Science were selected. The employed search criteria are shown in Table 2.2. These search criteria were adapted to each specific database to ensure the robustness of the search.

Table 2.2. Database search criteria.

Identification	**Description**
Databases	*SCOPUS, Web of Science*
Language	English
Scientific Areas	all
Magazines	all
Types of articles	literature review
Search field	title, abstract, keywords
Search date	February 2019
Years searched	2009-2019

In order to ensure the adequate selection of articles, the search was limited to English-language journals, and excluded conference reviews, books, etc. Furthermore, the search was narrowed down by applying keywords based on the research questions (see Figure 2.1).

The search period was adjusted to the last 10 years as the research purpose was to find out what future research lines (for the next decade) were proposed by the authors. Some of the studied authors [14–17] analysed literature reviews and primary works. In line with the aforementioned researchers, Brandenburg et al. [14] analysed reviews from 1999 to 2012, Ho et al. [17] did so from 2006 to 2012, Malviya and Kant [15] from 2007 to 2013 and Barbosa-Póvoa et al. [18] from 2007 to 2016.

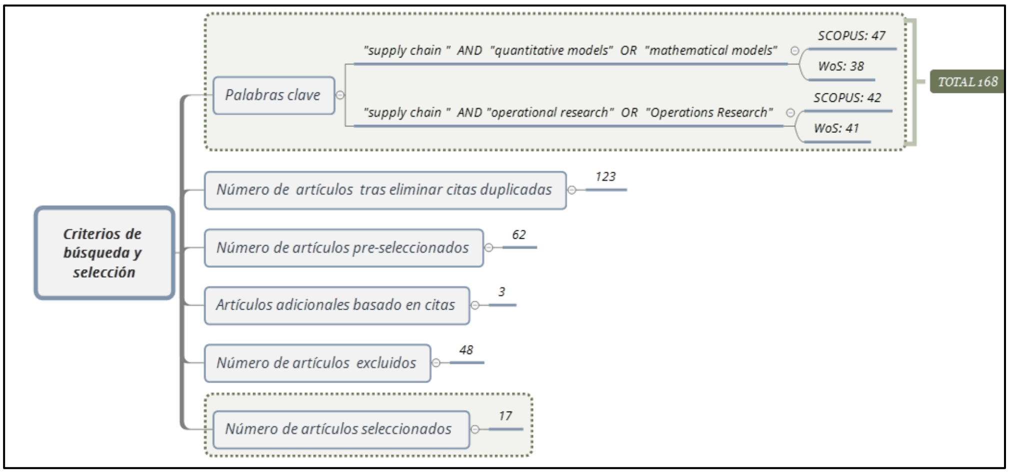

Figure 2.1. Search criteria and selecting articles.

Figure 2.1 summarises the selection process of the literature reviews herein considered. From the first search in the selected databases, 168 references were obtained, and the elimination of duplicates left 123 articles. Reading the abstracts of the 123 articles allowed us to assess whether the articles matched our research questions. By applying this criterion, the number of articles dropped to 62, which were considered for further reviews. The full text of these 62 articles was reviewed in-depth by analysing their response to the following questions: does the study present models or methods to solve supply chain optimisation problems?; does the study describe a relation with procurement, production and distribution plans?; does the study describe a perspective and a sector of application?; does the study propose future research directions?. After evaluating this research, we identified three articles that were cited, but not captured, by our search criteria. These three articles were not grouped as literature reviews, but as articles. After reading these articles, we identified their relevance and assessed whether they matched our research questions. The collection yielded 65 articles that were analysed in-depth. Subsequently, 48 articles were excluded because they did not adequately match our research questions. Finally, we selected 17 to be studied (see Table 2.3).

Table 2.3. The selected review articles.

Year	Authors	Title
2009	David Peidro, Josefa Mula, Raúl Poler, Francisco-Cruz Lario	*Quantitative models for supply chain planning under uncertainty: a review.*
2010	Josefa Mula, David Peidro, Manuel Díaz-Madroñero, Eduardo Vicens	*Mathematical programming models for supply chain production and transport planning.*

Table 2.3. Continued. The selected review articles.

Year	Authors	Title
2014	Dennis Stindt, Ramin Sahamie	*Review of research on closed loop supply chain management in the process industry.*
2014	Marcus Brandenburg, Kannan Govindan, Joseph Sarkis, Stefan Seuring	*Quantitative models for sustainable supply chain management: Developments and directions.*
2015	Rakesh Kumar Malviya, Ravi Kant	*Green supply chain management (GSCM): a structured literature review and research implications.*
2015	Çağrı Sel, Bilge Bilgen	*Quantitative models for supply chain management within dairy industry: a review and discusion.*
2015	Kannan Govindan, Hamed Soleimani, Devika Kannan	*Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future.*
2015	William Ho, Tian Zheng, Hakan Yildiz, Srinivas Talluric	*Supply chain risk management: a literature review.*
2016	Muhammad Salman Habib, Young Hae Lee, Muhammad Saad Memon	*Mathematical Models in Humanitarian Supply Chain Management: A Systematic Literature Review.*
2016	Wladimir E. Soto-Silva, Esteve Nadal-Roig, Marcela C. González, Lluis M. Pla-Aragones	*Operational research models applied to the fresh fruit supply chain.*
2017	Carlos Franco, Edgar Alfonso-Lizarazo	*A Structured Review of Quantitative Models of the Pharmaceutical Supply Chain.*
2018	Nasim Zandi Atashbar, Nacima Labadie, Christian Prins	*Modelling and optimisation of biomass supply chains: a review.*
2018	Faiza Hamdi, Ahmed Ghorbel, Faouzi Masmoudi, Lionel Dupont	*Optimization of a supply portfolio in the context of supply chain risk management: literature review.*
2018	Cigdem Gonul Kochan, David R. Nowicki	*Supply chain resilience: a systematic literature review and typological framework.*
2018	Ana Paula Barbosa-Póvoa, Cátia da Silva, Ana Carvalho	*Opportunities and challenges in sustainable supply chain: An operations research perspective.*
2019	Isabel Mundi, M. M. E. Alemany, Raúl Poler & Vicente S. Fuertes-Miquel	*Review of mathematical models for production planning under uncertainty due to lack of homogeneity: proposal of a conceptual model.*
2019	J.B. Oliveiraa, M. Jin, R.S. Lima, J.E. Kobza, J.A.B. Montevechia	*The role of simulation and optimization methods in supply chain risk management: Performance and review standpoints.*

2.3.2 Descriptive analysis

In this phase, the 17 selected articles were analysed to answer RQ3. The evaluated characteristics were: publication date, type of publication and journal. Of the journals to which publications belonged, the *European Journal of Operational Research* and the *International Journal of Production Research* stood out (Table 2.4).

Table 2.4. Distribution of the articles based on journals.

Journal	**Articles *n*=17**
European Journal of Operational Research	5
International Journal of Production Research	3
Mathematical Problems in Engineering	1
Benchmarking: An International Journal	1
Complexity	1
European J. Industrial Engineering,	1
Flexible Services and Manufacturing Journal	1
The International Journal of Advanced Manufacturing Technology	1
International Journal of Physical Distribution & Logistics Management	1
Journal of Intelligent Manufacturing	1
Simulation Modelling Practice and Theory	1

Analysing the publication dates provides information on the evolution of the research carried out into different supply chain perspectives. The selected articles covered a 10-year period, and it is noteworthy that 27.8% were published in 2018. The year 2015 was equally significant with 22.2%, while the remaining dates represented less than 11.1% (see Figure 2.2).

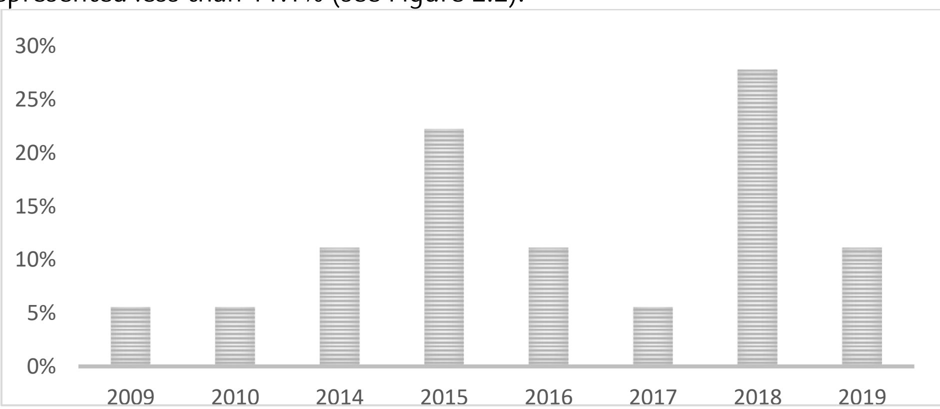

Figure 2.2. Classification of articles by publication year.

2.3.3 Category selection

The main analysis themes and structural dimensions included in this selection are described in Tables 2.5 and 2.6. The processes taking place in the supply chain can be classified with the SCOR (*Supply Chain Operations Reference*) model. This approach describes business processes to classify them into three categories, i.e. Procurement (S, *Source*), Production/ Manufacturing/ Manufacturing (M, *Make*), Distribution (D, *Deliver*), to which subtypes and schemes are added [19]. This classification solves RQ4 (Table 2.5).

Table 2.5. Types and subtypes of plans according to the SCOR model.

<table>
<tr><th>Supply chain</th><th>Type of plan</th><th>Subtypes</th><th colspan="4">Schemes</th></tr>
<tr><td>Supplier</td><td>Procurement (S)</td><td>S/ Material requirements plan
S/ Raw material inventory planning
S/Procurement planning
S/ Procurement planning
S/ Inventory planning</td><td rowspan="2">Procurement & Production (SM)</td><td rowspan="2">S/Inventory planning &
M/ Production planning

S/ Material requirements plan &
M/ Production planning</td><td rowspan="4">Procurement & Production & Distribution (SMD)</td><td rowspan="4">S/ Procurement planning & M/ Production planning &
D/ Distribution planning

S/Inventory planning & M/ Production planning & D/ Distribution planning</td></tr>
<tr><td rowspan="2">Production/ Manufacturing</td><td rowspan="2">Production (M)</td><td rowspan="2">M/Production planning
M/ Production scheduling
M/Production Sequencing</td></tr>
<tr><td rowspan="2">Production & Distribution (MD)</td><td rowspan="2">M/ Production Planning &
D/ Distribution Planning

M/ Production Planning &
D/ Transport Planning</td></tr>
<tr><td>Customer</td><td>Distribution (D)</td><td>D/Demand planning
D/Distribution planning
D/Order promising
D/Transport planning</td></tr>
</table>

Andres et al. [20] propose a classification of models and algorithms used to solve procurement, production and distribution plans as part of European Project "*Cloud Collaborative Manufacturing Networks* (*C2NET*)", presented in the deliverable "*Taxonomy of optimisation and simulation solutions for Manufacturing* *and Logistics Processes"* [21]. Table 2.6 answers RQ5. It shows this classification and other parameters considered to assess the reviews.

Table 2.6. Classification of categories according to the taxonomies proposed by [14, 21, 22].

Types of models	Analytical, Simulation, Mathematical.
Analytical	Multicriteria decision making (MCDM); Analytic Hierarchical Process (AHP); Analytic Network Process (ANP); Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS); Elimination and Choice Expressing Reality (ELECTRE); Multicriteria Optimisation and Compromise Solution (VIKOR)
Simulation	Agent-Based Simulation (ABS); Discrete Event Simulation (DES); System Dynamics Simulation (SDS); Monte Carlo Simulation (Monte Carlo Simulation); Other Simulation Methods
Mathematical	Linear Programming (LP); Integer Linear Programming (ILP); Mixed Integer Linear Programming (MILP); Non-Linear Programming (NLP); Mixed Integer/Integer Non-Linear Programming; Quadratic Programming (QP); Dynamic Programming (DP); Stochastic Programming (SP); Robust Programming (RP); Constraint Programming (CP); Multi-Objective Linear Programming (MOLP) / Multi-Objective Non-Linear Problem (MONLP) / Multi-Objective Mixed-Integer Non-Linear Programming (MOMINLP); Hybrid Approach (HA); Fuzzy Programming (FP); Goal Programming (GP).
Resolution methods	Optimising Algorithms (OA), Heuristics (HA), Metaheuristics (MA)

Optimisers (OA)	**Heuristics (HA)**	**Metaheuristics (MA)**
OA/ Decomposition OA/ Lomnicki OA/ Strategic-operational optimisation OA/ Branch and Bound OA/ Criss-cross OA/ Lompen OA/ Simplex	HA/ Multi-Objective Master Planning HA/ Campbell-Dudeck HA/ Local Improvement HA/ Primal-Dual Heuristics HA/ Decomposition and Aggregates HA/ Greedy HA/ Lagrangian HA/ Minimum Spanning Tree HA/ Nearest Neighbour	MA/Colony Optimisation MA/ Evolutionary Computation MA/Genetics MA/GRASP MA/Iterative Local Search MA/Neural Networks MA/ Scatter Search (SS) MA/ Simulated Annealing MA/ Tabu Search MA/TSGW MA/ Variable neighbourhood search

2.3.4 Validation

In this phase, the analysed articles were validated according to the selected characteristics, approaches and dimensions by the hierarchical agglomerative grouping technique with a deductive and inductive process.

The assessment ensured that reviews were appropriately and sufficiently well-informed to, thus, condition articles to match the parameters considered for classification purposes. This was one of the reasons why several publications were discarded. The analysis helped to examine the organisation, categorisation and structure, and the main findings of the systematic review, to motivate future research lines.

2.4 Results

This section describes the results obtained with the categorisation and evaluation of the selected reviewed articles by analysing elements like types of used schemes, models and resolution methods.

2.4.1 Perspectives for the analysis

The selected reviewed articles present different analysis perspectives: supply chain management, supply chain under uncertainty, closed-loop supply chain management, sustainable supply chain management, supply chain risk management, green supply chain management and supply chain resilience. This research analyses 2,309 articles over an approximate search period from 1983 to 2019. Table 2.7 shows which sectors these studies focus on. Several research works focus on a specific sector by studying all the publications that refer to the sector in relation to the analysed perspective. Other reviews analyse all the sectors from the analysis perspective. It is important to highlight that most articles analyse the reviews that concentrate between 2007 and 2013, which represent 60.64% of the articles during this period (Figure 2.3), where 2012 is the year with the most articles: 241 (10.75%).

Another aspect analysed by reviews is the decision-making levels during the planning process, where research analyses strategic, tactical and operational levels. Table 2.7 indicates which studies consider this aspect.

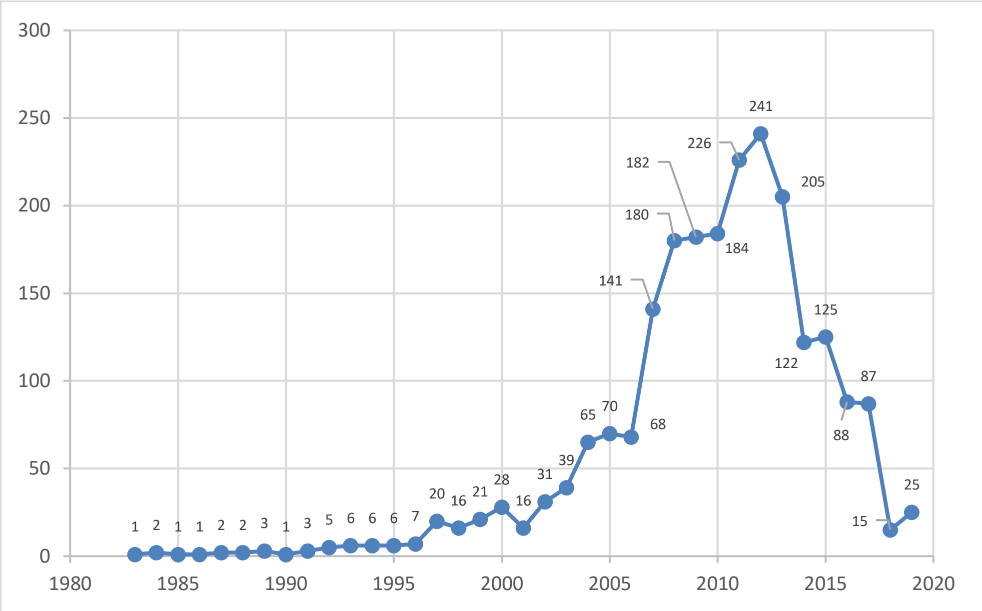

Figure 2.3 Number of published articles per year cited in the analysed reviewed articles.

Table 2.7. Analysis of the focus of the research works.

Author	Journal	Re-viewed articles	Analysis period	Analysed perspective	Study of decision levels	Analysed sector	Study focus
Peidro et al. [23]	The International Journal of Advanced Manufacturing Technology	103	1988-2007	Supply chain under uncertainty	x	Multisectoral	It focuses on supply chain planning under uncertainty by adopting quantitative approaches.
Mula et al. [24]	European Journal of Operational Research	44	1989-2009	Supply chain	x	Multisectoral	It studies mathematical programming models for supply chain production and transport planning, based on the analysis of eight aspects: structure, decision level, modelling approach, purpose, information sharing, model limitations, novelty provided, practical application.
Brandenburg et al. [14]	European Journal of Operational Research	134	1994-2012	Sustainable management of your supply chain	-	Multisectoral	It studies quantitative models for sustainable supply chain management.

Table 2.7. Continued. Analysis of the focus of the research works.

Author	Journal	Reviewed articles	Analysis period	Analysed perspective	Study of decision levels	Analysed sector	Study focus
Stindt and Sahamie [6]	Flexible Services and Manufacturing Journal	167	1994-2012	Closed loop supply chain management	-	Chemical Industry, Metal/Steel Industry, Construction Industry, Paper/Pulp and Paper Industry, Pharmaceutical Industry, Plastics/Polymers Industry, Textile Industry	Describes quantitative approaches to closed-loop supply chain planning in the process industry
Malviya and Kant [15]	Benchmarking: An International Journal	177	1998-2013	Green supply chain management	-	Multisectoral	It identifies and analyses research methods, data analysis techniques, multicriteria decision-making methods and the main industries actively involved in green supply chain management.

Table 2.7. Continued. Analysis of the focus of the research works.

Author	Journal	Re-viewed articles	Analysis period	Analysed perspective	Study of decision levels	Analysed sector	Study focus
Sel and Bilgen [25]	European J. Industrial Engineering	78	1983-2013	Supply chain management	x	Dairy	It explores quantitative models for production planning and scheduling, distribution planning and vehicle routing problems (VRP) in dairy supply chain management.
Govindan et al. [26]	European Journal of Operational Research	382	2007-2013	Closed loop supply chain	x	Multisectoral	It presents a literature review of the optimisation methods used in reverse logistics and closed loop supply chains.
Ho et al. [17]	International Journal of Production Research	159	2003-2013	Supply chain risk management	-	Multisectoral	It examines quantitative and qualitative methods of supply chain risk management according to four main processes: identification, assessment, mitigation and monitoring of risks.
Habib et al. [27]	Mathematical Problems in Engineering	140	2005-2015	Supply chain management	-	Humanitarian	It explores the mathematical optimisation techniques and algorithms developed in humanitarian supply chain operations.

Table 2.7. Continued. Analysis of the focus of the research works.

Author	Journal	Re-viewed articles	Analysis period	Analysed perspective	Study of decision levels	Analysed sector	Study focus
Soto-Silva et al. [28]	European Journal of Operational Research	28	1976-2015	Supply chain	x	Fresh fruit	It focuses on operational research models to solve decision problems related to the fresh fruit supply chain.
Franco and Al-fonso-Lizarazo [29]	Complexity	46	1984-2016	Supply chain	x	Pharmacist	It analyses network design, in-ventory models and optimisation of a pharmaceutical supply chain.
Zandi Atashba r et al. [30]	International Journal of Production Research	110	1996-2017	Supply chain	x	Biomass	It describes models, methods and solution approaches to optimise biomass supply chains.
Hamdi et al. [31]	Journal of In-telligent Man-ufacturing	124	2003-2014	Supply chain risk manage-ment	-	Multisectoral	It describes optimisation tech-niques and the quantitative, qualitative and hybrid approach to supply chain risk management.

Table 2.7. Continued. Analysis of the focus of the research works.

Author	Journal	Reviewed articles	Analysis period	Analysed perspective	Study of decision levels	Analysed sector	Study focus
Kochan and Nowicki [22]	International Journal of Physical Distribution & Logistics Management	228	2003-2017	Supply chain resilience	-	Multisectoral	It analyses quantitative and simulation methods; reviews definitions related to supply chain resilience and identifies measures and assessment techniques.
Barbosa -Póvoa et al. [18]	European Journal of Operational Research	220	2007-2016	Sustainable supply chain	x	Multisectoral	It refers to operational research methods to support sustainable supply chain activities.
Mundi et al. [32]	International Journal of Production Research	87	1995-2018	Supply chain under uncertainty	x	Petroleum/Agri-food/Remanufacturing/ Timber sector/Mining sector/Ceramic sector	It analyses mathematical models for production planning under uncertainty due to non-homogeneity.
Oliveira et al. [33]	Simulation Modelling Practice and Theory	52	2000-2017	Supply chain risk management	-	Multisectoral	It investigates simulation and optimisation methods for the supply chain risk management approach.

2.4.2 Supply chain processes

The selected papers focus their analysis on addressing procurement, production and distribution issues. Many of these articles conceptualise, categorise and describe the plans and models involved in supply chain planning processes. However, each publication includes its own methodology and classification criteria. To present a comparative table, the analysed planning processes are classified into the SCOR model categories, as shown in Table 2.8.

Table 2.8. Classification according to SCOR models.

	Supply chain process		
Author	**Procurement (Source)**	**Production (Make)**	**Distribution (Deliver)**
Peidro et al. [23]	x	x	x
Mula et al. [24]	x	x	x
Stindt and Sahamie [6]	-	x	-
Brandenburg et al. [14]	x	x	x
Malviya and Kant [15]	x	x	x
Sel and Bilgen [25]	x	x	x
Govindan, Soleimani, and Kannan [26]	x	x	x
Ho et al. [17]	x	x	x
Habib, Lee, and Memon [27]	x	-	x
Soto-Silva et al. [28]	x	x	x
Franco and Alfonso-Lizarazo [29]	x	x	x
Zandi Atashbar, Labadie, and Prins [30]	x	x	x
Hamdi et al. [31]	x	x	x
Kochan and Nowicki [22]	-	-	-
Barbosa-Póvoa, da Silva, y Carvalho [16]	x	x	x
Mundi et al. [32]	x	x	x
Oliveira et al. [33]	x	x	x

2.4.3 Modelling approaches

Similarly, the models used to solve optimisation problems are classified to answer RQ6. This provides the analytical models (AHP, ANP, TOPSIS, ELECTRE, VIKOR) analysed by the majority of researchers. The same can be stated of the simulation methods detailed in Table 2.6. The most widely used mathematical modelling approaches are linear programming methods, mixed integer linear programming, non-linear programming, stochastic programming, and multi-objective programming with its variants and fuzzy programming. Table 2.9 describes the types of models analysed in the reviews.

Generally speaking, researchers use different solvers, such as CPLEX or Gurobi, to solve models. However, only a few studies consider this aspect in their reviews [6, 28, 31, 34].

Table 2.9. Types of models found in the reviews.

Author	Types of models														
	A	**S**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Peidro et al. [23]	x	x	x	x	x	x		x	x			x	x	x	
Mula et al. [24]		x	x	x	x	x			x			x	x	x	
Stindt and Sahamie [6]	x		x		x				x				x		
Brandenburg et al. [14]	x	x	x		x	x		x	x				x		x
Malviya and Kant [15]	x	x	x												
Sel and Bilgen [25]	x	x	x	x	x				x		x	x	x	x	
Govindan, Soleimani, and Kannan [26]	x	x	x		x	x		x						x	x
Ho et al. [17]	x	x	x	x	x	x	x	x	x		x	x	x	x	x
Habib, Lee, and Memon [27]		x	x	x	x	x								x	
Soto-Silva et al. [28]		x	x	x	x	x		x	x			x	x		
Franco and Alfonso-Lizarazo [29]		x			x			x	x					x	
Zandi Atashbar, Labadie, and Prins [30]	x	x	x		x	x	x		x	x		x		x	x
Hamdi et al. [31]	x	x	x		x	x			x			x	x	x	x
Kochan and Nowicki [22]	x	x		x	x				x			x	x	x	x
Barbosa-Póvoa, da Silva, and Carvalho [16]		x													
Mundi et al. [32]			x			x			x			x	x	x	
Oliveira et al. [33]	x	x	x	x	x	x	x		x	x		x		x	

- **A.** Analytical Models
- **S.** Simulation models

1. *Linear Programming (*LP)
2. *Integer Linear Programming* (ILP),
3. *Mixed Integer Linear Programming* (MILP),
4. *Non-Linear Programming (*NLP)/Mixed *integer/Integer nonlinear programming*
5. *Quadratic Programming* (QP),
6. *Dynamic Programming* (DP),
7. *Stochastic Programming* (SP),
8. *Robust Programming* (RP),
9. *Constraint Programming (*CP),
10. *Multi-Objective Linear Programming/Multi-Objective Non-Linear Programming/Multi-Objective Mixed-Integer Non-Linear Programming* (MOLP)/*Multi-Objective Non-Linear Problem* (MONLP)/Multi-Objective *Mixed-Integer Non-Linear Programming* (MOMINLP),
11. *Hybrid Approach (HA*)
12. *Fuzzy programming* (FP)
13. *Goal Programming* (GP)

2.4.4 Solution methods

Nowadays, analysing the calculation methods followed to solve optimisation problems is extremely relevant because it is a very broad research field and many industry sectors emphasise its development. Table 2.10 describes the algorithms used in publications by bearing in mind that the classification is done in relation to the resolution methods proposed in Table 2.6, which specifies the categorisation of each algorithm type. Researchers generally propose using heuristic and metaheuristic algorithms for solving large problems (real problems), which leaves a large area to be explored: the so-called matheuristic algorithms. It is noteworthy that only two research works, namely Habib et al. (2016) and Zandi Atashbar et al. (2018), compare which methods or solution techniques solve optimisation models.

Table 2.10. Types of resolution methods.

Author	Optimiser	Heuristic	Metaheuristic	Matheuristic
Peidro et al. [23]	x	x	x	
Mula et al. [24]		x	x	
Stindt and Sahamie [6]	x	x	x	
Brandenburg et al.[14]		x	x	
Malviya and Kant [15]		x		
Sel y Bilgen [25]		x	x	
Govindan, Soleimani, and Kannan [26]	x	x	x	

Table 2.10. Continued. Types of resolution methods.

Author	Optimiser	Heuristic	Metaheuristic	Matheuristic
Ho et al.[17]			x	
Habib, Lee, and Memon [27]	x	x	x	
Soto-Silva et al.[28]		x	x	
Franco and Alfonso-Lizarazo [29]	x	x	x	
Zandi Atashbar, Labadie, and Prins [30]	x	x	x	x
Hamdi et al. [31]	x	x	x	x
Kochan and Nowicki [22]				
Barbosa-Póvoa, da Silva, and Carvalho[16]			x	
Mundi et al. [32]				
Oliveira et al. [33]	x	x	x	

2.5 Discussion and future research opportunities

This section discusses the results of the review and research lines proposed by the analysed reviews. Moreover, the studies in this analysis are compared to the perspective or approach to which they are addressed. Table 2.11 briefly summarises the main research lines proposed by the reviews. This section answers RQ7.

Table 2.11. Summary of future research lines from different supply chain perspectives.

Perspective	Future research lines	References
Supply chain under uncertainty	▪ Accurate identification of sources of uncertainty ▪ Development of optimisation models and solution techniques to address demand uncertainty for products with non-homogeneities ▪ Aggregate production planning study for reconfigurable manufacturing systems ▪ Study of aggregate production planning in the process industry in uncertain or deterministic scenarios by considering a rolling horizon ▪ Application to real cases	[24, 33, 35]

Table 2.11. Continued. Summary of future research lines from different supply chain perspectives.

Perspective	Future research lines	References
Closed loop supply chain	▪ Development of models that look specifically at a particular industry rather than a general application ▪ Use of approaches such as Interval Approaches and Chaos Theory ▪ Application of two-stage stochastic approaches ▪ Use of non-deterministic approaches ▪ Use of robust optimisation	[2, 6, 27]
Green supply chain	▪ Cross-sectorial industry benchmarking studies ▪ Cross-continental comparative industry studies ▪ Application to real cases	[35]
Sustainable supply chain	▪ Analysis of social aspects, and their quantification and integration with economic and environmental aspects ▪ Environmental risk management ▪ Study of hybrid approaches by combining metaheuristics, matheuristics or other types of more efficient methods ▪ Application to sectors like pharmaceuticals, clothing, energy and transport ▪ Sustainability analysis in areas like transport and warehousing	[14, 16]
Supply chain risk	▪ Infrastructure, financial and information risk analysis ▪ Investigation of production and process risk ▪ Measurement of the relation between risk factors and the type of risk by relating it to the probability of occurrence ▪ Validation of risk management methods to assess and select the best risk mitigation strategies by examining between individual and integrated strategies ▪ Analysis of the supply chains of services such as banking, insurance, medicine, etc. ▪ Use of simulation methods to reproduce risk dynamics and risk impacts	[32, 34, 37]

Table 2.11. Continued. Summary of future research lines from different supply chain perspectives.

Perspective	Future research lines	References
Supply chain risk	▪ Development of risk management models, such as the *Ant Colony model* or the *Normal Boundary Intersection* method ▪ Use of stochastic or fuzzy programming techniques ▪ Hybridisation of mathematical programming approaches with artificial intelligence techniques for automated decision support based on prediction and learning	[32, 34, 37]
Resilience in the supply chain	▪ Analysis of the relation linking green supply chain, resilience and resilience analyses in Industry 4.0 ▪ Use of analytical methods like AHP, ANP, TOPSIS, ELECTRE, VIKOR ▪ Explore *Multicriteria Decision-Making (*MCDM) methods. ▪ Development of two-stage stochastic programming techniques with multiple objectives and use of *Constraint Programming*	[23, 38]

Table 2.12 specifies some sectors that propose interesting lines of research in supply chain management.

Table 2.12. Summary of future research lines from a supply chain management perspective considering several sectors.

Supply chain management		
Sector	**Future research lines**	**References**
Humanitarian	▪ Realistic modelling that takes into account real-life aspects, such as policies, practices and procedures for disaster management and debris processing ▪ Study of humanitarian supply chain management by adopting green supply chain policies	[27]
Dairy	Study of models that consider issues like traceability and food safety aspects, and other aspects like waste minimisation	[25]

Table 2.12. Continued. Summary of future research lines from a supply chain management perspective considering several sectors

Sector	Future research lines	References
Fresh fruit	▪ Design of holistic approaches to design and manage agricultural and perishable supply chains ▪ Study organic fruit production ▪ Study integrated simulation and optimisation techniques by considering the evolution from a single-criteria to a multicriteria approach	[28]
Pharmaceuticals	▪ Study of quantitative methods for the healthcare area or for hospital logistics studies ▪ Use of combined or hybrid techniques to approximate the functioning of the pharmaceutical supply chain to real-life cases ▪ Use of techniques like fuzzy programming or robust programming	[29]
Biomass	Use of decomposition or relaxation techniques, metaheuristic techniques or evolutionary algorithms, and simulation-based optimisation methods	[30]

Below a detailed analysis of future research lines from different perspectives in the supply chain and supply chain management from a sectoral perspective is found.

2.5.1 Supply chain under uncertainty

Research into supply chain uncertainty converges insofar as the full set of potential sources of uncertainty is not yet identified regardless of the study field. Similarly, the analysed reviews indicate that studies applied to real cases are lacking.

In light of this, two reviews study the supply chain from the uncertainty perspective [24, 33]. Although these two studies were conducted 10 years apart, they both agree that future work should develop fuzzy programming models to handle imprecise and/or unavailable data. It is worth noting that Mundi et al. [32] use the work of [23] as a basis for their research, but add the non-homogeneity feature to outputs. Peidro et al. [23] suggest other research lines, such as developing new hybrid models by combining models based on both fuzzy set theory and simulation, which can consider predictive control approaches. They also highlight that modelling approaches are not applied to real cases. These authors emphasise using models based on artificial intelligence and analysing uncertainty management mechanisms from a quantitative perspective. They also suggest developing optimisation models, while Mundi et al. [32] indicate developing optimisation models and solution techniques to address uncertainty in the demand for products with non-homogeneity.

The supply chain perspective under uncertainty is a widely studied topic. One example of it is the review by Jamalnia et al. [34], which analyses aggregate production planning under uncertainty. It concludes that fuzzy programming models are the most widely studied, followed by stochastic programming. So we conclude that the future research lines identified by Peidro et al. [23] have been addressed by many authors and remain valid. However, this research area still contains gaps to be bridged, such as those mentioned in the study by Mundi et al. [32] and those presented by Jamalnia et al. [34]. The latter mentions that there are very few studies on aggregate production planning for reconfigurable manufacturing systems, and also in the process industry (oil refineries, beverage manufacturing and chemical processes that operate continuous and uninterrupted production processes) in uncertain or deterministic scenarios that consider a rolling horizon.

2.5.2 Closed loop supply chain

The closed loop supply chain presents an area with many research opportunities. Recent publications, like that of Kazemi et al. [2], state that most studies into the closed-loop supply chain focus only on direct economic consequences, such as operating costs and profits from sales. However, the closed-loop supply chain seeks to mitigate environmental damage and risks, and to improve social life. So modelling environmental, social and economic parameters together can be an important research area.

All these observations also relate to previous studies, like that of Govindan et al. [26], which also suggests studying non-deterministic approaches, such as Interval Approaches and Chaos Theory, to deal with uncertainty, and considering that different non-deterministic approaches can be integrated. They also contemplate employing two-stage stochastic approaches and robust optimisation to deal with the uncertainty that characterises real situations. They propose utilising non-linear programming and convex optimisation to deal with real problems. Govindan et al. [26] propose investigating the application of approximation algorithms or hybrid algorithms because they can present an acceptable solution for solving complex problems in shorter computational times.

Finally, they propose analysing uncertainty forecasting methods as their findings are mostly conceptual.

In the same vein, Stindt and Sahamie [6] propose developing sector-specific quantitative models and solution methods for each sector of the process or manufacturing industry, which take into account each sector's circumstances individually because general parameters of this industry have been analysed in models.

We highlight that research opportunities in this field are still to be exploited, which leads to the conclusion that the closed-loop supply chain is making very rapid progress in relation to the literature. One example of this is the study by Kazemi et al. [2], which analyses 94 studies between 2000 and 2017, and updates the study by Govindan et al. [26]. Both reviews agree with Stindt and Sahamie [6] about models developed specifically for particular industry types are lacking. The authors complement their findings by emphasising that the models that may work in one specific sector might not work in another. In turn, they consider using methods, such as Chaos Theory or Rough Set Theory, as well as robust optimisation, to deal with uncertainty.

2.5.3 Green supply chain

Industries are becoming increasingly committed to incorporate the "green" concept into supply chains. This means incorporating the environmental concept into all product stages, from design to end-of-life. In the final stage, products can be recycled, reused or reclaimed [38].

One of the main findings in the green supply chain context is that most authors propose simulation methods to model problems, while mathematical models are used to a limited extent [15]. Conversely to this finding, recent publications like that by Tseng et al. [39] reveal that more articles propose mathematical models for optimising decision making in green supply chain management.

All in all, green supply chain management is an area that, according to Tseng et al. [39], is being shown a lot of interest given the pressure placed by governments on companies to improve environmental performance. Although the future research lines set out in 2015 to 2019 have already been covered, according to Tseng et al. [39] some areas still need to be explored. The line of research suggesting cross-sectoral comparative industry studies and cross-continental comparative studies is worth mentioning, as such research is limited in the literature. Tseng et al. [39] also emphasise that studies presenting real-life data are lacking.

2.5.4 Sustainable supply chain

Sustainable supply chain management is an approach that pushes companies to improve from a sustainability perspective, i.e. companies taking care to integrate economic, social and environmental objectives into supply chain processes [40].

In relation to this topic, Brandenburg et al. [14] have studied the quantitative methods used in sustainable supply chain management. They describe how the models that have dealt with this issue are related mainly to manufacturing industries, such as the automotive and textile industries. Very few studies are framed within the chemical and petroleum sectors. These authors also identify that no attention is paid to environmental risk management and the incorporation of social aspects into the proposed models. Finally, Brandenburg et al. [14] also propose analysing sustainability in areas like transport and storage by highlighting that evolutionary algorithms and techniques, such as dynamic programming and local search methods, have not been studied in-depth.

A more up-to-date review of this topic is presented by Barbosa-Povoa et al. [18]. They identify how mathematical programming methods are the most widely used, followed by simulation techniques. As for combining techniques, the most widely used combination is mathematical programming and simulation techniques, followed by analytical methods and metaheuristics. Barbosa-Povoa et al. [18] agrees with Brandenburg et al. [14] that only a few models address social aspects.

Barbosa-Povoa et al. [18] highlight that optimisation techniques peaked in publications in 2015 and real industrial applications using optimisation techniques in their publications markedly grew. This work agrees with Brandenburg et al. [14] that the manufacturing sector (automotive, textile, etc.) has been well-studied. However in the 4 years difference between both reviews, publications proposing optimisation models applied to the process industry have increased and occupy first place, as Barbosa-Povoa et al. [18] mention. This also agrees with Brandenburg et al. [14] insofar as social aspects should be studied and quantified, and they propose studying hybrid approaches by combining metaheuristics, matheuristics, or other types of more efficient methods. For industrial approaches, sectors like pharmaceuticals, clothing, energy and transport require further study.

In short, sustainable supply chain management is an area that presents important research lines, such as those mentioned by Barbosa-Povoa et al. [18] who, in many of their research works, coincide with and extend the research by Brandenburg et al. [14]. These research lines are generally related to the fact that some industry sectors need to be studied and their models must combine economic, social and environmental aspects by employing robust techniques. It is also worth highlighting what Barbosa-Povoa et al. [18] mention, who highlight the existence of a research gap in topics, such as closed-loop supply chains and reverse supply chain management, that address economic, social and environmental issues in supply chain processes.

We conclude that reverse supply chain management is a growing topic with significant research areas. However, the search conducted in this article found no studies that analyse this topic in detail and can answer our research questions.

2.5.5 Supply chain risk

According to Baryannis et al. [36], researchers' interest in supply chain risk management has increased significantly in the last two decades for three reasons: (i) adoption of philosophies such as "*lean manufacturing*" or "*just-in-time*" in manufacturing processes, which has left less scope for error and change; (ii) exposure to more risks because companies are becoming more global and less vertical; (iii) likelihood of disasters or events occurring and disrupting the global supply chain, such as natural disasters, shortages, e.g.: raw materials, etc.

In this context, studies like those by Ho et al. [17] recommend analysing infrastructural risks, such as transport, financial and information risk, and examining manufacturing or production risks and process risks. They also propose measuring the relation between risk factors and the type of risk by relating this relation to probability of occurrence. Ho et al. [17] emphasise the validation of conceptual frameworks and risk management methods to evaluate and select the best risk mitigation strategies by examining between individual and integrated strategies to, thus, measure their efficiency and effectiveness. These authors also propose analysing supply chains of services, such as banking, insurance, medicine, etc.

Hamdi et al. [31] studied supplier selection from the supply chain risk management approach. They note that quantitative research is predominant in this field, especially in mathematical formulation terms. AHP approaches to supplier selection, and stochastic optimisation approaches used to model fluctuations and incoming changes in supply chains, are also prevalent. These authors propose investigating combining techniques to minimise the supplier risk, i.e. by analysing the case of simultaneous disruption of local, global and semiglobal suppliers.

Oliveira et al. [33] address the issue of risk mitigation strategies by concluding that there is no alignment between risk response and risk solution approaches because risk response strategies must be consistent with risk mitigation solutions. Their study analyses the application of simulation tools, optimisation models and performance measurement systems for supply chain risk management. On simulation and optimisation, these authors propose using simulation methods to reproduce risk dynamics and risk impacts, as well as risk management models, such as Ant Colony and the Normal Boundary Intersection method. As these methods do not appear in the reviewed articles, Oliveira et al. [33] suggest not only improving the simulation-based optimisation perspective, but also developing Six Sigma-based risk measures to assess the critical impacts of risk on supply chain performance.

As a result of this research, we conclude that the supply chain risk management area presents several interesting research lines, such as those put forward by Baryannis et al. [36], who reviewed 276 articles on supply chain risk management and its relation with artificial intelligence techniques. Of the 276 articles analysed by Baryannis et al. [36], 84% focus on risk response in models that avoid or mitigate risk and uncertainty effects, 4% combine the risk response with some form of risk assessment, 4% combine risk assessment with risk identification, 3% address risk identification individually, 2% assess risks and 3% use holistic approaches to risk identification, assessment and response. These authors also describe that most followed techniques are mathematical programming, which falls in line with the conclusions drawn by the study of Hamdi et al. [31]. In this sense, both reviews conclude that researchers have been more inclined to develop mathematical programming techniques. Artificial Intelligence techniques such as agent- and network-based models, automatic reasoning, machine learning and Big Data analysis are less applied. Both papers identify that techniques like stochastic programming or fuzzy programming are scarcely used. Finally, they mention that the artificial intelligence field for proactive and predictive risk management in supply chains is a marvellous research opportunity and propose investigating hybridisation between mathematical programming approaches together with an artificial intelligence technique to help automated decision making based on prediction and learning.

2.5.6 Resilience in the supply chain

One issue related to supply chain risk management is supply chain resilience. In this context, the study by Kochan and Nowicki [22] mentions that no unanimous supply chain resilience definition exists. Yet according to Burnard et al. [41], resilience offers companies a dynamic capacity to anticipate, respond and adapt to risks and threats.

On resilience in the supply chain, one of the most recent studies is that by Hosseini et al. [37], in which interesting research areas like using analytical methods, including AHP, ANP, TOPSIS, ELECTRE, VIKOR are raised, but have not been analysed in the supply chain resilience context. It also recommends future research lines to focus on exploring multicriteria decision-making (MCDM) methods, and conclude that such methods are applicable for assessing supply chain networks, and in relation to resilience, ecological and organisational criteria.

Another aspect proposed by Hosseini et al. [37] is to focus on two-stage stochastic programming with multiple objectives because supply chain resilience is intrinsically related to stochastic aspects likes capacity loss, capacity recovery, resource restoration and the expected recovery time. They also propose developing robust optimisation models which, according to their research, is yet to be addressed. These authors also propose employing Constraint Programming in the supply chain resilience context. They generally propose studying the relation among green supply chains, resilience and resilience analyses in Industry 4.0. Ultimately, the future research areas raised by these recent research works offer researchers several study possibilities.

2.5.7 Supply chain management.

Supply chain management is a very large area that is applicable to different sectors and involves distinct approaches. This section provides details of some sectors that propose interesting research lines.

2.5.7.1 Sector: Humanitarian

A new area that is beginning to emerge is the humanitarian supply chain. According to Habib et al. [27], this sector has a large unexplored research area as most of the articles on these topics emerged after the 2004 Indian Ocean earthquake, and they confirm that the commercial scope of supply chain management with a focus on sustainability has been considerably investigated, but humanitarian supply chain management has not. The review by Habib et al. [27] concludes that the formulation of humanitarian supply chain models is unrealistic and difficult to apply. These authors propose that humanitarian supply chain management should adopt green supply chain policies and, when generating new models, several real-life aspects like disaster management and debris processing policies, practices and procedures should be taken into account.

2.5.7.2 Sector: dairy

Sel and Bilgen [25] review and discuss quantitative models for supply chain management in the dairy industry. Most of the articles analysed by these authors have used mixed integer programming models, which is why they propose that these models should take into account key aspects for the sector, such as traceability and food safety. Other future research lines are defined in line with waste minimisation issues and Constraint Programming in production and distribution planning, but have not yet been addressed. In the same vein, Sel and Bilgen [25] mention that very few publications use the heuristics, metaheuristics or hybridisations of these methods. They also propose applying heuristics based on relaxed mixed integer programming models and rolling horizon approaches. These authors state that there are very few combinations of mathematical programming models with approximate solution methods in the dairy supply chain context. Other proposed further research suggestions include the development of stochastic or multiparametric programming models.

2.5.7.3 Sector: fresh fruit

Soto-Silva et al. [28] review the operations research models applied to the fresh fruit supply chain. These authors state that holistic approaches for the design and management of agricultural supply chains are lacking, and the same is true for perishable products. Topics like optimal crop scheduling and discrete event logistics simulation have been addressed in this field. Sustainability and environmental issues, as well as food security issues, are given a high profile. Soto-Silva et al. [28] conclude that the problems encountered in their review are related to transport, planning and allocation in production and distribution stages, with linear programming, integer linear programming or mixed integer linear programming models being the most widely used. In this area, and as mentioned in the review, the analysed articles are real cases. Indeed the authors propose analysing organic fruit production and, in optimisation issues, using integrated simulation and optimisation techniques and moving from a single-criteria approach to a multicriteria one.

2.5.7.4 Sector: pharmaceuticals

Franco and Alfonso-Lizarazo [29] analyse the pharmaceutical supply chain by mentioning that it is not an exhaustively studied topic mainly in the quantitative methods proposed in the healthcare area or hospital logistics studies. These authors describe how most of the analysed studies apply a stochastic form of uncertainty in some supply chain stage, and only 20% correspond to supply chain optimisation models, 52% to network design and 28% to inventory problems. Of all the presented models, 92% stochastically use demand data and the rest do so deterministically. They also point out that very few articles employ fuzzy programming, Franco and Alfonso-Lizarazo [29] highlight that a few articles apply fuzzy programming or robust programming, and propose combining techniques to approximate the functioning of pharmaceutical supply chains to real-life cases.

2.5.7.5 Sector: biomass

Zandi Atashbar et al. [30] mention that most research studies into supply chain management in the biomass sector come from agriculture or chemistry. Researchers in these areas are experts in these topics, but very few specialists are found in the operations research area because they are involved in the biomass sector, which is an important research area and for input of knowledge acquired from other industrial sector areas. Zandi Atashbar et al. [30] also identify how decomposition or relaxation techniques and metaheuristic techniques or evolutionary algorithms are barely used, and propose applying simulation-based optimisation methods.

This section analyses review articles that deal with the supply chain management concept by considering different relevant sectors. However, other authors propose reviews in the supply chain management context regardless of the sector. Thus Mula et al. [24] study the supply chain independently of the sector by identifying that proposals to simultaneously optimise production and transport planning are lacking, and propose that the generation of these models should take into account transport characteristics like: environmental restrictions and transport mode considerations. These authors also propose integrating tactical or operational decision levels and a collaborative planning structure to manage information sharing with supply chain partners. Mula et al. [24] also recognise a future research line, that of integrating optimisation tools: simulation, fuzzy optimisation, multi-agent systems and evolutionary algorithms.

In short, the number of studies that analyse models and algorithms for the optimisation of supply chain procurement, production and distribution plans continues to increase. Notwithstanding, a small number of works clearly address the review of specific areas, with generally a few developments with real practical applications in the research area herein addressed.

2.6 Conclusions

This study reviews quantitative models and operations research methods to solve optimisation problems related to procurement, production and distribution in the supply chain to gain a better understanding of the supply chain areas with currently research trends. After contemplating the reviews in the literature, as far as we know, no review focuses on analysing these reviews, which poses a pressing need as research growth makes it difficult for researchers to be clear about not only the supply chain area that needs to be investigated, but also the tools employed to solve supply chain optimisation problems in supply chains.

Consequently, this study provides a comprehensive analysis of the current research status by considering that these studies focus specifically on a particular area, and present a content analysis that comprises a differentiation of the categories that answer the posed research questions. In particular, supply chain processes are identified, consolidated and synthesised with the SCOR model, and methods and models are put forward in the reviews to solve optimisation problems by exploring key issues, research trends and the developments made in the different supply chain areas.

In line with all this and to answer RQ7, the analysis shows that most reviews agree that very few studies employ real data, and that comparative studies between different industry sectors are lacking because success in one area can be extrapolated to another. So it would be interesting to analyse this issue. Many models and conceptual frameworks appear and act as an important theoretical basis. However, it is important to validate these models and to reach a consensus about conceptualisations to, thus, generate an integral vision.

Another important finding is that sustainability and environmental approaches are increasingly considered in modelling. However, there is still a large area to explore because, despite its growth, reviews agree that the variables to which models are subjected need to incorporate the new constraints demanded by today's governments and markets. In addition, robust optimisation and fuzzy programming methods are still a research opportunity in modelling approaches. Similarly at decision levels, it is still important to analyse their combination, and topics like the rolling horizon have only been used in some articles and very few reviews briefly mention the topic. This makes it a significant area to be explored.

Finally, it is very important to highlight that a growing number of articles present mathematical and analytical models, which is an area where research is still to be done: simulation models and their combination with other methods. Many models employ heuristic or metaheuristic methods for solutions, which means that the hybridisation area of these methods or the use of matheuristic methods remains to be explored. Although several studies agree that the most widely used mathematical models are linear/integer/mixed integer programming models, given the size of real problems it would still be interesting to analyse matheuristic methods with large datasets, which are not currently approachable by commercial solvers. This is, hence, a remarkable research area that will allow the transformation of mathematical programming methods into models to be solved with matheuristic algorithms.

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Chapter 3

Models and algorithms for production planning, scheduling and sequencing problems: a holistic framework and a systematic review.

Guzman, Eduardo, Beatriz Andres, and Raul Poler. 2021. "*Models and Algorithms for Production Planning, Scheduling and Sequencing Problems: A Holistic Framework and a Systematic Review*." Journal of Industrial Information Integration, 100287. https://doi.org/10.1016/j.jii.2021.100287.

Abstract:

Production planning, scheduling and sequencing comprise the core of the manufacturing companies' performance. The new and changing market demands make manufacturing a challenge because companies must produce by using the minimum possible number of resources to provide high-quality products and to respond quickly to market demands. Thus the need for efficient production planning, scheduling and sequencing has become a very important research area for companies and researchers in recent decades. We evaluated the current state of such research with a holistic framework that comprised the plans aggregation and disaggregation levels, the modelling approaches to represent the different types of plans and their characteristics, the solution approaches with the adopted algorithms, the application areas, the intra- and inter-enterprise levels of integration, the sizes of the datasets used to validate the models and algorithms, the development tools, and the quality of the solutions obtained in relation to the problems' data size. The systematic literature review is arranged within the framework and grouped around different types of plans, including production planning, scheduling and sequencing, and their combinations. Finally, some gaps in the related research are identified and future research opportunities are proposed.

3.1 Introduction

In recent decades, researchers and industrial professionals have voiced concern about production planning. Several approaches have been developed to formulate and solve production planning problems. Developing models for real problems is a complex task, and the solution procedure is difficult in most cases. For this reason, a plethora of solution techniques and methods has been developed to provide different types of solutions.

The literature describes different models and approaches to solve production planning, scheduling and sequencing problems. The general aim of research works was to determine the resources needed so that production meets customer demands. The production planning problem has been extensively studied because it allows manufacturers to improve enterprise profits by better using manufacturing resources. In fact, the decision-making process in production planning allows not only the resources needed to carry out future manufacturing operations to be determined, but also all the production activities performed to optimise companies' objectives to be effectively coordinated. This allows resources to be allocated to production as and when required at the lowest cost [1].

The scientific literature based on tactical and operational production planning concepts is a vast fruitful area to which plenty of attention has been paid. The number of publications has rapidly increased, and the variety of proposed methods, trends and structures is very wide. These trends need to be aligned to address production planning, scheduling and sequencing problems and solutions in enterprises. The present review seeks to provide both an understanding of the common and unique characteristics of the proposed models of production planning, scheduling and sequencing problems and an accurate classification of different optimisation criteria to solve them. Accordingly, we pose the following research questions:

RQ1. How can production planning, scheduling and sequencing problems be classified?

RQ2. What types of modelling approaches are used in production planning, scheduling and sequencing problems, and what characteristics do they have?

RQ3. What methods or techniques are proposed to solve production planning, scheduling and sequencing problems?

RQ4. What methods or techniques can solve real large-scale problems, and what is the obtained solution quality?

Before investigating the modelling approaches and solution approaches proposed in the literature to deal with production planning, scheduling and sequencing problems, we analysed the existing review works to justify the research need of this paper.

The production planning literature is currently extensive. Nam and Logendran [2] conducted a review of Aggregate Production Planning (APP) from 1950 to 1990 to summarise the various existing techniques within a framework. By reducing searches to papers published in the recent decade, we found that Cheraghalikhani et al. [3] focused on APP methodologies, characteristics and structures of models and solving approaches, and many papers emphasise APP models under uncertainty; see Jamalnia et al. [4].

Many works in the literature discuss techniques, methods, levels, and solution approaches related to production planning. Mula et al. [5] analysed models for production planning under uncertainty by classifying them into four typologies: conceptual models, analytical models, artificial intelligence models and simulation models. Díaz-Madroñero et al. [6] reviewed optimisation models for tactical production planning. These authors analysed different characteristics, including the problem type, aim, number of products, time period, nature of demand, capacity constraints, extensions, modelling approach, solution approach, development tool, application, limitations and benefits.

Although much research has been conducted in the production planning area in general, the analysed reviews differ in several aspects. Some papers are descriptive, which highlights the importance of a specific field. One work worth highlighting is that by Mundi et al. [7], which reviewed production planning models by considering the uncertainty given by lack of homogeneity on products (LHP). These authors classified the reviewed papers according to the sectors affected by LHP inherent uncertainty, the modelled inherent LHP uncertainty types and approaches for modelling. Lage and Filho [8] reported production planning and control (PPC) in remanufacturing by proposing a classification based on four categories: PPC activities, characteristics, remanufacturing subsystem-focused and research type.

Other reviews have analysed production planning from a combined perspective. One example is that by Mula et al. [9], who reviewed mathematical programming models for production and transport planning. They classified papers according to supply chain structure, decision level, modelling approach, purpose, shared information, limitations, novelty and application. Akçcal and Çetinkaya [10] studied quantitative models for inventory and production planning in closed-loop supply chains. They classified deterministic and stochastic problems according to modelling of demand, return processes and solution methodologies. On the supply chain, Peidro et al. [11] conducted a literature review that focused on supply chain planning under uncertainty by adopting quantitative approaches, similarly to Stindt and Sahamie [12] and Govindan et al. [13], whose reviews considered closed-loop supply chain planning.

After analysing previous literature reviews and, as far as we are aware, we concluded that our paper significantly differs from extant publications. We identified that most authors did not consider the holistic framework herein proposed. Therefore, this review aims to provide an overview of the key elements of production planning, scheduling, and sequencing problems. We propose a holistic framework to characterise all the aggregation and disaggregation levels. We place particular emphasis on the decision-making level at which they are contextualised. Continuing with the analysis of the most relevant aspects when posing a problem, such as planning horizon, type of modelling approach, the objectives pursued by mathematical models and the techniques applied to solve problems, we observe which tools are the most widely used to solve these problems. We also analyse applications and evaluate the quality of the problem's solution according to the size of data.

Finally with this systematic review of articles based on the holistic classification framework, we seek to identify current research trends in production planning, scheduling and sequencing, as well as future research gaps and directions.

In order to answer these four research questions, this paper is organised as follows. Section 3.2 describes the methodology followed to perform the systematic literature review and details the proposed framework to review production planning, scheduling and sequencing problems. In Section 3.3, a detailed analysis of aggregation levels, the modelling approach, the solution techniques, the objectives raised, the development tool, the applications area and the quality of solutions, are applied to production planning, scheduling and sequencing problems. Section 3.4 highlights and discusses the main results. Finally, Section 3.5 draws the main conclusions and directions for future research.

3.2 Literature review methodology

The systematic literature review employed a structured methodology, and followed a scientific and transparent process, to reduce papers' selection bias by a thorough literature search. The synthesis that characterised the systematic literature review allowed existing findings, research guidelines and gaps to be identified [14]. This paper followed a 4-step methodology in accordance with Seuring and Müller [15] and Seuring and Gold [16]: (i) collecting material (Section 3.2.1); (ii) descriptive analysis (Section 3.2.2); (iii) selecting or identifying categories (Section 3.2.3); (iv) evaluating material (Section 3.2.4) .

3.2.1 Collecting material

The references collected for this study covered a 20-year (2000-2020) time frame. We conducted searches in December 2020 in the Elsevier SCOPUS and Web of Science citation databases. The collected works included all the English language articles registered as 'Articles', with no limitations set to scientific journals. Searches included the title, abstract and keyword fields, and three search terms were defined. Each term was a combination of the keyword 'Product* Plan*' OR 'Product* Schedul*' OR 'Product* Sequenc*', with an additional keyword: mathematical programming, linear programming, heuristic, metaheuristic or matheuristic (see Figure 3.1). The selected keywords were chosen to collect the most relevant papers. The modifier asterisk was used in the Boolean search as a source word for all the derivative keywords. Figure 3.1 depicts the strategy adopted to follow the structured literature review process.

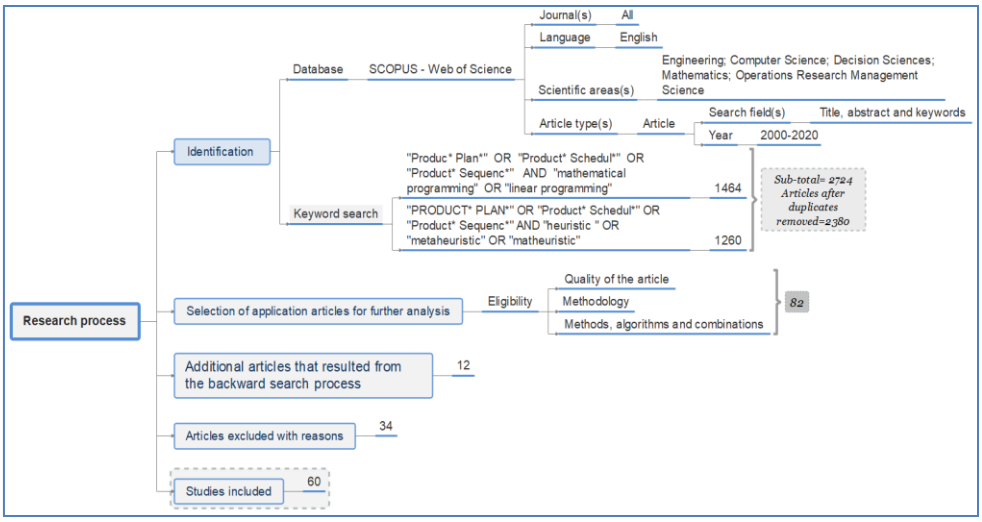

Figure 3.1. Structured literature review process.

The keyword search gave 2,380 articles after removing duplicates. The abstracts of these articles were reviewed to assess if they matched our research questions. Throughout this process (i.e., from 2,380 studies to 82), the exclusion criteria for why papers were unrelated to production planning, scheduling and sequencing modelling approaches were as follows:

- Not including the production processes whose approaches cover production planning, manufacturing operational process scheduling and sequencing processes
- Lack of an optimisation model or heuristic, metaheuristic, or matheuristic algorithms. Simulation and analytic methods were excluded from the review. although these methods may appear, they go beyond the scope of this paper.

After analysing abstracts, 82 papers were retained for full reading. Subsequently to this analysis, we added 12 articles that resulted from the backward search process and, thus, resulted in 94 papers. Additional papers were included as they were cited in the articles that derived from the keyword search and were applicable to the research topic. Of this subset of 94 articles, 34 were not considered relevant to the review because they did not satisfactorily answer our research questions. This left 60 papers for the analysis, evaluation and classification processes.

3.2.2 Descriptive analysis

This study analysed 60 scientific papers published between 2000 and 2020, and Figure 3.2 illustrates their publication trend. In turn, a slightly increasing trend in the last 3 years was identified. Some years provided significantly fewer papers than previous years; for example, more articles were retrieved in 2014 than in 2015.

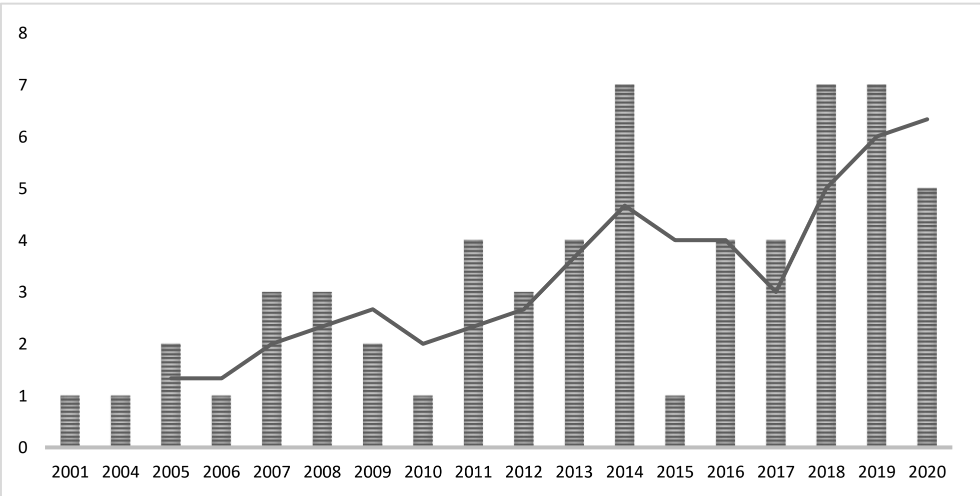

Figure 3.2. Distribution of the reviewed papers according to year.

Most of the articles selected for the final review appeared in 20 different journals. Figure 3.3 shows the distribution of the articles reviewed from these journals. Of the 20 journals, International Journal of Production Research published the most papers with 26.66% of all the reviewed articles. Of the 20 journals, Computers and Industrial Engineering, Computers and Operations Research, European Journal of Operational Research and International Journal of Production Economics were equally representative, and collectively published 43.33% of all the reviewed articles. Overall, 42 publications appeared in the top five journals.

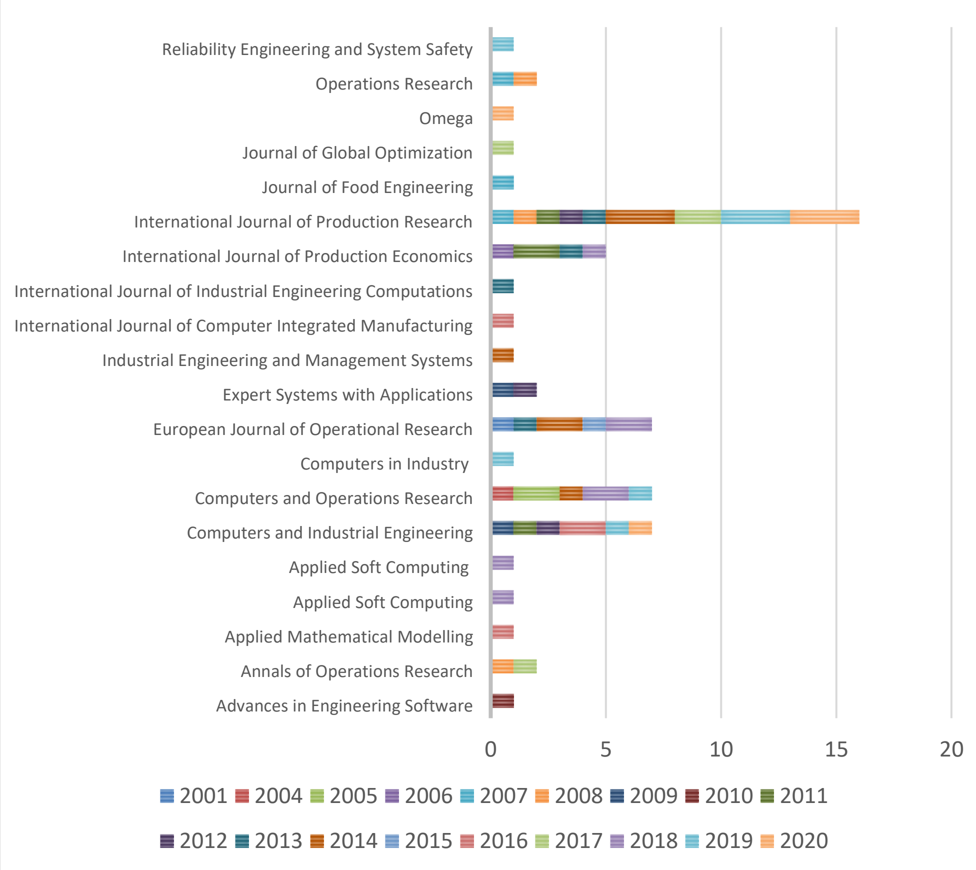

Figure 3.3. Distribution of articles for publication year and journal.

3.2.3 Category selection

In order to answer RQ1, we proposed a holistic framework that summarised the most important aspects characterising production planning, scheduling and sequencing problems. This holistic framework resulted from integrating the literature reviews [6, 9, 17–19] and from deducting the analysed papers. This framework details a set of categories, such as: decision level, plan aggregation, planning horizon, modelling approach, mathematical model objectives, solution approach, development tool, proposed solution, application area, actual case application, data set size, solution quality. Table 3.1 presents the resulting framework, which represents a significant contribution of this work and can be general applied to any production planning, scheduling and sequencing problem.

Table 3.1. Framework proposed to represent production planning, scheduling and sequencing problems.

Categories	Analytical categories	
Decision level	Strategical, Tactical, Operational	
Plan aggregation	Aggregated Plan (AP), Master Plan (MP), Dispatching Plan (DP)	
Planning horizon	Day, Week, Month, Year	
Modelling approach	Binary Programming (BP) Constraint Programming (CP) Dynamic Programming (DP) Fuzzy Programming (FP) Fuzzy Goal Programming (FGP) Fuzzy Linear Programming (FLP) Fuzzy Multi-Objective Linear Programming (FMOLP) Goal Programming (GP) Integer Programming (IP) Integer Linear Programming (ILP) Integer-Weighted Goal Programming (IWGP) Linear Programming (LP) Mixed Integer Linear Programming (MILP) Mixed Integer Non-Linear Programming (MINLP)	Multi-Objective Linear Programming (MOLP) Multi-Objective Mixed-Integer Linear Programming (MOMILP) Multi-Objective Mixed-Integer Non-Linear Programming (MOMINLP) Multi-Objective Non-Linear Programming (MONLP) Non-Linear Programming (NLP) Quad-Objective Mixed Integer Linear Programming (QOMILP) Quadratic Programming (QP) Robust Programming (RP) Stochastic Programming (SP)
Mathematical model objectives	Cost, Time, Product, Resources, Service, Sustainability	

Table 3.1. Continued. Framework proposed to represent production planning, scheduling and sequencing problems.

Categories	Analytical categories		
Solution approach	Optimizer Algorithm (OA)	OA/ Branch and Bound (BB) OA/ Branch and Cut (BC) OA/ Criss-cross (CC) OA/ Decomposition strategy (DS) OA/ Lomnicki (LO)	OA/ Lompen Algorithm (LM) OA/ Simplex (SI) OA/ Solution procedure of model P* (SPP*)
	Heuristic Algorithm (HA)	HA/ Benders Decomposition (BD) HA/ Beam Search (BM) HA/ Campbell-Dudeck Algorithm (CD) HA/ Decomposition & Aggregation (DA) HA/ Fix-Price-Optimise (FPO) HA/ Greedy (GR) HA/ Iterative Variable Neighbourhood (IVN) HA/ Lagrangian Relaxation (LGR) HA/ Local Improvement Procedure (LIP) HA/ LP and Fix (LF)	HA/ LP Relaxation (LPR) HA/ Minimum Spanning Tree (MS) HA/ Multi-Objective Master Planning Algorithm (MOMPA) HA/ Nawaz, Enscore and Ham (NEH) HA/ Nearest Neighbour (NN) HA/ Primal-Dual Based Heuristic (PDBH) HA/ Relax and Fix (RF) HA/ Relax-Price-Fix (RPF)
	Metaheuristic Algorithm (MA)	MA/ Ant Colony Optimisation (ACO) MA/ Evolutionary Computation (EC) MA/ Genetic Algorithm (GA) MA/ GRASP (GR) MA/ Iterated Local Search (ILS) MA/ Iterated Greedy (IG) MA/ Memetic Algorithm (MA) MA/ Multi-objective Simulated Annealing (MOHSA) algorithm MA/ Non-dominated Sorting Genetic Algorithm II (NSGA-II) MA/ Particle Swarm Optimisation (PSO) MA/ Scatter Search (SS)	MA/ Simulated Annealing (SA) MA/ Subpopulation Genetic Algorithm (SPGA) MA/ Tabu Search (TS) MA/ Tabu Search Grabowski and Wodecki (TSGW) MA/ Variable Tabu Search (VTS) MA/ Variable Neighbourhood Search (VNS) MA/ Variable Neighbourhood Descent (VND) MA/ Weighted Sum Multi-Objective Genetic Algorithm (WMOGA)

Table 3.1. Continued. Framework proposed to represent production planning, scheduling and sequencing problems.

Categories	Analytical categories		
Solution approach	Matheuristic Algorithm (MTA)	MTA/ Ant Colony + Mathematical Model (ACO_MM) MTA/ Biased Random-Key Genetic Algorithm + Mathematical Model (BRKGA_MM) MTA/Fixed Variable List Algorithm and Clustering Sequence Algorithm + Mathematical Model (FVLA_CSA_MM) MTA Genetic Algorithm + Mathematical Model (GA_MM)	MTA/ Iterated Local Search + Mathematical Model (ILS_MM) MTA Simulated annealing + Mathematical Model (SA_MM) MTA/ Tabu Search + Mathematical Model (TS_MM)
Development tool	Programming Languages, Modelling language, Solver		
Proposed solution	Model + Solution (MS), Model + Solver+ Solution (MSS), Model + Algorithm description (MAD) Model + Algorithm description+ Solution (MADS), Model + Algorithm description+ Solver+ Solution (MADSS), Model + Algorithm description+ Algorithm Pseudocode + Solver + Solution (MADPCSS)		
Applications area	Sectorial - Transversal		
Real case application	Yes (Y) / No (N)		
Enterprise integration level	Intra-enterprise level – Inter-enterprise level		
Data set size	Small (S) – Medium (M) – Large (L)		
Quality solution	Optimal (OP), Near – Optimal (N-OP) – Good (GD)		

3.2.4 Material evaluation

All the articles were evaluated and coded according to the holistic framework proposed in Section 3.2.2. Validation was carried out by considering the characteristics, approaches and level of aggregation of each article. To do so, we used the grouping technique and applied deductive and inductive methods [20]. The evaluation ensured that articles had sufficient information to be validated.

3.3 Results analysis

3.3.1 Decision level

Production planning, scheduling and sequencing problems can be decomposed and classified according to the extent or effect of the decision in time terms [9]. Several authors, such as [6, 21–24] among others, have classified these problems as strategical, tactical and operational problems.

Strategical or long-term planning models address a time period lasting between 5 and 10 years. This decision level implies a wide range of uncertainty, which normally affects enterprises' design, configuration and location. Moreover, strategical decisions deal with the development of new products, the identification of distribution channels, suppliers' selection and the selection of information technology [25].

Tactical planning models aim to plan mid-term activities. These models address planning horizons that last between 1 month or several months and 2 years. The decisions made at the tactical level are planned to be executed and comply with the decisions made at the strategical level. Tactical decisions include activities like production planning, material handling, distribution and storage planning, production capacity allocation, inventory management and maintenance activities [6, 9, 25].

The operational level is characterised by addressing short-term decisions that are generally made weekly, daily or hourly by focusing essentially on sequencing, scheduling, packaging, lot size calculation, routes allocation and vehicle load. This level seeks to guarantee an optimal flow of products along the production chain [23, 25, 26].

We should also bear in mind that distinctions of decision levels cannot always be made because some problems may involve planning at many levels and are incorporated into different decision levels. By way of example, the works of Rasmi et al. [27] present an Aggregate Production planning (APP) problem that incorporate decisions at the strategical and tactical levels in a multi-objective mixed-integer linear program (MOMILP) model, which evaluate economic, social, environmental and cultural aspects for an appliance manufacturer. Moreover, Omar and Teo [28], Xue et al. [29], Aghezzaf et al. [30], Fumero et al. [31] and Fumero, Corsano and Montagna [32] propose tactical-operational decision making, which is often used for models dealing with mid-term decisions that are taken daily, weekly or monthly, and generally up to 1 year.

In line with this, Omar and Teo [28], Fumero et al. [31], Fumero, Corsano and Montagna [32] propose dealing with production planning and scheduling jointly. Xue et al. [29] address production planning and scheduling by the hierarchical production planning approach. Finally, Aghezzaf et al. [30] propose a robust hierarchical production planning approach for master planning and scheduling. Table 3.2 classifies the reviewed works in relation to their decision-making level. Of all the reviewed papers, 28.33% address production planning at the tactical level, and propose solutions to aggregate and master plans. Over half the reviewed papers (61.67%) make decisions at the operational level by addressing scheduling and sequencing problems, 8.33% of the analysed papers deal with planning problems at several decision-making levels, namely tactical and operational, and only 1.66% present strategical and tactical decisions.

Table 3.2. The decision-making levels of the reviewed works.

Decision level	Reference
Strategical & Tactical	Rasmi et al. [27]
Tactical	R.-C. Wang & Fang [33]; Leung & Chan [34]; Baykasoglu & Gocken [35]; Sillekens et al. [36]; Mirzapour Al-E-Hashem et al. [37]; Zhang et al. [38]; Ramezanian et al. [39]; Chakrabortty & Akhtar Hasin [40]; Khalili-Damghani & Shahrokh [41]; Makui et al. [1]; Tavaghof-Gigloo et al. [42]; Gholamian et al. [43]; de Kruijff et al. [44] ; Mehdizadeh et al. [45]; Djordjevic et al. [46] ; Bensmain et al. [47].
Operational	Grabowski & Wodecki [48]; D. Gupta & Magnusson [26]; Nonås & Olsen [49]; Bellabdaoui & Teghem [50]; Hooker [51]; P Doganis & Sarimveis [52]; Gaglioppa et al. [53]; Moon et al. [54]; Philip Doganis & Sarimveis [55]; Fakhrzad & Khademi Zare [56]; Mohammadi et al. [57]; Guimarães et al. [58]; Cheng et al. [59]; Chen et al. [60]; Motta Toledo et al. [61]; Na & Park [62]; Franz et al.[63]; Mattik et al. [64]; Golle et al. [65]; Baumann & Trautmann [66]; Abdeljaouad et al.[67]; Aroui et al.[68]; Zeppetella et al. [69]; Torkaman et al. [70]; Lopes et al. [71]; Woo & Kim [72]; Verbiest et al. [73]; Mönch & Roob [74]; Ekici et al. [75]; Chansombat et al. [76]; de Armas & Laguna [77]; S. Wang et al. [78]; De Smet et al. [79]; Yang & Xu [80]; Otto & Li [81]
Tactical & Operational	Omar & Teo [28]; Xue et al. [29]; Aghezzaf et al. [30]; Fumero et al.[31]; Fumero et al.[32];Rodoplu et al. [82]

3.3.2 Plan aggregation

Plan Make, identified in SCOR views [83], forms part of one of the most relevant planning decisions for companies. Plan Make aims to achieve effective planning and management for all production operations, and in such a way to optimise company objectives. It focuses on determining the optimal number of items to be produced, the inventory, and other key production factors, to meet the variable demand in a planning horizon. Plan Make can be divided by considering three different decision-making production levels that comprise production planning, scheduling and sequencing [84].

In manufacturing environments, production planning supports decision makers in determining the use of resources, which are generally decisions made about the quantity to be produced, the inventory level, the required workforce size or the allocation of the necessary assets and resources to carry out the manufacturing process to meet the real or planned demand on a given horizon [85,86]. Production planning problems can cover mid-term or long-term planning horizons using aggregated or disaggregated information. Hax and Meal [87] distinguished production planning problems according to their horizon time and aggregation, which ranged from a long-term aggregation level (aggregated plan) to a short-term detailed level (dispatching plan).

The production planning category distinguishes two types of plans: aggregate plans and master plans. In aggregated plans, the used unit is product families, which refers to the groups of products belonging to the same type that shares similar configurations [29]. Production plans can be disaggregated into more detailed programmes, which define the product quantities to be produced during shorter time periods than the aggregated plan, which are normally weekly or monthly periods [88].

Production planning problems represented 30% of all the reviewed papers, the majority of which dealt with aggregated plans (see Table 3.3). We found only one article, that of de Kruijff, Hurkens, and de Kok [44], which addressed the master plan and proposed a mid-term production planning model for high-tech and low-volume industries.

The literature contains a vast variety of point views when contextualising scheduling and sequencing plans, and some do not clearly indicate how the functions of each one should be carried out. The present work considers that the scheduling plan deals with efficient resources allocation given a set of due dates, release dates, demand for products and operational restrictions to help to decide the number of products to be produced during each time period. Accordingly, the scheduling plan implies finding a way to assign times (at which each operation in the sequence will start and finish), corresponds to the activity of timetabling operations [89], while sequencing plans involves the sequencing of jobs given a set of shared resources (jobs, materials, machines) so that they meet certain production constraints; such as capacity, production levels, precedence, start and due dates, machine capabilities, machine availabilities, lot-size restrictions, resource requirements and resource availabilities [85, 86, 89] A sequencing plan specifies the order in which jobs are to be processed at a shared workstation.

Considerably more research interest has been shown in scheduling problems and their combinations (45%) because the practical application of such problems to industry is more frequent. Scheduling problems have been combined with production planning problems [28–32], and also with sequencing problems [58, 59, 70, 77]. Fewer sequencing problems have been studied (see Table 3.3) as 25% of the research works analysed these problems. These problems have often been combinatorial and presented as NP-Hard, so most research works have applied specific algorithms to solve them.

A distinctive feature of scheduling and sequence problems is listed at the lowest production hierarchy level, namely at the operational decision-making level. Once sequence and scheduling plans have been computed, they are reflected in production orders. Implementing these orders to start the production of each item is called dispatching [90].

Table 3.3. Plan type and plan aggregation of the reviewed works.

Plan type	Plan's Aggregation	Planning Horizon	Planning Period	Reference
Production Planning	Aggregated Plan	Year	Week	Sillekens et al. [36]; de Kruijff et al. [44]
			Month	Mirzapour Al-E-Hashem et al. [37]; Tavaghof-Gigloo et al. [42]; Bensmain et al. [47];
		Quarterly	Month	Leung & Chan, [34]
		Month	Week	Makui et al. [1]; Djordjevic et al. [46]
		Week	Day	Fang et al. [91]
		NS(*)	Month	Chakrabortty & Akhtar Hasin [40]
			NS	R.-C. Wang & Fang [33]; Baykasoglu & Gocken [35]; Zhang et al. [38]; Ramezanian et al. [39]; Khalili-Damghani & Shahrokh [41]; Gholamian et al. [43]; Mehdizadeh et al. [45]; Rasmi et al. [27]
	Master Plan	Month	Week	de Kruijff et al. [44]

Table 3.3. Continued. Plan type and plan aggregation of the reviewed works.

Plan type	Plan's Aggregation	Planning Horizon	Planning Period	Reference
Scheduling	Dispatching Plan	Month	Week	Mattik et al. [64]
		Week	Day	Philip Doganis & Sarimveis [55]
			NS	Motta Toledo et al. [61]; De Smet et al. [79]
		Day	Day	Nonås & Olsen [49]
			Hour	Doganis & Sarimveis [52]
		NS	NS	Grabowski & Wodecki [48]; Gupta & Magnusson [26]; Hooker [51]; Gaglioppa et al. [53]; Fakhrzad & Khademi Zare, [56]; Zeppetella et al. [69]; Chansombat et al. [76]; Verbiest et al., [73]; S. Wang et al. [78]; Yang & Xu, [80]; Otto & Li, 2020 [81]; Prata, de Abreu, et al., 2020 [92]; Prata, Rodrigues, et al. [93]; Rodoplu et al. [82]
		Day	Minute	Woo & Kim [72]
Sequencing	Dispatching Plan	Week	NS	Baumann & Trautmann [66]
		Day	NS	Franz et al. [63]
		NS	NS	Mohammadi et al. [57]; Bellabdaoui & Teghem [50]; Moon et al. [54]; Chen et al. [60] ; Golle et al. [65] Na & Park [62]; Abdeljaouad et al. [67]; Aroui et al. [68]; Lopes et al. [71]; Mönch & Roob [74]; Ekici et al. [75]
Production Planning & Production Scheduling	Aggregated Plan & Dispatching Plan	Year	Quarterly	Xue et al. [29]; Fumero et al. [31]
			Month	Omar & Teo [28]
		Week	Hour	Fumero et al. [32]
	Master Plan & Dispatching Plan	Month	Week	Aghezzaf et al. [30]
Production Scheduling & Production Sequencing	Dispatching Plan	Day	Hour	de Armas & Laguna [77]
		NS	NS	Guimarães et al. [58]; Cheng et al. [59]; Torkaman et al. [70]

(*) NS: not specified.

The analysis performed on the plans' aggregation features enables to provide a concrete definition of production planning, sequencing, and scheduling problems. The proposed delimitation describes the different planning levels. Tactical or medium-term level uses aggregated data, once the results of this phase are available, you can move on to a detailed short-term scheduling phase. Input data for planning problems at the tactical level is generally measured in months or weeks rather than days or hours, as is done in scheduling and sequencing plans. Planning issues at the tactical level seek to minimize production costs, warehousing costs, inventory costs, and others detailed in section 3.3.4. The results obtained from this process generally describe the monthly or weekly production quantities for all products, requiring a number of resources (machines, operations) and capacities. Scheduling and sequencing activities are done in the short term, although, as mentioned above, some papers present a combined approach in which the results of medium-term planning are the input of scheduling or sequencing plans (short-term). Short-term plans seek to optimize each stage and each installation (machines or resources), in shorter time horizons [94].

3.3.3 Modelling approach and solution techniques

The literature describes a wide variety of models and approaches to solve production planning, scheduling and sequencing problems. The analysed works have generally sought to develop models and to apply them to real planning problems using large-sized input data. As this leads to complexity, the procedure to find a solution in data management and computational efficiency terms is difficult. This is why there are different types of techniques to model and solve production planning, scheduling and sequencing problems. The objective of the present paper was to analogously present the mathematical programming methods followed to raise different model types, the techniques to solve them and the software used to treat these problems. Table 3.4 presents the applied modelling approach and solution techniques in the reviewed works to answer RQ1 and RQ2. The first column in Table 3.4 refers to the modelling approach. The analysis allowed us to conclude that mixed integer linear programming (MILP) models were the most widely used to deal with production planning, scheduling and sequencing problems. Indeed 73.33% of the analysed papers adopted this approach, while only two authors resorted to fuzzy linear programming (FLP) [33, 46]. Other modelling approaches indicated during the review included fuzzy goal programming (FGP) [41], multi-objective linear programming (MOLP), mixed integer non-linear programming (MINLP) [47, 79, 40], multi-objective mixed-integer linear programming (MOMILP) [45], multi-objective mixed-integer non-linear programming (MOMINLP) [37], quad-objective mixed integer linear programming (QOMILP) [27] and the robust programming (RP) model [1]. Hooker [51] combined two methods: mixed integer linear programming (MILP) and constraint programming (CP). Omar and Teo [28] combined and applied two techniques, firstly MILP to solve the aggregate plan, and then an integer programming (IP) model to disaggregate the plan.

The second column in Table 3.4 refers to the solution algorithms proposed in the reviewed works. Considering the complexity of the models and their applications, different types of techniques appeared to solve distinct production problems. Andres et al. [95] classified these techniques into four groups: (i) optimiser algorithms (OA), which respond to techniques that ensure that the best possible solution is provided, and are commonly integrated into predetermined solutions; (ii) heuristic algorithms (HA), which do not guarantee the optimal solution, but a solution/s that is/are relatively good by coming close to the global optimum [96]; (iii) metaheuristic algorithms (MA), which consist of higher-level heuristics [96] and can provide a sufficiently high-quality solution through an iterative master process that guides and modifies subordinate heuristics (partial search algorithm) operations [6, 97]; (iv) matheuristic algorithms (MTA) represent a hybridisation or combination of heuristic and metaheuristic algorithms and exact methods [98]

Regarding the techniques for solving production planning, scheduling and sequencing problems, 71.66% of the articles described the algorithm used to solve these problems, while 28.33% did not use a specific algorithm, but described the type of commercial solvers employed. Some commercial solvers like Gurobi or Cplex incorporate parametrisation features to efficiently solve optimisation problems. Nevertheless, the reviewed papers did not report any software parameter to provide clues about the algorithms employed in the commercial solver.

The majority of the reviewed articles applied metaheuristic algorithms (37.20%), where genetic algorithms were the predominant metaheuristic procedure. Some authors performed combinations or hybridisations of algorithms, and a summary of the most relevant ones follows. Fakhrzad and Khademi Zare [56] introduced a hybrid genetic algorithm (genetic algorithm + local search) that, jointly with a Lagrangian algorithm, addressed the lot size determination in multistage production scheduling problems. With this hybridisation, the authors obtained near-optimal solutions in a medium dataset. Chen et al. [60] presented a hybrid approach based on two metaheuristic algorithms, the variable neighbourhood search and particle swarm optimisation (VNPSO), to solve multistage and parallel-machine scheduling problems. This hybrid algorithm was compared to the traditional particle swarm optimisation (PSO) algorithm, and the authors concluded that the obtained solutions and the calculation time were better in the hybrid algorithm than in the traditional PSO for obtaining almost optimal solutions for large instances. Aroui et al. [68] presented two metaheuristic algorithms (genetic algorithms and simulated annealing) and a hybrid algorithm composed of a genetic algorithm and simulated annealing (GASA) to solve a problem to sequence assembly lines of mixed models to minimise workload. The authors tested MILP and algorithms in an industrial case of a truck assembly line. The results obtained from the different algorithms demonstrated that the hybrid algorithm provided better solutions and better calculation times than MILP in large instances. GASA was also better than simulated annealing algorithms but required longer calculation times and SA provides better solutions than the genetic algorithm.

Finally, is worth mentioning the work of Torkaman et al. [70], who proposed a hybrid simulated annealing (HSA) algorithm that used a genetic algorithm to obtain an initial solution. This hybrid algorithm was used to solve multistage, multiperiod and multiproduct lot sizing problems with remanufacturing and sequence-dependent setups and a setup carry-over in a flow shop system. This hybrid algorithm was compared to the four heuristic algorithms and a MILP model. The authors concluded that the MILP model achieved better solutions than the hybrid algorithm when computing small datasets. Nevertheless, the MILP model needed a longer calculation time than HSA. Accordingly, HSA in larger instances was more efficient than the mathematical model and heuristic methods, thus the proposed hybrid algorithm can be used in this type of problem to obtain better calculation times in medium and large datasets.

In terms of heuristic algorithms (30.23%), the most widely used techniques were LP Relaxation (LPR) [32, 38, 53] and Benders decomposition [1, 44, 51]. For optimiser algorithms (16.27%), some frequently used techniques included Branch and Bound (BB) [42, 49, 64]. Finally, MTA (16.27%), the metaheuristic combinations (genetic algorithms) and MILP models were the most frequently used [61,72].

Table 3.4 shows the various combinations or associations of each development tool classified as programming languages, modelling languages and solvers. As regards programming languages, only a few authors (25.00%) indicated the programming languages that they used to conduct their research, while others simply did not specify (NS) them. The employed languages were C, C#, C++, Julia, Java, Python and Visual Basic, whereas C++ was the most preferred one (46.66%). Modelling languages included AIMMS, GAMS, ILOG, JUMP LINGO, MATLAB and OPL, and 58.33% of the reviewed studies described which modelling language they used, of which LINGO and ILOG were the most frequently reported ones. Of them all, 81.66% informed about the solvers utilised to solve production planning, scheduling and sequencing problems. Solvers were CPLEX, CP Optimiser, LINGO, Xpress, Gurobi and OM Patners, and the most representative ones were CPLEX (50.00%) and LINGO (18.33%).

The proposed solution column summarises the findings of the reviewed articles. For those papers proposing model and solution (MS), readers can find a mathematical programming model and its solution. By way of example, we cite Wang and Fang [33] and Djordjevic et al. [46], who proposed a fuzzy linear programming model, but only indicated the obtained results. Model, solver and solution (MSS) added the solver. In this case, Khalili-Damghani and Shahrokh [41] used a fuzzy goal programming model and solved it by LINGO. Algorithm description (MAD) showed a model and described the algorithm, but these research types were not studied because they went beyond the scope of RQ4.

Model, algorithm description and solution (MADS) showed the model, and described the algorithm and the obtained solution, but not the used solver; e.g., Fang et al. [91] formulated the aggregate production planning problem as an MILP model, and solved it by the Lagrangian relaxation technique (LGR), but did not describe the used solver. Model, algorithm description, solver and solution (MADSS) similar proposed solutions to MADS and included the used solver; e.g., Chen et al. [60] studied a sequencing problem and formulated an MILP model by developing a hybrid approach based on VNS and PSO. The MILP model was formulated with the IBM ILOG CPLEX software package and was solved by BB algorithms, which were implemented in C++. Model, algorithm description, algorithm pseudocode, solver and solution (MADPCSS) added the pseudocode algorithm to MADSS, and there were only seven papers of this type: Mehdizadeh et al. [45] de Kruijff et al. [44]; Gupta and Magnusson [26]; Motta Toledo et al. [61]; Hooker [51]; Franz et al. [63]; Aroui et al. [68].

Table 3.4. The modelling approach and solution techniques of the reviewed works.

Modelling approach	Algorithm	Programming Languages	Modelling language	Solver	Proposed solution	Reference
FLP	-	NS	NS	NS	MS	R.-C. Wang & Fang [33]; Djordjevic et al. [46]
FGP	-	NS	LINGO	LINGO	MSS	Khalili-Damghani & Shahrokh [41]
FMOLP	OA/ SI	NS	GAMS	CPLEX	MSS	Gholamian et al. [43]
FP	MA/ TS	NS	NS	NS	MADS	Baykasoglu & Gocken [35]
GP	OA/ SI	NS	NS	LINDO	MSS	Leung & Chan [34]
IP	MTA/ (BRKGA + IP)	C++	NS	LP-Solve	MADS	Mönch & Roob [74]
ILP	Hybrid MA/ GA + HA/ LGR	Visual Basic	NS	LINGO	MADSS	Fakhrzad & Khademi Zare [56]
ILP	HA/ IVN	NS	ILOG CPLEZ	CPLEX	MADPCSS	Otto & Li [81]
MILP	-	NS	NS	OM Partners	MSS	Bellabdaoui & Teghem [50]
	-	NS	NS	CPLEX	MSS	P Doganis & Sarimveis [52]; Golle et al. [65]
		NS	OPL	CPLEX	MSS	Aghezzaf et al. [30]
	-	NS	GAMS	CPLEX	MSS	Philip Doganis & Sarimveis [55] ; Fumero et al. [31]
	-	C	NS	Gurobi	MSS	Baumann & Trautmann [66]
	-	NS	ILOG CPLEX	CPLEX	MSS	Zeppetella et al. [69]; Lopes et al. [71]
	-	NS	NS	Gurobi	MSS	Chansombat et al. [76]

Table 3.4. Continued. The modelling approach and solution techniques of the reviewed works.

Modelling approach	Algorithm	Programming Languages	Modelling language	Solver	Proposed solution	Reference
MILP	-	Julia	JUMP	Gurobi	MADS	S. Wang et al. [78]
MILP	HA/ BD	NS	AIMMS	CPLEX	MADPCSS	de Kruijff et al. [44]
MILP	HA/ GR	NS	OPL MATLAB	CPLEX	MADPCSS	D. Gupta & Magnusson [26]
MILP	HA/ LF HA/ RF	NS	ILOG CPLEX	CPLEX	MSS	Sillekens et al. [36]
MILP	HA/ LGR	C#	NS	NS	MADS	Fang et al. [91]
MILP	HA/ LPR	NS	NS	CPLEX	MSS	Gaglioppa et al. [53]
MILP	HA/ LPR	NS	GAMS	CPLEX	MSS	Fumero et al. [32]
MILP	HA/ LPR HA/ BM	C#	LINGO	LINGO	MADSS	Zhang et al. [38]
MILP	HA/ NEH	NS	LINGO	LINGO	MADSS	Abdeljaouad et al. [67]
MILP	MA/ GA	NS	NS	NS	MADS	Moon et al. [54]
MILP	MA/ GA	C++	NS	CPLEX	MADSS	Cheng et al. [59]
MILP	MA/ GA	NS	ILOG CPLEX	CPLEX CP Opti-miser	MADSS	Na & Park [62]
MILP	MTA/ GA + MILP	C++	NS	CPLEX	MADPCSS	Motta Toledo et al. [61]
MILP	MA/ MOHSA	NS	MATLAB	NS	MADS	Mohammadi et al. [57]
MILP	MA/GA MA/ SA Hybrid MA/GA + MA/SA	NS	ILOG CPLEX MATLAB	CPLEX	MADPCSS	Aroui et al. [68]
MILP	MA/GA MA/ TS	NS	LINGO-MATLAB	LINGO	MADSS	Ramezanian et al. [39]

Table 3.4. Continued. The modelling approach and solution techniques of the reviewed works.

Modelling approach	Algorithm	Programming Languages	Modelling language	Solver	Proposed solution	Reference
MILP	MA/TSGW	C++	NS	NS	MADS	Grabowski & Wodecki [48]
	MA/VNS MA/ VTS	NS	ILOG CPLEX	CPLEX	MADPCSS	Franz et al. [63]
	MA/PSO Hybrid MA/ VNS + MA/ PSO	C++	ILOG CPLEX	CPLEX	MADSS	Chen et al. [60]
	OA/ BB	NS	NS	CPLEX	MADSS	Nonås & Olsen [49]
	OA/ BB OA/ SI	NS	NS	FICO Xpress Opti-mizer - CBC	MSS	Tavaghof-Gigloo et al. [42]
	OA/ SPP*	NS	LINGO	LINGO	MADSS	Xue et al. [29]
	OA/BB HA/ LPR	NS	OPL	CPLEX	MSS	Mattik et al. [64]
	MTA/ILS + MILP	NS	NS	Gurobi	MADS	Verbiest et al. [73]
	MTA/ GA + MILP / MTA/ SA + MILP	NS	ILOG CPLEX	CPLEX	MADS	Woo & Kim [72]
	MTA/ TS + MILP	C++	NS	CPLEX	MADS	Ekici et al. [75]
	HA/ RF	Python	NS	CPLEX	MADPCSS	Rodoplu et al. [82]
	MTA/FVLA_CSA_MM	Julia	JUMP	CPLEX	MADPCSS	Prata et al. [93]
	MA/ VND - MA/ IG	NS	MATLAB	NS	MADPCSS	Yang & Xu [80]
	-	Java SE 8	NS	CPLEX	MSS	de Armas & Laguna [77]
	MTA/ RPF + FPO + MILP	C++	ILOG CPLEX	CPLEX	MADSS	Guimarães et al. [58]

Table 3.4. Continued. The modelling approach and solution techniques of the reviewed works.

Modelling approach	Algorithm	Programming Languages	Modelling language	Solver	Proposed solution	Reference
MILP	Hybrid MA/ SA + MA/ GA	NS	GAMS MATLAB	CPLEX	MADSS	Torkaman et al. [70]
MILP – CP	HA/ BD	NS	OPL	CPLEX	MADPCSS	Hooker [51]
MILP - IWGP	-	NS	LINGO	LINGO	MSS	Omar & Teo [28]
MINLP	Hybrid MA/GA + HA/ RF based rolling horizon heuristic	NS	LINGO	LINGO	MADPCSS	Bensmain et al. [47];
	HA/RF	NS	NS	Gurobi	MADPCSS	De Smet et al. [79]
MOLP	MA/ GA	NS	MATLAB	NS	MADS	Chakrabortty & Akhtar Hasin [40]
MOMILP	MA/ SPGA MA/ WMOGA MA/ NSGA-II	NS	LINGO MATLAB	LINGO	MADPCSS	Mehdizadeh et al. [45]
MOMINLP	OA/ BB	NS	LINGO	LINGO	MSS	Mirzapour Al-E-Hashem et al. [37]
QOMILP	-	NS	NS	NS	MS	Rasmi et al. [27]
RP	HA/ BD	NS	GAMS	NS	MADS	Makui et al. [1]

3.3.4 Mathematical model objectives

This section reviews mathematical programming models in detail. Mathematical models often describe a problem through the objective function, as well as constraints to define the problem's structure. Therefore, to answer RQ2 and to study the characteristics of problems, we analysed the objective functions of the models proposed in the reviewed papers (see Table 3.6).

Table 3.5 summarises the typical objectives used to support decision making in production planning, scheduling and sequencing problems. The objectives were classified according to their nature: (i) cost-based objectives (OC), costs or profits representing variables related to monetary units; (ii) time-based objectives (OT) evaluate the time units required to perform certain processes, i.e. jobs, machines, material processing, manufacturing cycles, order processing, etc; (iii) product-based objectives (OP), which intend to improve the efficiency of operations and aim to ensure that manufacturing meets the appropriate quantity and quality to cover customer demands; (iv) resource-based objectives (ORS), which seek to achieve the optimal use of resources, such as people, materials and machinery; (v) service-based objectives (OS), which assess delays, shortage or expiration dates, and the quality of goods and services for final customers; (vi) sustainability-based objectives (OST), which seeks to strike a balance in the utilisation of resources for production at environmental, social and economic dimensions. In order to gain profounder knowledge, the review analysis allowed a group of 64 subtypes of objectives belonging to each defined category (OC, OT, OP, ORS, OS and OST; see Table 3.5) to be identified.

Table 3.5. Production planning, scheduling and sequencing objectives.

Type of objectives	Subtype	Designation	Subtype	Designation
Costs (OC)	Production cost minimisation	OC1	Holding cost minimisation	OC21
	Variable production cost minimisation	OC2	Changeover cost minimisation	OC22
	Remanufacturing cost	OC3	Supply chain cost minimization	OC23
	Setup cost minimisation	OC4	Shortage cost minimisation	OC24
	Inventory cost minimisation	OC5	Changing shift model minimisation (cost)	OC25
	Cost to change from production capacity level	OC6	Transportation, inventory and shortage costs minimisation	OC26
	Normal/ Extra time (overtime) production cost minimisation	OC7	Subcontract cost minimisation (outsourcing)	OC27
	Labour minimisation (hiring cost and lay-off cost)	OC8	Fixed cost per unit minimisation	OC28

Table 3.5. Continued. Production planning, scheduling and sequencing objectives.

Type of objectives	Subtype	Designation	Subtype	Designation
Costs (OC)	Cost of workers' salary minimisation	OC9	Repairs and deterioration machines cost minimisation	OC29
	Labour training cost	OC10	Machine utilisation cost minimisation	OC30
	Workforce changing cost (skilled and unskilled workforce)	OC11	Cost's preventive maintenance minimisation	OC31
	Normal and overtime labour cost minimisation	OC12	Capital cost minimisation	OC32
	Backorder minimisation (quantity or cost)	OC13	Start-up cost	OC33
	Idle time cost minimisation	OC14	Contamination cost	OC34
	Tardiness penalty costs; earliness penalty costs minimisation	OC15	Cost value of jobs of family	OC35
	Investment cost minimisation	OC16	Maintenance costs minimisation	OC36
	Profit maximisation	OC17	Delivery and tardiness costs minimisation	OC37
	Transport cost minimisation	OC18	Total costs minimisation	OC38
	Raw Material purchasing cost minimisation	OC19		
	Raw material inventory holding cost	OC20		
Time (OT)	Lead time minimisation	OT1	Mean flow time minimisation of jobs	OT9
	Production time minimisation	OT2	Time of sequences minimisation	OT10
	Warehouse time minimisation	OT3	Cycle time minimisation	OT11

Table 3.5. Continued. Production planning, scheduling and sequencing objectives.

Type of objectives	Subtype	Designation	Subtype	Designation
Time (OT)	Preparation times minimisation	OT4	Work overload minimisation	OT12
	Transition time minimisation	OT5	Makespan minimisation	OT13
	Setup time minimisation	OT6	Total weighted completion time minimisation	OT14
	Tardiness minimisation	OT7		
	Earliness minimisation	OT8		
Products (OP)	Product sold maximisation	OP1	Inventory quantity minimisation	OP4
	Shortage product minimisation	OP2	Faulty products minimisation	OP5
	Total production maximisation	OP3	Quality of products maximisation	OP6
Resources (ORS)	Labour minimisation hiring and lay-off (quantity)	OR1	Machine utilisation maximisation	OR2
Service (OS)	Customer service level maximisation	OS		
Sustainability (OST)	Environmental issues minimisation	OST1	Social factors minimisation	OST3
	Cultural elements maximisation	OST2		

The production planning process at the tactical level generally finds objectives related to searches for financial benefits. These financial benefits are represented by reductions in the different cost types. The costs to be minimised at this level are mainly related to production, hiring or firing, inventory and storage, subcontracting, and production in normal time and overtime. In the combined production planning and scheduling approach are less frequent in the literature, since they require greater coordination of operations, so the models and techniques must be incorporated into a single framework [94]. This approach moves from a first phase that uses aggregated data to a second phase that employs more detailed information. Thus, in the aggregated phase, objectives are generally sought to minimise production, inventory, setup, backorder, and normal and overtime costs, while the objectives in the scheduling stage are essentially based on times, such as lead time, setup time, tardiness and earliness.

Production scheduling models focus on optimising the facilities and resources in different areas on shorter planning horizons. The objectives pursued by scheduling models seek to reduce setup, holding and production costs and times, and to minimise makespan and tardiness.

The objectives sought by the combined scheduling and sequencing approaches are primarily to minimise setup and holding costs. Finally, the sequencing problem mainly pursues minimising makespan, tardiness and work overload, but also tends to reduce setup, transition, mean flow, sequence and cycle times.

Table 3.6. The main objectives of the proposed models.

Ref. / Goals in the objective function	Costs	Time	Product	Resources	Service	Sustain-ability
R.-C. Wang & Fang [33]	OC1; OC7; OC8; OC17					
Grabowski & Wodecki [48]		OT13				
D. Gupta & Magnusson [26]	OC4; OC5					
Nonås & Olsen [49]		OT7				
Bellabdaoui & Teghem [50]		OT10				
Hooker [51]	OC28	OT7; OT13				
Omar & Teo [28]	OC1; OC4; OC5; OC12; OC13	OT6; OT7; OT8				
P Doganis & Sarimveis [52]	OC1; OC4; OC8; OC21					
Philip Doganis & Sarimveis [55]	OC21; OC22; OC30					
Gaglioppa et al. [53]	OC1; OC4; OC5					
Moon et al. [54]		OT7; OT9; OT13				
Fakhrzad & Khademi Zare [56]	OC2; OC4; OC17; OC21					
Leung & Chan [34]	OC17		OP5	OR2		
Baykasoglu & Gocken [35]	OC1; OC7; OC12		OP1; OP4	OR1		
Aghezzaf et al. [30]	OC1; OC5	OT1				
Mirzapour Al-E-Hashem et al. [37]	OC1; OC5; OC8; OC10; OC18; OC19; OC20; OC23		OP2			

Table 3.6. Continued. The main objectives of the proposed models.

Ref. / Goals in the objective function	Costs	Time	Product	Resources	Service	Sustain-ability
Sillekens et al. [36]	OC1; OC6; OC8; OC12; OC21; OC28					
Xue et al. [29]	OC1; OC4; OC5; OC8; OC12; OC13					
Mohammadi et al. [57]		OT4; OT5; OT6; OT7				
Ramezanian et al. [39]	OC1; OC4; OC5; OC8; OC13; OC27					
Zhang et al. [38]	OC1; OC5; OC16					
Chakrabortty & Akhtar Hasin [40]	OC1; OC5; OC7; OC8; OC13; OC27					
Cheng et al. [59]		OT13				
Guimarães et al. [58]	OC4; OC21					
Chen et al. [60]		OT13				
Franz et al. [63]		OT12				
Golle et al. [65]		OT12				
Khalili-Damghani & Shahrokh [41]	OC1; OC8; OC9; OC10; OC13; OC20; OC21		OP6		OS	
Mattik et al. [64]		OT7; OT13				
Motta Toledo et al. [61]	OC4; OC5; OC24					
Na & Park [62]		OT7				
Baumann & Trautmann [66]		OT13				
Abdeljaouad et al. [67]		OT13				
Fumero et al. [31]	OC17					
Gholamian et al. [43]	OC1; OC8; OC10; OC19; OC20; OC23; OC26		OP2	OR1		
Makui et al. [1]	OC1; OC4; OC5; OC8; OC11					

Table 3.6. Continued. The main objectives of the proposed models.

Ref. / Goals in the objective function	Costs	Time	Product	Resources	Service	Sustain-ability
Tavaghof-Gigloo et al. [42]	OC12; OC21; OC25; OC27					
Aroui et al. [68]		OT12				
Fang et al. [91]	OC1					
Fumero et al. [32]	OC17					
Zeppetella et al. [69]	OC1; OC17					
de Kruijff et al. [44]	OC13; OC21; OC22					
Lopes et al. [71]		OT11				
Mehdizadeh et al. [45]	OC17; OC29					
Torkaman et al. [70]	OC1; OC3; OC4; OC21					
Chansombat et al. [76]	OC1; OC4; OC14; OC15; OC21; OC31					
Mönch & Roob [74];		OC35				
Verbiest et al. [73];	OC32; OC33; OC34					
Woo & Kim [72]		OT13				
Ekici et al. [75]		OT7; OT8				
de Armas & Laguna [77]			OP3			
Djordjevic et al. [46]		OT1; OT2; OT3; OT4				
Rasmi et al. [27]	OC17					OST1; OST2; OST3
Bensmain et al. [47]	OC5; OC36					
S. Wang et al. [78]		OT14				
De Smet et al. [79]	OC4; OC7; OC21					
Yang & Xu [80]	OC37					
Otto & Li [81]	OC38					
Prata [93]	OT13					
Rodoplu et al. [82]	OC1					

3.3.5 Applications area and enterprise integration level

Some important aspects when modelling production planning, scheduling and sequencing problems are the industrial sector, the specific industry and the product type to which the model is proposed. The impact of applying a model generated for a specific industry to another industry or sector type can be insignificant in some cases, but can be transcendental in others because the required costs and time directly affect the profitability and feasibility of processes. In order to analyse the impact of a model, and by analysing its extrapolation to another industry or sector, the reviewed models were classified into two categories: sectorial and transversal (see Table 3.7). The sectorial category responded to vertical measures and focused on a specific sector or industry. The transversal category referred to all those production operations that have had or could have an impact on multiple manufacturing sectors, and generally responded to horizontal measures [99].

According to Table 3.7, 30% of the articles were classified in the sectorial category and 70% in the transversal category. The problems that arose in the sectorial category generally responded to a specific industry's needs and often used real data: Omar & Teo [28]; Doganis & Sarimveis [55]; Leung & Chan [34]; Mirzapour Al-E-Hashem et al. [37]; Cheng et al. [59]; Chen et al. (2013) [60]; Mattik et al. [64]; Aroui et al. [68]; de Armas & Laguna [77]; Ekici et al. [75]. Other studies did not use real data, but tests with similar data to those of a real case were carried out: Nonås and Olsen [49]; Sillekens et al. [36]; Motta Toledo et al. [61]; Baumann & Trautmann [66], Franz [63]; de Kruijff et al. [44]; Chansombat et al. [76] were also classified as sectorial. The papers classified in the transversal category could be applied or adapted to various industrial sectors. Some studies, such as those by Tavaghof-Gigloo et al. [42] Khalili-Damghani & Shahrokh [41] Makui et al. [1] Djordjevic et al. [46], used real data from one industry (see Table 3.7). Although these studies were validated in a specific industry type, the proposed techniques and approaches could be applied to other sectors. In this category, several works conducted tests with similar data or instances to those of a real case [30, 40, 43, 50, 58, 73].

Enterprise integration is an Industrial Information Integration Engineering (IIIE) category. IIIE is a multidisciplinary research area, according to Chen, 2016 [100], "it is a set of foundational concepts and techniques that facilitate the industrial information integration process". Chen, 2016 [100] and Chen, 2020 [101] in their literature reviews on industrial information integration defined 37 and 27 categories, respectively, one of which was enterprise integration. According to Andres and Poler [102], enterprise integration was classified at two levels: intra- and inter-enterprise levels.

The intra-enterprise level refers to solving production planning, scheduling and sequencing as internal enterprise activities; that is, not sharing information with other supply chain network actors. However, information can be integrated at different plans aggregation levels computed in the same enterprise. That is, the output of an aggregated plan is integrated into a tactical plan (master plan). In the same way, the master plan solution is integrated and used as the input of operational plans, namely sequencing or scheduling mathematical models. Omar and Teo [28] presented an integrated approach to determine the batches to be processed in a batch processing environment of multiple products and identical parallel machines. This approach was hierarchically divided into three levels. The first level solved the problem in aggregate by focusing on production decisions, inventories and backorders. A second level disaggregated the problem into monthly batches. A third level solved the sequencing of batches on parallel machines. Xue et al. [29] presented a modelling approach that integrated production planning and scheduling for decision support for senior and middle managers. The MILP model described aggregated production planning, family de-aggregation and production scheduling with sequence-dependent setup times. Fumero et al. 2016 [31] reported an MILP model that presented a hierarchical approach to integrate different decision-making levels (production planning and scheduling decisions) on multiproduct batch plants. Aghezzaf, et al. [30] provided a model that hierarchically integrated planning decisions from semifinished products at an aggregated level up to finished products; that is, with disaggregated information. Fumero et al. 2017 [32] provided MILP that integrated planning and scheduling for the production planning of multiproduct batch plants in several stages operating in the campaign mode.

The inter-enterprise level is associated with the collaborative planning among different supply chain stakeholders. The majority of papers addressed production planning, scheduling and sequencing from the intra-enterprise perspective, while only one paper, that of Mirzapour Al-E-Hashem et al. [37], considered the collaborative network perspective. Mirzapour Al-E-Hashem et al. [37] contemplated multi-objective aggregate production planning to a multisite, multiperiod, multiproduct aggregate production planning problem. By developing a MOMINLP, this model proposed two objective functions. The first aimed to minimise total supply chain losses and the second to minimise the sum of the maximum amount of shortages between customers' zones during all periods. The computational tests of this model demonstrated its efficiency for supply chain production planning.

Table 3.7. Industry sectors and application type.

Reference	Sectorial	Transversal	Real case	Industry application
R.-C. Wang & Fang [33]		X	N	
Grabowski & Wodecki [48]		X	N	
Nonås & Olsen [49]	X		N	Maritime and shipyard industry
D. Gupta & Magnusson [26]		X	N	
Bellabdaoui & Teghem [50]		X	Y	Steelmaking-continuous casting
Omar & Teo [28]	X		Y	Chemical and pharmaceutical
Hooker [51]		X	N	
P Doganis & Sarimveis [52]		X	N	Dairy
Philip Doganis & Sarimveis [55]	X		Y	Dairy
Gaglioppa et al. [53]		X	N	Process Industries
Moon et al. [54]		X	N	
Leung & Chan [34]	X		Y	Surface and materials science
Fakhrzad & Khademi Zare [56]		X	N	
Baykasoglu & Gocken [35]		X	N	
Mirzapour Al-E-Hashem et al. [37]	X		Y	Wood and Paper
Sillekens et al. [36]	X		N	Automotive
Xue et al. [29]		X	N	Digital Electronic
Aghezzaf et al. [30]		X	Y	X-ray film
Mohammadi et al. [57]		X	N	
Ramezanian et al. [39]		X	N	
Zhang et al. [38]		X	N	
Cheng et al. [59]	X		Y	Solar cell manufacturing
Chen et al. [60]	X		Y	Solar cell manufacturing
Guimarães et al. [58]		X	N	Beverage industry
Chakrabortty & Akhtar Hasin [40]		X	N	Textile
Mattik et al. [64]	X		Y	Steel
Motta Toledo et al. [61]	X		N	Food (soft drinks)
Franz et al. [63]	X		N	Automotive
Na & Park [62]		X	N	

Table 3.7. Continued. Industry sectors and application type.

Reference	Sec-torial	Transversal	Real case	Industry application
Khalili-Damghani & Shahrokh [41]		X	Y	Automotive colours and resins
Baumann & Trautmann [66]	X		N	Consumer goods sector,
Golle et al. [65]		X	N	
Abdeljaouad et al. [67]		X	N	
Gholamian et al. [43]		X	N	Wood and Paper
Tavaghof-Gigloo et al. [42]		X	Y	Electronics manufacturer
Makui et al. [1]		X	Y	Paper Industry
Fumero et al. [31]		X	N	
Aroui et al. [68]	X		Y	Automotive
Fang et al. [91]		X	N	Iron and Steel
Fumero et al. [32]		X	N	
Zeppetella et al. [69]		X	N	
de Kruijff et al. [44]	X		N	High-tech low volume
Torkaman et al. [70]		X	N	Automotive
Mehdizadeh et al. [45]		X	N	
Lopes et al. [71]		X	N	
Mönch & Roob [74]		X	N	
Verbiest et al.[73]		X	N	Chemical
Woo & Kim [72]		X		
Ekici et al. [75]	X		Y	Electronics manufacturer
de Armas & Laguna [77]	X		Y	Pipe-insulation industry
Chansombat et al. [76]	X		N	Capital goods
Djordjevic et al. [46]		X	Y	Automotive
Rasmi et al. [27]	X		Y	Household appliances
Bensmain et al. [47]		X	N	
S. Wang et al. [78]		X	N	Coating
De Smet et al. [79]	X		N	Paper
Yang & Xu [80]		X	N	
Otto & Li [81]		X	N	
Prata [93]		X	N	
Rodoplu et al. [82]		X	N	Textile

3.3.6 Solution quality and problem scale

Currently, mathematical models seek to capture the most relevant aspects of industry processes in a simplified way. Accordingly, very few or no models reflect all the aspects of a real-world company's processes. The use of mathematical models can be compromised between complexity and reality. Therefore, employing optimisation algorithms, heuristics, metaheuristics and matheuristics allows the best performance of solutions for real world problems (large problem scales) without committing the efficiency of the required computational resources.

In this context, we classified the quality of solutions into three categories: (i) optimal (OP), characterised by being able to provide exact and optimal solutions; (ii) near-optimal (N-OP), containing solutions that generate an optimisation gap that is generally less than 2%; (iii) good (GD), which encompasses reasonable solutions in time and quality terms without reaching an optimum solution.

Table 3.8 compares the quality of the solutions with the problem scale, which refers to the data size or numerical instances of problems. According to the amount of data used to validate the proposed models, three categories of problem scale were defined: (i) a small dataset, which allows rapid tests to be run; (ii) a medium dataset, which is significantly bigger in size and dimension, and allows optimal or near-optimal solutions to be found in reasonable computation times; (iii) a large dataset, generally corresponding to instances that simulate real data or are in fact real data extracted from company manufacturing processes.

Finally, to answer RQ4, over 55.0% of the papers used small datasets to test the performance of the models and algorithms, most of these documents reached optimal solutions and 20 papers tested the problems with large-scale data. Of these papers, only the work of Chansombat et al. [76] obtained an OP solution. These authors proposed MILP for a problem that integrated production and preventive maintenance scheduling into the capital goods industry. This type of problem is generally solved with metaheuristic methods and they achieved N-OP solutions. However, the mathematical model presented by the authors achieved OP solutions for small, medium and large datasets.

In the area of production planning the use of large-scale dataset was less frequent. in approaches where the production planning and scheduling are jointly modelled and solved, no large-scale dataset studies were tested. However in these two approaches, most studies presented real industrial applications or generated similar data to the real ones of a company or industry, such as those presented by [1,30,34,37,40,42–44,46]. The size of the datasets generated by these studies were useful enough because they represented real cases. Therefore, it was not necessary to create or generate larger datasets. However, half the studies that tested real instances and medium datasets obtained OP results, but the other half obtained N-OP or GD solutions.

Production scheduling and sequencing problems are generally NP-Hard, which makes them difficult to solve when large datasets are considered. In the combined approaches that jointly solved scheduling and sequencing problems, tests were performed primarily with medium datasets and N-OP solutions were obtained (see Figure 3.4).

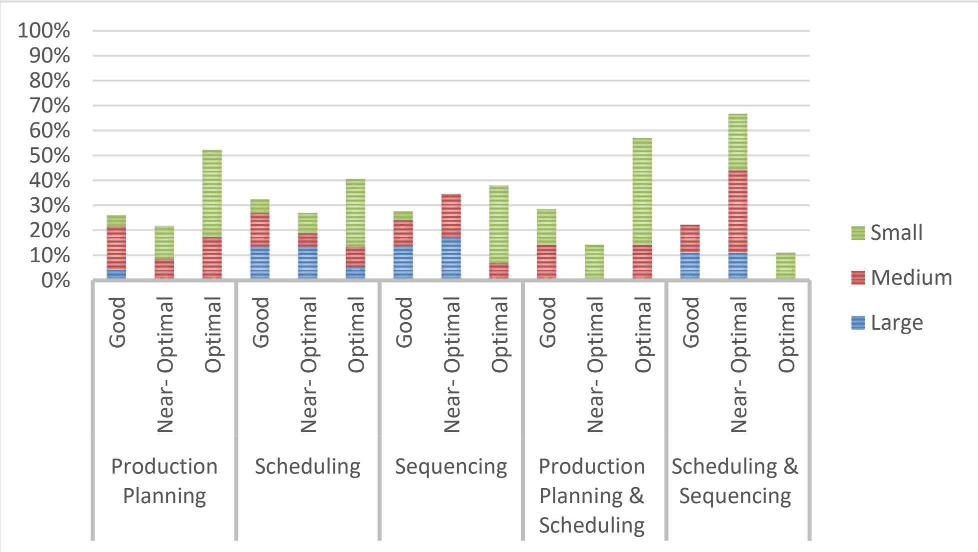

Figure 3.4. Distribution of the scale of problems and solution quality.

The application of different types of methods for production planning, scheduling and sequence problems, and the amount of data, provided distinct solutions (see Table 3.8); for example, those presented by Grabowski and Wodecki [48]. They proposed a Tabu Search Grabowsk and Wodecki (TSGW) algorithm to address a flow workshop scheduling problem with makespan criteria, and reported N-OP solutions for a problem with a large dataset consisting of 500 jobs and 20 machines. Hooker [51] proposed an algorithm based on decomposition benders for a programming problem. By applying it to a large dataset, they achieved N-OP solutions. Cheng et al. [59] presented a variation of the genetic algorithm, which they have called the hybrid code genetic algorithm. They presented N-OP solutions to problems with large datasets in a multistage and parallel-machine scheduling problem in the solar cell industry. Golle et al. [65] reported two models for sequencing products on a mixed-model assembly line to minimise work overload. These models were tested with different data sizes and provided N-OP solutions with a large dataset using CPLEX. Mattik et al. [64] worked with numerical tests using parameters and data deriving from a real case in the steel industry and used MILP accompanied by LP relaxation in addition to the Branch and Bound procedures. With these solution approaches, the authors obtained almost OP solutions for medium and large datasets. Baumann and Trautmann [66] presented a hybrid method for the short-term scheduling of make-and-pack production processes and represented the problem through MILP. This model was able to provide N-OP solutions for large-scale and real-life instances for consumer goods companies.

From the review, we conclude that the resolution of production planning, scheduling and sequencing when mathematical model approaches were applied to large dataset instances was not efficient in terms of calculation time and the quality of solutions. Over 71.66% of the reviewed papers used different types of methods and around 28 distinct types of techniques were tested (see Table 3.4). In this regard, matheuristic and metaheuristic algorithms obtained better results in large instances, as well as the hybridisations of metaheuristic algorithms [60,68].

Table 3.8. Problem scales and solutions quality.

Authors	Problem Scale			Solution Quality		
	Small (S)	Medium (M)	Large (L)	OP	N-OP	GD
R.-C. Wang & Fang [33]	x			S		
Grabowski & Wodecki [48]	x	x	x	S-M	L	
Nonås & Olsen [49]	x			S		
D. Gupta & Magnusson [26]	x					S
Bellabdaoui & Teghem [50]	x			S		
Omar & Teo [28]		x		M		
Hooker [51]	x	x	x	S-M	L	
P Doganis & Sarimveis [52]	x			S		
Philip Doganis & Sarimveis [55]	x			S		
Gaglioppa et al. [53]	x	x		S		M
Moon et al. [54]	x	x		S		M
Leung & Chan [34]	x			S		
Fakhrzad & Khademi Zare [56]	x	x		S	M	
Baykasoglu & Gocken [35]	x				S	
Mirzapour Al-E-Hashem et al. [37]		x		M		
Sillekens et al. [36]	x					S
Xue et al. [29]	x				S	
Aghezzaf et al. [30]	x			S		
Mohammadi et al. [57]		x			M	
Ramezanian et al. [39]	x	x		S		M
Zhang et al. [38]		x				M
Cheng et al. [59]	x	x	x	S	M-L	

Table 3.8. Continued. Problem scales and solutions quality.

Authors	Problem Scale			Solution Quality		
	Small (S)	Medium (M)	Large (L)	OP	N-OP	GD
Chen et al. [60]	x	x	x	S	M-L	
Guimarães et al. [58]	x	x	x		S-M	L
Chakrabortty & Akhtar Hasin [40]	x				S	
Mattik et al. [64]		x	x		M-L	
Motta Toledo et al. [61]			x			L
Franz et al. [63]	x	x	x	S	M	L
Na & Park [62]	x	x				S-M
Khalili-Damghani & Shahrokh [41]	x			S		
Baumann & Trautmann [66]		x	x		M-L	
Golle et al. [65]	x	x	x	S	M-L	
Abdeljaouad et al. [67]	x	x	x	S		M-L
Gholamian et al. [43]		x		M		
Tavaghof-Gigloo et al. [42]		x		M		
Makui et al. [1]		x		M		
Fumero et al. [31]	x			S		
Aroui et al. [68]	x		x	S		L
Fang et al. [91]	x	x			S-M	
Fumero et al. [32]	x			S		
Zeppetella et al. [69]	x				S	
de Kruijff et al. [44]		x			M	
Torkaman et al. [70]	x	x			S-M	
Mehdizadeh et al. [45]	x	x		S		M
Mönch & Roob [74]	x		x	S	L	
Verbiest et al. [73]	x	x	x	S		M-L
Woo & Kim [72]	x	x	x	S-M	L	
Lopes et al. [71]		x		M		
Ekici et al. [75]			x			L
de Armas & Laguna [77]		x				M
Chansombat et al. [76]	x	x	x	S-M-L		
Djordjevic et al. [46]	x			S		
Bensmain et al. [47]	x	x	x	S		M-L
S. Wang et al. [78]	x	x				S-M
De Smet et al. [79]	x	x	x	S		M-L
Yang & Xu [80]	x	x	x		S	M-L
Otto & Li [81]			x			L
Prata [93]	x		x		S-L	
Rodoplu et al. [82]	x		x	S	L	

3.4 Discussion and perspectives

The range of experiments carried out in the papers addressing production planning, scheduling and sequencing problems illustrate the vast variety of techniques addressed in the literature to solve such enterprise planning problems. It must be stated that MILP were the most widely used (44 of 60) to represent the different types of production planning, scheduling and sequence Problems. In production planning problems, we found that the majority of models dealt with aggregated plans and applied MILP as the modelling approach, and also applied heuristic and metaheuristic algorithms to solve them. LINGO was identified as the most widely used solver. Production planning problems were mainly classified as transversal models, which allowed their application regardless of industry and sector type. The proposed approaches were validated with small and medium datasets, and collectively achieved optimal solutions. Production scheduling problems were predominantly modelled with MILP models, and heuristic and metaheuristic algorithms were implemented to solve them. The CPLEX commercial software was extensively used to obtain N-OP solutions with medium and large datasets. Although some solutions were almost OP, only a few real cases appeared. In sequencing problems, MILP was still the most widely used modelling approach. The developed models were well tested with metaheuristic algorithms, such as the genetic algorithm and variable neighbourhood search algorithm, for which CPLEX was the most widely used commercial software. Multiple tests were run with a medium dataset, which usually obtained N-OP and GD solutions. Although no predominant sector appeared in our review, we detected that the automotive industry presented real cases.

Of the reviewed papers, only one study applied MOMINLP [37] to a problem of multi-objective aggregate production planning. To solve the proposed MOMINLP, the authors formulated this problem as an MOMINLP model and then transformed it into a linear model. Afterwards, MOMINLP was reformulated as a robust MOLP model, and this robust multi-objective model was then solved as a single-objective problem. Similarly, only two studies employed MINLP approaches [47,79]. MINLP models are generally used to address chemical engineering design problems [103]. Currently, there are different types of solvers to deal with MINLP models, such as AlphaECP, Antigone, AOA, BONMIN, BARON, Couenne, DICOPT, Juniper, LINDO, Minotaur, Muriqui, Pavito, SBB, SCIP and SHOT. These solvers have been tested with different instances by Kronqvist et al. [104]. The use of such a model is an area that involves many researchers who seek to develop solver software. For this reason, it is necessary to further investigate models and algorithms for this problem type [104]. Therefore, modelling MINLP, MOMINLP and MOMILP for production planning, scheduling and sequencing problems is considered as a novel area to be explored.

Our systematic literature review enabled us to recognise an important research line for solving production planning, scheduling and sequencing problems, which includes the adoption of: (i) hybrid methods, as the combinations or hybridisations of metaheuristic or heuristic algorithms; (ii) the interoperation of mathematical models with metaheuristic or heuristic algorithms, designated in the literature as matheuristic algorithms. The papers applying MTA have been demonstrated to give good results as well as hybrid algorithms. According to Pellerin et al. [105], hybrid metaheuristic algorithms have been extensively studied in the past two decades. These authors [105] also analysed the performance of 36 different hybrid metaheuristic algorithms, applied to a resource-constrained project scheduling problem, and concluded that these techniques gave N-OP solutions quickly and efficiently. Here we found a gap in the literature as the MTA research line has not yet been studied in such depth as the hybrid metaheuristic algorithms area.

Some studies proposing MTA are analysed in Section 3.3.3 and obtained N-OP solutions for planning purposes. Some examples include the work carried out by Woo and Kim [72], in which proposed a combination of an MILP model with a simulated annealing algorithm and a genetic algorithm to deal with a parallel machine scheduling problem with time-dependent deterioration and multiple rate-modifying activities. In this problem, the authors were able to obtain N-OP solutions and suggested researching other matheuristics with other types of combinations to improve the computation time of the algorithms they presented. Verbiest et al. [73] described an MTA made up of an MILP model with an iterative local search algorithm for multiproduct batch plant designs on parallel production lines. With this combination they obtained good results in acceptable times, but proposed furthering their research to extend problems with more restrictions. The work by Ekici et al. [75] presented a combined of an ILP model with a Tabu search algorithm to address the unrelated parallel machine scheduling problem with sequence-dependent setups. This paper used real-world instances to test the proposed matheuristic technique, and this technique provided good solutions for the addressed problem.

Consequently, the design of MTA can be a flexible and useful tool for solving a wide range of planning problems [104, 105]. Thus matheuristic techniques have the advantage of reducing and simplifying problems into smaller problems or subproblems that can be solved using mathematical models and different types of solvers, which also benefits from the synergies among optimisation, heuristic and metaheuristic techniques [107]. Therefore, future work should aim to validate the efficiency of matheuristics in large instances and in real problems. At present, there is limited evidence for the performance of these techniques. Accordingly, matheuristic techniques offer a wide field to be explored given the different combinations that can be developed.

3.5 Conclusions and future research

Production planning, scheduling and sequencing are usually the most critical activities that a company performs. For companies, the objective of these activities is to use the fewest resources in the shorted possible time to meet demand. In recent years, various methods and solution techniques have appeared in the literature to overcome such problems. We conducted a systematic literature review to offer a comprehensive perspective of production planning, scheduling and sequencing problems published from 2000 to 2020. This review leads to three main contributions. Firstly, from the studied and the analysed articles we present a holistic framework that characterises planning problems. Secondly, we organise and classify the existing papers according to the proposed holistic framework after identifying the aggregation and decision levels, the type of models, the objectives characterising each modelling approach, the followed resolution techniques, the development of tools, the application areas and sectors, the enterprise integration level, the experiments carried out to test real cases, the data size with which the problem was solved, and the quality of the obtained solutions. Finally, our contribution consists in identifying research opportunities.

According to the reviewed topic, future research lines are next determined. This review indicates that a gap still exists in developing mathematical models. Accordingly, novel modelling approaches should be developed to address and associate the parameters related to production and sustainability (for its three pillars: social, economical and environmental), and these should also address uncertain parameters. Another research area is to develop transversal formulations when modelling a planning problem. Transversal formulations could comprise general and modular formulations that can be adapted to the context of the application, and these formulations can be evaluated in different activity sectors.

Additionally, the development of matheuristic algorithms to propose new modelling approaches and solution techniques is needed to avoid large computational efforts, and to obtain GD or N-OP solutions when larger and more complex production planning, sequencing and scheduling problems are posed at the industrial level. We also recommend studying non-linear mathematical models, using different types of non-linear solvers, and comparing the computational results of these solvers to those solving linear models. Finally, we propose mathematical models being generated from an inter-enterprise perspective as most of the presented papers have focused on intra-enterprise models without considering any type of collaboration between supply chain companies. Considering the importance of collaboration in planning, production scheduling and sequencing terms [102], we suggest that the problems of production planning, scheduling, and sequencing should be treated from a collaborative perspective, in which the different network partners share information. Several authors describe the advantages of inter-enterprise models, such as those presented by Hall and Potts [108], who describe that the implementation of Inter-enterprise architecture can reduce the total cost of the system by 20-25%. In addition, the implementation of inter-enterprise models provides additional benefits, such as harmonisation of processes, alignment of the commercial strategy, reduction of technological costs and risks, improved customer service and better responsiveness [109]. Therefore, the proposed framework will play a major role in guiding future research as it allows the key features of a production planning, scheduling and sequencing problem to be identified.

3.6 References

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Chapter 4

A decision-making tool for algorithm selection based on a fuzzy TOPSIS approach to solve replenishment, production and distribution planning problems.

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Abstract:

A wide variety of methods and techniques with multiple characteristics are used in solving replenishment, production and distribution planning problems. Selecting a solution method (either a solver or an algorithm) when attempting to solve an optimization problem involves considerable difficulty. Identifying the best solution method among the many available ones is a complex activity that depends partly on human experts or a random trial-and-error procedure. This paper addresses the challenge of recommending a solution method for replenishment, production and distribution planning problems by proposing a decision-making tool for algorithm selection based on the fuzzy TOPSIS approach. This approach considers a collection of the different most commonly used solution methods in the literature, including distinct types of algorithms and solvers. To evaluate a solution method, 13 criteria were defined that all address several important dimensions when solving a planning problem, such as the computational difficulty, scheduling knowledge, mathematical knowledge, algorithm knowledge, mathematical modeling software knowledge and expected computational performance of the solution methods. An illustrative example is provided to demonstrate how planners apply the approach to select a solution method. A sensitivity analysis is also performed to examine the effect of decision-maker biases on criteria ratings and how it may affect the final selection. The outcome of the approach provides planners with an effective.

4.1 Introduction

The supply chain comprises different sequential activities, such as replenishment, production and distribution, which must all be planned and optimized. The main management function of companies is planning [1]. Planning activities aim to effectively coordinate and schedule a company's available resources [2]. Planning is accompanied by a set of decisions to be made by the planning manager; for example, a planner must make decisions about the quantity of materials needed for production by taking into account storage capacity and production batches to reduce production and inventory costs, production scheduling and sequencing on machines, and to finally make decisions about the delivery flow of finished products to customers or distribution centers [3].

Many real-world combinatorial optimization problems, such as those in transportation and logistics [4–6] and manufacturing [7–9], pose a huge challenge due to the high complexity of most companies' operations given the type of industry to which they belong. They are also subject to not only dynamic conditions, such as customer demands, processing times, returns on investment, but also to uncertainties, such as unavailability of items, changes in market conditions and shortages due to changes in demand [10].

Thus, planning problems seek to maximize profit or gain while minimizing costs and meeting market, environmental and societal constraints. For example, in supply planning problems, there is a direct relation between inventory costs and the costs associated with distribution planning, such as transportation costs and on-time delivery to customers [11]. Therefore, the difficulty of such problems is substantial due to the amount of data they handle [12], nonlinearities and discontinuities, complex constraints, possible conflicting objectives and uncertainty [13]. Hence different types of solvers are used to solve these problems, as are algorithms because of their computational difficulty [14].

Given the large number of algorithms for solving replenishment [15], production [16] and distribution planning problems [17], how to effectively select an algorithm for a given task or a specific problem is an important, but also difficult issue. Peres and Castelli [18] highlight that rules which standardize the formulations of existing combinatorial optimization problems (COP) in planning are lacking, which means that researchers have to start building an algorithm from scratch, which thus limits the interoperability of this field because the algorithms in the literature must be adjusted to solve a specific problem. These authors conclude that the consolidation of combinatorial optimization problems is lacking and note that this is important for the field of COPs to reach a higher degree of maturity.

The algorithm selection problem (ASP) is an active research area in many fields, such as operations research [19–21] and artificial intelligence (AI) [22, 23]. For many decades, researchers have developed increasingly sophisticated techniques and algorithms to solve difficult optimization problems [18]. These techniques include mathematical programming approaches, heuristics, metaheuristics, nature-inspired metaheuristics, matheuristics and various hybridizations [24]. Literature reviews such as that presented by Jamalnia et al. [25], who reviewed the aggregate production planning problem under uncertainty between 1970 and 2018, detailed the use of approximately 24 different techniques to solve this type of problem out of 92 reviewed papers. Kumar et al. [26] presented a literature review covering the period from 2000 to 2019 of the quantitative approaches used to solve production and distribution planning problems. They found 13 different techniques and types of solvers, including CPLEX and LINGO, to solve this type of problem out of 74 papers. Pereira et al. [27] analyzed the tactical sales and operations planning problem. To do so, they reviewed 103 papers, where the year was not limited. They detailed about 35 different techniques to solve this type of problem. Hussain et al. [28] conducted a literature review of the applications of metaheuristic algorithms and found 140 different metaheuristic algorithms in 1222 publications over a 33-year search period (1983 to 2016).

Different research papers have conducted experimental studies to determine the performance of an algorithm [29–32] or several algorithms according to a problem type with a collection of datasets available in the literature [33–35]. For example, Pan et al. [36] compared three constructive heuristics and four metaheuristics (discrete artificial bee colony, scatter search, iterated local search, iterated greedy algorithm) for the distributed permutation flowshop problem, for which they made extensive comparative evaluations based on 720 instances. However, these comparisons do not provide any enlightening results because they are generally limited to a set of algorithms and to a specific problem set [24].

In practice, algorithm performance vastly varies from one problem state to another. In many cases, heuristic [37], metaheuristic [28] and matheuristic [38] techniques involve randomization, such as genetic algorithm, particle swarm optimization, bee swarm optimization, bat algorithm, artificial tribe algorithm and firefly algorithm [39–43], which results in performance variability, even across repeated trials in a single problem instance [44]. Risk is an important additional feature of algorithms because the planner or the person in charge of selecting an algorithm for planning must be willing to settle for average or lower performance in exchange for a reasonable answer or may also find a better solution than that expected in the same resolution time. This situation is often encountered in companies that attempt to maximize their profits because these problems are solved by constructing mixed strategies, i.e. strategies that meet the desired risk and return.

Nowadays if a study demonstrates the superiority of one algorithm over other algorithms, that algorithm can be expected to be useful for other problem types for which it has not yet been tested. No-free-lunch (NFL) theorems [45] describe that there is no single algorithm that outperforms all algorithms in all the instances of a problem [24].

Therefore, the selection of the most suitable algorithm to solve an optimization problem for replenishment, production and distribution planning is a very difficult task. Algorithm selection requires advanced knowledge of the efficiency of algorithms, the characteristics of the problem, as well as mathematical and statistical knowledge. However, having the necessary knowledge to find a solution with algorithms does not guarantee success [46].

Algorithm selection depends mainly on the expected results and the data that the company has at the time. Therefore, the properties or characteristics of the business problem must be examined. For this purpose, the linearity of the problem, the number of parameters and the characteristics that the solution supports must be analyzed.

Evaluating algorithms to solve a problem usually involves more than one criterion, such as problem type, problem knowledge, performance, computation time, the quality of the expected solution and programming knowledge. Therefore, algorithm selection can be modeled as a multicriteria decision-making problem [22].

The objective of multicriteria decision making (MCDM) is to identify the most eligible alternatives from a set of alternatives based on qualitative and/or quantitative criteria with different units of measurement to select or rank them [47]. Different techniques such as AHP, ELECTRE, PROMETHEE, SAW, TOPSIS and VIKOR are used to solve MCDM problems [3]. Several studies have been conducted to compare the performance of these techniques; for example, that presented by Zanakis et al. [48], which compared eight MCDM techniques (four variations of AHP, ELECTRE,TOPSIS and SAW). It concluded that different techniques are affected mainly by the number of alternatives because as alternatives increase, methods tend to generate similar final rankings. Opricovic and Tzeng [49] performed a comparative analysis of the VIKOR and TOPSIS methods. Both these methods are based on an aggregation function that represents the closeness to the ideal. The study revealed that the main differences between the two methods were the employed normalization method types.

Opricovic and Tzeng [50] compared the extended VIKOR method to ELECTRE II, PROMETHEE and TOPSIS. The obtained results showed that ELECTRE II, PROMETHEE and VIKOR gave similar results, while TOPSIS presented different results in some alternatives. Chu et al. [51] made a comparison of the VIKOR, TOPSIS and SAW methods. The study revealed that SAW and TOPSIS presented similar classifications, while VIKOR presented different results. These authors concluded that VIKOR and TOPSIS provided results that were close to reality. Ozcan et al. [52] presented a comparative analysis of the TOPSIS, ELECTRE and Grey Theory techniques for the warehouse location selection problem, where the Grey Theory provided different results to TOPSIS and ELECTRE. Instead, the last two obtained similar results.

In situations in which information is not quantifiable or incomplete, as in real-world problems where data may be incomplete or imprecise, i.e., nondeterministic, data can be represented in a fuzzy way using linguistic variables to represent decision makers' preferences in complex or not well-defined situations. Imprecision in MCDM problems can be modeled using the fuzzy Set Theory, which is used to extend different MCDM techniques. In this background, Ertuğrul and Karakaşoğlu [53] conducted a comparative study of the fuzzy AHP and fuzzy TOPSIS methods for the facility location selection problem. Both methods obtained the same results, i.e., the same rank order of alternatives.

Other studies have used an extension of the classical fuzzy set called the intuitionistic fuzzy set, as proposed by Atanassov [54]. Intuitionistic fuzzy sets have been applied in many fields, such as facility location selection [55], supplier selection [56], evaluation of project and portfolio management information systems [57, 58], and personnel selection [59]. Büyüközkan and Güleryüz [60] compared the performance of ranked fuzzy TOPSIS and intuitionistic fuzzy TOPSIS by detailing how the alternatives ranking barely differed between the two approaches.

From the above comparisons, it is clear that many techniques are available for multi-criteria decision making [61]. These techniques have their advantages and limitations over others depending on the type of problem [62].

Different MCDM techniques have been used for the classification algorithm selection problem, such as the study by Lamba et al. [63] in which TOPSIS and VIKOR were used to evaluate 20 classification algorithms. Both methods obtained similar results. Peng et al. [22] used four different MCDM techniques (TOPSIS, VIKOR, PROMETHEE II and WSM) to select multiclass classification algorithms. The TOPSIS, VIKOR and PROMETHEE II methods achieved similar classifications, while WSM obtained slightly different ones. Peng et al. [64] evaluated ranking algorithms for financial risk prediction purposes. Using TOPSIS, PROMETHEE and VIKOR, they obtained similar results for the three main ranking algorithms. They concluded that the followed techniques were advantageous for choosing a classification algorithm.

Along these lines, TOPSIS stands out as a widely used technique that is efficient for selecting classification algorithms. It has been successful in different areas such as supply chain and logistics management, environment and energy management, health and safety management, business and marketing management, engineering and manufacturing, human resource management and transportation management [47, 65–67] and, according to Chu et al. [51], is able to represent reality. It is also useful for companies because it can be run with a spreadsheet [68]. For all these reasons and given the fact that the choice of a solution method is subject to vagueness and uncertainty, we use the fuzzy TOPSIS method.

In this context, the present paper aims to answer this question: which solution method is suitable for a replenishment, production and distribution planning problem given a portfolio of algorithms or solvers?

To answer this question, and by taking into account that no research to date has analyzed the selection of algorithms for planning with a multicriteria decision method, a decision-making tool to select algorithms for a planning problem based on fuzzy TOPSIS is presented. To validate the use of the tool herein proposed, an illustrative example is presented, which has been validated by four different manufacturing companies. This paper is organized as follows. Section 4.2 deals with the literature review. The adopted methodology is shown in Section 4.3 and the numerical application of the methodology is presented in Section 4.4. The sensitivity analysis of the results is provided in Section 4.5. Finally, Section 4.6 includes the conclusions and future research lines.

4.2 Algorithm selection problem literature review

Algorithm selection has been widely addressed by the scientific community in both the mathematics [69, 70] and Artificial Intelligence (AI) [71, 72] areas. In the mathematical area, Stützle and Fernandes [73] report how the characteristics of problem instances make the performance of metaheuristics relative to the properties of instances. Therefore, it is necessary to explore the relation between algorithms and instances. In the AI area, different models have been developed to predict which algorithm is the best one for a problem instance, which is conducted by analyzing the relation between the characteristics of an instance and a set of training data used by an algorithm. In this way, with an algorithms portfolio it is possible to predict which algorithm in a new problem instance is most likely to work [74].

Growing interest has been shown in the ASP to put previously developed algorithms to best use to solve a specific problem instead of developing new ones [75]. According to Leyton-Brown et al. [76], some algorithms are better than others on average, and there is rarely a best algorithm for a given problem. Instead "it is often the case that different algorithms perform well on different problem instances. This phenomenon is most pronounced among algorithms for solving NP-Hard problems, because runtimes for these algorithms are often highly variable from instance to instance". In this context, Rice [77] proposes the first description of methodologies to select algorithms. Kotthoff [75] defines this as the "task of algorithm selection involves choosing an algorithm from a set of algorithms on a per-instance basis in order to exploit the varying performance of algorithms over a set of instances".

In this regard, algorithm selection approaches have been successfully applied in different problem domains [78]. The following table summarizes a literature review of the various papers that have approached ASP from different perspectives (Table 4.1).

Table 4.1. Research studies addressing the algorithm selection problem.

Author	Proposal
Lagoudakis and Littman [79]	Algorithm selection using reinforcement learning.
Xu et al. [80]	A scalable and completely automated portfolio construction. The authors improve the ASP methodology by integrating local search solvers as candidate solvers by predicting performance scores instead of runtime, and by using hierarchical hardness models that take into account different types of instances.
Smith-Miles [81]	A unified framework to take the algorithm selection problem as a learning problem and to use this framework to tie together cross-disciplinary developments in tackling the algorithm selection problem. The authors generalize metalearning concepts to algorithms that focus on tasks, including sorting, forecasting, constraint satisfaction and optimization.

Table 4.1. Continued. Research studies addressing the algorithm selection problem.

Author	Proposal
Bischl et al. [35]	An algorithm selection problem as a cost-sensitive classification task that is based on an Exploratory Landscape Analysis.
Hoos et al. [82]	A modular open-solver architecture that integrates several different portfolio-based algorithm selection approaches and techniques.
Kotthoff [75]	An algorithm selection for combinatorial search problems.
Tierney and Malitsky [83]	An algorithm selection benchmark based on optimal search algorithms to solve the container premarshalling problem (CPMP), an NP-hard problem from the container terminal optimization field.
Cunha et al. [84]	A metalearning method is used to select the best recommendation algorithms within different scopes to allow to understand the relations between data characteristics and the relative performance of recommendation algorithms, which can be used to select the best algorithm(s) for a new problem. This work analyzes the algorithm selection problem for Recommender Systems by focusing on Collaborative Filtering.
Bożejko et al [85]	A local and optima network analysis and machine learning is used to select appropriate algorithms on an instance-to-instance basis.
Drozdov et al [86]	Graph convolutional network-based generative adversarial networks for the algorithm selection problem in classification terms.
Vilas Boas et al. [87]	Integer programming-based approaches to build decision trees for the algorithm selection problem. These techniques allow the automation of three crucial decisions by discerning the most important problem features to determine problem classes by grouping problems into classes, and then selecting the best algorithm configuration for each class.
Marrero et al. [88]	An efficient parallel genetic algorithm (GA) is proposed as a first step to solve the algorithm selection problem. GA is able to attain competitive results in optimal objective value terms and in a short time. The computational results show that the approach is able to efficiently scale and considerably reduce the average elapsed time to solve Knapsack Problem (KNP) instances.
De Carvalho et al. [21]	A cross-domain evaluation for multi-objective optimization. The authors investigate how four state-of-the-art online hyperheuristics with different characteristics perform to find solutions for 18 real-world multi-objective optimization problems. These hyperheuristics were designed in previous studies and tackle the algorithm selection problem from different perspectives: election-based, based on Reinforcement Learning and based on a mathematical function.

In manufacturing environments, formulations are usually very complex [78] because they present a variety of specific constraints related to the company's scope. Generally, these formulations can serve as blocks or subproblems for other formulations of other specific manufacturing environments. In this way, many formulations or algorithms can obtain similar results to the formulations proposed above. When selecting a formulation or algorithm, tuning the parameters of the different techniques is a very demanding task because each algorithm has different characteristics and the number of times that a parameter tuning has to be performed against different instances of a problem when performing a comparison can exponentially grow [33]. Furthermore, to compare algorithms and select one, the feature set of the instances must be taken into account because the characterization of instances determines a solution approach's performance. In practice, the information needed to establish the characteristics is not always available [89], and experimental results may lead to the fact that there is no single best or worst algorithm for all problem instances [46]. In this context, and as shown in Table 4.1, several approaches have been proposed to address the algorithm selection challenge, including heuristic algorithms, metaheuristics, hybrid metaheuristics, hyperheuristics, and machine-learning techniques. Many of these approaches integrate similarities, such as using a set of instances to learn, measuring or predicting the performance of the best algorithm. The success of algorithm selection approaches for some problem domains has motivated us to develop a decision-making tool to support planners of companies to select a solution method (algorithm or a solver) for replenishment, production and distribution planning problems.

4.3 Solution methodology

For combinatorial optimization problems with realistic discrete decision variables, such as scheduling, sequencing, distribution and transportation planning problems, performing an exhaustive search space for this problem type is not a realistic option despite having a finite search space. The literature includes several heuristic, metaheuristic and matheuristic algorithms, as well as tests with commercial and non-commercial high-performance solvers to solve such problems. So, this question arises: which algorithm is to be chosen for a combinatorial optimization problem?

Generally one way of finding an algorithm to solve a combinatorial optimization problem is to exhaustively run all the available algorithms and choose the best solution [90]. However, this method requires unlimited computational resources and companies have limited computational, programming and mathematical resources, which makes it impossible to test all the algorithms or to use several solvers to test one instance or several for a specific problem. Weise et al. [12] emphasize that there is a variety of methods to solve different types of problems with acceptable performance, but they can be outperformed by very specialized methods.

Weise et al. [12] consider that there is no optimization method that is better or can outperform others, and the NFL Theorem [45] corroborates this theory. This theorem states that no optimization algorithm is likely to outperform several existing types of methods in different types of problems.

In turn, the same authors mention that the efficiency of an optimization algorithm is based on knowledge of a problem. Radcliffe [91] emphasizes that the algorithm's performance will improve with adequate knowledge of the problem. However, knowledge of one type of problem can be misleading for another type of problem [89] because there is no algorithm that outperforms others in all instances of a problem. Therefore, an algorithm's performance will be based on experience and empirical results.

Algorithm selection schemes are based mainly on approaches that either run a sequence of algorithms in a limited execution time [80, 82] or predict the performance of an algorithm for a given instance and select the algorithm with the best predicted performance [92].

Real-world planning problems are subject to inaccuracies and uncertainties, conflicts between constraints and objectives, discontinuities and nonlinearities [13]. Therefore, determining which algorithm is appropriate poses a challenge that can be analyzed using a multicriteria decision technique for ranking and prioritizing algorithms because algorithm selection involves multiple decisions that require the simultaneous assessment of the various advantages and disadvantages.

In most companies, the complexity of operations has several components that must be addressed at the same time. Evaluating an algorithm to solve a problem often involves more than one criterion, such as problem type, problem knowledge, performance, computation time, the quality of the expected solution and programming knowledge.

MCDM techniques integrate different criteria and an order of preference to evaluate and select the optimal option among multiple alternatives based on the expected outcome. The objective of these techniques is to obtain an ideal solution to a problem in which a decision makers' experience does not allow them to decide among the various considered parameters. As a result, a ranking is obtained according to the selected criteria, their respective values and the assigned weights [93].

There are many criteria in real-life problems that can directly or indirectly affect the outcome of different decisions. Decision making often involves inaccuracies and vagueness that can be effectively dealt with using fuzzy sets. This method is especially important for clarifying decisions that are difficult to quantify or compare, especially if decision makers have different perspectives, as in this study. Therefore, we herein adopt the fuzzy TOPSIS methodology to model an algorithm or solver selection given a solution methods portfolio to solve replenishment, production and distribution planning problems.

In decision making problems, the Fuzzy Set Theory was introduced by Zadeh [94] to overcome the ambiguity and uncertainty of human thought and reasoning by using linguistic terms to represent decision makers' choices.

The TOPSIS method was originally proposed by Hwang and Yoon [95]. It is based on choosing an alternative that should have the shortest distance between the positive ideal solution (PIS) and the negative ideal solution (NIS), i.e., the selected alternative is obtained with the closest solution to the PIS and is farthest away from the NIS. The main limitation of this technique is that it cannot capture ambiguity in the decision making process [96]. To overcome this limitation, Chen [97] developed the Fuzzy TOPSIS Method to quantitatively evaluate the score of different alternatives by conferring weight to the different criteria described with linguistic variables. This section briefly describes the employed Fuzzy Set Theory and Fuzzy TOPSIS Method.

4.3.1 Fuzzy Set Theory and fuzzy numbers

The Fuzzy Set Theory [94, 98, 99] is associated with the TOPSIS method, and are related to another by the degree of membership of the elements in fuzzy sets. A fuzzy set is characterized by the membership function, which can come in different formats, e.g. triangular, sigmoid or trapezoidal. The membership function assigns a degree of membership to each object according to its relevance $\mu_A(x): x \rightarrow [0.0, 1.0]$. To represent a fuzzy set, a tilde '~' is placed [68].

For our study, we consider a triangular fuzzy number, $\tilde{A}$, which is denoted by its vertices *(l, m, u*), as shown in Figure 4.1. Triangular fuzzy numbers are used to adapt decision makers' preference to capture the vagueness of linguistic evaluations, where *l, u* and m respectively, denote the lower bound, the upper bound and the crisp central value.

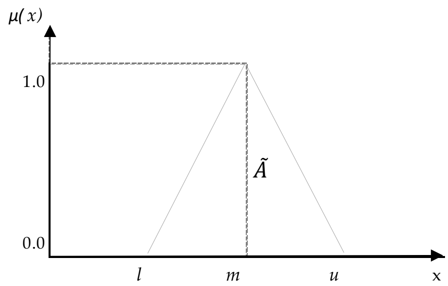

Figure 4.1. Fuzzy triangular number.

Membership function d of triangular fuzzy number $\tilde{A}$ is defined as:

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-l}{m-l}, & l \leq x \leq m, \\ \dfrac{u-x}{u-m}, & m \leq x \leq n, \\ 0, & otherwise \end{cases} \tag{1}$$

where $\tilde{A} = (l_A, m_A, u_A)$ and $\tilde{B} = (l_B, m_B, u_B)$ are two triangular fuzzy numbers with bases *l, m, u.* Then, the basic operational laws for triangular numbers are defined as:

$$\tilde{A}\,(+)\,\tilde{B} = (l_A, m_A, u_A)\,(+)\,(l_B, m_B, u_B) = (l_A + l_B, m_A + m_B\,, u_A + u_B) \tag{2}$$

$$\tilde{A}\,(-)\,\tilde{B} = (l_A, m_A, u_A)\,(-)\,(l_B, m_B, u_B) = (l_A - l_B, m_A - m_B\,, u_A - u_B \tag{3}$$

$$\tilde{A}\,(\times)\,\tilde{B} = (l_A, m_A, u_A)\,(\times)\,(l_B, m_B, u_B) = (l_A \times l_B, m_A \times m_B\,, u_A \times u_B)\,for\ l_A\,, l_B > 0\,;\ m_A\,, m_B > 0;\ u_A\,, u_B > 0 \tag{4}$$

$$\tilde{A}\,(\div)\,\tilde{B} = (l_A, m_A, u_A)\,(\div)\,(l_B, m_B, u_B) = \left(\frac{l_A}{u_B}, \frac{m_A}{m_B}, \frac{u_A}{l_B}\right) for\ l_A\,, l_B > 0\,;\ m_A\,, m_B > 0;\ u_A\,, u_B > 0 \tag{5}$$

$$k\tilde{A} = kl_A, km_A, ku_A \tag{6}$$

$$\tilde{A}^{-1} = (l_A, m_A, u_A)^{-1} = \left(\frac{1}{u_A}, \frac{1}{m_A}, \frac{1}{l_A}\right) \text{ for } l_A\,, l_B > 0\,;\ m_A\,, m_B > 0;\ u_A\,, u_B > 0 \tag{7}$$

By assuming that fuzzy numbers $\tilde{A}$ and $\tilde{B}$ are real numbers, then the distance measure is identical to the Euclidean distance. Therefore, the vertex method is defined to calculate the distance between two fuzzy numbers (see Equation 8). Although there are several ways of measuring distances between fuzzy numbers [100], the vertex method is a simple and efficient method [97, 101].

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3}[(l_A - l_B)^2 + (m_A - m_B)^2 + (u_A - u_B)^2]} \tag{8}$$

4.3.2 The Fuzzy TOPSIS Method

The main fuzzy TOPSIS idea is based on defining the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS). The chosen alternative should have the shortest distance to the FPIS and the farthest distance to the FNIS. TOPSIS follows a systematic process and logic that seek to express the logic of human choice [102]. The basic fuzzy TOPSIS method steps are described in the following way (see [97, 103, 104]):

Step 1. Consider a set of k decision makers ($D_1, D_2,..., D_k$) with m alternatives ($A1, A2,..., An$) and n criteria ($C1, C2,..., Cn$) for which the decision matrix is established:

$$\widetilde{D} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} \tilde{X}_{11} & \tilde{X}_{12} & \dots & \tilde{X}_{1n} \\ \tilde{X}_{21} & \tilde{X}_{22} & \dots & \tilde{X}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{X}_{n1} & \tilde{X}_{n2} & \dots & \tilde{X}_{nm} \end{bmatrix} \end{array} \; i = 1,2,\dots,m; \; j = 1,2,\dots,n \tag{9}$$

$$\widetilde{W} = [\widetilde{w}_1, \widetilde{w}_2, \dots, \widetilde{w}_n]$$

Considering that the perception of algorithms and solvers varies according to knowledge and experience with algorithms for planning, the average value method is applied; where $\tilde{x}_{ij}^{k}$ is the rating or score of the alternative A_i in relation to criterion C_j evaluated by the K-th decision maker (Equation 10). The weights of criteria are aggregated using Equation 11, where $\widetilde{w}_j^{k}$ describes the weight of each criterion C_j according to decision makers D_k.

$$\tilde{x}_{ij} = \frac{1}{k}\left(\tilde{x}_{ij}^{1} + \tilde{x}_{ij}^{2} + \dots + \tilde{x}_{ij}^{k}\right) \tag{10}$$

$$\widetilde{w}_j = \frac{1}{k}\left(\widetilde{w}_j^{1} + \widetilde{w}_j^{2} + \dots + \widetilde{w}_j^{k}\right) \tag{11}$$

Step 2. Normalize the fuzzy decision matrix. Decision matrix $\widetilde{D}$ with m alternatives and n criteria is normalized to eliminate inconsistencies with the different units of measurement or scales to preserve the ranges of the normalized triangular fuzzy numbers. $\tilde{R}$ represents the normalized decision matrix (Equation 12):

$$\tilde{R}_j = \left[\tilde{r}_{ij}\right]_{m \times n}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \tag{12}$$

The normalization process is performed by Equations 13 and 14, where B and C represent the set of benefit and cost criteria, respectively.

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{ij}{u_j^+}, \frac{u_{ij}}{u_j^+}\right), \text{and } u_j^+ = max_i u_{ij} \ if \ j \in B \quad (13)$$

$$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right), \text{and } l_j^- = min_i l_{ij} \ if \ j \in C \quad (14)$$

Step 3. Construct the weighted normalized fuzzy decision matrix $\tilde{V}$(Equation 15). $\tilde{v}_{ij}$ is obtained by multiplying the weights of criteria $\tilde{w}_j$ and the normalized fuzzy decision matrix $\tilde{r}_{ij}$ values:

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m\times n}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (15)$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \times \tilde{w}_j \quad (16)$$

Step 4. Obtain the FPIS (FPIS, A^+) and the FNIS (FNIS, A^-), as shown in Equation 17 and Equation 18, respectively. The ideal solutions can be defined according to Chen [97] as: $\tilde{v}_j^+ = (1, 1, 1)$ and $\tilde{v}_j^- = (0, 0, 0)$

$$A^+ = \{\tilde{v}_1^+, \tilde{v}_j^+, \dots, \tilde{v}_m^+\} \quad (17)$$

$$A^- = \{\tilde{v}_1^-, \tilde{v}_j^-, \dots, \tilde{v}_m^-\} \quad (18)$$

Step 5. Calculate the distances for each alternative, where D_i^+ indicates the distance between the scores of alternative A_i to the FPIS (Equation 19), and D_i^- denotes the distances between the values of alternative A_i to the FNIS (Equation 20), where $d(\tilde{v}_a, \tilde{v}_b)$ represents the distance between two fuzzy numbers.

$$D_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), \ i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (19)$$

$$D_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-), \ i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (20)$$

Step 6. Determine proximity coefficient CC_i, which evaluates the rank order of all the alternatives A_i according to their overall performance. The proximity coefficient is calculated as shown in Equation 21.

$$CC_i = \frac{D_i^-}{(D_i^+ + D_i^-)} \quad (21)$$

Step 7. Rank alternatives A_i, using a decreasing order of CC_i values, the shortest distances from the FPIS, i.e. close to 1, to indicate that the overall performance of alternative A_i is better because it is farther away from the FNIS. Having obtained the ranking order, decision makers select the most feasible alternative A_i.

4.4 The methodological approach for algorithm selection problem

This paper employs a three-stage methodology to select an algorithm or solver to solve a replenishment, production and distribution planning problem (see Figure

4.2). The objective of this section is to present a numerical analysis to demonstrate the performance of the proposed methodology.

The three stages of the proposed methodology are described in the following subsections.

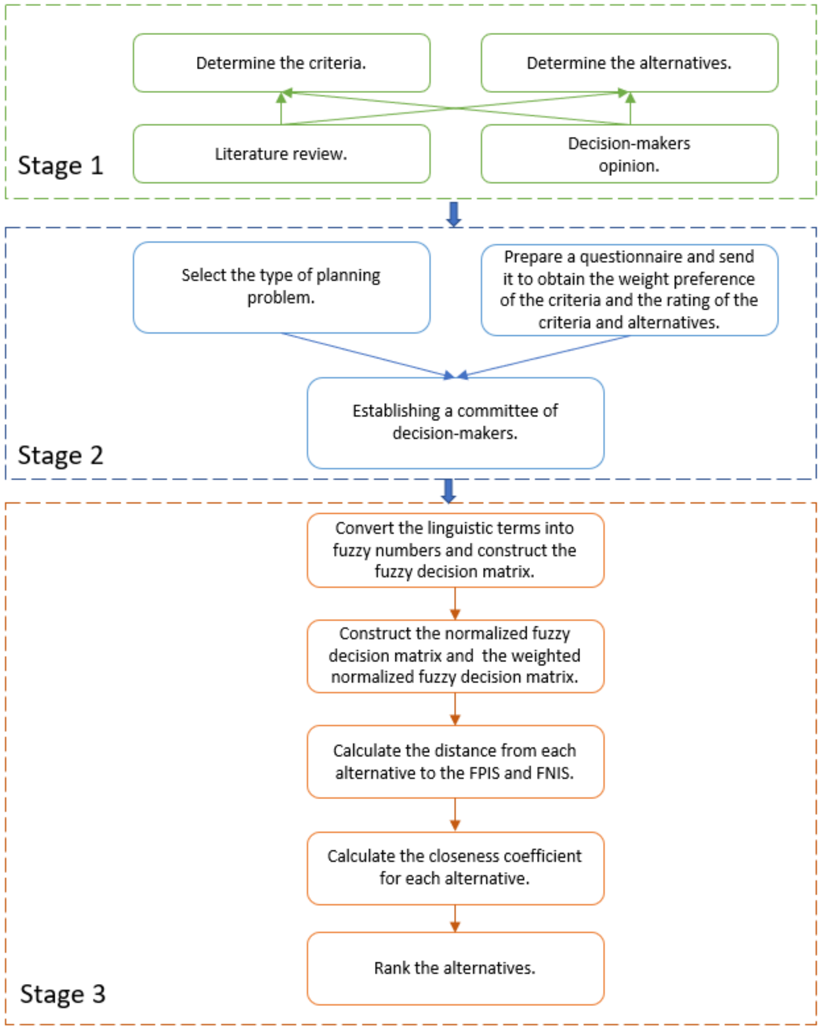

Figure 4.2. A methodological approach for algorithm selection problem.

4.4.1 Stage 1 - Define criteria and alternatives

We first identify the different criteria that are taken into account when selecting a solution method; these criteria can be identified in the literature and are based on the opinion of experts in the field [105]. According to each identified criterion, the decision maker evaluates the suitability of a solution method for the type of problem; that is, how algorithms or solvers can be suitable and formulated for a given problem.

In this research, 13 criteria are identified based on an exhaustive review of the literature (see [8, 18, 25, 27, 106, 107]) and the assessments of experts in the field of operations research. These criteria are presented in Table 4.2.

Table 4.2. Criteria for algorithm selection.

Id	Criteria	Definition
C1	Problem type	The replenishment (source), production (make) and distribution (deliver) planning problem type is determined by the SCOR (Supply Chain Operation Reference) methodology [106, 108] (see Figure 4.3). Each problem type has its own characteristics and computational difficulty. According to Weise et al. [12], it is very difficult to make accurate estimates of a problems' computational performance because a solution method's performance will almost always depend on experience, the empirical results based on related research areas and the rules of thumb established for these problems. So a problem's computational performance depends on different factors. Some of the main factors of a problem's complexity are: problem size, linearity, variables and presence of constraints [109]. Based on these considerations, criteria C2-C7 are proposed.
C2	Equation type	It expresses the equations present in the problem. These equations can be linear or non linear.
C3	Variable type	It represents the elements to be modeled. Variables can be integer, binary and continuous. Planning problems generally contain a combination of variables: Continuous + Integer, Integer + Binary, Continuous + Binary, Continuous + Integer + Binary. These combinations normally generate greater computational difficulty. Each combination can generate a different behavior for the solution method because algorithm or solver performance is linked with the amount of resources used. These resources can be: amount of memory, processing time to deal with each type of variable [12].
C4	Number of instantiated variables	It determines the number of variables present in a problem, which is a determining factor when establishing the expected response time to obtain an answer.

Table 4.2. Continued. Criteria for algorithm selection.

Id	Criteria	Definition
C5	Type of constraints and solutions	The constraint type determines the computational difficulty that the problem will have because constraints express limitations of resources. Some constraints can be expressed as follows: decision >= data (e.g. production >= demand) decision <= data (e.g. load <= capacity) decision == data (e.g. production >= demand) decision >= decision (e.g. production of A >= production of B) decision <= decision (e.g. load of M <= load of N) decision == decision (e.g. inventory A == inventory B) continuity equations of some variables (e.g. Inventory == Inventory prior period + Production - Demand) One factor that affects a problem's difficulty is when the expected solutions to the problem contain a route or sequence. These routing planning or sequencing problems are generally NP-hard [110, 111].
C6	Number of constraints	The number of constraints contained in a problem can be a limiting factor for establishing the problem's difficulty. Therefore, the evaluator analyzes whether the set of constraints can be adapted to an algorithm or to a solver.
C7	Dataset size	When representing the problem input data size, a problem's computation is directly related to the amount of data.
C8	Programming knowledge	Programming knowledge is a determining factor when selecting an algorithm because it determines decision makers' ability to program one algorithm or several algorithms when having to test different algorithms in the hope to obtain a solution that meets the company's needs.
C9	Mathematical knowledge	Mathematical knowledge is important when choosing whether to express the problem as a mathematical model or to directly choose an algorithm. Algorithms generally require certain mathematical knowledge.
C10	Knowledge of algorithms	One aspect to take into account in companies is knowledge of the different algorithms.

Table 4.2. Continued. Criteria for algorithm selection.

Id	Criteria	Definition
C11	Software	This criterion is considered if the company has mathematical modeling software, but is not considered if the company does not. If the company has specific optimization software, the decision maker defines the scope of its performance against each alternative to solve a planning problem.
C12	Quality of solutions	This criterion establishes the quality of the expected solutions to the problem. These solutions can be optimal, near-optimal or good.
C13	Calculation time	The computation time sets the amount of expected time to obtain a solution for the problem.

Second, we identify the portfolio of solution methods (alternatives). This portfolio is composed of a set of nine algorithms and four solvers, identified as the most commonly used ones in the planning problems reported in [107, 112]. Alternatives are divided between different algorithm types, which are:

- Heuristic algorithms (HA). They are used when solvers or exact techniques cannot reach solutions in acceptable computation times. These techniques do not provide optimal solutions, but can offer solutions that come very close to the optimum in acceptable computation times [113];
- Metaheuristic algorithms (MA). According to Swan et al. [114], these techniques are: "an iterative master process that guides and modifies the operations of subordinate heuristics to efficiently produce high-quality solutions. At each iteration, it manipulates either a complete (or partial) single solution or a collection of such solutions";
- Matheuristic algorithms (MTA). They combine mathematical programming techniques and heuristic or metaheuristic algorithms [115].

The alternatives in this classification are A1 - HA/Benders decomposition, A2 - HA/LP and Fix, A3 - HA/LP Relaxation, A4 - MA/Tabu Search, A5 - MA/Genetic Algorithm, A6 - MA/Simulated annealing, A7 - MA/Variable Neighborhood Search, A8 - MTA/ Genetic Algorithm + Mathematical Model, A9 - MTA/Simulated annealing + Mathematical Model. Different solver types used to solve planning problems are also considered. For this purpose, commercial and non-commercial solvers are identified to deal with mathematical models with linear and nonlinear equations. These are: A10 - CPLEX (Commercial), A11 - CBC (Non-Commercial), A12 - BONMIN (Non-Commercial - NonLinear), A13 - LINDO (Commercial – Linear /NonLinear).

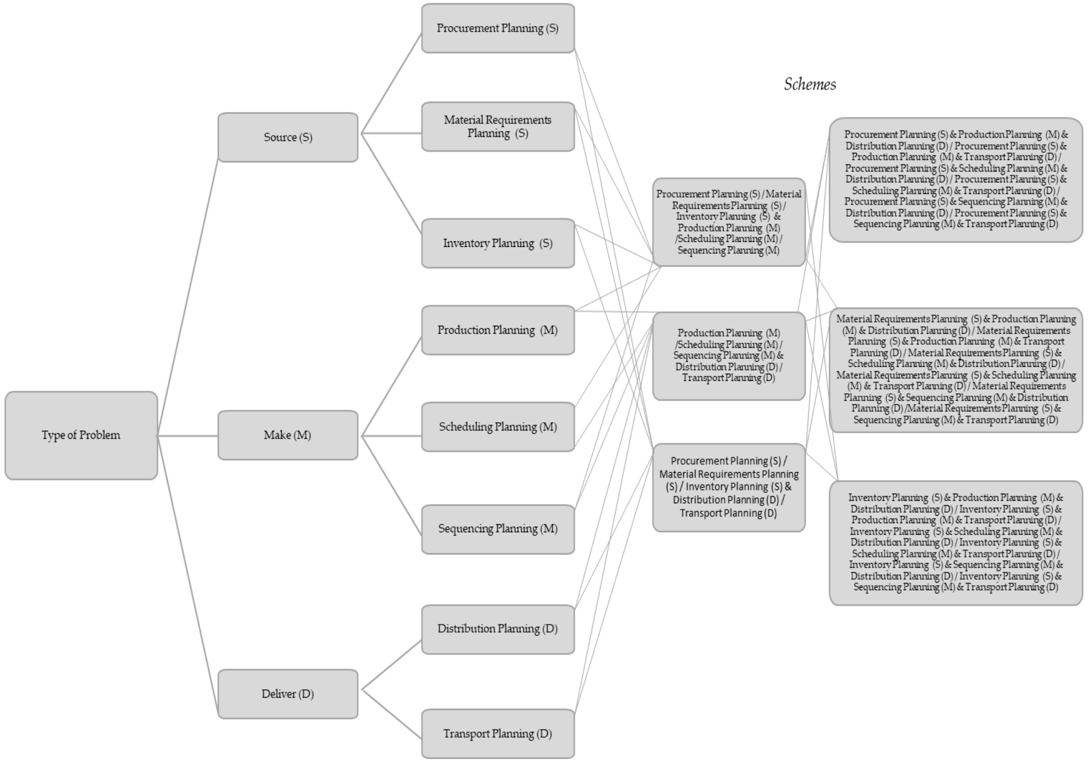

Figure 4.3. Replenishment, production and distribution planning problem types.

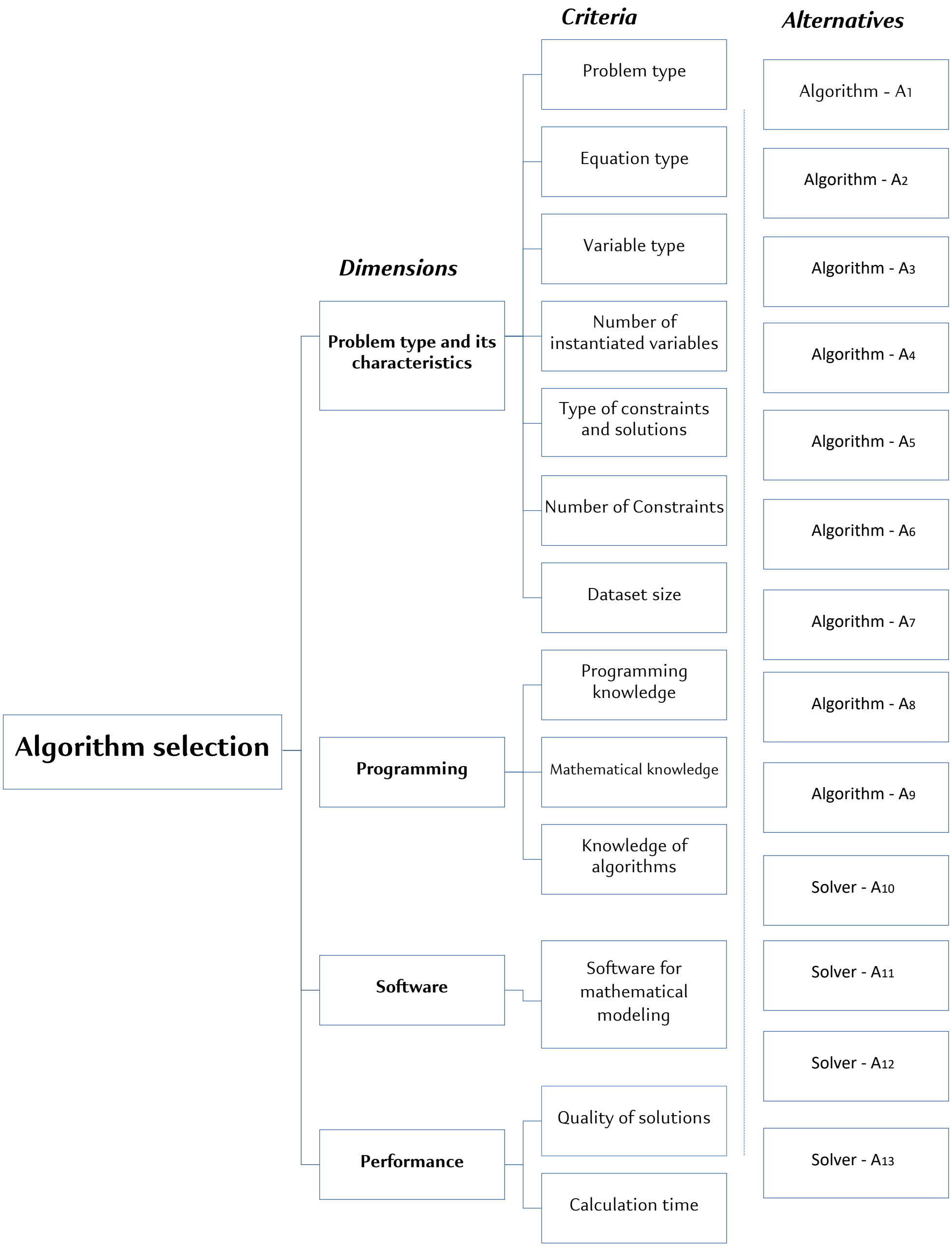

Figure 4.4. Hierarchical structure for algorithm selection.

The hierarchical structure that has been defined and constructed to assist in the process of selecting an algorithm or solver is shown in Figure 4.4. This structure is composed of four layers: the first one corresponds to the objective of this study; the second structure corresponds to the characterization of the different dimensions that have been proposed, which is composed of four dimensions (the problem type and its characteristics, programming knowledge, the software and the expected performance of algorithms or solvers); in the third layer comes the categorization of the 13 identified criteria; in the last one, methods or solution alternatives appear. The correlation between layer 3 and 4 is related to the performance of an algorithm or a solution method.

4.4.2 Stage 2 - Problem statement

In this stage, the type of planning problem to be addressed was defined, for which four expert decision makers working in different manufacturing companies in the planning area were invited to propose a planning problem. The decision makers proposed that the problem to be studied should be a production planning problem falling within the make classification, as shown in Figure 4.3.

Once the problem type has been defined, a questionnaire is developed to obtain the weight of preference of criteria and to thus evaluate alternatives according to the criteria. To devise the questionnaire, it is necessary to construct a fuzzy linguistic scale.

Linguistic scales are used to transform linguistic terms into fuzzy numbers [96]. Linguistic terms are subjective categories of the linguistic variable [116]. Zadeh [117] introduced the linguistic variable concept. A linguistic variable is a variable whose values allow computation with words instead of numbers [118]. Linguistic variables are used to represent decision makers' assessments, estimates and subjectivity [119].

To evaluate the criteria, we use a scale between 0 and 1. To rate the alternatives, we employ a scale from 0 to 10 [97]. The linguistic scales that evaluate the weights of the criteria and alternatives are shown in Table 4.3.

Table 4.3. Linguistic scales to assess the criteria and alternatives (Chen [97]).

Linguistic expression for rating alternatives (algorithms)				***Linguistic variable for the relative importance weight of criteria***			
Linguistic expression	***l***	***m***	***u***	**Linguistic expression**	***l***	***m***	***u***
Very Low (VL)	0.1	0.1	2.5	Very Low Importance (VLI)	0.01	0.03	0.25
Low (L)	0.1	2.5	5.0	Low Importance (LI)	0.01	0.25	0.50
Moderate (M)	2.5	5.0	7.5	Medium Importance (MI)	0.25	0.50	0.75
High (H)	5.0	7.5	10.0	High Importance (HI)	0.50	0.75	1.00
Very High (VH)	7.5	10.0	10.0	Very High Importance (VHI)	0.75	1.00	1.00

Finally, decision makers were invited to review the questionnaire and to check its content. Based on this review, we were able to adjust the questionnaire.

In this same stage, we invited the four decision makers who worked in the planning area to evaluate the alternatives and to determine the weights of the criteria. For this purpose, we asked the decision makers to use the linguistic scale described in Table 4.3. An extract of the questionnaires used by the decision makers is shown in Table A1 and A2.

Table 4.4 details the fuzzy weights of each criterion based on the linguistic scales selected by the decision makers. The decision makers' ratings of the alternatives against all criteria are shown in Tables A3-A6.

Table 4.4. Decision makers' linguistic assessment of the criteria.

	D1	**D2**	**D3**	**D4**
C1	MI	MI	MI	MI
C2	LI	LI	LI	LI
C3	VHI	VHI	VHI	VHI
C4	HI	HI	HI	HI
C5	LI	LI	LI	LI
C6	HI	MI	MI	MI
C7	HI	VHI	VHI	MI

Table 4.4. Continued. Decision makers' linguistic assessment of the criteria.

	D1	D2	D3	D4
C8	LI	MI	HI	HI
C9	LI	MI	HI	HI
C10	MI	MI	LI	HI
C11	LI	LI	LI	LI
C12	VHI	VHI	VHI	VHI
C13	VHI	VHI	VHI	VHI

4.4.3 Stage 3 - Application of the Fuzzy TOPSIS Method

In this stage, the Fuzzy TOPSIS Method is used to analyze the different alternatives in relation to the identified criteria. The process used to apply the Fuzzy TOPSIS Method consists of five steps, which are detailed below.

Step 1. Based on the linguistic assessments of the alternatives (see Table A3-A6), the linguistic terms are converted into fuzzy numbers according to Table 4.3 and the fuzzy decision matrix is constructed. The aggregation of the ratings is performed using the fuzzy arithmetic mean, and the aggregate ratings for each alternative are obtained using Equation 10 (see Table 4.5).

In order to obtain the aggregate weights of each criterion, the fuzzy weights of each criterion are used, which are extracted by converting the linguistic terms of the four decision makers (see Table 4.4) into fuzzy numbers according to Table 4.3; for example, the fuzzy weights of criterion C7 of the four decision makers are D_1= (0.50, 0.75, 1.00), D_2=(0.75, 1.00, 1.00), D_3=(0.75, 1.00, 1.00), D_4= (0.25, 0.50, 0.75), and applying Equation 11, the aggregate fuzzy weight of C7= (0.56, 0.81, 0.93) is obtained. The results of the aggregate fuzzy weights of all the criteria are tabulated in Table 4.6.

Table 4.5. Decision matrix with the aggregated scores.

	C1			C2			C3			C4			C5			C6			C7		
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
A1	0.10	2.50	5.00	1.33	3.15	5.63	0.70	3.13	5.63	0.70	1.93	4.38	1.30	2.55	5.00	2.53	5.00	7.50	4.38	6.88	9.38
A2	3.15	5.63	8.13	4.38	6.88	9.38	3.78	6.25	8.75	0.70	2.53	5.00	1.90	3.78	6.25	2.53	5.00	7.50	4.38	6.88	9.38
A3	6.88	9.38	10.00	4.38	6.88	9.38	4.38	6.88	9.38	2.53	5.00	7.50	2.50	5.00	7.50	3.13	5.63	8.13	4.38	6.88	9.38
A4	6.88	9.38	10.00	4.38	6.88	9.38	0.70	1.33	3.75	3.78	5.65	7.50	4.38	6.88	8.75	3.75	6.25	8.75	4.38	6.88	9.38
A5	6.88	9.38	10.00	6.25	8.75	9.38	4.38	6.88	9.38	5.00	7.50	9.38	4.38	6.88	8.75	3.75	6.25	8.13	4.38	6.88	9.38
A6	2.50	5.00	7.50	2.50	5.00	7.50	1.33	3.75	6.25	1.90	4.38	6.88	1.90	4.38	6.88	1.30	3.75	6.25	4.38	6.88	9.38
A7	2.50	5.00	7.50	1.90	3.78	6.25	0.10	2.50	5.00	1.90	4.38	6.88	1.90	3.78	6.25	1.90	4.38	6.88	4.38	6.88	9.38
A8	0.70	3.13	5.63	0.10	1.90	4.38	0.10	2.50	5.00	1.90	4.38	6.88	1.90	3.78	6.25	1.90	4.38	6.88	4.38	6.88	9.38
A9	0.70	3.13	5.63	0.10	1.90	4.38	0.10	2.50	5.00	1.90	4.38	6.88	1.90	3.78	6.25	1.90	4.38	6.88	4.38	6.88	9.38
A10	4.38	6.88	9.38	5.63	8.13	9.38	3.75	6.25	8.75	3.13	5.63	8.13	3.75	6.25	8.75	2.50	5.00	7.50	4.38	6.88	9.38
A11	2.50	5.00	7.50	2.50	5.00	7.50	1.90	4.38	6.88	2.50	5.00	7.50	2.50	5.00	7.50	2.53	5.00	7.50	4.38	6.88	9.38
A12	0.10	1.90	4.38	0.10	0.70	3.13	0.10	2.50	5.00	0.70	2.53	5.00	0.10	1.90	4.38	0.70	3.13	5.63	0.70	3.13	5.63
A13	0.10	1.90	4.38	0.10	1.90	4.38	0.10	2.50	5.00	0.70	2.53	5.00	0.10	1.90	4.38	0.70	3.13	5.63	0.70	3.13	5.63

	C8			C9			C10			C11			C12			C13		
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
A1	0.10	2.50	5.00	0.10	2.50	5.00	0.10	1.90	4.38	0.10	0.10	2.50	1.30	2.55	5.00	1.93	4.38	6.88
A2	1.33	3.75	6.25	1.33	1.95	4.38	1.93	4.38	10.00	0.10	2.50	5.00	1.30	2.55	5.00	2.53	5.00	7.50
A3	1.95	4.38	6.25	3.13	5.63	8.13	1.93	4.38	7.50	0.10	2.50	5.00	2.50	5.00	7.50	3.13	5.63	8.13
A4	7.50	10.00	10.00	1.33	1.95	4.38	3.78	5.65	10.00	0.10	0.10	2.50	7.50	10.00	10.00	4.38	6.88	9.38
A5	5.63	8.13	10.00	1.95	4.38	6.25	5.00	7.50	10.00	7.50	10.00	10.00	5.00	7.50	10.00	6.88	9.38	10.00
A6	0.70	3.13	5.63	2.50	5.00	7.50	1.33	3.75	5.00	1.33	3.75	6.25	2.50	5.00	7.50	2.55	5.00	7.50
A7	0.70	3.13	5.63	2.50	5.00	7.50	0.10	0.70	10.00	0.10	2.50	5.00	2.50	5.00	7.50	1.90	4.38	6.88
A8	0.10	2.50	5.00	0.10	2.50	5.00	0.10	2.50	5.00	0.10	2.50	5.00	2.50	5.00	7.50	1.90	4.38	6.88
A9	0.10	2.50	5.00	1.90	4.38	6.88	0.10	2.50	10.00	0.10	2.50	5.00	2.50	5.00	7.50	1.90	4.38	6.88
A10	3.13	5.63	8.13	4.38	6.88	9.38	5.00	7.50	10.00	4.38	6.88	9.38	5.63	8.13	9.38	5.63	8.13	9.38
A11	0.70	3.13	5.63	2.50	5.00	7.50	2.50	5.00	7.50	2.50	5.00	7.50	3.75	6.25	8.13	6.25	8.75	9.38
A12	0.10	2.50	5.00	0.10	1.90	4.38	0.10	2.50	10.00	0.10	2.50	5.00	0.10	2.50	5.00	0.10	2.50	5.00
A13	0.10	2.50	5.00	0.10	2.50	5.00	0.10	2.50	10.00	0.10	2.50	5.00	0.10	2.50	5.00	0.10	2.50	5.00

Table 4.6. Aggregate fuzzy weights for each criterion.

Criteria	Aggregate fuzzy weights
C1	(0.25, 0.50, 0.75)
C2	(0.01, 0.25, 0.50)
C3	(0.75, 1.00, 1.00)
C4	(0.50, 0.75, 1.00)
C5	(0.01, 0.25, 0.50)
C6	(0.31, 0.56, 0.81)
C7	(0.56, 0.81, 0.93)
C8	(0.32, 0.56, 0.81)
C9	(0.32, 0.56, 0.81)
C10	(0.25, 0.50, 0.75)
C11	(0.01, 0.25, 0.50)
C12	(0.75, 1.00, 1.00)
C13	(0.75, 1.00, 1.00)

Step 2 and Step 3. Using Equations 13 and Equation 14, the normalized fuzzy decision matrix is obtained. For criteria C1–12, Equation 13 is used because the objective of these criteria is to maximize. For criterion C13, Equation 14 is applied because the aim is to minimize the computation time criterion. Table A7 shows the results of the normalized matrix.

After normalization, the weighted normalized decision matrix is calculated using Equation 16. The results are shown in Table A8.

Step 4. It is followed to calculate the FPIS and the FNIS because the positive triangular fuzzy numbers fall within the range [0, 1], and the FPIS and the FNIS are obtained by Equations 17 and 18. Then, the relative distance is calculated between the algorithms (alternatives) and is computed with Equations 19 and 20 (see Table 4.7).

Table 4.7. Distances between alternatives.

	D+	D-
A1	6.051	2.149
A2	5.596	2.724
A3	5.192	3.296

Table 4.7. Continued. Distances between alternatives.

	D+	D-
A4	5.136	3.370
A5	4.770	3.802
A6	5.595	2.748
A7	5.677	2.786
A8	5.861	2.467
A9	5.766	2.654
A10	4.918	3.597
A11	5.391	3.004
A12	6.176	2.279
A13	6.144	2.323

Step 5. It is followed to determine the closeness coefficient using Equation 21. CC_i The obtained values represent the total score of each algorithm for a production planning problem. Table 4.8 shows the obtained results.

Table 4.8. Closeness quotient and algorithms ranking.

Alternative	Algorithm	CC_i	Rank
A1	HA/Benders decomposition	0.262	13
A2	HA/LP and Fix	0.327	8
A3	HA/LP Relaxation	0.388	4
A4	MA/Tabu Search	0.396	3
A5	MA/Genetic Algorithm	0.444	1
A6	MA/Simulated annealing	0.329	6
A7	MA/Variable Neighborhood Search	0.329	7
A8	MTA Genetic Algorithm + Mathematical Model	0.296	10
A9	MTA Simulated annealing + Mathematical Model	0.315	9
A10	CPLEX (Commercial)	0.422	2
A11	CBC (Non-Commercial)	0.358	5
A12	BONMIN (Non-Commercial - NonLinear)	0.270	12
A13	LINDO (Commercial – Linear/ NonLinear)	0.274	11

When applying the proposed methodological approach based on the Fuzzy TOPSIS Method for a production planning problem, the GA is the most suitable solution method. This finding is not new because the literature review by Guzman et al. [107] concludes that GAs are the most widely used for this problem. Second in the ranking is CPLEX, which is the most widespread solver [107].

4.5 Sensitivity analysis

This section evaluates the effects of the different weightings of the criteria, i.e. we aim to evaluate the answers given by decision makers and how they influence algorithm selection. The aim of the sensitivity analysis is to make minor variations in the weights and to observe the influence of this variation on algorithm choice. The weights for the rating of algorithms range from very low importance (VLI) to very high importance (VHI). Using this rating, we performed an analysis of 10 combinations, where each combination was expressed as an experiment.

The criteria that were evaluated with the highest weight were the type of variables (C3), the quality of solutions (C12) and computation time (C13) (see Table 4.4). These parameters in a planning problem are dominant when choosing an algorithm. Therefore, we made a minimal variation and looked for criteria with lower scores, such as: problem type (C1), knowledge of algorithms (C10), dataset size (C7), programming knowledge (C8). The details of the experiments are shown in Table 4.9, where the second column details the changes in the weights of the criteria, and the third column shows the results of the proximity coefficient, while the last column expresses the alternatives ranking.

Table 4.9. Quantitative results of the sensitivity analysis.

Experiment No.	Changes in weights of criteria	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	Alternatives Ranking
E1	C1= (0.50, 0.75, 1.00)	0.267	0.337	0.402	0.409	0.457	0.338	0.337	0.302	0.321	0.433	0.366	0.274	0.279	A5 > A10 > A4 > A3 > A11 > A6 > A7 > A2 > A9 > A8 > A13 > A12 > A1
E2	C1= (0.75, 1.00, 1.00)	0.268	0.341	0.410	0.418	0.465	0.341	0.341	0.304	0.323	0.439	0.370	0.275	0.279	A5 > A10 > A4 > A3 > A11 > A6 > A2 > A7 > A9 > A8 > A13 > A12 > A1
E3	C3= (0.50, 0.75, 1.00)	0.260	0.322	0.383	0.395	0.438	0.327	0.328	0.295	0.314	0.417	0.355	0.268	0.273	A5 > A10 > A4 > A3 > A11 > A7 > A6 > A2 > A9 > A8 > A13 > A12 > A1
E4	C5= (0.25, 0.50, 0.75)	0.268	0.335	0.398	0.408	0.455	0.338	0.337	0.304	0.323	0.434	0.367	0.274	0.279	A5 > A10 > A4 > A3 > A11 > A6 > A7 > A2 > A9 > A8 > A13 > A12 > A1
E5	C10= (0.50, 0.75, 1.00)	0.266	0.336	0.396	0.406	0.455	0.335	0.336	0.301	0.323	0.434	0.366	0.278	0.282	A5 > A10 > A4 > A3 > A11 > A2 > A7 > A6 > A9 > A8 > A13 > A12 > A1
E6	C10= (0.75, 1.00, 1.00)	0.267	0.339	0.399	0.410	0.461	0.338	0.336	0.302	0.324	0.440	0.370	0.278	0.283	A5 > A10 > A4 > A3 > A11 > A2 > A6 > A7 > A9 > A8 > A13 > A12 > A1
E7	C8= (0.01, 0.25, 0.50), C12= (0.50, 0.75, 1.00)	0.254	0.317	0.376	0.370	0.422	0.319	0.319	0.287	0.306	0.404	0.346	0.262	0.267	A5 > A10 > A3 > A4 > A11 > A6 > A7 > A2 > A9 > A8 > A13 > A12 > A1
E8	C10= (0.75, 1.00, 1.00), C11= (0.50, 0.75, 1.00)	0.268	0.342	0.402	0.411	0.473	0.342	0.339	0.305	0.326	0.448	0.375	0.280	0.285	A5 > A10 > A4 > A3 > A11 > A6 > A2 > A7 > A9 > A8 > A13 > A12 > A1
E9	C7= (0.50, 0.75, 1.00)	0.262	0.327	0.388	0.396	0.443	0.329	0.329	0.296	0.315	0.422	0.358	0.270	0.275	A5 > A10 > A4 > A3 > A11 > A6 > A7 > A2 > A9 > A8 > A13 > A12 > A1
E10	C7= (0.75, 1.00, 1.00)	0.268	0.333	0.394	0.402	0.449	0.335	0.335	0.302	0.321	0.428	0.364	0.272	0.277	A5 > A10 > A4 > A3 > A11 > A6 > A7 > A2 > A9 > A8 > A13 > A12 > A1

The sensitivity analysis shows that alternatives A5 (GA), A10 (CPLEX), A4 (Tabu Search) have the best scores and occupy the first three positions. Hence, the variation in the weights in the chosen criteria minimally affects these alternatives; for example, A5 reaches the first position in all the experiments. The main variations occur in the sixth, seventh and eighth positions with alternatives A2, A6 and A7. However, the last ranking positions remain unchanged in the classification. In this context, decision makers can use these variations or make other modifications to weightings to prioritize a criterion and to, thus, facilitate the evaluation process in decision making.

4.6 Conclusions

The complexity of real-world problems should be seen as not only an obstacle, but also as a research challenge for effective solutions for large-scale planning problems. Relatively small companies often face very complex problems.

It is usually very difficult for production planners in companies to determine or choose an algorithm. The algorithm selection process normally involves the experimental evaluation of several algorithms with different dataset sizes. However, these sets of experiments require considerable computational resources and long processing times. This adds to the disadvantage of having fewer resources to invest in commercial solvers. In addition, efforts often have to be duplicated when attempting to replicate the algorithms or models available in the literature.

To overcome these drawbacks, the methodological approach based on the fuzzy TOPSIS proposed herein intends to be a support tool to select a solution method for replenishment, production and distribution planning problems. To this end, 13 different criteria were defined and used to select nine different algorithm types (heuristic, metaheuristic, and matheuristic) and four solvers (commercial and non-commercial) that are often employed in planning problems. All these criteria address several important dimensions when solving a planning problem. These dimensions are related to the computational difficulty of the planning problem, programming skills, mathematical skills, algorithmic skills, mathematical modeling software skills, and also to expected computational performance the solution methods. These criteria were analyzed based on the linguistic values given by four planning experts from different manufacturing companies. The problem selected to apply the proposed approach was that of production planning. For this problem, the results of the methodology showed that the GA was the best alternative, while Benders' decomposition was the worst.

Given our study results, it can be concluded that it is possible to select a set of suitable candidate algorithms for solving optimization problems with the proposed approach. In this way, not only can one algorithm be selected, but so can other algorithms that provide similar solutions at the same time. The results of this methodology can guide companies to choose whether to use a commercial or non-commercial algorithm or solver. This can help companies to determine whether they should invest in a solver or use mathematical modeling or algorithm programming software and, at the same time, to understand planning staff's training needs.

There are different approaches for algorithm selection [44, 70, 75, 79]. These approaches are heuristic, metaheuristic and AI, and they offer benefits and disadvantages. However, these techniques can be restrictive for companies because they involve a large number of computational resources and experiments that can be affected by accuracy, the number of tested instances, instance generation, consistency, and in AI techniques, training time. The proposed approach requires very few resources, is very useful thanks to its simplicity and is easily replicable. The main limitation of this technique is the appropriate selection of criteria and the balance between them, which is a subjective issue that requires experts in the planning problems field, not to mention the personal bias of experts' opinions.

Future research could be conducted to experiment the proposed approach with the portfolio of algorithms and solvers defined in [107], where some 50 algorithms are identified, including optimizing, heuristic, metaheuristic and matheuristic algorithms, as well as different types of commercial solvers. Alternatives and criteria could be evaluated with more decision makers. Other MCDM techniques such as ELECTRE, PROMETHEE, intuitionistic fuzzy TOPSIS, or novel methods such as the performance calculation technique of the integrated multiple multi-attribute decision making (PCIM-MADM) [120], which incorporates four techniques (COPRAS, GRA, SAW and VIKOR) into a single final classification index, could be used.

Appendix A.

Table A1 shows a section of the questionnaire format used by decision makers to evaluate the algorithm selection criteria. Table A2 presents the questionnaire used to score the chosen alternatives, i.e., the selected algorithms and solvers against the 13 identified criteria.

Table A1. Questionnaire used to know decision makers' preferences for the identified criteria

	Very Low Importance (VLI)	Low Importance (LI)	Medium Importance (MI)	High Importance (HI)	Very High Importance (VHI)
C1					
C2					
C3					
C4					
C5					
C6					
C7					
C8					
C9					
C10					
C11					
C12					
C13					

Table A2. Questionnaire used to know the decision makers' preferences for the 13 alternatives according to the criteria

	C1				
	Very Low (VL)	Low (L)	Moderate (M)	High (H)	Very High (VH)
A1					
A2					
A3					
A4					
A5					
A6					
A7					
A8					
A9					
A10					
A11					
A12					
A13					

Tables A3-A6 show the decision makers' alternatives ratings against all the criteria

Table A3. Decision maker 1's linguistic assessment.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
A1	L	H	M	M	M	M	M	L	L	L	VL	M	H
A2	M	H	H	M	M	M	M	L	VL	L	L	M	H
A3	VH	H	H	M	M	M	M	L	M	L	L	M	H
A4	VH	H	VL	M	M	M	M	VH	VL	H	VL	VH	H
A5	VH	VH	H	M	M	M	M	H	L	H	VH	H	VH
A6	M	M	L	M	M	M	M	L	M	L	L	M	L
A7	M	M	L	M	M	M	M	L	M	VL	L	M	M
A8	L	L	L	M	M	M	M	L	L	L	L	M	M
A9	L	L	L	M	M	M	M	L	M	L	L	M	M
A10	H	VH	H	M	H	M	M	M	H	H	H	VH	VH
A11	M	M	M	M	M	M	M	L	M	M	M	M	VH
A12	L	L	L	M	L	M	M	L	L	L	L	L	L
A13	L	L	L	M	L	M	M	L	L	L	L	L	L

Table A4. Decision maker 2's linguistic assessment.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
A1	L	L	L	L	VL	L	H	L	L	VL	VL	VL	M
A2	H	H	H	L	M	L	H	L	VL	M	L	VL	M
A3	VH	H	H	H	M	M	H	L	M	M	L	M	M
A4	VH	H	VL	H	M	M	H	VH	VL	H	VL	VH	H
A5	VH	VH	H	H	M	M	H	H	L	H	VH	H	VH
A6	M	M	L	M	M	L	H	L	M	L	L	M	L
A7	M	M	L	M	VL	L	H	L	M	VL	L	M	M
A8	L	L	L	M	VL	L	H	L	L	L	L	M	M
A9	L	L	L	M	VL	L	H	L	M	L	L	M	M
A10	H	VH	H	M	H	M	H	M	H	VH	H	VH	VH
A11	M	M	M	M	M	L	H	L	M	M	M	M	VH
A12	L	VL	L	VL	VL	L	L	L	L	L	L	L	L
A13	L	L	L	VL	VL	L	L	L	L	L	L	L	L

Table A5. Decision maker 3's linguistic assessment.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
A1	L	VL	L	VL	VL	M	H	L	L	L	VL	VL	L
A2	L	M	L	L	VL	M	H	H	H	H	L	VL	M
A3	H	M	M	L	M	M	H	VH	H	H	L	M	M
A4	H	M	M	VL	VH	H	H	VH	H	VL	VL	VH	H
A5	H	M	M	VH	H	VH	H	VH	VH	H	VH	H	VH
A6	M	M	L	L	M	L	H	M	M	H	H	M	H
A7	M	VL	L	L	M	M	H	M	M	L	L	M	M
A8	M	VL	L	L	M	M	H	L	L	L	L	M	M
A9	M	VL	L	L	M	M	H	L	L	L	L	M	M
A10	M	H	M	H	M	M	H	H	M	M	M	M	M
A11	M	M	L	M	M	M	H	M	M	M	M	M	M
A12	VL	VL	L	L	L	L	L	L	VL	L	L	L	L
A13	VL	VL	L	L	L	L	L	L	L	L	L	L	L

Table A6. Decision maker 4's linguistic assessment.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
A1	L	L	L	VL	M	H	H	L	L	L	VL	M	L
A2	H	H	H	VL	M	H	H	L	VL	L	L	M	L
A3	VH	H	H	M	M	H	H	L	M	L	L	M	M
A4	VH	H	VL	VH	H	H	H	VH	VL	H	VL	VH	M
A5	VH	VH	H	H	VH	M	H	H	L	H	VH	H	H
A6	M	M	H	M	L	M	H	L	M	L	L	M	H
A7	M	M	L	M	M	M	H	L	M	VL	L	M	L
A8	L	L	L	M	M	M	H	L	L	L	L	M	L
A9	L	L	L	M	M	M	H	L	M	L	L	M	L
A10	H	M	M	M	M	M	H	M	H	H	H	H	H
A11	M	M	M	M	M	H	H	L	M	M	M	VH	VH
A12	L	VL	L	L	L	L	L	L	L	L	L	L	L
A13	L	L	L	L	L	L	L	L	L	L	L	L	L

Table A7. Normalized fuzzy decision matrix.

	C1			C2			C3			C4			C5			C6			C7			C8			C9			C10			C11			C12			C13		
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
A1	0.01	0.25	0.50	0.14	0.34	0.60	0.07	0.33	0.60	0.07	0.21	0.47	0.15	0.29	0.57	0.29	0.57	0.86	0.47	0.73	1.00	0.01	0.25	0.50	0.01	0.27	0.53	0.01	0.19	0.44	0.01	0.01	0.25	0.13	0.26	0.50	0.01	0.02	0.05
A2	0.32	0.56	0.81	0.47	0.73	1.00	0.40	0.67	0.93	0.07	0.27	0.53	0.22	0.43	0.71	0.29	0.57	0.86	0.47	0.73	1.00	0.13	0.38	0.63	0.14	0.21	0.47	0.19	0.44	1.00	0.01	0.25	0.50	0.13	0.26	0.50	0.01	0.02	0.04
A3	0.69	0.94	1.00	0.47	0.73	1.00	0.47	0.73	1.00	0.27	0.53	0.80	0.29	0.57	0.86	0.36	0.64	0.93	0.47	0.73	1.00	0.20	0.44	0.63	0.33	0.60	0.87	0.19	0.44	0.75	0.01	0.25	0.50	0.25	0.50	0.75	0.01	0.02	0.03
A4	0.69	0.94	1.00	0.47	0.73	1.00	0.07	0.14	0.40	0.40	0.60	0.80	0.50	0.79	1.00	0.43	0.71	1.00	0.47	0.73	1.00	0.75	1.00	1.00	0.14	0.21	0.47	0.38	0.57	1.00	0.01	0.01	0.25	0.75	1.00	1.00	0.01	0.01	0.02
A5	0.69	0.94	1.00	0.67	0.93	1.00	0.47	0.73	1.00	0.53	0.80	1.00	0.50	0.79	1.00	0.43	0.71	0.93	0.47	0.73	1.00	0.56	0.81	1.00	0.21	0.47	0.67	0.50	0.75	1.00	0.75	1.00	1.00	0.50	0.75	1.00	0.01	0.01	0.01
A6	0.25	0.50	0.75	0.27	0.53	0.80	0.14	0.40	0.67	0.20	0.47	0.73	0.22	0.50	0.79	0.15	0.43	0.71	0.47	0.73	1.00	0.07	0.31	0.56	0.27	0.53	0.80	0.13	0.38	0.50	0.13	0.38	0.63	0.25	0.50	0.75	0.01	0.02	0.04
A7	0.25	0.50	0.75	0.20	0.40	0.67	0.01	0.27	0.53	0.20	0.47	0.73	0.22	0.43	0.71	0.22	0.50	0.79	0.47	0.73	1.00	0.07	0.31	0.56	0.27	0.53	0.80	0.01	0.07	1.00	0.01	0.25	0.50	0.25	0.50	0.75	0.01	0.02	0.05
A8	0.07	0.31	0.56	0.01	0.20	0.47	0.01	0.27	0.53	0.20	0.47	0.73	0.22	0.43	0.71	0.22	0.50	0.79	0.47	0.73	1.00	0.01	0.25	0.50	0.01	0.27	0.53	0.01	0.25	0.50	0.01	0.25	0.50	0.25	0.50	0.75	0.01	0.02	0.05
A9	0.07	0.31	0.56	0.01	0.20	0.47	0.01	0.27	0.53	0.20	0.47	0.73	0.22	0.43	0.71	0.22	0.50	0.79	0.47	0.73	1.00	0.01	0.25	0.50	0.20	0.47	0.73	0.01	0.25	1.00	0.01	0.25	0.50	0.25	0.50	0.75	0.01	0.02	0.05
A10	0.44	0.69	0.94	0.60	0.87	1.00	0.40	0.67	0.93	0.33	0.60	0.87	0.43	0.71	1.00	0.29	0.57	0.86	0.47	0.73	1.00	0.31	0.56	0.81	0.47	0.73	1.00	0.50	0.75	1.00	0.44	0.69	0.94	0.56	0.81	0.94	0.01	0.01	0.02
A11	0.25	0.50	0.75	0.27	0.53	0.80	0.20	0.47	0.73	0.27	0.53	0.80	0.29	0.57	0.86	0.29	0.57	0.86	0.47	0.73	1.00	0.07	0.31	0.56	0.27	0.53	0.80	0.25	0.50	0.75	0.25	0.50	0.75	0.38	0.63	0.81	0.01	0.01	0.02
A12	0.01	0.19	0.44	0.01	0.07	0.33	0.01	0.27	0.53	0.07	0.27	0.53	0.01	0.22	0.50	0.08	0.36	0.64	0.07	0.33	0.60	0.01	0.25	0.50	0.01	0.20	0.47	0.01	0.25	1.00	0.01	0.25	0.50	0.01	0.25	0.50	0.02	0.04	1.00
A13	0.01	0.19	0.44	0.01	0.20	0.47	0.01	0.27	0.53	0.07	0.27	0.53	0.01	0.22	0.50	0.08	0.36	0.64	0.07	0.33	0.60	0.01	0.25	0.50	0.01	0.27	0.53	0.01	0.25	1.00	0.01	0.25	0.50	0.01	0.25	0.50	0.02	0.04	1.00

Table A8. Weighted normalized fuzzy decision matrix.

	C1			C2			C3			C4			C5			C6			C7			C8			C9			C10			C11			C12			C13		
	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
A1	0.00	0.13	0.38	0.00	0.08	0.30	0.06	0.33	0.60	0.04	0.15	0.47	0.00	0.07	0.29	0.09	0.32	0.70	0.26	0.60	0.94	0.00	0.14	0.41	0.00	0.15	0.43	0.00	0.10	0.33	0.00	0.00	0.13	0.10	0.26	0.50	0.01	0.02	0.05
A2	0.08	0.28	0.61	0.00	0.18	0.50	0.30	0.67	0.93	0.04	0.20	0.53	0.00	0.11	0.36	0.09	0.32	0.70	0.26	0.60	0.94	0.04	0.21	0.51	0.04	0.12	0.38	0.05	0.22	0.75	0.00	0.06	0.25	0.10	0.26	0.50	0.01	0.02	0.04
A3	0.17	0.47	0.75	0.00	0.18	0.50	0.35	0.73	1.00	0.13	0.40	0.80	0.00	0.14	0.43	0.11	0.36	0.75	0.26	0.60	0.94	0.06	0.25	0.51	0.11	0.34	0.70	0.05	0.22	0.56	0.00	0.06	0.25	0.19	0.50	0.75	0.01	0.02	0.03
A4	0.17	0.47	0.75	0.00	0.18	0.50	0.06	0.14	0.40	0.20	0.45	0.80	0.01	0.20	0.50	0.13	0.40	0.81	0.26	0.60	0.94	0.24	0.56	0.81	0.04	0.12	0.38	0.10	0.28	0.75	0.00	0.00	0.13	0.56	1.00	1.00	0.01	0.01	0.02
A5	0.17	0.47	0.75	0.01	0.23	0.50	0.35	0.73	1.00	0.27	0.60	1.00	0.01	0.20	0.50	0.13	0.40	0.75	0.26	0.60	0.94	0.18	0.46	0.81	0.07	0.26	0.54	0.13	0.38	0.75	0.01	0.25	0.50	0.38	0.75	1.00	0.01	0.01	0.01
A6	0.06	0.25	0.56	0.00	0.13	0.40	0.11	0.40	0.67	0.10	0.35	0.73	0.00	0.13	0.39	0.05	0.24	0.58	0.26	0.60	0.94	0.02	0.18	0.46	0.08	0.30	0.65	0.03	0.19	0.38	0.00	0.09	0.31	0.19	0.50	0.75	0.01	0.02	0.04
A7	0.06	0.25	0.56	0.00	0.10	0.33	0.01	0.27	0.53	0.10	0.35	0.73	0.00	0.11	0.36	0.07	0.28	0.64	0.26	0.60	0.94	0.02	0.18	0.46	0.08	0.30	0.65	0.00	0.04	0.75	0.00	0.06	0.25	0.19	0.50	0.75	0.01	0.02	0.05
A8	0.02	0.16	0.42	0.00	0.05	0.23	0.01	0.27	0.53	0.10	0.35	0.73	0.00	0.11	0.36	0.07	0.28	0.64	0.26	0.60	0.94	0.00	0.14	0.41	0.00	0.15	0.43	0.00	0.13	0.38	0.00	0.06	0.25	0.19	0.50	0.75	0.01	0.02	0.05
A9	0.02	0.16	0.42	0.00	0.05	0.23	0.01	0.27	0.53	0.10	0.35	0.73	0.00	0.11	0.36	0.07	0.28	0.64	0.26	0.60	0.94	0.00	0.14	0.41	0.06	0.26	0.60	0.00	0.13	0.75	0.00	0.06	0.25	0.19	0.50	0.75	0.01	0.02	0.05
A10	0.11	0.34	0.70	0.01	0.22	0.50	0.30	0.67	0.93	0.17	0.45	0.87	0.00	0.18	0.50	0.09	0.32	0.70	0.26	0.60	0.94	0.10	0.32	0.66	0.15	0.41	0.81	0.13	0.38	0.75	0.00	0.17	0.47	0.42	0.81	0.94	0.01	0.01	0.02
A11	0.06	0.25	0.56	0.00	0.13	0.40	0.15	0.47	0.73	0.13	0.40	0.80	0.00	0.14	0.43	0.09	0.32	0.70	0.26	0.60	0.94	0.02	0.18	0.46	0.08	0.30	0.65	0.06	0.25	0.56	0.00	0.13	0.38	0.28	0.63	0.81	0.01	0.01	0.02
A12	0.00	0.10	0.33	0.00	0.02	0.17	0.01	0.27	0.53	0.04	0.20	0.53	0.00	0.05	0.25	0.03	0.20	0.52	0.04	0.27	0.56	0.00	0.14	0.41	0.00	0.11	0.38	0.00	0.13	0.75	0.00	0.06	0.25	0.01	0.25	0.50	0.02	0.04	1.00
A13	0.00	0.10	0.33	0.00	0.05	0.23	0.01	0.27	0.53	0.04	0.20	0.53	0.00	0.05	0.25	0.03	0.20	0.52	0.04	0.27	0.56	0.00	0.14	0.41	0.00	0.15	0.43	0.00	0.13	0.75	0.00	0.06	0.25	0.01	0.25	0.50	0.02	0.04	1.00

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Chapter 5

An MILP model for the lot-sizing/scheduling of automotive plastic components with raw materials and packaging availability.

Eduardo Guzman, Beatriz Andres, and Raul Poler. 2022. "*An MILP model for the lot-sizing/scheduling of automotive plastic components with raw materials and packaging availability*." Accepted for publication in Lecture Notes in Management and Industrial Engineering

Abstract:

This paper examines the lot-sizing/scheduling problem for plastic automotive components manufacturing. The scenario in which the problem is tackled refers to a second-tier supplier in the automotive supply chain. Here the studied second-tier supplier is characterized by transforming plastic granules in injection machines using specific moulds that produce components or finished products. Each mould can be set up on distinct machines to inject one same automobile component, or even two different components or more in the same mould. The same mould is assembled on different injection machines and can have distinct production rates subject to the machine on which it is set up. Our research work puts forward a mixed integer linear programming (MILP) model to minimize setup, the inventory of raw materials and plastic components, stockout, backorder costs and machine-mould assignation costs. We demonstrate the usability of this model with randomly generated instances. The results of the experiments show that our MILP converges toward optimal solutions in large instances by reaching efficient solutions in reference to both quality and execution times. The novelty of this model lies in it considering the arrival of materials as raw material for the injection of parts into moulds, the use of raw materials and the availability of containers for packaging finished products. Moulds can also be set up only during specific time periods in accordance with the quantity of available labour during each time period.

5.1 Introduction

Production and scheduling planning are central functions in manufacturing industries whose relevance is increasingly important due to the complexity of the operations required to manufacture final products from raw materials and the growing attention paid to supply chain management. The production planning and scheduling problem represent an important area of production planning and operations research [1]. Production decisions for a manufacturing environment are concerned about establishing the most efficient utilization of available resources to produce items, while also meeting customer requirements. The lot-sizing/scheduling problem frequently appears in manufacturing systems with complex configurations and finite capacities. In both practice and theory, lot-sizing/scheduling decisions are often made in parallel at the production planning and scheduling levels. The objective at the planning level is to draw a production plan, i.e., determining the production quantities (corresponding to the batch sizes processed in workshops) for each horizon period to meet demands and to minimize different costs (production, maintenance and setup costs). These batches are sequenced in production assets at the scheduling level [2].

A substantial number of papers have dealt with lot-sizing/scheduling, the majority of which are mathematical models for this problem, where the objective function seeks to minimize production costs. Our study centres on modelling a real industrial case to solve the lot-sizing/scheduling problem that is subject to internal/external materials requirement planning (MRP) restrictions. The problem is linked with an automotive plastic component producer that acts as a second-tier supplier in the automotive supply chain. The herein studied second-tier supplier is characterized for its specific moulds for producing components or finished products. This problem is particularly characteristic of the automotive industry because:

- the aim of having to produce the plastic components of a specific car model is to supply them during most of the model's lifetime, e.g., 5 years;
- the increasing costs of plastic raw materials caused by the pandemic crisis have led second-tier suppliers to purchase larger amounts of plastic pellets (raw materials), which always entails contemplating warehouse space limitations and discount prices;
- specific reusable containers are purchased by the first-tier supplier to receive the second-tier supplier's components. As reusable containers are expensive, there is only a limited number of them. The number of reusable

containers can be slightly adjusted to the agreed demand for the supply period, which normally coincides with a car model's lifetime. When reusable containers are not available for second-tier suppliers, injected parts have to be stored in cardboard containers until reusable containers arrive. Then the components stored in cardboard containers must be moved to the reusable ones, which incurs an extra handling cost [3].

The case study is framed within the European project Zero-Defect Manufacturing Platform (ZDMP) in the Preparation Stage: Start-up optimization, in which tasks like the optimization of equipment, materials, energy and energy efficiency are addressed [4].

This research work proposes a mixed integer linear programming (MILP) model for the lot-sizing/scheduling problem to manufacture plastic automotive components that contemplates the use, availability and arrival of materials, including raw materials, to inject parts into moulds, as well as containers for packing the finished components to be delivered to the first-tier supplier. It aims to minimize setups, the inventory of raw materials and plastic components, stockouts, backorder costs and machine-mould assignation costs.

This work is set out as so. Section 5.2 starts by reviewing the related literature. Section 5.3 describes the studied problem and the mathematical formulation. Section 5.4 discusses the computational experiments and the results. Section 5.5 offers some concluding remarks and future research lines.

5.2 Literature review

Substantial research has been conducted on various aspects of lot-sizing/scheduling problems in distinct industries [5] like those presented by Almada-Lobo et al. [6], who studied two linear mixed-integer programming formulations for a multi-item capacitated lot-sizing problem with sequence-dependent setup costs and times for the glass container industry. de Armas and Laguna [7] developed an MILP formulation for a capacitated lot-sizing/scheduling problem toward pipe insulation manufacturing, which included multiple- and single-level items processed on parallel machines according to a planning horizon.

The literature also describes several articles that have addressed injection moulding lot-sizing/scheduling problems. They include Nagarur et al. [8], who present a goal programming model for the injection moulding of PVC pipe fittings. This model aimed to minimize total production costs, inventory and shortages. Ghosh Dastidar and Nagi [9] address the production scheduling problem in an injection moulding facility that produces healthcare products. Their work presents an MILP model that schedules parallel work centres with changeover costs, sequence-dependent setup times and multiple capacitated resources in a single-stage case. Martínez et al. [10] describe an MILP model that addresses the lot-sizing/scheduling problem for a Brazilian moulded pulp packaging plant. With their model, they seek to establish which moulding patterns can be utilized, for how long, and how they can be sequenced. Ríos-Solís et al. [11] present an MILP model and a heuristic method based on a mathematical programming method for a lot-sizing/scheduling problem. The aim is to determine the maximum profit made with assembled products during many periods. This model deals with plastic injection moulding as part of manufacturing, pursues precise production assignment from parts to moulds and from moulds to machines, seeks to maximize the total value of manufactured products and deduces maintenance costs. Mula et al. [12] propose an MILP model for solving the capacitated lot-sizing problem with sequence-dependent setups and parallel machines for injection moulding in the automotive industry. Moulding involves injecting two different parts or products into the same mould. Both parts need the same sequence order and available capacity at the same time.

Andres et al. [13] set up an MILP model for the production/lot-sizing/scheduling problem on parallel flexible injection moulding machines with common setup operators. To produce automotive plastic components, the model allocates moulds to machines during a given time period and calculates the number of components to be manufactured. A sequence-dependent setup time is followed for this purpose. The model also bears in mind the common setup operators who change moulds on machines.

As far as we know, mathematical models do not contemplate the availability of materials/packaging for the delivery of components from the second-tier to the first-tier supplier. The herein proposed model extends that by Andres et al. [13] because the proposed MILP model takes into account the arrival, use and availability of not only the raw materials for injecting parts in moulds, but also the packaging for the finished components. Moreover, moulds can be changed only during time windows and depend on the amount of labour available during each period. The proposed model contemplates similar assumptions to those reported by Andres et al. [13], which envisages that moulds can be set up on different injection machines, and MILP output supplies mould-machine assignments.

5.3 Problem description and formulation

The proposed MILP the lot-sizing/scheduling of automotive plastic components with common setup labour and limited raw and packaging materials availability to transport components from the second- to the first-tier supplier is incorporated in a source and make scheme which is classified according to SCOR views [14]. The Plan Source (S) deals with the calculation of the raw materials, items or components to be supplied during each time period and on a specific planning horizon so that the Plan Make (M) can be fulfilled with no backorder penalizations. For the Source and Make Plans (SM), the production plan (M) is computed according to the production requirements identified in the procurement plan (S) [15, 16].

The SM planning scheme is followed by the second-tier supplier to deliver automotive plastic components to assemble them at the first-tier supplier and OEMs (original equipment manufacturers). The SM plan is generated to identify the period and quantity of: (i) the materials and components to be purchased from suppliers (plan S); (ii) the components to be manufactured in the company to assemble and produce the final product (plan M); see Figure 5.1.

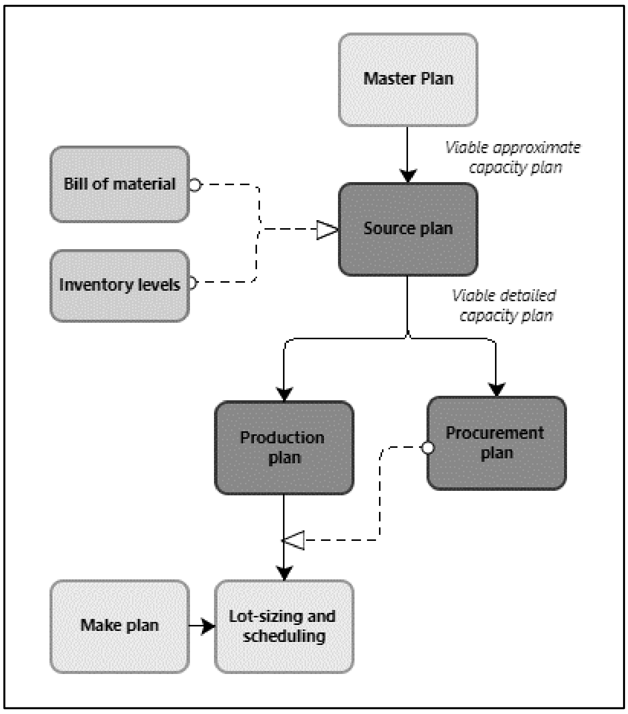

Figure 5.1. Outline of the Source and Make Plans

The firm under study has several moulds that are set up on different injection machines to produce the range of plastic components to be delivered to the first-tier supplier, and finally to the various OEMs forming part of the distinct automotive supply chains characterized by selling to several car brands. The MILP model under discussion is based on the following assumptions:

- Plastic components are injected into moulds, which are assembled on parallel flexible injection machines. Injection machines inject plastic granules which are transformed into automotive semifinished products
- The second-tier supplier has specific moulds for producing each automotive plastic component. When two moulds are available to produce the same plastic component, these moulds can come into play at different processing times because of their technical characteristics
- Each mould can produce one part, or two parts or more, in the same mould
- Each mould can be placed on distinct injection machines to manufacture the same automotive component. However, the same mould set up on different machines has several production rates depending on the machine it is assembled on
- The company works three shifts per day 5 days a week and works overtime shifts on day 6 of the week if production does not end during normal working hours. On day 6, no setup operators are available
- One of the company's study requirements is that, after installing the mould on a machine, the mould must remain at least 24 h to not saturate operators’ work and to not involve too many setups because the installation time is estimated to go from 1 to 3 h, and it obviously has an associated setup cost. If a longer production time is necessary, the mould is set up for the required time periods without incurring installation costs
- When the production time lasts longer than 24 h, the mould remains assembled for the necessary time periods with no incurred installation costs
- Backorders are highly penalized in the automotive sector because they work with just-in-time (JIT) models
- The mould can be changed only during specific time windows. Mould changes are counted to not exceed setup operators’ capacity. Table 5.1 describes the indices, parameters and variables of this problem.

Table 5.1.Notation

Index:	
i	Index of machines $i \in \{1, \ldots, I\}$
j	Index of moulds $j \in \{1, \ldots, J\}$
k	Index of parts $k \in \{1, \ldots, K\}$
l	Index of setup operators $l \in \{1, \ldots, L\}$
r	Index of materials (raw materials / packaging) $r \in \{1, \ldots, R\}$
t	Index of time periods $t \in \{1, \ldots, T\}$
Model parameters:	
a_j	Total amount of moulds j available for production
ca_{kr}	Use of material r required to produce each unit of part k
cb_k	Backorder cost of part k
ci_k	Inventory cost of part k
cim_k	Inventory cost of materials r
cov_{kt}	Stock coverage defined as number of time periods for the stock minimum coverage of part k during time period t
cs_j	Setup cost of preparing mould j
cst_k	Coverage stockout cost of part k
d_{kt}	Demand of part k during time period t
INV_{k0}	Initial inventory of part k
$INVr_0$	Initial inventory of material r
$INVMAX_k$	Maximum inventory units for part k during time period t
$INVMIN_k$	Minimum inventory units for part k during time period t
$INVMAXmat_r$	Maximum inventory units for material r during time period t
nc_t	Number of mould changes permitted during time period t
p_{jk}	Number of parts k produced when mould j is set up
ro_{ij}	1 if mould j can be set up on machine i and 0 otherwise
rc_{ij}	Assignation cost of mould j on machine i
rp_{rt}	Quantity received of material r during each period t
sla_{ijl}	Amount of setup operators l required to setup mould j on machine i
scl_{ijl}	Cost of setup operator l to setup mould j on machine i
sls_t	Number of workers l available during each period t

Table 5.1. Continued. Notation

Decision variables	
B_{kt}	Backorder of part k during time period t
INV_{kt}	Inventory level of part k at the end of time period t
SA_{iljt}	1 if mould j is set up on machine i by setup operator l during time period t, and is not set up on machine i during time period t-1; 0 if mould j is set up by setup operator l on machine i during time period t-1
S_{iljt}	1 if mould j is set up by setup operator l on machine i during time period t; 0 otherwise
ST_{kt}	Coverage stockout of part k during time period t
Cam_{rt}	Material (raw material, packaging) r consumed during period t
$INVm_{rt}$	Inventory of material r during period t
X_{kt}	Amount of part k to be produced during time period t

Next the formulation of the MILP model proposed for the lot-sizing/scheduling of automotive plastic components with available raw materials and packaging takes place. The objective function minimizes the setup and labour costs, machine-mould assignation, raw materials/packaging and plastic components inventory costs, backorder costs and costs for coverage stockouts.

$$\begin{aligned}\boldsymbol{Min\ z} = &\sum_i \sum_l \sum_j \sum_t \boldsymbol{cs_j \cdot SA_{iljt}} \\ &+ \sum_i \sum_j \sum_t \sum_l \boldsymbol{scl_{ijl} \cdot SA_{iljt}} \\ &+ \sum_i \sum_l \sum_j \sum_t \boldsymbol{ro_{ij} \cdot rc_{ij} \cdot SA_{iljt}} + \sum_k \sum_t \boldsymbol{ci_k \cdot INV_{kt}} \\ &+ \sum_r \sum_t \boldsymbol{cim_r \cdot INVm_{rt}} \\ &+ \sum_k \sum_t \boldsymbol{cst_k \cdot ST_{kt}} + \sum_k \sum_t \boldsymbol{cb_k \cdot B_{kt}}\end{aligned} \qquad (1)$$

Subject to:

Sequence constraints

$$\sum_j \sum_l S_{iljt} \cdot ro_{ij} \leq 1 \qquad \forall i, t \qquad (2)$$

$$\sum_i \sum_l S_{iljt} \cdot ro_{ij} \leq a_j \qquad \forall j, t \qquad (3)$$

Constraint (2) establishes that 1 or 0 moulds *j* are set up by setup operator *l* to be produced during each time period *t*. Constraint (3) guarantees that the total number of available moulds *j* can only be set up for production as a maximum by setup operator *l* during each time period *t*.

Production and capacity constraints

$$X_{kt} = \sum_i \sum_j \sum_l p_{jk} \cdot ro_{ij} \cdot S_{iljk} \qquad \forall k, t \qquad (4)$$

$$Cam_{rt} = \sum_k ca_{kr} \cdot X_{kt} \qquad \forall k, r, t \qquad (5)$$

Constraint (4) determines the number of parts *k* to be manufactured during time period *t,* and ensures that a specific mould *j* can be set up on machine *i* during time period *t* while producing product *k*. Constraint (5) establishes the amount of raw materials and packaging *r* used during time period *t.*

Setup constraints

$$\begin{aligned} SA_{iljt} &= S_{iljt} && \forall i, l, j, t = 1 \\ SA_{iljt} &\geq S_{iljt} - S_{iljt-1} && \forall i, l, j, t > 1 \end{aligned} \qquad (6)$$

$$SA_{iljt} \leq 1 \qquad \forall i, l, j, t \qquad (7)$$

$$\sum_i \sum_j SA_{iljt} \leq nc_t \qquad \forall l, t, \qquad (8)$$

Constraint (6) records the first setup of mould *j* carried out by operator *l* on machine *i* to identify the first time that mould *j* is set up during time period *t* on machine *i*. Constraint (7) ensures that SA_{iljt} takes binary values. Constraint (8) limits the number of mould *j* changes allowed during time period *t*, which are set up by operator *l* on machine *i*.

Labour constraint

$$\sum_i \sum_j SA_{iljt} \cdot sla_{ijl} \leq sls_t \qquad \forall l, t \qquad (9)$$

Constraint (9) limits the number of mould changes permitted during time period *t* to the number of available workers *l* by bearing in mind the number of setup operators *l* needed to set up mould *j* on machine *i*.

Inventory balance equations

$$INV_{kt} = INV_{k0} + X_{kt} - d_{kt} + B_{kt} \qquad \forall k, t = 1 \qquad (10a)$$

$$INV_{kt} = INV_{kt-1} + X_{kt} - d_{kt} + B_{kt} - B_{kt-1} \qquad \forall k, t > 1 \qquad (10b)$$

$$INVm_{rt} = INV_{r0} + rp_{rt} - \sum_{k} ca_{kr} \cdot X_{kt} \qquad \forall k, r, t = 1 \qquad (11a)$$

$$INVm_{rt} = INVm_{kt-1} + rp_{rt} - \sum_{k} ca_{kr} \cdot X_{kt} \qquad \forall k, r, t > 1 \qquad (11b)$$

Inventory balance equations (10a) and (10b) limit the appropriate values for inventories, the quantities to produce and the backorders for each time period *t=1* and *t>1,* respectively. Constraints (11a) and (11b) ensure the uninterrupted supply of raw materials and packaging *r* for time periods *t=1* and *t>1.*

Stock coverage constraint.

$$INV_{kt} \geq INVMIN_{k} \qquad \forall k, t \qquad (12)$$

$$INV_{kt} \leq INVMAX_{k} \qquad \forall k, t \qquad (13)$$

$$INVm_{rt} \geq \sum_{k} ca_{kr} \cdot X_{kt} \qquad \forall k, r, t \qquad (14)$$

$$INVm_{rt} \leq INVMAX_{r} \qquad \forall r, t \qquad (15)$$

$$ST_{kt} \geq cov_{kt} - INV_{kt} \qquad \forall k, t \qquad (16)$$

Constraints (12) and (13) restrict the inventory levels for each part *k* during time period *t*. Constraint (14) guarantees that the materials inventory corresponds to the quantity of material that need to be produced during the same period by considering a lead time of 0 and the batching technique is lot-for-lot. Constraint (15) limits the inventory levels for raw materials and packaging *r* during time period *t*. Constraint (16) is for the stock coverage of parts.

Bound and nature variables.

$$SA_{iljt}, S_{iljt} \in \{0,1\} \qquad \forall i, l, j, t \qquad (17)$$

$$X_{kt}, INV_{kt}, B_{kt}, ST_{kt}, \in \mathbb{Z} \qquad \forall k, t \qquad (18)$$

$$Cam_{rt}, INVm_{rt} \in \mathbb{Z} \qquad \forall r, t \qquad (19)$$

Constraint (17) determines the binary nature of both variables' setup S_{iljt} and setup amount SA_{iljt} Constraints (18) and (19) determine the represented variables' integer nature.

5.4 Computational experiments

An MILP model for the lot-sizing/scheduling of automotive plastic components, along with the availability of raw materials/packaging, was developed in Python 3.9.2 with Pyomo [17], employed as an extensible python-based open-source optimization modelling language for linear programming, and with Gurobi 9.0. All the experiments were run on a PC equipped with an Intel(R) Core (TM) i7- 1165G7 CPU @ 2.80 GHz, 16GB of RAM with the Windows 10 Pro operating system.

5.4.1 Generating datasets

This section presents the experimental results. The conducted model's performance is depicted by 13 test problems. Data values are generated to reflect real automotive component industry data (see Table 5.2). The datasets needed for the experiments were built as in Andres et al. [13]. Data values are defined as shown below:

Table 5.2. Value generation for the data parameters

Parameter	Value	Parameter	Value
a_j	1	$INVMIN_k$	Random (10, 100)
ca_{kr}	1	$INVMAXmat_r$	99999
cb_k	99999	$INVMINmat_r$	Random (100, 150)
ci_k, cim_r	*U* (0.1, 1)	nc_t	Random (1, 2)
cov_{kt}	Random (10, 100)	p_{jk}	Random (20, 50)
cs_j	Random (50, 100)	ro_{ij}	Random (0, 1)
cst_k	1	rc_{ij}	Random (1, 2)
d_{kt}	Random (10, 100) if *T* = first of the five periods of the week, otherwise 0 if *T* = *period 6* and *T*= period 7 of the week	rp_{kt}	Random (0, 50)
INV_{k0}	Random (10, 150)	sla_{ilj}	1
$INVr_0$	Random (1000, 1500)	scl_{ilj}	*U* (2.5, 8.5)
$INVMAX_k$	Random (10000, 50000)	sls_l	nc_t

The algorithm developed to build the synthetic datasets is found at http://hdl.handle.net/10251/172395

5.4.2 Computational results

This section offers details of the case study of a second-tier supplier in an automotive supply chain. The results derived from the run time and the objective function value for solving problems are tabulated in Table 5.3. A simplified view of the solution is seen in Figure 5.2 to provide details of the problem that the second-tier supplier faces.

The size of datasets, including the number of machines (*I*), moulds (*J*), parts (K), material (*R*), setup labour (*L*) and periods (*T*), appears in the second column of Table 5.3. In most resolved instances (Small - S, Medium - M, Large – L), the model's computational performance (CPU time) is efficient for all instances. The solution for large instances provides optimal solutions in computational times under 20 seconds. The results obtained in the objective function do not include the backorder cost.

Table 5.3. MILP model results.

Data-set	Problem size						Objective	Lower bound	Upper bound	GAP (%)	CPU (sec)
	I	*J*	*K*	*R*	*L*	*T*					
S1	2	4	6	3	1	3	505.84	505.84	505.84	0.00	0.03
S2	6	8	2	3	2	7	6503.13	6503.13	6503.13	0.00	0.29
S3	8	10	30	3	2	7	8673.92	8673.92	8673.92	0.00	0.26
S4	10	12	40	3	2	7	13841.98	13841.98	13841.98	0.00	0.41
M1	12	14	60	3	2	14	40097.58	39696.60	40097.58	0.01	1.64
M2	14	16	80	3	4	14	50359.57	49855.97	50359.57	0.01	1.51
M3	16	18	100	3	4	14	59831.37	59233.05	59831.37	0.01	2.08
M4	18	20	110	3	4	14	68995.23	68305.28	68995.23	0.01	5.67
L1	20	24	140	3	4	14	80587.91	80587.91	80587.91	0.00	2.04
L2	22	26	160	3	4	14	132509.80	131184.70	132509.80	0.01	14.09
L3	25	28	180	3	6	21	165415.31	163761.16	165415.31	0.01	11.94
L4	30	35	200	3	6	21	182957.97	181128.39	182957.97	0.01	18.52
L5	40	45	300	3	6	21	271586.75	268870.88	271586.75	0.01	15.92

Small instance S1 comprises two machines and four moulds, six parts, one operator and three periods. Figure 5.2 depicts how moulds can produce one part or more. In this case, the data generated synthetically, mould 1 produces parts 4, 5 and 6, mould 3 produces part 3 and mould 4 generates parts 1 and 2. The obtained results appear in Tables 5.4 - 5.6. With regard to the results of the sequence of the moulds on the machines Figure 5.2 illustrates that the operator puts mould 1 on machine 1 and manufactures for three periods, once mould 1 is placed the operator puts mould 3 on machine 2 and mould 4 is put on the same machine in period 2 (see Table 5.5). Table 5.6 describes the consumption and inventory, where r=1 corresponds to the raw material (plastic granules) and r=2 and r=3 to the packaging of the automotive semifinished products.

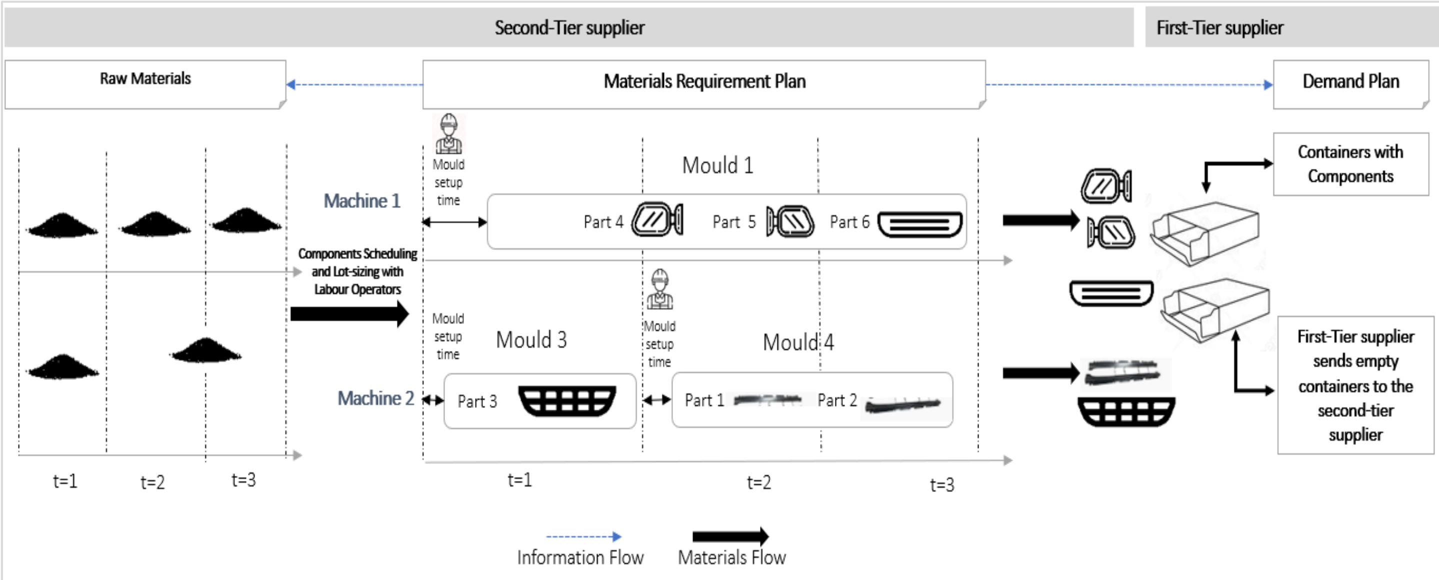

Figure 5.2. Representation of the realistic lot-sizing/scheduling model with raw materials and packaging availability

Table 5.4. Numerical results of instance S1: backorders, inventories, stockout, lot-sizing.

k	t	B_{kt}	INV_{kt}	ST_{kt}	X_{kt}
1	1	0	20	0	0
1	2	0	30	0	20
1	3	0	40	0	20
2	1	10	10	10	0
2	2	10	10	10	50
2	3	10	10	10	50
3	1	0	10	10	50
3	2	10	10	10	0
3	3	20	10	10	0
4	1	0	10	5	50
4	2	0	10	5	50
4	3	0	10	5	50
5	1	0	10	25	50
5	2	0	10	25	50
5	3	0	10	25	50
6	1	0	10	0	50
6	2	0	10	0	50
6	3	0	10	0	50

Table 5.5. Numerical results of instance S1: scheduling.

i	l	j	t	S_{iljt}	SA_{iljt}
1	1	1	1	1	1
1	1	1	2	1	0
1	1	1	3	1	0
1	1	2	1	0	0
1	1	2	2	0	0
1	1	2	3	0	0
1	1	3	1	0	0
1	1	3	2	0	0
1	1	3	3	0	0
1	1	4	1	0	0
1	1	4	2	0	0
1	1	4	3	0	0
2	1	1	1	0	0
2	1	1	2	0	0
2	1	1	3	0	0

Table 5.5. Continued. Numerical results of instance S1: scheduling.

i	*l*	*j*	*t*	S_{iljt}	SA_{iljt}
2	1	2	1	0	0
2	1	2	2	0	0
2	1	2	3	0	0
2	1	3	1	1	1
2	1	3	2	0	0
2	1	3	3	0	0
2	1	4	1	0	0
2	1	4	2	1	1
2	1	4	3	1	0

Table 5.6. Numerical results of instance S1: use and inventory of materials.

r	*t*	Cam_{rt}	$INVm_{rt}$
1	1	200	850
1	2	220	680
1	3	220	460
2	1	200	800
2	2	220	630
2	3	220	410
3	1	200	800
3	2	220	580
3	3	220	410

5.5 Conclusion

This research work develops an MILP model to integrate lot-sizing/scheduling decisions about automotive plastic components with raw materials/packaging availability to minimize setup and labour costs, components and raw materials inventory costs, backorder costs, machine-mould assignations and penalization costs for coverage stockouts. Both moulds and parts are employed as central indices for planning/scheduling on parallel machines. This work also contemplates the mould changes time window, the several setup times according to the number of workers assigned to mould change and mould-machine assignments. It also includes the arrival of materials, use of raw materials and availability of packaging containers.

This paper validates MILP performance and proves computationally efficient for different instance types, including large datasets that replicate the amount of data employed in real automotive industries. In future studies, the model's assumptions can be extended by adopting other practical conditions, such as constraints for transporting finished products, waiting times for containers for packing finished products to be delivered and limited space to store finished products.

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Chapter 6

A MILP model for reusable containers management in Automotive plastic components supply chain.

Guzman, E., Andres, B., & Poler, R. 2021. *"A MILP Model for Reusable Containers Management in Automotive Plastic Components Supply Chain".* In: IFIP Advances in Information and Communication Technology, vol 629. Springer, Cham. https://doi.org/10.1007/978-3-030-85969-5_15

Abstract:

The automotive sector operates under the just-in-time (JIT) approach, but variations in demand mean that first-tier suppliers generate an accumulation of stocks at second-tier suppliers. Second-tier suppliers have a limitation of storage space, reason to limit their production to the size of the warehouse, but always attending the first-tier demand plan. A further limitation of the second-tier supplier is the number of empty reusable containers that the first-tier supplier delivers to the second-tier supplier and that are used to package the injected plastic components. The reusable filled containers are returned to the first-tier supplier, according to the plastic components demand plan. Thus, a closed-loop logistic is carried out between first and second-tier suppliers. This study proposes, from the second-tier perspective, a mixed integer linear programming (MILP) model for fleet sizing decisions of the cardboard containers in a production system. The model determines the number of cardboard containers that second-tier supplier has to use when the production is higher than the number of available reusable containers.

6.1 Introduction

An increasing trend for companies is to work towards meeting environmental and economic requirements and reducing the environmental and social impact of their activities. There is also a rapidly growing interest in reusable packaging, such as wooden pallets and plastic crates and others. Several companies sell products in packaging that can be reused. Returnable transport items (RTI), which represent a specific type of reusable packaging material, including pallets, plastic boxes, or containers (air and maritime), are used today in various industries, for example, in the food sector, in the automotive industry or in the consumer goods industry [1].

The use of reusable packaging is justified by the benefits it can generate, such as the amortization of the price of packaging over its useful life [2]. The literature provides several studies showing the environmental benefits associated with reusable containers [3]. Glock and Kim [1] argued that the use of reusable packaging materials rather than single-use packaging materials has the significant contribution of reducing global CO2 emissions from production and transportation, and can significantly minimize the gross energy consumption and the waste generation from transportation.

The difficulty of the reusable container management problem is to have an appropriate supply of empty containers to meet the customer demand. Part of this supply is the result of returns of previously issued containers. A challenging factor is that, during the lead time, the same container may be emitted, returned, re-emitted, etc.

The aim of this research is to investigate the production and fleet-sizing of cardboard containers decisions of a production system when reusable containers are utilized. This model has applicability to the automotive industry, which uses reusable containers to protect and transport plastic parts produced by the second-tier supplier and shipped to the first-tier supplier. The focus of our model is to determine the optimal levels of production and storage rate to minimize the setup times and the quantity of cardboard containers to be purchased when reusable containers, which are property of first-tier supplier, are insufficient to store the parts produced by the second-tier supplier.

The structure of the paper is as follows. Section 6.2 provides an overview of related work. Section 6.3 develops a mixed integer linear programming (MILP) model for Reusable Containers Management and contains numerical and negotiation examples. Section 6.4 concludes the article and offers suggestions for future research.

6.2 Literature review

This section provides a literature review of relevant contributions in the related research field. The literature focuses on packaging costs and emissions as a target to optimize the use of packaging. Most relevant studies are presented next. Accorsi et al. [4] propose a mixed-integer linear programming (MILP) model to address the use of reusable packaging in the food industry. The model establishes the number of available packaging and forces to meet the demand for packaging over the planning horizon by encouraging reutilization and recycling. Rajae et al. [2] present a MILP model that addresses the problem of reusable containers in a reverse supply chain, in a multi-tiered network and under a carbon emmision constraint. Goudenege et al. [5] developed a generic reverse logistics management model focused on investing in and managing reusable packaging at the lowest cost in order to reduce the amount of cardboard used by the company under study. Glock et al. [1] examine a supply chain consisting of a single supplier and several retailers that use returnable transportation items, such as containers or boxes, to facilitate the shipment of products from the supplier to the retailers. The paper presents two mathematical models used to determine the cycle time, container size, individual retailer order quantities, and shipping sequence with the intention of minimizing the average total system costs. Park and Kim [6] present an analytical model for fleet-sizing of containers that are used for the protection (storage of finished parts), transportation and storage of parts between a component plant and multiple assembly plants. Atamer et al. [7] analyse the pricing and production decisions of a manufacturer selling a single product when using reusable containers with stochastic customer demand, and two supply scenarios are analysed: (1) new containers and (2) containers returned by customers. In our paper we consider different characteristics addressed in the literature, with the novelty that integrates the decisions of production scheduling and sequencing to determine the optimal use of reusable containers and cardboard containers required to store and send plastic components. The problem modelled adjusts to a real problem that have transmitted to us the first and second-tier supplier of an automotive supply chain.

6.3 Problem definition

We consider a second-tier supplier that produces plastic components for its assembling in the first-tier supplier. The second-tier supplier produces the parts in moulds that are assembled on injection machines. The machine setup has a high cost associated; therefore, production is constrained by the number of moulds changed in a specific period and the amount of periods that the mould must be mounted within the machine. The main aim is to minimize the costs of production, storage, and machine setups, without incurring in backorders on the first-tier demand plan. Once the second-tier supplier has produced the plastic components, according to its optimal production plan, the parts are sent to the first-tier supplier in reusable containers, which are of its property. Reusable containers are limited in capacity and number, when the second-tier supplier produces more parts than he can store in the reusable containers, he has to store in temporary cardboard containers, until empty plastic containers arrive. The use of cardboard containers implies that the second-tier supplier must incur handling costs because they must put the parts in the cardboard containers and then switch to the reusable containers. In addition, the manufacturer must purchase the cardboard containers. Figure 6.1 shows the closed loop of reusable containers.

The optimization of the second-tier supplier production and scheduling plan, results in grouping production in batches and thus having to stock products. If there are sufficient reusable containers, the produced parts are stored and wait in the warehouse to be delivered to the first-tier supplier, and after a lead time the reusable containers re-circulate and are returned to the second-tier supplier. When there are not sufficient reusable containers, second-tier supplier stores the parts in the cardboard containers.

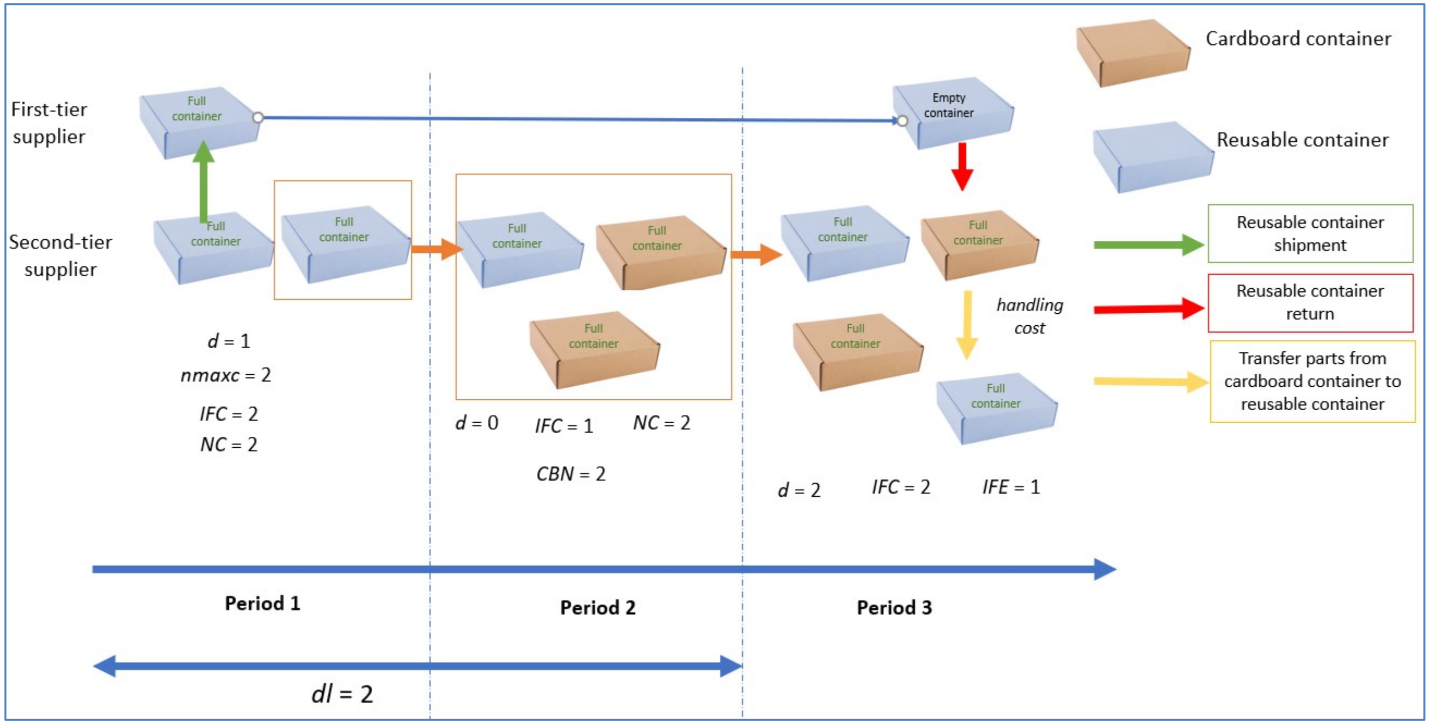

Figure 6.1. Closed loop of reusable containers scheme

6.3.1 A MILP model for Reusable Containers Management

This study proposes, from the second-tier perspective, a Mixed Integer Linear Programming (MILP) model for the production, lot-sizing, and scheduling of automotive plastic components, which takes into consideration the number of reusable containers in circulation throughout the closed-loop logistic. Moreover, the model also determines the number of cardboard containers that second-tier supplier has to use when the production is higher than the number of available reusable containers. This model allows to deter- mine the optimal number of reusable containers that should be bought by the first-tier supplier in order not to incur in extra costs due to the use of cardboard containers, which will increase the price of plastic components produced in the second-tier supplier, compromising the supply chain sustainability. This information is useful for both first and second-tier suppliers since with this data both suppliers in the supply chain can negotiate the final price of plastic components, which is contractually dependent on the number of returnable containers delivered by the first-tier supplier to the second-tier supplier (Table 6.1).

Table 6.1. Nomenclature for Reusable Containers Management model

Index	
t	time period index $t \in \{1, \ldots, T\}$
Data	
ch	handling cost of cardboard container
cb	purchase cost of the cardboard container
cc	container capacity
cs	setup cost of preparing tool
cap	warehouse volume storage capacity
d_t	demand of containers at period t
inv0	initial inventory of reusable containers
dl	delay between sending a full reusable container to the first-tier supplier and returning an empty reusable container to the second-tier supplier
$invp_0$	initial inventory of parts
$invec_0$	initial inventory of empty reusable containers
$invfc_0$	initial inventory of filled reusable containers (filed of plastic parts)

Table 6.1. Continued. Nomenclature for Reusable Containers Management model

Data	
nmaxc	maximum number of reusable containers
nc_t	number of mould changes permitted during time period t
x_t	number of parts that the machine is able to produce during time period t
v	volume of containers
Decision variables	
CBN_t	number of cardboard containers
INV_t	inventory of parts at the end of time period t
IEC_t	inventory of empty reusable containers
ICF_t	inventory of filled reusable containers
NC_t	number of containers required
SA_t	1 when the mould is set up on machine during period *t*, 0 when mould is set up on machine during period *t-1*
S_t	1 when the mould is set up on machine during period *t*, 0 otherwise
Xn_t	number of parts to produce during period t

The MILP model formulation for managing the availability of reusable containers in automotive plastic components supply chain is represented below. The objective function minimizes total costs, which comprise setup costs, and investment and handling cost of reusable containers.

$$Min\ z = \sum_t cs \cdot SA_t \quad + \sum_t ch \cdot cb \cdot CBN_t \tag{1}$$

Subject to:

Sequence and setup constraints

$$S_t \leq 1 \qquad \forall t \tag{2}$$

$$SA_t \geq S_t - S_{t-1} \qquad \forall t \tag{3}$$

$$SA_t \leq nc_t \qquad \forall l, t, \tag{4}$$

Constraint (2) guarantees that one or neither mould could be set up in production during each period *t*. Constraint (3) guarantees the first tool setup on the machine in period t. Constraint (4) guarantees the number of tool changes allowed during period t.

Production constraint

$$Xn_t <= S_t \cdot x_t \qquad \forall t \qquad (5)$$

Constraint (5) determines the number of parts produced during time period t

Inventory constraints

$$INV_t = invp_0 + Xn_t - d_t * cc \qquad \forall t = 1 \qquad (6)$$
$$INV_t = INV_{t-1} + Xn_t - d_t * cc \qquad \forall t > 1$$
$$NC_t = INV_t / cc \qquad \forall t \qquad (7)$$
$$IFC_t = invfc_0 - d_t \qquad \forall t = 1 \; if \; N\boldsymbol{C}_t > invec_0 \qquad (8)$$
$$IFC_t = N\boldsymbol{C}_t - d_t \qquad \forall t = 1 \; if \; N\boldsymbol{C}_t \leq invec_0 \qquad (9)$$
$$IFC_t = IFC_{t-1} + IEC_{t-1} - d_t \qquad \forall t > 1 \; if \; N\boldsymbol{C}_t > IEC_{t-1} \qquad (10)$$
$$IFC_t = N\boldsymbol{C}_t - d_t \qquad \forall t > 1 \; if \; N\boldsymbol{C}_t \leq IEC_{t-1} \qquad (11)$$
$$IEC_t = invec_0 \qquad \forall t = 1 \; if \; N\boldsymbol{C}_t > invec_0 \qquad (12)$$
$$IEC_t = invec_0 - IFC_t \qquad \forall t = 1 \; if \; N\boldsymbol{C}_t \leq invec_0 \qquad (13)$$
$$IEC_t = d_{t-dl} \qquad \forall t > 1 \; if \; N\boldsymbol{C}_t > IEC_{t-1} \qquad (14)$$
$$IEC_t = IEC_{t-1} - d_{t-dl} \qquad \forall t > 1 \; if \; N\boldsymbol{C}_t \leq IEC_{t-1} \qquad (15)$$
$$CBN_t = N\boldsymbol{C}_t - invec_0 \qquad \forall t = 1 \; if \; N\boldsymbol{C}_t > invec_0 \qquad (16)$$
$$CBN_t = 0 \qquad \forall t = 1 \; if \; N\boldsymbol{C}_t \leq invec_0 \qquad (17)$$
$$CBN_t = N\boldsymbol{C}_t - IEC_{t-1} \qquad \forall t > 1 \; if \; N\boldsymbol{C}_t > IEC_{t-1} \qquad (18)$$
$$CBN_t = 0 \qquad \forall t > 1 \; if \; N\boldsymbol{C}_t \leq IEC_{t-1} \qquad (19)$$
$$v \cdot (IEC_t + IFC_t + CBN_t) \leq cap \qquad \forall t \qquad (20)$$
$$nmaxc \geq IEC_t + IFC_t + d_t \qquad \forall t \qquad (21)$$

Constraint (6) defines the inventory level of parts that have not been packaged and delivered in a reusable container, i.e., it determines the inventory of overproduction due to the batch sizes. Constraint (7) establishes the required number of reusable and cardboard containers needed for packaging plastic parts. Constraints (8 to 11) manage the inventory of filled reusable containers and control the allocation of plastic parts to reusable and cardboard containers. Constraints (12 to 14) control the inventory of empty reusable containers. Constraints (16 to 19) determine the allocation of parts that have been packaged in cardboard containers, due to the fact that there are missing empty reusable containers reusable containers on the second-tier supplier side. It is determined that after a delay time a filled reusable container sent to the first-tier supplier is released as empty reusable container to the second-tier supplier. Constraint (20) is referred to as the storage capacity constraint, which guarantees that the reusable and cardboard container inventory in the warehouse in period t is always less than the capacity of the manufacturer's warehouse. Constraint (21) limits the number of filled and empty reusable containers, since there is a limited number of reusable containers delivered from the first-tier supplier to the second-tier supplier.

Bound and nature variables.

$$SA_t,\ S_t \in \{0,1\} \qquad \forall t \qquad (22)$$

$$INV_t, ICF_t, IEF_t, CBN_t,\ NC_t, Xn_t \in \mathbb{Z} \qquad \forall t \qquad (23)$$

Constraint (22) denotes the binary character of the variables S_t and SA_t. Constraint (23) specifies the integer character of the variables represented.

6.3.2 Numerical Experiment

The model is formulated in Python and solved with Gurobi. The data in this case study has been generated randomly. Table 6.2 shows the solutions that arrive at one of the generated instances, in this case we have considered 6 periods, in this scenario, as can be seen in Table 6.2, the second level supplier has to use cardboard containers (CBN_t) in several periods causing it to incur handling costs. Gurobi takes a few seconds to find the optimum solution on a computer configured with 11th Gen Intel(R) Core (TM) i7-1165G7 @ 2.80GHz processors and 16 GB of RAM.

Table 6.2 Results of MILP model for Reusable Containers Management.

t	CBN_t	IEC_t	IFC_t	INV_t	NC_t	S_t	SA_t	Xn_t
1	0	1	0	60	15	1	1	32
2	9	15	0	40	10	1	0	20
3	0	10	2	60	15	1	0	72
4	3	13	0	52	13	1	0	44
5	4	13	0	68	17	1	0	84
6	6	17	0	76	19	1	0	84

6.4 Collaboration scheme

Figure 6.2 depicts the process of negotiating the price of plastic components produced by the second-tier supplier. The price of the plastic components is determined by (i) the number of reusable containers that the first-tier supplier delivers to the second-tier supplier; (ii) the number of cardboard containers that the second-tier supplier has to buy (if the number of empty reusable containers is insufficient to store the plastic components produced by the second-tier supplier); (iii) and the costs associated with the plastic components production process, setup costs.

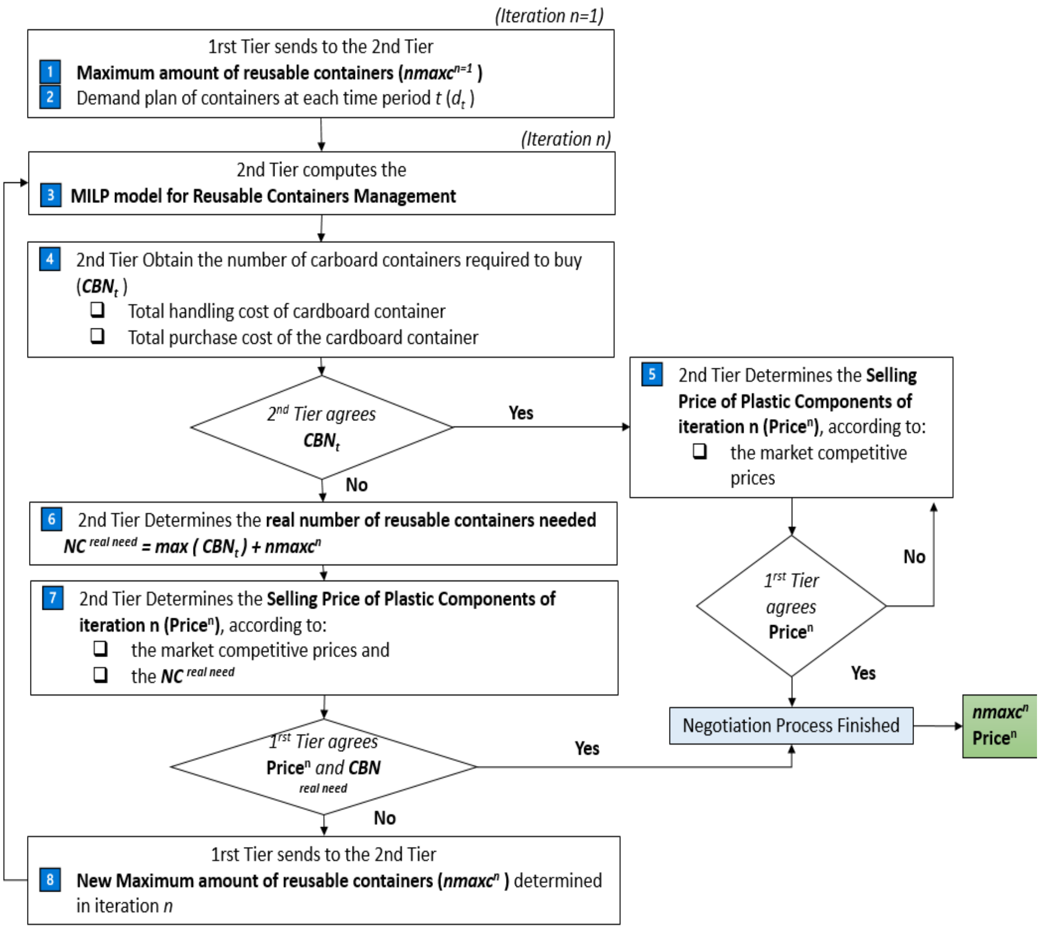

Figure 6.2. Flow chart of negotiation process

6.5 Conclusions

In this paper, we provide an integrated approach to help companies consider options when managing their reusable containers. This paper proposes a MILP model for optimizing the scheduling of automotive plastic components, which takes into account the use of reusable containers that are required for the protection and transportation of finished products from a second-tier manufacturer to a first-tier supplier. It also determines the number of cardboard containers to be purchased by the second-tier supplier when reusable containers are not available, so the second-tier supplier must incur handling costs to store the parts in cardboard containers until reusable containers are available. Future research lines are led to (i) include in the model the carbon emissions derived from the transport of reusable containers; (ii) the consideration of backorders penalization in the objective function; (iii) and the algorithm implementation of the proposed collaboration scheme, in order to determine the optimal number of reusable containers and the competing price of plastic components.

6.6 References

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Chapter 7

Matheuristic Algorithm for Job-Shop Scheduling Problem Using a Disjunctive Mathematical Model.

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Abstract:

This paper focuses on the investigation of a new efficient method for solving machine scheduling and sequencing problems. The complexity of production systems significantly affects companies, especially small- and medium-sized enterprises (SMEs), which need to reduce costs and, at the same time, become more competitive and increase their productivity by optimizing their production processes to make manufacturing processes more efficient. From a mathematical point of view, most real-world machine scheduling and sequencing problems are classified as NP-hard problems. Different algorithms have been developed to solve scheduling and sequencing problems in the last few decades. Thus, heuristic and metaheuristic techniques are widely used, as are commercial solvers. In this paper, we propose a matheuristic algorithm to optimize the job-shop problem which combines a genetic algorithm with a disjunctive mathematical model, and the Coin-OR Branch & Cut open-source solver is employed. The matheuristic algorithm allows efficient solutions to be found, and cuts computational times by using an open-source solver combined with a genetic algorithm. This provides companies with an easy-to-use tool and does not incur costs associated with expensive commercial software licenses.

7.1 Introduction

Nowadays, rapidly growing economic markets, competitive pressures and increasingly challenging business environments are forcing increasingly more companies, especially small- and medium-sized enterprises (SMEs), to innovate their industrial manufacturing systems. SMEs have had to respond and adapt to a constantly changing organizational environment to deliver high-quality customized products. Consequently, SMEs supply chains are not static as they must respond to continuous change by adapting their control techniques, and coordinating and managing change in the way they operate and configure their businesses. Companies also have to manage their evolution toward participation in collaborative networks [1].

The market in which these companies currently operate is intensely volatile, which makes effective supply chain (SC) management critical to improve organizational performance as manufacturing systems become increasingly dynamic [2] due to new challenges in manufacturing industries, such as Industry 4.0 and the Internet of Things (IoT).

Researchers are showing much interest in improving the performance of enterprises and SC to generally cope with these dynamic environments by devising mechanisms and techniques that provide SMEs with affordable tools in cost, easy-to-use and computational efficiency terms. The search for solutions for company scheduling problems, such as job-shop scheduling problems (JSP), remains a relevant research topic [3]. This is because most of these real-world scheduling problems are too complex to be optimally solved and are often NP-hard. This means that exact techniques and some algorithms cannot solve them in effective computational times when the problem is too large. At the same time, solving them with commercial solvers is neither economically viable nor computationally efficient.

Mathematical formulations like mixed integer linear programming (MILP) models for JSP, have been around since the 1960s [4]. The leading formulations for this problem type are disjunctive formulation, rank-based formulation and time-indexed formulation [5].

Ku and Beck [5] compared these mathematical formulations with different solvers (CPLEX, GUROBI and SCIP, the first two are commercial and the last one is not), which showed that the disjunctive model outperformed the rank-based and time-indexed models.

In this context, a new matheuristic algorithm combining a genetic algorithm and the disjunctive model (MILP) is proposed in this study. Matheuristic algorithms are constructed by "the interoperation of metaheuristics and mathematical programming techniques" [6]. According to Ball [7] and Talbi [8], combinations or hybridizations of matheuristics can be classified into three approaches: 1) decomposition approaches, where the problem is decomposed into subproblems to be optimally solved; 2) improvement heuristics or metaheuristics, where the mathematical programming model is used to enhance an initial solution obtained by some heuristic or metaheuristic method; and 3) approaches employing the mathematical programming model to provide approximate solutions in which a relaxation of the problem toward optimality is solved.

The method presented in our study consists of a combination of a genetic algorithm and linear programming (LP) model (GA-LP) that is included in approach 2 of this classification. The main objective of this work is to test the non-commercial COIN-OR Branch and Cut (CBC) solver [9] for solving the JSP, combined with a genetic algorithm, in large or real instances. The experimental results confirm the feasibility and effectiveness of the proposed matheuristic compared to the solutions provided by the solver.

Accordingly, the document is structured as follows. Section 7.2 reviews work related to the application of matheuristic algorithms to the JSP. Section 7.3 presents the proposed JSP mathematical model in detail. Section 7.4 describes the matheuristic approach. Section 7.5 presents the computational experiments and discusses the results. Finally, Section 7.6 covers the conclusions of the performed work and future research lines.

7.2 Literature Review: Matheuristic Resolution Approaches

A wide variety of papers describes different models and algorithms to solve scheduling problems [10]. Many of these techniques correspond to mathematical models, heuristic and metaheuristic algorithms [11]. The application of these techniques depends on the application area, i.e., SC planning under uncertainty [12], closed loop SC [13], SC sustainable management [14] or green SC management [15]. These studies reviewed the models and algorithms employed to solve optimization problems in their specific field.

In this paper, we focus on the scheduling problem to be addressed at the operational decision-making level, and we pay particular attention to the JSP which is considered to be NP-hard. To address this problem, heuristic (H) and metaheuristic (MH) approaches have received much attention in the literature.

Indeed, many literature surveys have been carried out over time. Thus, deterministic and stochastic optimization models have been developed to solve the JSP [3, 16, 17]. Moreover, other approaches including decomposition heuristics, dispatching heuristics, disjunctive representations of the problem, discrete simulation or rolling horizon approaches can be found in the literature [18].

To offer readers an overview on the studied topic, we reviewed how the literature has applied matheuristic approaches to solve the JSP. In our research, we applied the keywords "matheuristic" AND "job-shop scheduling problem". Seventeen papers coincide with our research in the Scopus database. Some tackle flow shop scheduling problems, and others refer to reviews. After analyzing the abstracts and the whole contents of the papers, nine papers remained of the initial seventeen (see Table 7.1). Our review research is not without limitations as the search results may not fully cover all the matheuristic proposed in the literature for being named differently from the keywords used in our research "matheuristic", e.g., hybrid algorithms.

As a general overview, the JSP was tackled from different perspectives, namely flexible JSP, dynamic JSP, resource constrained JSP, parallel machine JSP or just-in-time JSP. This review revealed that the most widely used metaheuristics are led by genetic algorithms and tabu search algorithms. The matheuristics presented to address the JSP integrates an MILP with a metaheuristic algorithm in most cases. Others consider an MILP combined with a constructive heuristic to increase the intelligence of the MILP and to reduce computational resolution times in large sized experiments.

Table 7.1 highlights some relevant characteristics of the matheuristic proposed in the analyzed works in terms of: (i) the type of addressed JSP; (ii) the proposed matheuristic; (iii) the integrated approaches used to define the matheuristic, including a heuristic algorithm combined with an MILP or a metaheuristics combined with an MILP; (iv) the employed programming language and modeling language, as well as the solver used to compute the exact method; and (v) the experiment size (job x machine). These features are based on the solution approaches defined in the framework proposed by [10].

In order to provide a profounder analysis, Al-Hinai and Elmekkawy [18] propose an approach to obtain a predictive schedule that minimizes machine breakdowns and responds to a flexible JSP. To this extent, a 2-stage hybrid genetic algorithm (HGA) is proposed: (i) the first stage optimizes the primary objective by minimizing the makespan and considering deterministic data without machine breakdowns; (ii) the second stage optimizes a bi-objective function (by considering robustness and stability) and integrates machine assignments and operations sequencing with the expected machine breakdowns. Continuing with the scope of a flexible JSP, a hybrid tabu search algorithm with a fast public critical block neighborhood structure (TSPCB) is proposed by Li et al. [19].

These authors present a mixture of four machine assignment rules and four operation scheduling rules to improve the quality of the initial solutions and provide the hybrid algorithm with good exploration capability. Then, they put forward an efficient neighborhood structure to perform local searches in the machine allocation module, which integrates three adaptive approaches. Finally, they present a speedup local search method with three types of insertion and swap neighborhood structures based on the public critical block theory. In line with this, Li and Gao [20] report an effective HGA that hybridizes the genetic algorithm (GA) and tabu search (TS) to address the flexible JSP with a view to minimize the makespan. The GA has a powerful global searching ability, and the TS has a valuable local searching ability.

Thiruvady et al. [21] deal with the Resource Constrained Job Scheduling (RCJS) problem by proposing two MIP-based matheuristic approaches that rely on the solution merging concept to learn from a population of solutions and to use an MIP to generate a "merged" solution in the subspace, which is spanned by a pool of heuristic solutions. The first approach is the Merge Search (MS) and the second is Construct, Merge, Solve and Adapt (CMSA).

Rohaninejad et al. [22] address the JSP of parallel machines with incompatible job families and proposes an efficient matheuristic algorithm based on the hybridization of a GA and a local search (LS) method based on mixed integer programming (MIP). The GA is used to optimize the subproblems related to determining the sequence of parts and the allocation of parts to machines. The allocation of parts to batches is performed by an effective heuristic named batching heuristic (GA_BH) by combining a GA with a batching heuristic (BH). Moreover, the authors propose a combination of a GA and a dispatching rule called Apparent Tardiness Cost (GA_ATC). Dang et al. [23] also deal with the JSP of parallel machines with tool replacements to schedule a set of jobs with tool requirements on identical parallel machines in a work center. To do so, the authors propose a mathematical model for the problem and a matheuristic that combines a GA and an integer linear programming (ILP) formulation to solve large datasets. The matheuristic integrates ILP into the GA framework as a local search step to enhance GA performance.

Ahmadian and Salehipour [24] deal with the just-in-time job-shop scheduling problem (JIT–JSP) with distinct due dates for operations with earliness and tardiness penalties. For this purpose, the authors propose a matheuristic algorithm that decomposes the problem into smaller subproblems to obtain optimal or near-optimal sequences to perform the operations for the subproblems, which provides a feasible schedule for the complete problem. The algorithm forms the subproblems by applying two neighborhoods. The employed algorithms are the Giffler Thompson (GT) algorithm, the Shifting Bottleneck Heuristic (SBH) algorithm, the variable neighborhood search (VNS), and the relaxation neighborhood.

Son et al. [25] address the problem of scheduling jobs with limited splitting on a single machine in the available time windows. These authors present an MILP formulation for this problem and propose different heuristics related to the assignment strategy, such as: assignment heuristic (AH); heuristic based on the shortest/longest processing time rules (HSLPTR); heuristic based on max flow resolution (HMAXFR); and heuristic based on a matching and assignment approach (MAAS). They also apply a combination between the proposed heuristics and metaheuristics, such as tabu search and the GA.

These authors also introduce another approach called exact for subset-jobs matheuristic, which combines mathematical programming, and a priority heuristic rule called the single-attribute priority rule.

Cota et al. [26] propose a solution to address the JSP with unrelated parallel machines with sequence-dependent setup times, and independent non-preemptible jobs, minimizing the makespan and the total consumption of electricity. The authors define a multi-objective smart pool search matheuristic for finding solutions near the Pareto front, in which different MILP problems are generated with different weights for aggregating both objective functions involved in the proposed formulation.

From the review, we can state that very few papers apply combined or hybrid algorithms, such as matheuristic algorithms. In other production fields, matheuristics have obtained good solutions. The research of Cabrera-Guerrero et al. [27] demonstrates that the combination of techniques, or hybridization, can be advantageous for solving complex problems, which is also demonstrated in [28]. Verbiest et al. [28] used a combination of an iterated local search algorithm (metaheuristics) with an MILP model to optimize production lines, design installed lines and allocate products. Their study compares the matheuristic approach with an exact method (MILP) to verify that the matheuristic offers efficient solutions and in a shorter calculation time. According to the results of the studied works, we conclude that matheuristic techniques are suitable for solving problems in realistic instances and allow good results to be obtained in acceptable computing times. Nevertheless, experiments are carried out on commercial solvers, which can be a drawback for those enterprises that cannot afford these tools. Moreover, the maximum data size used for experiments are 120 jobs on six machines, and 20 jobs on 10 machines, which cannot be completely representative of enterprises' realistic data.

Although matheuristics is becoming increasingly well-known for its effectiveness and computational efficiency when dealing with large and NP-hard problems, there is still a long way to go in this field. The contribution of this research aims to provide a solution to the NP-hard JSP with the proposed matheuristic approach by combining a GA and an LP model using a non-commercial solver (CBC) and an open-source operating system (Linux) for a large set of instances.

Table 7.1 Literature review of matheuristic to solve the job-shop problem.

Reference	Job-Shop Problem Type	Matheuristic	Integrated Approaches		Programming Languages /Modeling Language/ Solver	Experiment Size (Job × Machine)
			H+MILP	MH+MILP		
Al-Hinai and Elmekkawy [18]	Flexible JSP	HGA		MILP + GA	C++ / - / - /	20 × 15
Li et al. [19]	Flexible JSP	TSPCB		MILP + TSPCB	C++ / - / - /	20 × 15
Li and Gao [20]	Flexible JSP	HGA TS		GA + TS	C++ / GAMS / CPLEX	15 × 10
Thiruvady et al. [21]	Resource-constrained JSP	MS /CMSA / ACO	Constructive heuristic	MILP + ACO / MS / CMSA	C++ / OpenMP / Gurobi	6 × 20
Rohaninejad et al. [22]	JSP Parallel Machines	GA_BH / GA_ATC / GA_MLS		MIP+GA	CPLEX	6 × 4
Dang et al. [23]	JSP Parallel machine	GA		ILP + GA	/ - /IBM ILOG / CPLEX	120 × 6
Cota et al. [26]	JSP with unrelated parallel machines	-	Multi-objective smart pool search matheuristic + MILP	-	/- / IBM ILOG / CPLEX	15 × 5
Ahmadian and Salehipour [24]	Just-in-time JSP	_	GT algorithm / SBH / VNS / Relaxation neighborhoods	_	C++ /- / CPLEX	20 × 10
Son et al. [25]	Bounded-splitting jobs scheduling problem on a single machine in available time windows	GA / TS	AH / HSLPTR / HMAXFR MAAS	TS + MAAS / GA + MAAS	/- /-/ CPLEX	200 × 1

7.3 Job-Shop Scheduling Problem: Disjunctive Mathematical Formulation

The JSP is an optimization problem in which a set of jobs to manufacture products is assigned to machines at particular times, while attempting to minimize the makespan [17]. Job-shop scheduling is still a problem that has been analyzed since 1954 [29], and is currently tackled given its impact on production costs and efficiency. Nowadays, the JSP remains in essence, but researchers focus on proposing resolution methods that enable enterprises to obtain optimal or near-optimal solutions in shorter computational times to boost the principles of agility, responsiveness and flexibility, all of which are framed within achieving resilience.

The literature proposes different mathematical formulations to model the JSP. Pan [30] presents a comparative analysis of these formulations, namely time-indexed formulation, rank-based formulation and disjunctive formulation. He concluded that the disjunctive model is more efficient because it has the fewest binary variables. More recent studies, such as that presented by Ku and Beck [5], confirm the functionality and effectiveness of the disjunctive model. Although other mathematical formulations exist, they are often combinations or variations of the formulations that we reviewed.

With this background, disjunctive formulation was chosen to model the JSP. To solve the JSP disjunctive problem, we propose combining disjunctive formulation (MILP model) and the GA to generate a matheuristic solution method, whose main aim is to find efficient solutions for large-sized problems and achieve shorter computational times.

The work is then validated by comparing the obtained solutions among the acquired results to solve the JSP disjunctive MILP with a coin-OR Branch & Cut open-source solver.

In this section, we formally define the JSP disjunctive MILP (see Table 7.2). The disjunctive model is presented in Ku and Beck [5]. The JSP is given by a *J* finite set of *n* jobs or parts, and a finite set *M* of m machines or work centers. For each job *j* ∈ *J*, the list $(\sigma_1^j, \ldots, \sigma_h^j, \ldots, \sigma_m^j)$ of machines with the processing order of job *j* is provided. Only one job can be processed by each machine at a time. Once started, it must finish processing on that machine without any interruptions.

Table 7.2. The mathematical notations used in the JSP formulation.

Sets	
J	set of jobs, $J \in \{1,\ldots, n\}$.
M	set of machines $M \in \{1,\ldots, m\}$
Parameters	
p_{ij}	represents the processing time of job j on machine i.
σ_h^j	denotes the *h-th* operation of job j
σ_m^j	means the final operation of job j
V	sum of the processing times of all the operations $V = \sum_{j\in J}\sum_{i\in M} pij$
Variables	
x_{ij}	start time of job j on machine i.
z_{ijk}	1 if job j is before job k on machine i; 0 otherwise

$$\min \boldsymbol{Cmax} \tag{1}$$

$$\text{s.t. } x_{ij} \geq 0, \qquad \forall j \in J, i \in M \tag{2}$$

$$x_{\sigma_h^j, j} \geq x_{\sigma_{h-1}^j, j} + p_{\sigma_{h-1}^j, j}, \qquad \forall j \in J, h = 2, \ldots, m \tag{3}$$

$$x_{ij} \geq x_{ik} + p_{ik} - V \cdot z_{ijk}, \qquad \forall j, k \in J, j < k, i \in M \tag{4}$$

$$x_{ik} \geq x_{ij} + p_{ij} - V \cdot (1 - z_{ijk}), \qquad \forall j, k \in J, j < k, i \in M \tag{5}$$

$$Cmax \geq x_{\sigma_m^j, j} + p_{\sigma_m^j, j}, \qquad \forall j \in J \tag{6}$$

$$z_{ijk} \in \{0, 1\} \qquad \forall j, k \in J, i \in M \tag{7}$$

$$x_{ij} \in \mathbb{Z} \ \forall j, k \in J \tag{8}$$

The purpose is to obtain a scheduling of jobs on machines to minimize the makespan (*Cmax*). Constraint (2) guarantees that each job's start time equals or exceeds 0. Constraint (3) assures that each operation of a job is carried out in the required order. Disjunctive Constraints (4) and (5) establish that there cannot be two jobs scheduled on one machine at the same time. It is necessary to assign V a large enough value to guarantee the correctness of (4) and (5). The completion time of any operation must not exceed the sum of the processing times of all the operations. Constraint (6) guarantees that the makespan is the longest completion time of the last operation of all the jobs as a minimum [5].

7.4 Materials and Methods

7.4.1 Proposed Matheuristic Approach

The aim of this section is to provide a matheuristic approach to solve the JSP quickly and efficiently, particularly for large-sized problems. To do so, we design a matheuristic approach by applying the metaheuristic procedure (GA) in an LP model (GA-LP). The flowchart of the matheuristic approach is shown in Figure 7.1. All the elements of the proposed matheuristic are separately detailed in the following subsections. The general procedure of the proposed approach is as follows:

Step 1: set the input parameters of the matheuristic (GA-LP);

Step 2: generate the initial population: generate individuals using dispatching heuristic rules and generate individuals randomly;

Step 3: evaluate whether the individuals forming the initial population are feasible;

Step 4: eliminate nonviable individuals and insert the feasible ones into the population;

Step 5: convert the integer chromosome generated by the GA into a binary chromosome;

Step 6: evaluate binary individuals using the LP model;

Step 7: normalize individuals' fitness;

Step 8: select two individuals from the population (parents) and use genetic operators (crossover and mutation);

Step 9 evaluate the chromosomes of the offspring and check if chromosomes are feasible. Then, go to step 3.

Step 10: Are the termination criteria met?

If the termination criteria are met, the solution is obtained; otherwise, go to step 8.

To properly define the proposed matheuristic, we pose a simple JSP example shown in Table 7.3. The data presented in Table 7.3 indicate that there are n = 4 jobs (J_1, J_2, J_3, J_4). The processing order of the jobs on the machines (σ_{mo}) are seen in the second column; for example, J_1 has σ_{11}, in which the first index represents the machine and the second denotes the processing order; i.e., job 1 has to be processed first on machine 1, followed by machines m_2, m_3, *and* m_4, respectively.

The processing time of job *j* on machine *i* (p_{ij}) is shown in the third column of this table.

Table 7.3. The job-shop scheduling problem data.

Job	Processing Order of Jobs	Processing Times
1	σ11, σ22, σ33, σ44	p11 = 1; p21 = 4; p31 = 2; p41 = 1
2	σ14, σ23, σ32, σ41	p12 = 2; p22 = 3; p32 = 6; p42 = 2
3	σ11, σ23, σ32, σ44	p13 = 3; p23 = 7; p33 = 2; p43 = 3
4	σ14, σ22, σ33, σ41	p14 = 4; p24 = 1; p34 = 5; p44 = 8

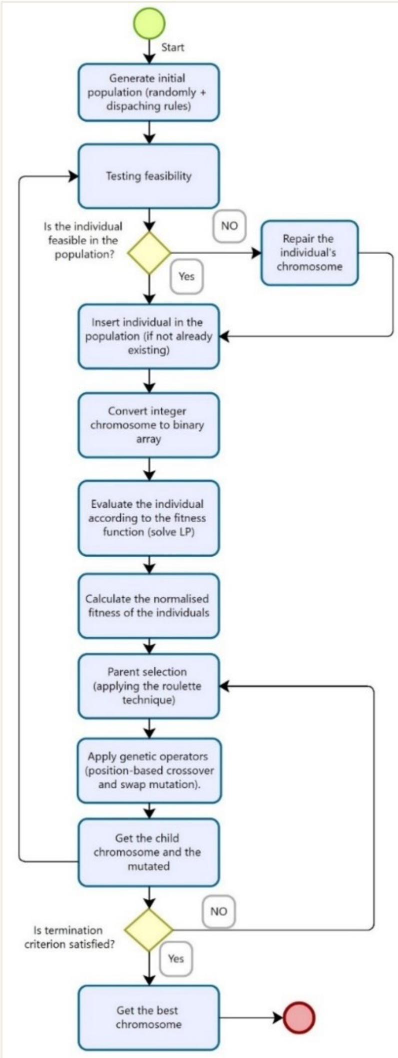

Figure 7.1. Flow chart of the matheuristic algorithm.

7.4.2 Initial Population

Genetic algorithms consist of a set of individuals. Each individual has a chromosome structure composed of genes where the value of each gene represents the jobs performed by each machine. The whole chromosome represents the solution to the problem (see Figure 7.2).

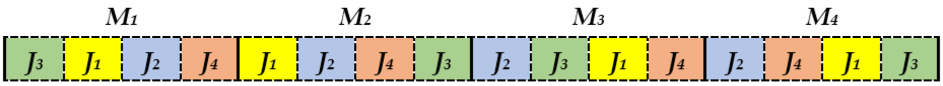

Figure 7.2. Individual's structure.

The GA starts by randomly generating a set of individuals, which is called the initial population. The chromosome of the randomly created individuals can cause the fitness function value to be deficient and can also generate infeasible solutions. Therefore, in the proposed methodology, we use heuristic priority rules to obtain better fitness values by, thus, employing genetic operators so that better solutions can be obtained. In our approach, 80% of the initial population is randomly generated and the rest is generated with the following heuristic priority rules:

- **First In First Out—FIFO:** the first job to arrive is the first to be served;
- **Last In First Out—LIFO:** the last job to arrive is the first to be served;
- **Shortest Operation Time—SOT:** the job that has the shortest processing time is selected. It achieves high flow rate and utilization rates;
- **Longest Operation Time—LOT:** the job with the longest processing time is selected. The longest operations are considered to be the most important and should be processed first;
- **Shortest Remaining Operation Time—SROT:** the priority job is the job with the lowest sum of the processing times for all the remaining operations to be performed;
- **Longest Remaining Operation Time—LRPT:** the priority job is the job with the largest sum of the processing times for all the remaining operations to be performed;
- **Less Remaining Operations—LRO:** the priority job is that with the fewest remaining operations to be performed;
- **Most Remaining Operations—MRO:** the priority job is that with the most remaining operations to be performed;
- **Work In Next Queue—WINQ:** the highest priority is given to the job that would be moved to the machine with the least work to do;

- **Due Date—DD:** the job with the closest delivery date is selected;
- **Static Slack -SS:** the job with the shortest time remaining until the delivery date is selected;
- **Dynamic Slack—DS:** time remaining until the delivery date minus the sum of all the remaining operation times. That with the shortest DS is selected;
- **SS/Remaining Operation Time—SS/TPR**: Static Slack divided by the sum of the remaining operation times of the remaining operations. The smallest one is selected;
- **DS/Remaining Operation Time—DS/TPR:** Dynamic Slack divided by the sum of the remaining operation times of the remaining operations. The smallest one is selected;
- **SS/Remaining Operations—SS/RO:** Static Slack divided by the number of remaining operations. The smallest one is selected;
- **DS/Remaining Operations—DS/RO:** Dynamic Slack divided by the number of remaining operations. The smallest one is selected.

7.4.3 Feasibility Tester

Randomly generated individuals in the initial population or individuals generated by the crossover and mutation operators may generate infeasible solutions. To avoid the LP having to evaluate infeasible solutions, which makes the matheuristic processing time longer, we present an approach to check the feasibility of individuals. To exemplify the feasibility checker, Table 7.4 shows the one feasible sequence and one infeasible sequence that should be corrected.

Table 7.4. Sequence of jobs on machines.

Machines	Feasible Sequence	Infeasible Sequence	Corrected Sequence
1	J_3 J_1 J_2 J_4	J_3 J_1 J_2 J_4	J_3 J_1 J_2 J_4
2	J_1 J_2 J_4 J_3	J_1 J_2 J_4 J_3	J_1 J_2 J_4 J_3
3	J_2 J_3 J_1 J_4	J_2 J_1 J_3 J_4	J_3 J_2 J_1 J_4
4	J_2 J_4 J_1 J_3	J_1 J_2 J_4 J_3	J_2 J_1 J_4 J_3

Infeasibility occurs when jobs do not satisfy the processing order on machines. Table 7.3 shows the processing order of the jobs on machines where, for example, J_1 has the processing order: σ_{11}, σ_{22}, σ_{33}, σ_{44}, i.e., J_1 should be processed first on M_1 and then on machines M_2, M_3, M_4 respectively. Figure 7.3 illustrates the feasible solution for all the jobs to fulfill the processing constraints.

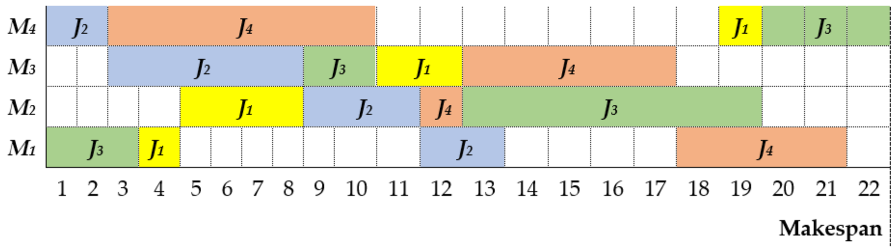

Figure 7.3. Feasible solution representation and its Gantt chart.

To exemplify the feasibility tester, we present an unviable solution (see Table 7.4). In Figure 7.4, we represent the solution, but, as observed, the sequence of J_1 does not comply with the processing order. In the same way, J_2 cannot be located as the processing order of J_2 is σ_{14}, σ_{23}, σ_{32}, σ_{41}. This means that it must first be processed on M_4 and then on M_3, M_2, M_1. However, J_1 on machine 4 leads to the processing order not being fulfilled because predecessor J_1 on machine 3 is processed after the job of its successor J_1 on machine 4. This is what causes the infeasibility in the chromosome of the individuals. Therefore, the chromosome must be repaired.

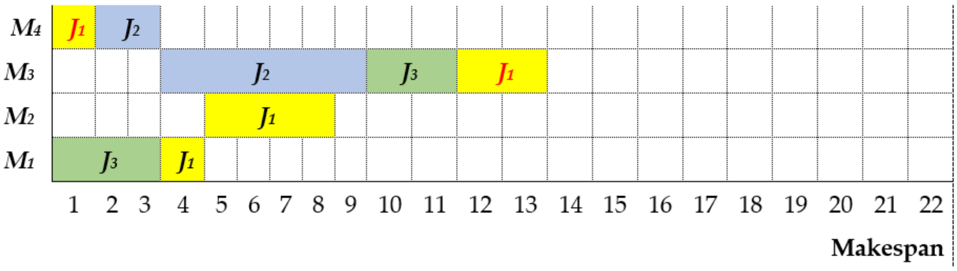

Figure 7.4. Infeasible solution representation and its Gantt chart.

After verifying infeasibility, the feasibility tester changes the location of J_1 and J_2 on machine 4 and, in the same way, the positions of J_1, J_2, J_3 on machine 3 (see Table 7.4). After using the feasibility checker in Figure 7.5, the representation of the solution that meets all the precedence constraints is shown.

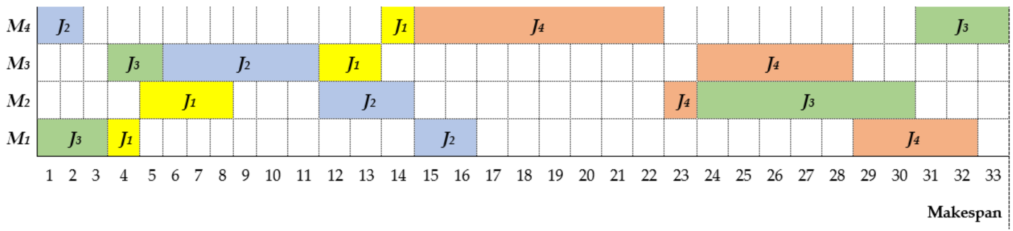

Figure 7.5. Repaired solution representation and its Gantt chart.

7.4.4 Fitness Function

The individuals in the population are evaluated with the fitness function, which measures the quality of solutions. The evaluation of individuals is performed using the disjunctive relaxed MILP model, i.e., an LP model. Thus, binary variable z_{ijk} represents whether job j is prior to job k on machine i, and is calculated by the GA. Hence, this variable is fixed to the LP. The binary variable is calculated sequentially with the GA, i.e., while the GA generates individuals, the LP evaluates that the chromosome meets the constraints of the disjunctive model described in Section 7.3.

As individuals have an integer chromosome and variable z_{ijk} is binary in nature, we convert the chromosome. For this purpose, we use the position of each gene as shown in Figure 7.6. Machine 1 has sequences J_3, J_1, J_2, J_4. We start by looking for the location of the first predecessor job, that is job 1, and this gene is in position 2. Then, we look for the successor job, which is job 2 that meets the condition of the position of the predecessor job being inferior to the successor job. Thus, we assign 1. This same condition is met by predecessor job J_1 and successor job J_4, but this condition is not met by J_3, which is in position 1. Table 7.5 shows the result obtained with this process.

	M_1				M_2				M_3				M_4			
	J_3	J_1	J_2	J_4	J_1	J_2	J_4	J_3	J_2	J_3	J_1	J_4	J_2	J_4	J_1	J_3
Position	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16

Figure 7.6. Position of genes on integer chromosomes.

Table 7.5. Precedence of jobs with binary array z_{ij}.

i	*j*	*k*	*z*
1	1	2	1
1	1	4	1
1	2	4	1
1	3	1	1
1	3	2	1
1	3	4	1
2	1	2	1
2	1	3	1
2	1	4	1
2	2	3	1
2	2	4	1

Table 7.5. Continued. Precedence of jobs with binary array z_{ij}.

i	*j*	*k*	*z*
2	4	3	1
3	1	4	1
3	2	1	1
3	2	4	1
3	3	1	1
3	3	2	1
3	3	4	1
4	1	3	1
4	1	4	1
4	2	1	1
4	2	3	1
4	2	4	1
4	4	3	1

7.4.5 Selection

Before applying the selection operator, the normalized fitness of the individuals in the population is calculated with the difference between the highest fitness value and the fitness value of each individual.

The selection operator is in charge of deciding which individuals in the population will have the opportunity to reproduce. As a selection operator, we employ a roulette wheel approach [31]. This approach consists of the best individuals, according to their fitness, having the best opportunity to be selected with a uniform selection probability within the range [0...1].

7.4.6 Crossover Operator

The crossover operator used by the GA is the Partially Mapped Crossover Operator. Given the fact that the chromosome of the individuals has an ordered set of permutations, this operator allows for the creation of non-repeated permutation, which it does by choosing two crossover points at random that delimit the area to be inherited. The offspring takes any value of this area from one parent and the rest from the other, which can produce duplicates. To remove duplicates, this method uses a map, on which it checks the relation between the copied sections, and verifies if there is a duplicate gene or a missing gene in the chromosome.

7.4.7 Mutation Operator

In this paper, we use swap mutation. This procedure is as shown in Figure 7.7, where we randomly select two positions from each machine, and then swap the genes at the selected positions to generate a mutated offspring. Our GA employs a mutation probability (pm = 1). As the mutated offspring can give a worse fitness value than the normal offspring [32], we insert the normal and the mutated one into the population if they do not exist after passing the feasibility tester.

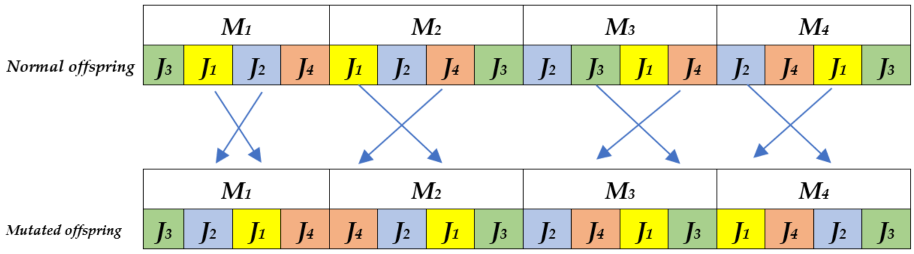

Figure 7.7. An example of a swap mutation operator.

7.5 Computational Experiments

The purpose of this study is to evaluate the performance of the non-commercial CBC solver with both the mathematical model and the matheuristic one on large or similar instances to those used by SMEs. To evaluate the performance of the proposed matheuristic, we test the performance of the disjunctive MILP model by using a CBC solver. For this purpose, we generate experiments that consist of a set of different sized problems (20 × 15, 20 × 20, 30 × 20). To do so, we use the large-scale instances of Taillard [33], specifically the instances labeled Ta11-Ta13, Ta26-Ta28 and Ta41-Ta43. The dataset can be found in [34]. The JSP is NP-hard for $n \geq 3$ and m ≥ 2 [5].

The software followed in this research is a non-commercial optimization solver from the Computational Infrastructure for Operation Research (COIN-OR) community called the COIN-OR Branch and Cut Solver [9]. This open-source solver is generally employed for MILP problems. The MILP model and the matheuristic were implemented in Python with the Pyomo package [35]. Experiments were run by an Intel Core i7 2.80 GHz processor (8 GB RAM) in the Ubuntu 20.04.1 LTS operating system.

The GA-LP was run 10 times with the same problem instances. The stopping criterion of the mathematical model and matheuristic is 3600 s. The parameters used in the GA-LP are shown in Table 7.6. The average solutions (*Cmax*) of the GA-

LP and the time in which the methods reached the best solutions are shown in Table 7.7.

The results show that the CBC solver cannot obtain good results for the Ta12, Ta27, Ta42 and Ta43 instances because of its computational difficulty. It is noteworthy that the matheuristic algorithm obtained good solutions in relatively shorter computational times than the CBC solver.

Table 7.6. GA-LP parameters.

Population size	100
Crossover operator	Partially Mapped Crossover
Selection operator	Roulette wheel
Mutation operator	Swap
Mutation ratio	1

Figure 7.8 offers the results obtained with instances Ta11 (20 × 15), Ta25 (20 × 20) and Ta41 (30 × 20). The computational results of CBC for instances Ta12, Ta27, Ta42 and Ta43, are relatively bad, and do not converge to good solutions. For these instances, we changed the stopping criterion to check if the CBC solver can obtain better results, with a computing time of 4 h. We confirm that the result is still the same. The deviation value of these instances is not shown in Figure 7.8 as it cannot be compared with the matheuristic.

Table 7.7. Comparison of how the proposed approaches perform.

Problem	***n* × m**	**Methods**					
		CBC			**Matheuristic (GA-LP)**		
		Cmax	**CPU (sec)**	***D*[1] *(%)***	***Cmax***	**CPU (sec)**	***D (%)***
Ta11	20 × 15	2219	3567.57	35.55%	1637	198.67	0%
Ta12	20 × 15	-		-	1627	196.09	0%
Ta13	20 × 15	1902	3565.46	15.06%	1653	64.16	0%
Ta26	20 × 20	2483	2673.88	29.32%	1920	152.79	0%
Ta27	20 × 20	-		-	1982	234.88	0%
Ta28	20 × 20	1978	2948.2	3.55%	1910.2	267.64	0%
Ta41	30 × 20	3282	3227.24	32.82%	2471	366.47	0%
Ta42	30 × 20	-			2415	361.36	0%
Ta43	30 × 20	-			2350	373.08	0%

[1] Deviation = [(Obtained Value—Best Value)/Best Value]

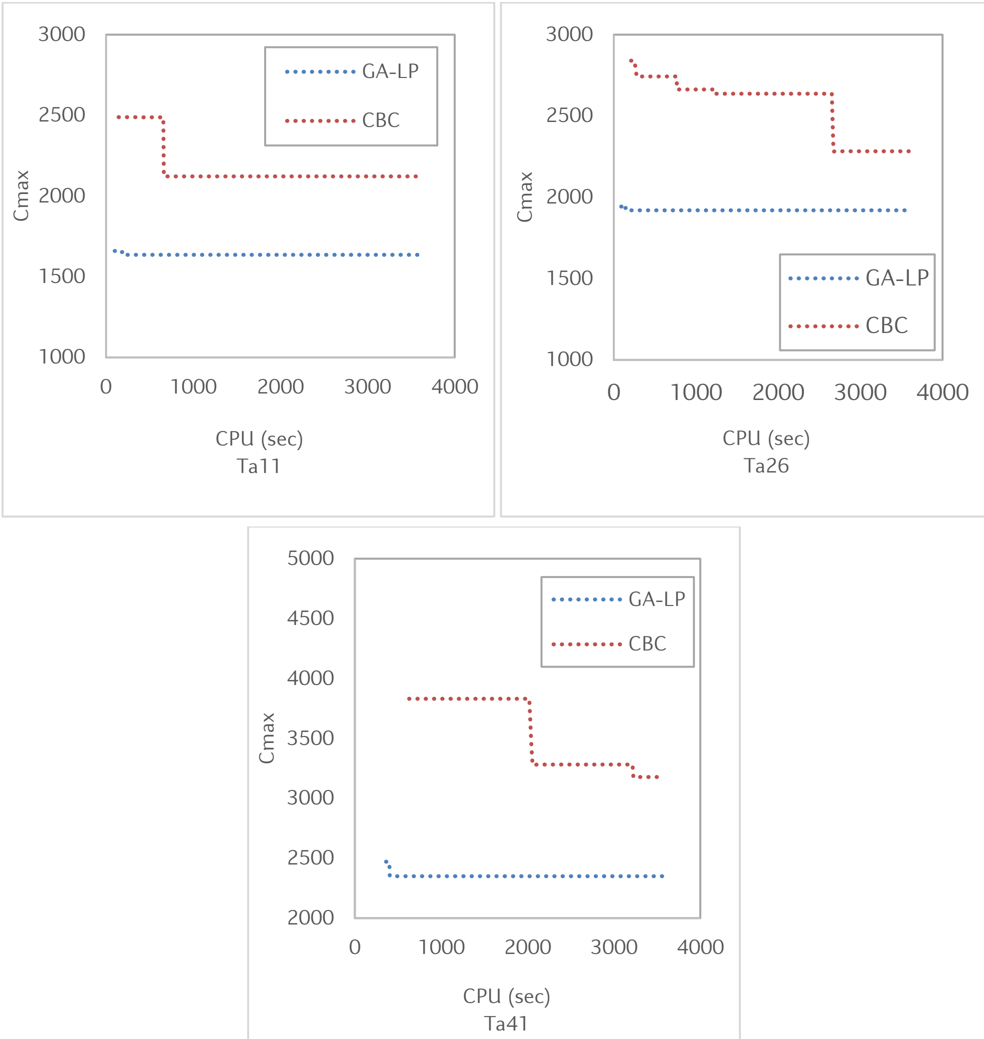

Figure 7.8. Experimental results.

From Figure 7.8, it is deduced that the matheuristic produces better results and allows good solutions in short computational times. Table 7.7 shows the results of deviations, where the GA-LP approach provides the best solution for each problem size. GA-LP provides better solutions than CBC, especially with rising computational difficulty. All these results indicate that, by using 20% of the individuals in the initial population with heuristic priority rules, we can improve the efficiency of the proposed method for large instances.

The Figure 7.9 shows the box plots of the two proposed methods for instances Ta11, Ta26 and Ta41. The distribution of the results can be observed in the box plot. The stability of the matheuristic algorithm results is more stable than the CBC. According to the results. we conclude that GA-LP provides better solutions for all the instances in quality and solution time terms.

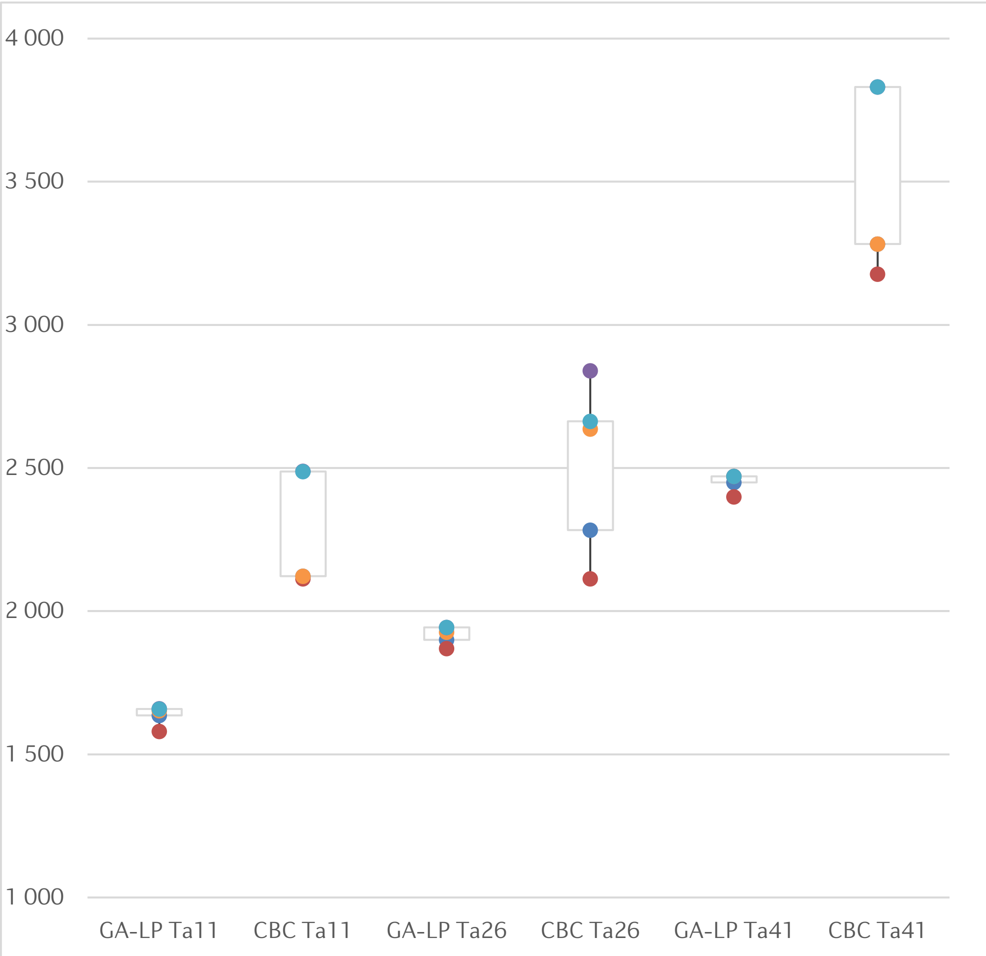

Figure 7.9. Box plot of all the methods.

7.6 Conclusions and Further Work

The new production paradigms offer plenty of opportunities and challenges as they support the transformation of technology and market conditions for companies. The adaptation of companies to Industry 4.0 means that companies must look for technological tools that help to optimize their manufacturing processes. The adaptation to this technology is determined by adapting different technological tools to the companies. In many cases, SMEs cannot cope with all the technological changes given their cost. Thus, the use of open-source software can act as a valuable tool for companies.

In order to contribute to the literature, this paper presents a matheuristic that combines a GA with a relaxed MILP, solved using a non-commercial solver. We apply different priority heuristic rules to provide faster and more efficient solutions for large problems. The proposed matheuristic achieves good results for large instances. In short computational times, the CBC solver does not offer good results for large instances, but the CBC solver-GA combination provides better solutions in shorter computational times. In the literature, no experiments appear with a non-commercial solver for this instance size. This means that matheuristic can be a useful tool for those SMEs that do not wish to pay for commercial solvers as matheuristic is a useful tool that is easily implemented.

The comparison of the mathematical model, and the matheuristic approach shows that the GA-LP with heuristic priority rules provides good results compared to the CBC results. CBC for the instances of 30 jobs and 20 machines provides the best results in almost 1 h, while the matheuristic approach achieves the best results for these instances in under 400 s. After analyzing the two approaches presented to solve the JSP, we see that the GA-LP is a robust method, is able to achieve good results on instances with different complexities and has a faster convergence rate compared to CBC.

Therefore, future research lines include: improving the GA as the applied genetic operators are standard ones and the operators designed for the concrete problem would perform better; attempting other hybridizations can be performed using: other metaheuristics, such as GRASP, Memetic Algorithm, Particle Swarm Optimization, Tabu Search, Variable Neighborhood Search, and others identified in [10]; testing instances with different job and machine sizes and varying processing times. Other non-commercial solvers can be tested, such as SCIP (Solving Constraint Integer Programs) with commercial solvers like Gurobi and CPLEX.

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Chapter 8

A matheuristic approach to production and distribution planning.

Guzman E, Poler R, Andres B. “*A matheuristic approach to production and distribution planning*”. Submitted to Advances in Production Engineering & Management. 2022

Abstract:

A number of research studies has addressed supply chain planning from various perspectives (strategical, tactical, operational) and demonstrated the advantages of integrating both production and distribution planning (PDP). The globalisation of supply chains and the fourth industrial revolution (Industry 4.0) mean that companies must be more agile and resilient to adapt to volatile demand, and to improve their relation with customers and suppliers. Hence the growing interest in coordinating production-distribution processes in supply chains. To deal with the new market’s requirements and to adapt business processes to industry’s regulations and changing conditions, more efforts should be made towards new methods that optimise PDP processes. This paper proposes a matheuristic approach for solving the PDP problem. Given the complexity of this problem, combining a genetic algorithm and a mixed integer linear programming model is proposed. The matheuristic algorithm was tested using the Coin-OR Branch & Cut open-source solver. The computational outcomes revealed that the presented matheuristic algorithm may be used to solve real sized problems.

8.1 Introduction

The globalisation of markets has lee to companies to optimise their processes and resources to remain competitive. Nowadays, optimisation is a relevant factor for improving firms' performance, and for turning the challenges that they face into competitive advantages [1]. One optimal strategy for profits that can minimise a company's total costs is to integrate different business functions, such as purchasing, inventory management, production and distribution [2]. Therefore, it is an important factor for optimizing supply chain enterprises to establish greater integration production and distribution planning (PDP) [3]. The PDP problem is defined by Safaei et al. [4] as a firm's scheduling process to manufacture the right products and to ship the quantities of the right products to the right place at the right time.

Increasing pressure to minimise total production and logistic costs means that supply chain agents are having to re-examine production-distribution policies, and to maximise the use of physico-technological assets [5]. Properly coordinating PDP in supply chains is a challenging problem because companies expand internationally and move to a competitive environment that requires greater collaboration. Efficient supply chain cooperation involves many coordinated decisions being made at several decision levels (e.g., strategical, tactical, operational) about products, financial resources and information.

In this context, the present research work develops an efficient matheuristic approach to solve the integrated PDP problem. A matheuristic algorithm is defined by Boschetti et al. [6] as *"the interoperation of metaheuristics and mathematical programming techniques"*. There are different approaches for combining metaheuristics with exact methods, and each technique has its individual advantages and disadvantages. However, the aim is to benefit from synergy. Several researchers present a taxonomy that classifies this type of cooperation. Table 8.1 shows several approaches by different authors, although some have similar characteristics.

Table 8.1. Classification of matheuristic approaches.

<table>
<tr><th>Approach</th><th colspan="2">Classes</th></tr>
<tr><td>Cooperation between exact and local search methods.
[7] based on Dumitrescu & Stützle [8]</td><td colspan="2">Exact algorithms to browsing through neighbourhoods in local search algorithms.
Exact algorithms intended for specific hybrid metaheuristics procedures.
Explore boundaries in constructive heuristics.
Local searches or constructive algorithms guided by data from integer programming model relaxations.
Exact algorithms for smaller problems using solutions from local searches</td></tr>
<tr><td rowspan="2">Combination between exact techniques and metaheuristic algorithms [9], [10]</td><td>Collaborative combinations.
Algorithms exchange information. None is contained in any other. Both procedures can be executed sequentially, interlaced or in parallel</td><td>Subclasses
Sequential execution
Parallel and intertwined execution</td></tr>
<tr><td>Integrative combinations.
One technique is component-integrated into another technique with a master-slave structure. An exact or metaheuristic algorithm can be presented with a master-type structure and at least one integrated slave</td><td>Incorporating exact algorithms into metaheuristics
Incorporating metaheuristics into exact algorithms</td></tr>
<tr><td>MASTER-SLAVE” structure with a guiding process and application process [11]</td><td colspan="2">- Metaheuristics operate at the master level and, thereby, control and guide actions to the exact technique
- The exact method operates as a master to call/control by the metaheuristic approach</td></tr>
</table>

When designing a matheuristic, the question is, which components can work together to generate an efficient algorithm? Although supplying a collaboration rule does not seem a feasible approach, the matheuristic design involves functionality and architecture. Thus the cooperation level can be ranked according to its hierarchy, as in Table 8.2 [12].

Table 8.2. Hierarchical matheuristic classification [12].

Hierarchy	Description
LRH (low-level relay hybrid)	It depicts hybrid schemes in which a metaheuristic approach is included in an exact approach to improve the search strategy
LTH (low-level teamwork hybrid)	It describes one search element of a metaheuristic to be replaced with another exact algorithm
HRH (high-level relay hybrid)	Autonomous algorithms are executed in a sequence. The stage can be either pre-processing or post-processing, i.e., two groups of algorithms (metaheuristics + exact algorithms) are provided with some data in sequence
HTH (High-level Teamwork Hybrid)	A combination of metaheuristics and exact algorithms that performs a parallel search and cooperate to find relaxed optimal solutions, better lower or upper bounds, optimum subproblem solutions, partial solutions, etc. Metaheuristics and exact algorithms solve partial, specialised or global optimisation problems and exchange helpful information.

Recent studies, such as that presented by Kumar et al. [13], provide a literature review of the quantitative approaches applied to combined PDP. These authors concluded that the main modelling approaches for this problem type are MILP (mixed integer linear programming), while the main applied solution approaches are those that resort to optimisation software, followed by genetic algorithms (GAs). Computational experiments in small instances use mainly LINGO and CPLEX to solve MILP and Matlab and C++ in large instances to solve heuristic and metaheuristic methods. In this review, we observe that matheuristic methods have not yet been discussed in-depth. As far as the authors know, to date no research has addressed the PDP problem using this type of matheuristic.

In this context, we propose developing a solution strategy for the PDP problem with a mathematical algorithm that is positioned in the hierarchical classification described in Table 8.2 as a High-level Teamwork Hybrid. This strategy is useful because the search space of the MILP model is considered to be too big for a solver to solve it. Therefore, we employ a GA that exchanges information in parallel to the MILP model to diminish the search space.

Given the complexity of PDP problems, they prove difficult when implementing large datasets or solving real SME problems with a MILP model. For this reason, some companies choose to use commercial solvers for this type of problem. However, some SMEs cannot afford to buy a commercial solver because of its high cost but, as digitisation needs are accelerating, many companies are considering how to be equipped with a digital infrastructure insofar as it does not constrain them and does not cost too much. So those SMEs that have implemented open-source software have made significant savings in technology spending because they do not have to pay annual software licences and have not run the risk of software becoming obsolete when licences expire [14].

Accordingly, this article contributes: (i) a new matheuristic approach to solve the PDP problem; (ii) the matheuristic algorithm was tested and compared to a non-commercial Coin-Branch & Cut (CBC) solver and employs a free open-source operating system (Linux). The proposed approach's effectiveness is proven by solving randomly generated test datasets with real data sizes.

The rest of this article is arranged as so: Section 8.2 briefly presents a literature review about the integrated approach to supply chain PDP; Section 3 offers a mathematical model; Section 8.4 details the matheuristic algorithm for solving the planning-distribution problem; Section 8.5 presents the evaluation of the matheuristic algorithm using large instances to simulate real-life companies. Finally, Section 8.6 defines some conclusions and future research directions.

8.2 Related works

This section reviews the literature about integrating decisions from PDP functions, along with the solution approaches suggested for these problems. This problem has been paid plenty of attention in recent years. Literature reviews like that by Chen [15] indicate several future research lines. One of them states that more effort should be made to create heuristic or metaheuristic methods for this type of problems, which are NP-hard, as there are very few solution algorithms for this type of problems. Years later Fahimnia et al. [16] describe that the use of heuristic, metaheuristic and simulation techniques predominate in the literature, but propose employing new techniques, and suggest having to extend the effectiveness of solution techniques to deal with realistic PDP problems as most techniques have been applied to deal with small- and medium-sized problems. Lastly, the work by Kumar et al. [13] indicates the extensive use of metaheuristic algorithms like heuristic algorithms, GAs and exact methods, but does not reveal the use of matheuristic algorithms.

Accordingly, related work like that of Raa et al. [5] proposes an aggregate PDP model for injection moulding production in the many facilities of a plastics manufacturer. This MILP is solved by the Gurobi solver for small instances. For large instances, these authors employ an iterative matheuristic that utilises a decomposition heuristic. Bilgen and Çelebi [1] offer a combined simulation and MILP approach for integrated production and distribution problems in the dairy industry. The MILP model is solved with CPLEX and the hybrid approach employs ARENA.

Su et al. [17] propose combining distinct algorithms like the GA and particle swarm optimisation (PSO). The GA comes with a learning scheme, and a hybrid algorithm that combines PSO techniques with the GA and a learning scheme to solve both partner selection and the PDP problem in a manufacturing chain design. Moattar Husseini et al. [18] put forward bi-objective MILP for integrated PDP with manufacturing partners. One of the objectives of this model is to minimise the total cost by covering production, inventory holding purchases from partners and transport-distribution costs. Another objective aims to maximise the quality level of the products that partners supply on the planning horizon. For this problem, they employ LINGO to solve the model in small instances. However, as the problem in large instances is classified as NP-hard, the authors solve it by a Non-Dominant GA II (NSGA-II) and a Multi-Objective PSO (MOPSO) algorithm. The computational results confirm the suitability and practicality of these two algorithms, but the MOPSO algorithm obtains better results in most instances. Devapriya et al. [19] report a PDP problem with a perishable product. The problem is modelled by MILP, is solved with CPLEX, employs a memetic algorithm to solve the problem in large instances, and obtains good solutions in a relatively shorter computational time.

Kazemi et al. [3] put forward a hybrid algorithm that combines a multi-agent system and three metaheuristic algorithms, including a GA, a tabu search and simulated annealing. They propose a MILP model that is solved with LINGO. They employ Matlab to evaluate the hybrid approach. Their results reveal that LINGO better works in small instances, while the hybrid approach delivers better solutions in large instances. In a multifactory supply chain, Gharaei and Jolai [20] study a multi-agent scheduling problem with distribution decisions. To do so, they propose using a MILP formulation to solve the problem with CPLEX by employing small and medium instances. They also develop a multi-objective evolutionary algorithm based on decomposition by combining the Bees algorithm and using Matlab, which well performs in long instances. Marandi and Fatemi Ghomi [21] put forward an integrated production-distribution scheduling problem. They aim to simultaneously find a production schedule and a vehicle routing solution to minimise the sum of delay and transportation costs. They apply CPLEX for small problems and propose a new algorithm for medium and large problems, namely the Improved Imperialist Competitive Algorithm, which applies a local search algorithm based on a simulated annealing algorithm.

The literature review highlights a growing research tendency to integrate PDP functions. It reveals that companies tend to collaborate with manufacturing partners to better respond to demanding market conditions, and they focus more on their core activities. Interest is shown in heuristic and metaheuristic methods, which are frequently employed to solve these problems with large instances. These instances normally represent the size of the data actually employed by real companies, although different variants of the PDP problem exist. Models tend to be solved mostly with a commercial solver, of which CPLEX is the most widespread. Despite previous works having discussed some combinations of the above algorithms, other combinations have not yet been addressed by the literature, such as those using matheuristic algorithms in practice.

Based on these results, this study considers an integrated PDP problem formulated as a MILP model. As the literature reports the potential effectiveness of GA-based algorithms [18], a combined solution approach with a GA and a mathematical model is herein considered. A non-commercial solver and an open-source operating system are also implemented. The next sections discuss the particulars of the posed problem, its formulation and the solution approach.

8.3 Problem definition

This section offers details of the studied problem and formulates the proposed model. The PDP problem herein contemplated is based on Park [22].

The MILP model takes these assumptions:

- For the production stage: many production plants produce multiple items with a limited capacity per time period. Each product type has a setup cost, while production plants have a limited storage capacity, and produced items are shipped directly to points of sale.
- For the distribution stage: distribution is performed with a fleet of homogeneous vehicles, which are parked in production plants.
- The vehicle movement incurs on: (i) a fixed cost in relation to the depreciation of vehicles, insurance, etc.; (ii) a variable cost according to the transported item, quantity and route.

For points of sale: an item's demand during a period at a point of sale consists of two components: (i) "core demand": the amount of main demand that the point of sale must meet by loyal customers in the long term; (ii) "forecasted demand": the total amount, including core demand. Unmet demand at a point of sale is considered a stockout (rejected demand) and does not allow deferred demand. Each point of sale can maintain a limited amount of inventory at a very high cost. An overview of the considered problem is demonstrated in Figure 8.1.

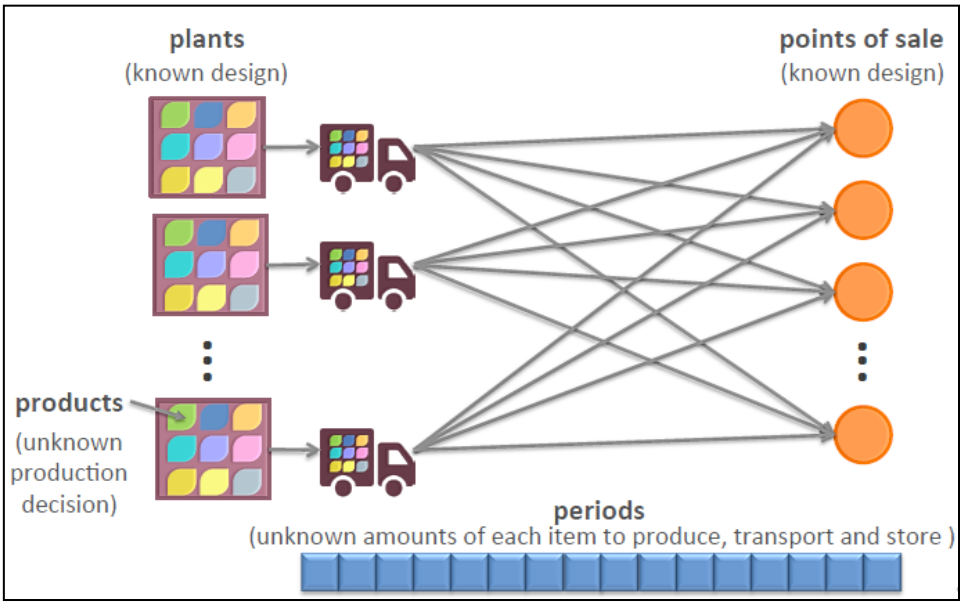


Figure 8.1. Illustration of the integrated production and distribution planning problem

8.3.1 Notation

The PDP problem nomenclature is shown below.

Table 8.3. The MILP model nomenclature.

Notation	Description
Sets	
i	Index of plants $i \in \{1, \ldots, I\}$
j	Index of points of sale, $j \in \{1, \ldots, J\}$
k	Index of products (parts) $k \in \{1, \ldots, K\}$
t	Index of time periods $t \in \{1, \ldots, T\}$
Parameters	
C_{ik}	cost of producing 1 unit of product k in plant i
s_{ik}	cost of setup for product k in plant i
o_{ik}	time of producing 1 unit of product k in plant i
u_{ik}	time of setup for product k in plant i
hp_{ik}	unit holding cost per period for product k in plant i
L_i	production capacity per period of plant i
$dijk$	cost of transporting 1 unit of product k from plant i to point of sale j

Table 8.3. Continued. The MILP model nomenclature.

Notation	**Description**
Parameters	
g	fixed cost per vehicle
B	capacity per vehicle
E_{jkt}	core demand of product k at point of sale j during period t
F_{jkt}	forecasted demand of product k at point of sale j during period t
p_{jk}	price of sale of 1 unit of product k at point of sale j
hr_{jk}	unit holding cost per period for product k at point of sale j
Wr_j	inventory capacity of point of sale j
v_{jk}	unit stockout cost of item k at point of sale j
Variables	
x_{ikt}	amount of product k produced at plant i during period t
q_{ijkt}	amount of product k transported from plant i to point of sale j during period t
Y_{ikt}	1 if product k is produced a plant i during period t; 0 otherwise
ap_{ikt}	inventory level of product k at plant i during period t
ar_{jkt}	inventory level of product k at point of sale j during period t
z_{ijt}	number of vehicles needed for distribution from plant i to point of sale j during period t

The objective function maximises sales revenues at points of sale, minus the costs of setup, production and inventory at plants, the costs of inventory and stockout at points of sale, and the costs of vehicles and transport.

$$\begin{aligned} MaxZ = {} & \sum_j \sum_k p_{jk} \cdot \sum_t \left(ar_{jkt-1} + \sum_i q_{ijkt} - ar_{jkt} \right) \\ & - \left(\sum_i \sum_k c_{ik} \cdot \sum_t x_{ikj} + \sum_i \sum_k S_{ik} \cdot \sum_t Y_{ikt} + \sum_i \sum_k hp_{ik} \right. \\ & \left. \cdot \sum_t ap_{ikt} \right) \\ & - \left(\sum_j \sum_k hr_{jk} \cdot \sum_t ar_{jkt} + \sum_j \sum_k v_{jk} \cdot \sum_t \left(F_{jkt} - ar_{jkt-1} \right. \right. \\ & \left. \left. + \sum_t q_{ijkt} + ar_{ijkt} \right) \right) \\ & - \left(g \cdot \sum_i \sum_j \sum_t z_{ijt} + \sum_i \sum_j \sum_k d_{ijk} \cdot \sum_i q_{ijkt} \right) \end{aligned} \tag{1}$$

Subject to:

Material flow constraints

$$ap_{ikt} = ap_{ikt-1} + x_{ikt} - \sum_j q_{ikt} \qquad \forall i,k,t \qquad (2)$$

$$ar_{jkt-1} + \sum_i q_{ijkt} - ar_{jkt} \geq E_{jkt} \qquad \forall j,k,t \qquad (3)$$

$$ar_{jkt-1} + \sum_i q_{ijkt} - ar_{jkt} \leq F_{jkt} \qquad \forall j,k,t \qquad (4)$$

Constraint (2) guarantees the inventory of all products in each plant at the end of every period. Constraint (3) ensures meeting "core demand" at each point of sale per product during each time period. Constraint (4) ensures that the demand served for any product at any point in time at any point of sale never exceeds the expected demand ("forecast demand").

Physical resource limitations

$$\sum_k o_{ik} \cdot x_{ikt} + \sum_k u_{ik} \cdot Y_{ikt} \leq L_i \qquad \forall i,t \qquad (5)$$

$$x_{ikt} <= M \cdot Y_{ikt} \qquad \forall i,k,t \qquad (6)$$

$$\sum_k ar_{jkt} \cdot \leq Wr_j \qquad \forall j,t \qquad (7)$$

$$z_{ijt} \sum_k \frac{q_{ijkt}}{B} \qquad \forall i,j,t \qquad (8)$$

$$ap_{ik0} = 0, ar_{ik0} = 0 \qquad \forall i,j,k \qquad (9)$$

Constraint (5) guarantees that, per plant during each period, the capacity consumption due to the processing and preparation times of processed items never exceeds the plant's available production capacity. Constraint (6) ensures that if a quantity of a certain product is produced in a plant during a period, a setup of this product is necessary. Constraint (7) ensures that the amount of products stored at a point of sale during every period must never exceed the point of sale's storage capacity. Constraint (8) computes the number of vehicles required to transport products from every plant to each point of sale during all periods. Constraint (9) represents the initial inventory levels in plants and at points of sale.

$$Y_{ikt} \in \{0,1\} \qquad \forall i,k,t \qquad (10)$$

$$x_{ikt}, q_{ijkt}, ap_{ikt}, ar_{ikt}, z_{ijt} \in \mathbb{Z} \qquad \forall i,j,k,t \qquad (11)$$

Constraints (10) and (11) indicate the binary nature of Y_{ikt} and the integer nature of some variables.

8.4 Matheuristic solution method

The PDP problem is a complex one to solve given the number of integer variables that corresponds to produced and transported products, the inventory level in the plant and at points of sale, and the vehicles needed for distribution, plus the binary variable that indicates in which plants products are produced. Given the difficulty of this problem, a solution methodology is offered and describes how the GA is combined with the MILP model to evaluate the solutions for the PDP problem. Figure 8.2 illustrates the flow chart of the matheuristic approach. The particulars of elements are described below.

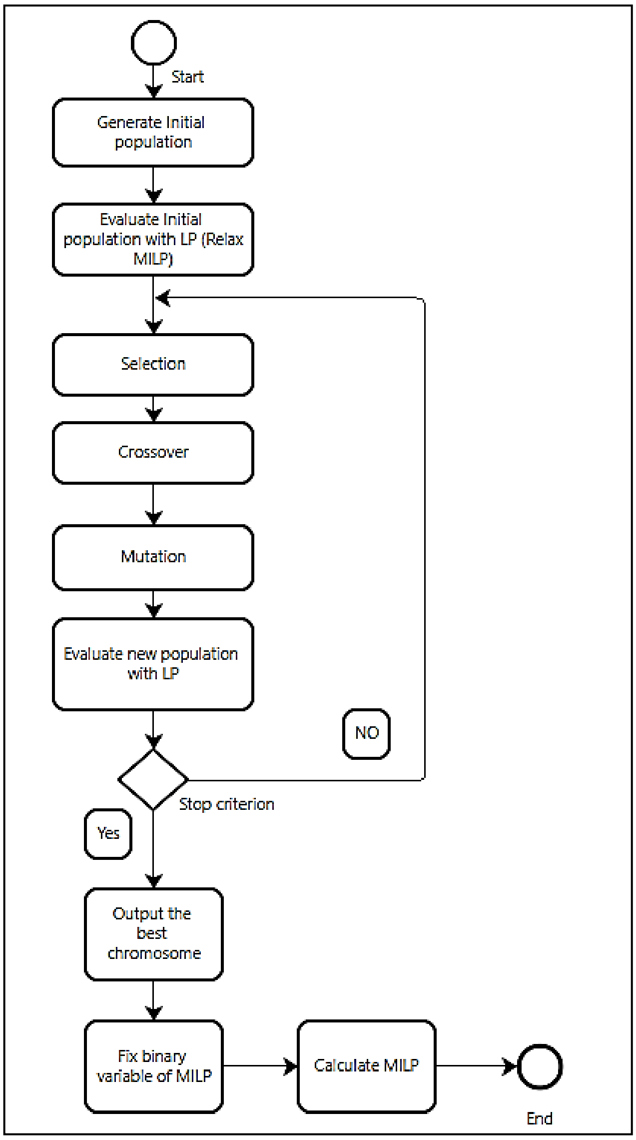


Figure 8.2. The flow chart of the proposed matheuristic approach

8.4.1 Initial population

Each individual in the population corresponds to binary decision variable $Y_{ikt,}$ which takes 1 if product k is produced in plant i during period t, and 0 otherwise. An individual's length is a one-dimensional matrix of size $I \times K \times T$ (multiplication of the quantities of every index). The population takes a binary structure and is generated randomly from a uniform distribution with a 50% probability of 1 appearing on an individual's chromosome. The computational results indicate that fewer infeasible individuals are generated if this probability is applied. Population size N_{pop} equals 10, so we employ this small size to increase the GA's speed. Koljonen and Alander [23] confirm that a small population size increases the optimisation speed to a certain extent. We prove that using this population size suffices to obtain good solutions.

8.4.2 Evaluation function

The fitness function measures the quality of an individual in the population. The problem looks for solutions that maximise the benefits that the objective function represents. The PDP problem's computational difficulty focuses mostly on binary variable Y_{ikt}, which refers to the decisions made about which product to produce in which plant. This means that the GA is in charge of producing a suitable binary chromosome with equal dimensions to the binary variable.

As this binary chromosome corresponds to each individual in the population, the evaluation of each individual is made by formulating the mathematical model. The computational and execution times of a MILP *versus* a linear programming (LP) model are longer given the SIMPLEX algorithm's computational efficiency *versus* the algorithms dedicated to solve problems with integer or binary variables, along with the problem's difficulty, which is considered NP-hard. The proposed MILP model comprises one binary variable and five integer variables. Thus, to improve matheuristic performance, we apply MILP model relaxation. The MILP relaxation to obtain LP is given by transforming integer variables into continuous variables, and by transforming the binary variable into data.

At this time the solver is in charge of solving LP and the GA is responsible for supplying the binary variable. The binary variable of the GA is fixed to LP. Thus, when executing the matheuristic, it can be quickly solved even for very large problems. In our experiments, on average LP obtains better results than MILP by 3.84%. Thus, to obtain a final result, we employ the best binary chromosome obtained during the evaluation process and launch MILP to gain a final result. This is explained in Section 8.4.6.

8.4.3 Selection

In the selection stage, a set of individuals from the current population is chosen to be used as the parents for the crossing stage. The roulette wheel approach [24] is taken to select the individuals with the best fitness values in accordance with the uniform probability of selection distributed over the range [0...1], and the worst individuals are eliminated from one generation to another so that the best individuals are more probably selected.

8.4.4 Crossover

The single point crossover technique [25] is applied. Two parents (P1 and P2) are selected by the fortune roulette wheel selection technique. Then the P1 and P2 chromosomes are cut at a point that is randomly generated and a new offspring (OF) is generated with the genetic information of its parents, as illustrated in Figure 8.3.

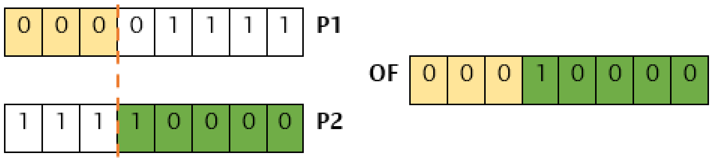


Figure 8.3. Single-Point Crossover

8.4.5 Mutation

Mutation allows the GA to explore a bigger region of the ranges of potential solutions by including random genetic changes, which are produced by introducing variations into individuals, and thus allowing the GA to not fall into local optima [26]. The swap mutation operator is implemented here. This mutation method randomly selects two genes from offspring and then exchanges the gene content in its offspring, as shown in Figure 8.4.

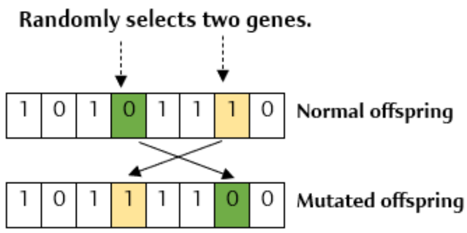


Figure 8.4. The Swap mutation operator

The offspring that undergo mutation are selected with uniform probability Pm=1. This means that all offspring are mutated but, in order not to lose the normal offspring, both the normal and mutated offspring remain in the resulting population. This avoids losing a good solution obtained by the crossing process as a mutation can provide a worse fitness value [27]. Then the two offspring (normal and mutated) are included in the population by replacing the two worst individuals in that population to leave a constant population size.

8.4.6 The matheuristic approach procedure

The best individual with the best fitness is selected at the end of the calculation time (stopping criterion) of the matheuristic GA. With this binary chromosome, MILP is launched.

In the evaluation function, MILP is relaxed to LP to reduce computational effort and to obtain a sufficiently good solution. To obtain a definitive solution, MILP is used, i.e., by removing relaxation and employing the binary chromosome of the individual with the best fitness provided by the GA.

The binary chromosome is set at the Yikt variable of MILP. This means that the binary chromosome becomes a parameter for the model. Then the MILP model is launched, the solver solves the integer variables and the GA provides the binary variable.

The advantage of using matheuristic, and not directly using the solver, lies in the search space of the MILP model being significantly reduced when a matheuristic is employed to deal with binary variables.

8.5 Numerical experiments

In the present section, a set of synthetic data is used to evaluate our approach. In this type of problem, real data sets are generally large, which renders it unsolvable with many plants, products, outlets and periods. To assess how the matheuristic and the non-commercial solver perform, in computational tests we apply large instances, which are randomly generated according to the outlined parameters and formulations in Park (2005). To create these data, we created a synthetic data generator, which appears at: https://bit.ly/3qBn363.

Park [22] analysed big datasets with similar characteristics to those in Table 8.4. Park used CPLEX to solve MILP but did not present any results for large instances because of the problems' computational difficulty, which is why he applied this solver only for small instances. We use the same data for plant size

(5), points of sales (from 40 to 65), products (5) and periods (from 10 to 12), as presented in the above-mentioned study.

The software followed in this research is a non-commercial optimisation solver from the Computational Infrastructure for Operation Research (COIN-OR) community called COIN-OR Branch and Cut Solver (CBC) [28]. This open-source solver is generally employed for MILP problems. The MILP model and matheuristic were implemented in Python with the Pyomo package [29]. Experiments were run by an Intel Core i7 2.80 GHz processor (6 GB RAM) in an Ubuntu 20.04.1 LTS operating system.

The performances of the matheuristic approach and the proposed MILP through computational experiments were compared to one another to identify the best performing method. The resulting GAP of the MILP solved by CBC and the matheuristic is calculated as indicated in equation (12).

$$GAP(\%) = \frac{|UB - Best_{sol}|}{|Best_{sol}|} \tag{12}$$

Where UB indicates the upper solver bound, and $Best_{sol}$ refers to the best solution generated by either the mathematical model or the matheuristic approach.

8.5.1 Experimental results

In order to demonstrate the proposed approach's efficiency and performance, the computational experiments with different large instances are provided. Table 8.4 compares the solution's efficiency among the solutions obtained by solving MILP with CBC and the matheuristic one with CBC. The first column in this table denotes the name of the instance, followed by the number of plants (*I*), points of sale (*J*), products (*K*) and periods (*T*). For all the instances, the applied criterion is the same calculation time that corresponds to 14,400 seconds. We executed the matheuristic algorithm 20 times for each instance in order to evaluate and avoid atypical performance.

Table 8.4. Performance comparison between CBC and Matheuristic

Instance	Problem				CBC			Matheuristic	
	I	*J*	*K*	*T*	**Total profit**	**Upper bound**	**GAP**	**Total profit**	**GAP**
I1	5	40	5	12	Unfeasible solution found	5746740.5	-	5117847	12.28 %
I2	5	50	5	10	5873321	6876383.6	17.08 %	6347862	8.33 %
I3	5	45	5	12	Unfeasible solution found	6785206.6	-	6157783	10.18 %
I4	5	60	5	10	6643133	8037979.9	21.00 %	7487111	7.36 %
I5	5	50	5	12	Unfeasible solution found	6932259.4	-	6294622	10.13 %
I6	5	65	5	10	Unfeasible solution found	8272162.9	-	7640947	8.26 %

The MILP solved by CBC obtained solutions for two (I2, I4) of the six instances, but it was unable to find optimal or good solutions. The matheuristic gave good solutions for all the instances. Figure 8.5 illustrates the total profit obtained by matheuristic and CBC. I2a and I4a show how the matheuristic approach evolves and converges towards good solutions, along with how CBC performs at around 7,200 computation seconds, while I4b and I4b show the behaviour of both the matheuristic and CBC at 14,400 processing seconds. For the I2 instance, CBC gave a feasible solution at 5,152.76 seconds (see Figure 8.5) with GAP = 17.10%. GAP improved up to 14,400 seconds by 0.02%. For the matheuristic for the same instance, it obtained feasible solutions from 71.05 seconds, with GAP less than 10% at 1,880 seconds (see Figure 8.6).

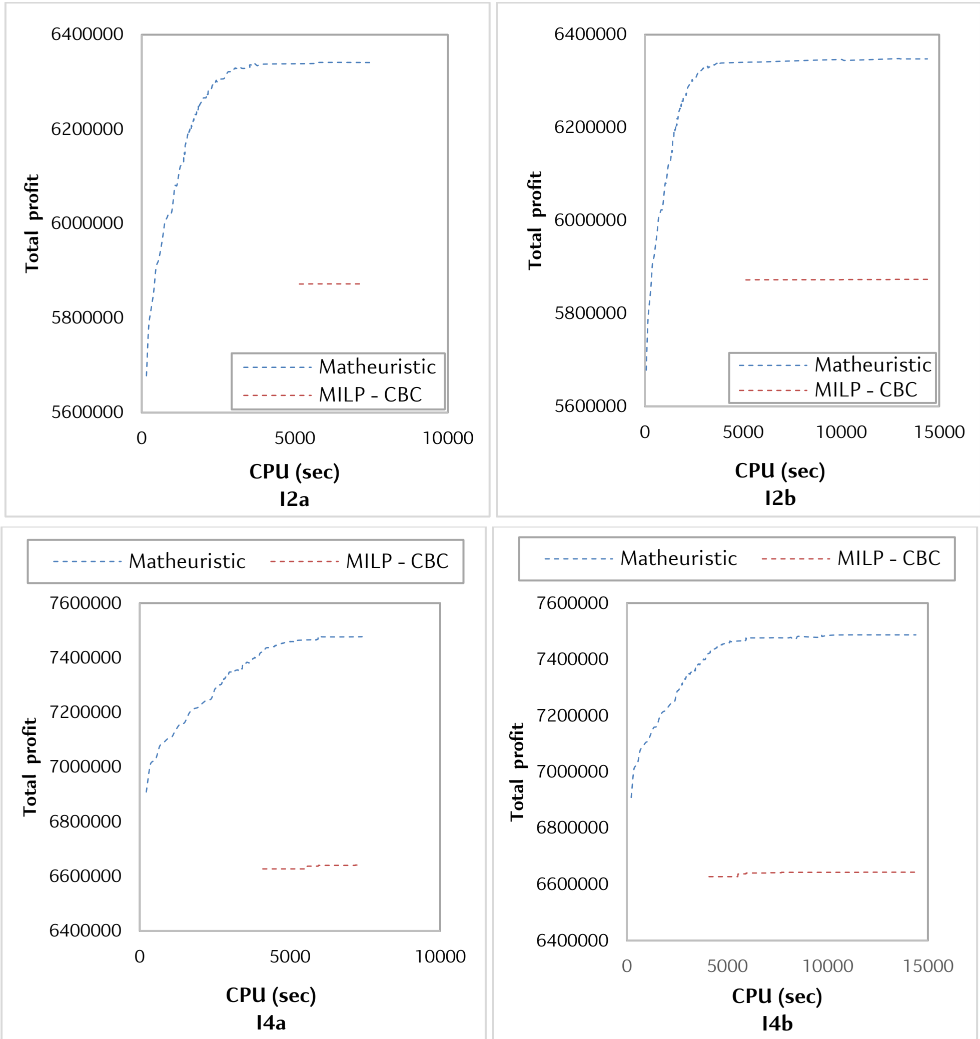


Figure 8.5. Time spent by matheuristic to find a feasible solution.

With the I4 instance, CBC performance visibly improves. It obtains solutions in 4,097 seconds and becomes the best solution in 5,538 seconds (see Figure 8.5). Matheuristic better performs than CBC by reaching feasible solutions in shorter computational times (see Figure 8.5) and reaches a GAP below 10% after 2,735 seconds (see Figure 8.6). This means that matheuristic outperforms CBC by 13.64%.

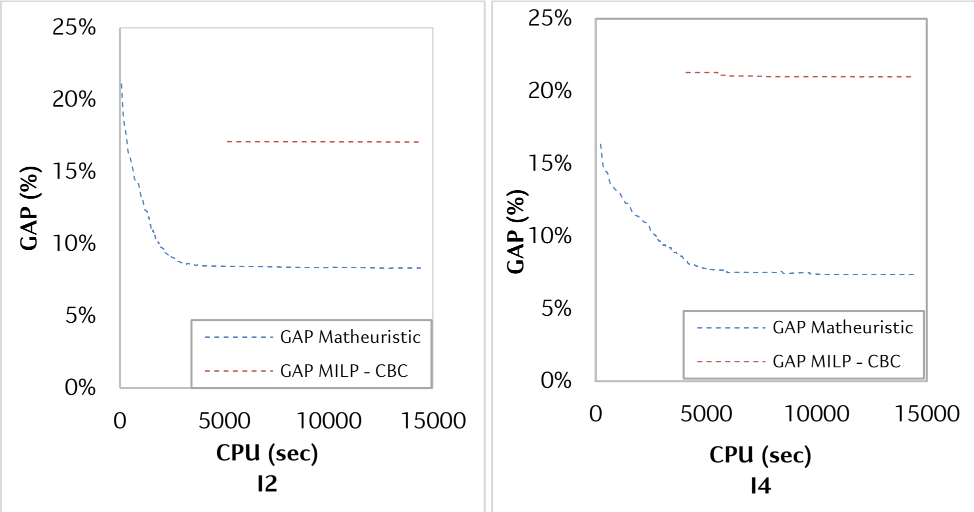
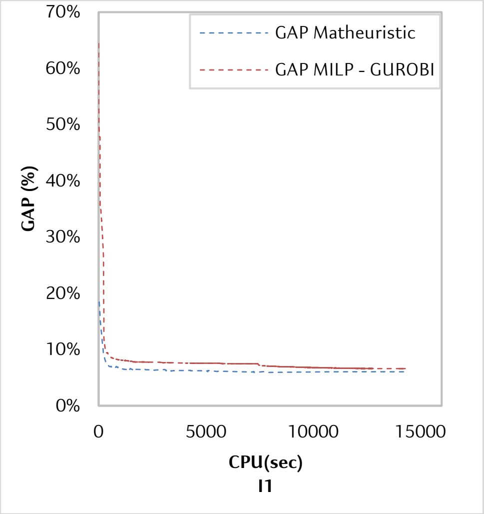
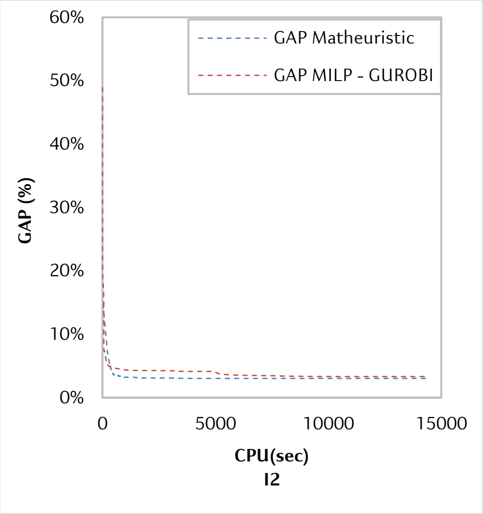


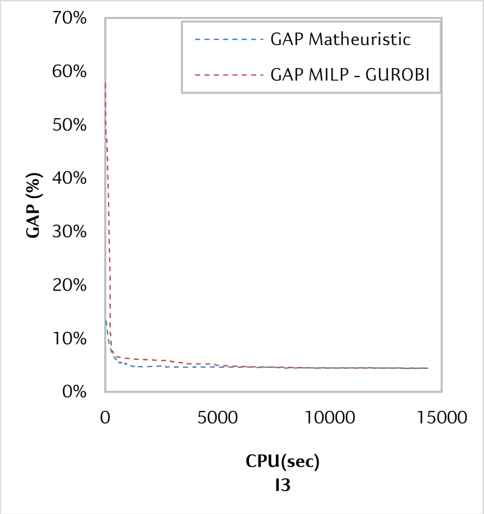
Figure 8.6. Comparison of matheuristic and MILP-CBC performance.

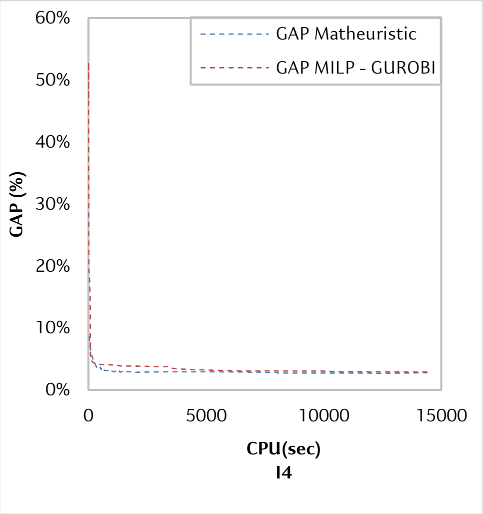
The complexity of the instances and the size of the problem mean that CBC is unable to find feasible solutions. Nevertheless, the combination of a GA with CBC gives better results with feasible solutions in shorter computational times. A matheuristic's efficiency is linked with the solver's speed because the solver is in charge of evaluating solutions by the GA's evaluation function. Moreover, as the evaluation function is the principal component of GAs [30], employing a non-commercial solver combined with a GA offers good results, as herein shown, and the matheuristic is more efficient in solving problems with many variables and parameters, and can be a useful alternative for large instances. When utilising a non-commercial solver like CBC, a matheuristic can support the solver to find better solutions.

In order to further demonstrate the efficiency of the proposed matheuristic, we compare it to Gurobi 9.1.1, i.e., the MILP and LP of the matheuristic are solved with Gurobi. We employ the same aforementioned computational conditions and apply a processing time of 14,400 seconds. The computational results given by Gurobi are better than those of CBC. Thus Gurobi obtains feasible solutions in all the instances in much shorter solution times. However, the matheuristic is better for achieving a lower GAP than Gurobi in all instances (see Figure 8.7).


GAP Matheuristic
GAP MILP - GUROBI
GAP (%)
70%
60%
50%
40%
30%
20%
10%
0%
0
5000
10000
15000
CPU(sec)
I1


GAP Matheuristic
GAP MILP - GUROBI
GAP (%)
60%
50%
40%
30%
20%
10%
0%
0
5000
10000
15000
CPU(sec)
I2


GAP Matheuristic
GAP MILP - GUROBI
GAP (%)
70%
60%
50%
40%
30%
20%
10%
0%
0
5000
10000
15000
CPU(sec)
I3


GAP Matheuristic
GAP MILP - GUROBI
GAP (%)
60%
50%
40%
30%
20%
10%
0%
0
5000
10000
15000
CPU(sec)
I4

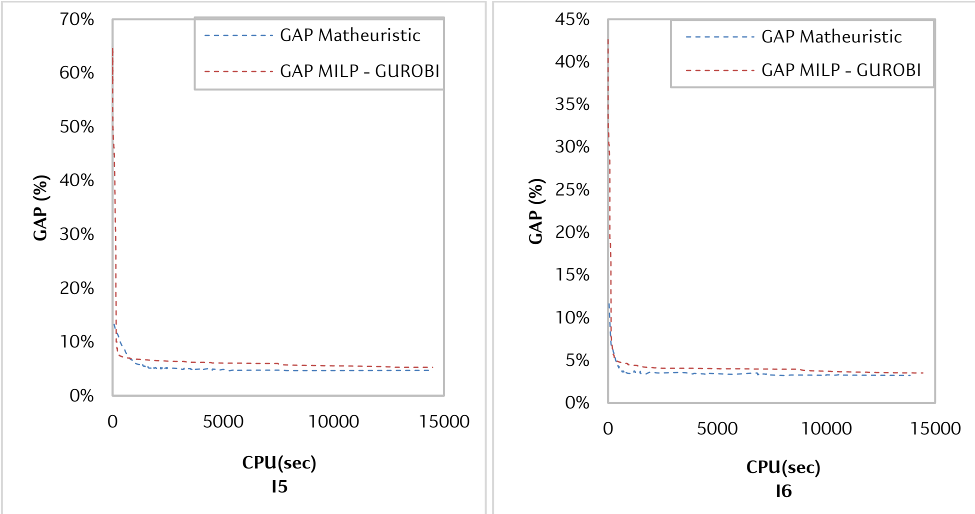


Figure 8.7. Comparison of matheuristic and Gurobi performance.

8.6 Conclusion

The PDP problem has long since been studied for the practical applications that it can offer industry. One such case is enterprises with different manufacturing plants in several locations, perhaps in the same city or country, or in others, which must decide the amount of products to be produced in plants, the quantity of products to be stored in plants during each period, the number of products to deliver to various points of sale according to product demand and the inventory of finished products at points of sales. Although several resolution techniques have been used for this problem and its variations, heuristic and metaheuristic algorithms can provide excellent results as combined or hybrid approaches. Likewise, combinations between metaheuristic techniques and exact approaches can offer better results for real-life problems because these combinations make the most of the benefits of both techniques [7]. In this context, the present paper intends to solve the PDP problem in real-world large data sizes. The problem is modelled as MILP, and a matheuristic solution approach is presented that combines a GA and an LP model.

Computational tests were performed on a large dataset capable of simulating real-world problems. The development of this approach stems from SMEs having to use open-source tools and the need to digitise companies because they must compete in today's market. Many SMEs cannot have access to software with paid licenses, due to the high-costs they may have to adapt the software to the needs of the enterprises. The main research contribution is about applying a matheuristic approach by employing a non-commercial solver (CBC). We also tested the performance of the non-commercial solver with an NP-hard MILP model. The computational tests run on different instances showed that our approach offers markedly improved results than the exact method. Matheuristic obtained competitive results in a short time. When solving MILP, CBC is unable to acquire feasible solutions for four of the six computed instances. However with our proposed matheuristic, and by also using CBC for solving relaxed LP, our results were good for all instances. Matheuristic can perform better even when using a commercial solver like Gurobi. Therefore, matheuristic can offer a real technical and economical application and is affordable mainly for SMEs that cannot pay a commercial solver or do not recurrently resort to one. This approach is feasible thanks to the proposed model's simplicity. The matheuristic also offers the benefit of making the most of the solver's features, regardless of them being commercial or not, because the matheuristic improves the solver's performance.

Other metaheuristics can be used for future work, such as memetic algorithms, ant colony optimisation or tabu search, and other highly complex problems can also be tested. Other genetic operators can be evaluated, or specific heuristics can be used to improve the GA's performance.

8.7 References

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Chapter 9

Conclusions.

Abstract:

This chapter presents the conclusions that derive from this doctoral thesis, as well as its contributions, to meet the overall objective set out in Chapter 1: design and implement new models and algorithms to calculate replenishment, production and distribution plans in industrial companies. Finally, future research lines are presented.

9.1 Main contributions

This doctoral thesis focuses on the main optimisation challenges in replenishment, production and distribution planning. To tackle the vast field of this topic, we set five specific objectives, which are listed in the introductory chapter, all of which have been successfully met. The different chapters of the thesis derive from these objectives, and the main contributions and results are presented below:

9.1.1 The replenishment, production and distribution planning holistic conceptual framework

The first objectives (*O1, O2*) of this doctoral thesis are to categorise the types of plans and to identify the different types of models and algorithms used for replenishment, production and distribution planning problems, and to know the current research state. To do so these aspects are discussed in Chapters 2 and 3.

Replenishment, production and distribution planning problems are conceptualised to identify the main dimensions, characteristics, formulations and resolution methods used in the different types of supply chains to evaluate the current state of these problems based on a tertiary study (analysis of literature reviews).

Subsequently, a holistic framework was generated, which includes the different works found in the literature on production planning, scheduling and sequencing. The proposed framework considers several categories to provide a taxonomy to classify the different planning problems studied in this thesis, including: (i) the planning aggregation level; (ii) the decision-making level associated with the plan; (iii) the type of models used to represent the plan; (iv) the objectives that characterise each modelling approach; (v) the resolution techniques followed; (vi) the software used for the computational calculation of plans; (vii) the areas and sectors of the application of production plans; (viii) the level of plans integration along the supply chain with other partners; (ix) the experiments performed to test real cases; (x) the size of the data with which planning problems are solved; (xi) the quality of the obtained solutions.

The state of the art developed in this thesis addresses an extremely wide variety of considerations related to the planning problem that has not been addressed to date, which is intended to answer the following research question:

RQ1. *How can replenishment, production and distribution planning problems and solution methods be categorised?*

In response to RQ1, Chapters 2 and 3 are presented from which we can discern those numerous conceptual frameworks are found in the literature, many of which generate a very broad theoretical basis, but have yet to be validated. It is also evident that more and more approaches take into account aspects like sustainability and the environment, while topics such as the rolling horizon are less recurrent. Lots of papers present mathematical models, and mixed integer linear programming and analytical models are the most frequently used ones, while simulation models and their combination with other methods are less frequent. Similarly, heuristic or metaheuristic methods are widely used, and CPLEX is the most frequently used solver. The systematic literature review generally highlights that there are still a few works that address planning process problems based on real cases. Nevertheless, the review allowed many of the presented model solving methods that can be used in different industrial sectors to be identified.

9.1.2 Methodology for selecting algorithms to solve planning problems

To fulfil O3, and in response to the following research question, Chapter 4 is presented.

RQ2. *How can the most suitable algorithm or solution method be selected to solve replenishment, production and distribution planning according to its complexity?*

Nowadays, algorithm selection is a very difficult task for companies because it involves a lot of mathematical, statistical and programming knowledge. The literature offers several algorithms and different techniques for solving planning problems, where the performance of algorithms has been tested in a defined area. However, companies that wish to use the available algorithms do not know which one is suitable and for which type of problem because the performance of an algorithm varies depending on the type of problem and the expected solution. Studies show that there is no single algorithm that outperforms all algorithms for all problem cases.

The algorithm selection process generally involves an experimental phase which, for small- and medium-sized enterprises (SMEs), can prove to be an obstacle because they have fewer resources to invest in commercial solvers or specific software for planning. The experimental phase implies programming and computing a set of algorithms and making comparisons of their performance, which is time-consuming for programmers, as well as the additional time needed for evaluating different datasets, which also requires significant computing resources. Then there are the difficulties of replicating an algorithm or mathematical model from the literature.

Given these problems, we generated a decision-making support tool based on the fuzzy TOPSIS method. This approach provides companies with a method and allows them to select an algorithm or solution method given a portfolio of them. The decision-making tool is based on four dimensions and 13 different decision criteria are defined according to these dimensions. The four dimensions are related to: (i) the type of problem and its characteristics; (ii) the planner's degree of knowledge related to scheduling and mathematical modelling; (iii) the company's endowment in mathematical modelling software and knowledge of its operation; (iv) the expected gap performance that the planner is willing to achieve by solving the planning problem.

With this background, the models and algorithms proposed in the literature, and the new ones developed within the scope of the present doctoral thesis with our novel approach based on Fuzzy TOPSIS for algorithm selection, a solution method can be selected from a set of methods or algorithms suitable to solve planning problems. Thus, it is possible to choose not only one algorithm, but others that offer similar solutions at the same time. The results of this decision-making support tool guide companies to decide whether to use a commercial or non-commercial algorithm or solver. In this way, companies can determine whether to invest in a commercial solver or use an open-source mathematical modelling or algorithm programming software and, at the same time, can understand planning staff's training needs with respect to the different types of software.

9.1.3 Models and algorithms for replenishment, production and distribution planning

In order to meet objectives *O4 – O5* and in response to:

> ***RQ3:*** *What new algorithms should be developed to solve real replenishment, production and distribution planning problems?*

A number of mathematical models and matheuristic algorithms were formulated to bridge the gaps encountered in replenishment, production and distribution planning problems from both individual enterprise perspective and a collaborative perspective, i.e., in which replenishment plans from the supplier affect the manufacturer's production plans.

We firstly formulate a mixed integer linear programming (MILP) model for a combined replenishment and production planning problem (see Chapter 5), in which we analyse the sizing and batch scheduling to manufacture plastic components. Our model is based on the case of a second-tier supplier in the automotive supply chain. This supplier produces plastic automotive components. To do so, it uses plastic granules that are placed inside injection moulding machines by means of moulds. The main characteristics of the addressed problem are that moulds can be assembled on different injection machines but, depending on the machine having a different production rate, two components or more can also be injected into a mould, and moulds can be assembled during specific time periods according to the manpower availability during that period. The problem considers the arrival of material and its consumption also takes into account the availability of containers for plastic components packaging.

The output of the model provides the allocation of moulds to machines for a specific time period, calculates the quantity of the parts to be produced, and designates the manpower needed for mould changes, the consumption and inventory of raw material, and the containers needed for the packaging of parts. The proposed formulation fulfils the objective of representing a real problem of a plastic component supplier. The problem is validated using different dataset sizes that were randomly generated. In general, all the data sizes provided optimal results in computation times of less than 1 minute.

Secondly, a mixed integer linear programming model is formulated (see Chapter 6) for a combined production and delivery planning problem in the aforementioned second-tier supplier. In this case, a model is formulated to analyse the number of containers needed to store the produced components.

The second-tier supplier employs two types of containers: the first type is plastic containers that are reusable and belong to the first-tier supplier; the second type is cardboard containers, which are temporary containers to store parts until the first-tier supplier sends plastic containers. The difficulty of the problem lies in managing the reusable containers and the adequate supply of empty available containers to meet the second-tier supplier’s needs and operating only according to the just-in-time philosophy.

The main problems of the combined production and delivery plan are related to: (i) variation in the demand from the first-tier supplier, which involves using large safety stocks in the second-tier supplier's warehouse; (ii) the second-tier supplier produces many automotive component parts to minimise start-up costs, which involves having to produce more parts than demanded by the first-tier supplier; (iii) overproduction results in excess stock, which has to be stored in cardboard containers, with subsequent processing when plastic containers become available again at the second-tier supplier's production plant. As plastic containers become scarce, the second-tier supplier has to incur the costs associated with purchasing the cardboard containers, as well as the storage and handling costs of having to switch automotive components from cardboard containers to plastic containers when they arrive. The limitation in this combined production and delivery plan arises in the amount of empty reusable containers that the first-tier supplier sends to the second-tier supplier.

In this context, a model was generated that allows to determine the number of reusable containers that should remain in circulation and to determine the number of plastic containers that the first-tier supplier should have to cover the demand of parts and, alternatively, the number of cardboard containers that the second-tier supplier should buy to meet demand. The model is useful for both the first-tier and second-tier suppliers because they can know the number of containers needed and can, therefore, negotiate the price of parts because buying containers increases the price of parts. Accordingly, the model is useful for setting the selling price of plastic parts on a planning horizon.

Thirdly, by considering the computational difficulty of scheduling problems and that (commercial and free) solvers cannot find good solutions in reasonable computational times, an efficient method (see Chapter 7) is developed to tackle the complex job shop problem. This is one of the most studied problems in the optimisation field and is presented as NP-hard.

A matheuristic method is proposed. It consists of the hybridisation of a genetic algorithm (GA) with a mixed integer linear programming solver for a disjunctive MILP and a priority heuristic.

The priority heuristic is generated to help to generate individuals from the initial population, which allows the GA to arrive at an initial solution more quickly. These heuristic rules are designed specifically for the sequencing problem. The exact solver plays a very relevant role for efficiently dealing with the continuous variable (simplex method) of the disjunctive mixed integer linear programming model. In this context the model retains its optimality and generality in the continuous variable. So, the combinatorial part is handled by the GA. While developing the problem, an open-source solver was used, in this case Coin-OR Branch & Cut (CBC), which gives good results. When comparing the results of CBC and the proposed matheuristic, the proposed algorithm is superior in all instances, and in both computational times and gaps. In this problem, we test our approach with large instances. Therefore, the proposed method is a significant contribution to the literature because the combination between a non-commercial solver and a metaheuristic algorithm is an easy-to-use method that does not generate any costs associated with licences or commercial software. Furthermore, the matheuristic method herein proposed is also a method that is easily scalable to other problems.

Finally, a matheuristic algorithm is designed for the combined production and distribution planning problem (see Chapter 8) using the open-source solver Coin-OR Branch & Cut (CBC) and the GA. In this case the GA evaluates the population by a relaxed mixed integer linear programming (MILP) model; that is, the integer variables of the model are transformed into continuous ones, and the binary variable is calculated with the GA. The result of the combined use of the GA and the relaxed MILP provides us with the best chromosome. This chromosome is then fixed to the MILP to obtain a final solution. The results obtained from this hybridisation compared to CBC show the superiority of the matheuristic. To reinforce our results, we use Gurobi (commercial solver) in which the matheuristic can obtain better results compared to this solver. Consequently, our proposal provides an efficient method that converges to good results in an acceptable computational time with real size instances. It is also a feasible model that can be replicated for other industrial sectors.

In synthesis, the general research question (GRQ) has been answered.

GRQ: *What suitable approach could effectively solve replenishment, production and distribution planning, which are computationally difficult to solve by exact solvers?*

From the analysis of chapters 2 and 3, the importance of the study of matheuristic algorithms was identified by determining the need to develop new tools for replenishment, production and distribution planning. Considering that many studies detail that commercial or non-commercial solvers cannot reach optimal solutions in reasonable computation times, due to the difficulty of the problems that are generally presented as NP-Hard and the amount of data that real problems have, the need arises to develop new tools that are efficient and can meet the needs of companies.

In order to establish which method could be efficient to solve replenishment, production and distribution planning problems (GRQ), and in order for companies to take advantage of the mathematical models created and not have to create a new heuristic or metaheuristic algorithm and leave aside the mathematical model, since creating an algorithm from scratch can cause an unaffordable expense for companies, a new matheuristic algorithm that combines a genetic algorithm with a MILP was built, thus achieving the general objective of the research (GRO). In this way, we generated a matheuristic algorithm that reuses the mathematical model and together with a genetic algorithm that is easy to replicate, since it complies with the basic fundamentals of the genetic algorithm, reaches good solutions in reasonable computational times. So, it can be inferred that it is an efficient method and that combined with a non-commercial solver such as the CBC can achieve good results.

9.2 Future research lines

Based on the work carried out in this thesis, several research lines have been opened up:

- In the mathematical modelling field, robust optimisation and fuzzy programming methods are an important area to explore, as is developing new modelling approaches that address and associate the parameters related to production and sustainability, which can also address uncertain parameters.
- It is also necessary to generate mathematical models that take into account collaboration. This means, models that represent the integration of the information transmitted between partners in a supply chain.
- Another research and development area is evaluating the mathematical models that are called transversal in this classification (presented in Chapter 3) and testing them in other areas of industry because these models have features that make them easily reproducible.
- Future research should be related to generate a portfolio of models and algorithms. In this portfolio, the algorithms that are present in the literature should be programmed so they can be used by companies, especially SMEs, as a source in their decision-making process. Likewise, the use of the Fuzzy TOPSIS methodological approach can be adapted to company-specific criteria. To do so, more dimensions and criteria can be considered.
- The formulation of matheuristic algorithms remains a large field to be explored. Matheuristic algorithms depend directly on the employed solver, although commercial solvers are widely used. It is important to verify not only the performance of non-commercial solvers, but also the combination of non-linear models and solvers for this type of models.
- Finally, many algorithms and models appear in the literature. However,

the combination of simulation models with different algorithms [1] is a broad area to explore, as is using combinatorial optimisation and neural networks, where optimisation methods can be employed to train the neural network.

9.3 Reference

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