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

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.

Keywords: Production planning; Scheduling; Sequencing; Mathematical programming; Metaheuristics.

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 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, 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 4 highlights and discusses the main results. Finally, Section 5 draws the main conclusions and directions for future research.

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 2.1); (ii) descriptive analysis (Section 2.2); (iii) selecting or identifying categories (Section 2.3); (iv) evaluating material (Section 2.4) .

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 Fig. 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 1 depicts the strategy adopted to follow the structured literature review process.

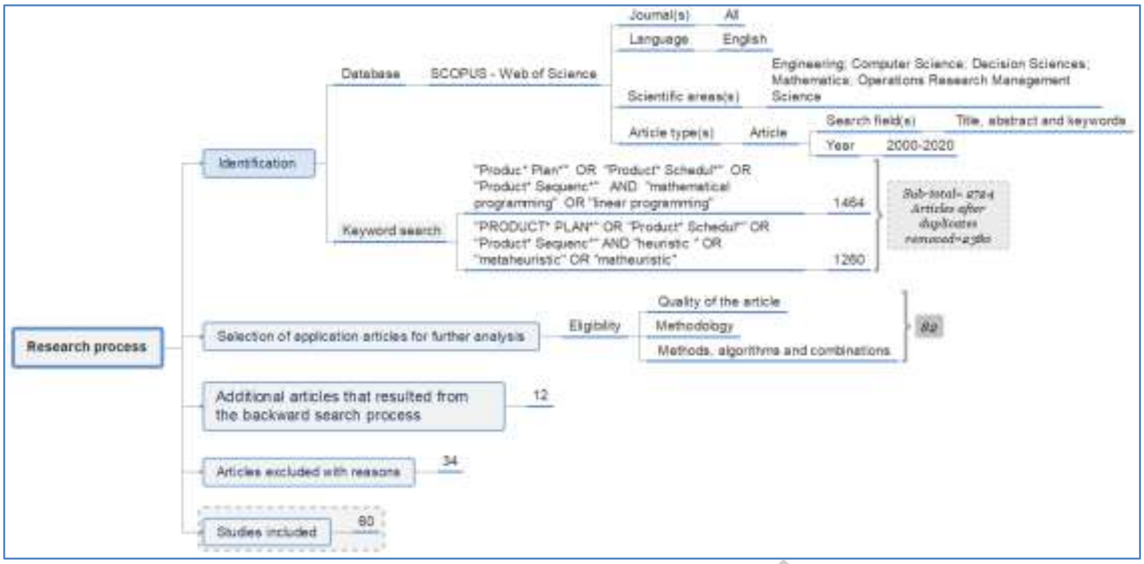

Fig. 1. Structured literature review process.

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.

2.2 Descriptive analysis

This study analysed 60 scientific papers published between 2000 and 2020, and Figure 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.

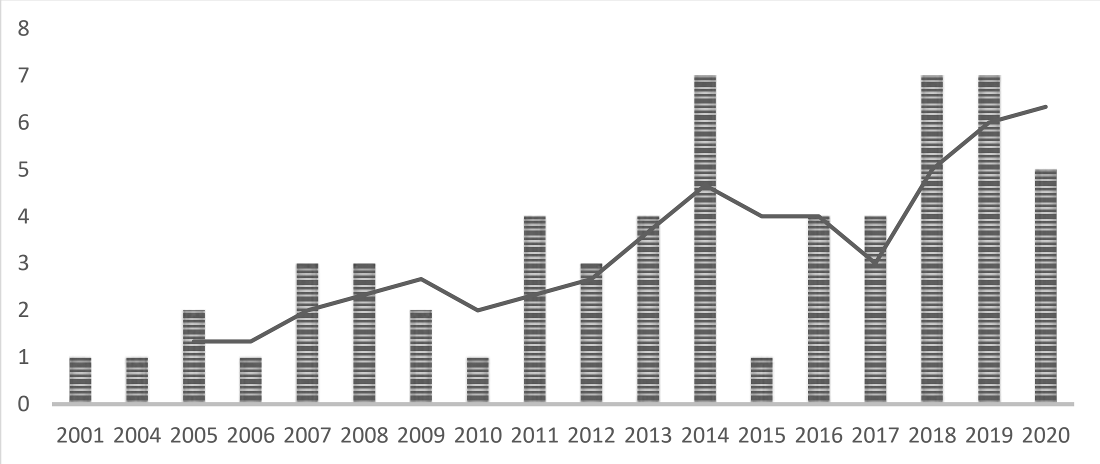

Fig. 2. Distribution of the reviewed papers according to year.

Most of the articles selected for the final review appeared in 20 different journals. Figure 3 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.

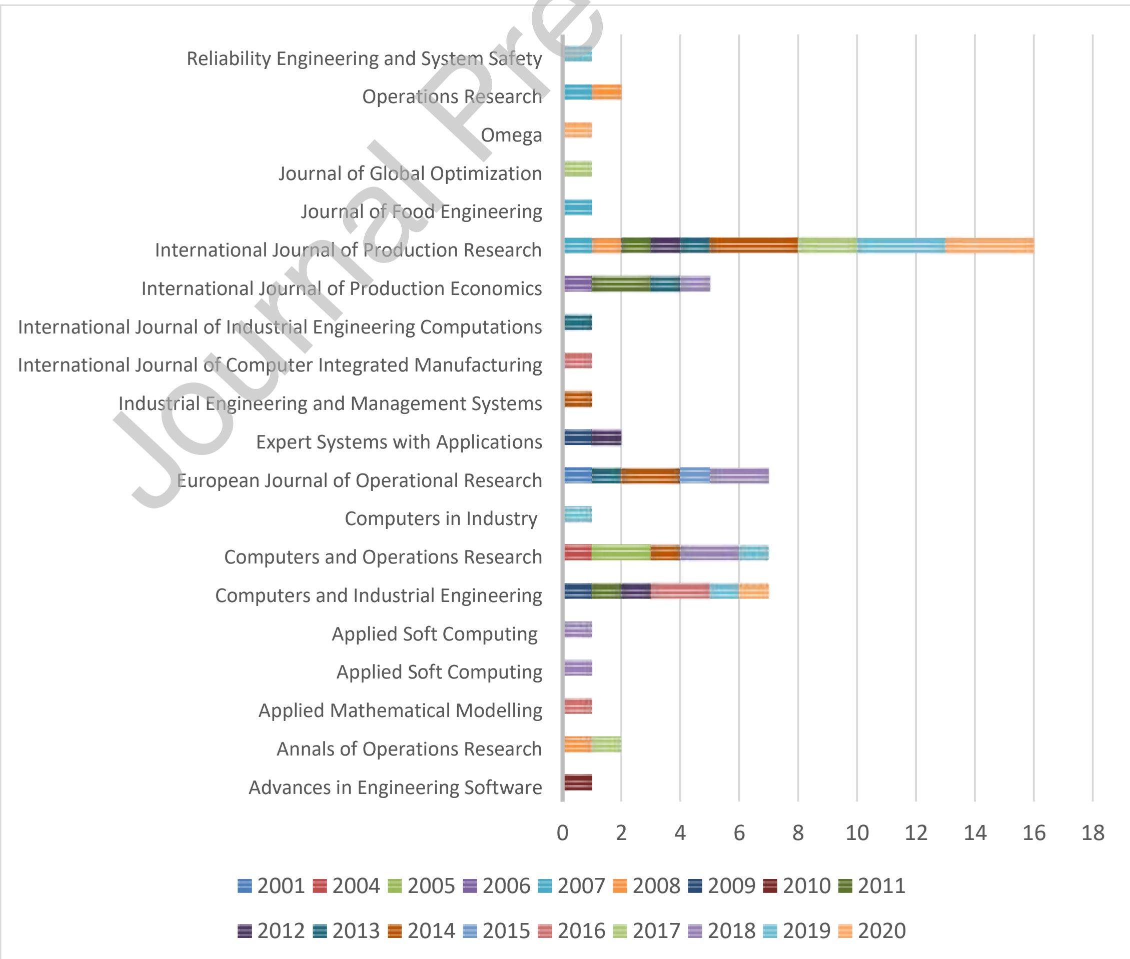

Fig. 3. Distribution of articles for publication year and journal.

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 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 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		
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)
	Matheuristic Algorithm (MTA)	MTA/ Ant Colony + Mathematical Model (ACO_MM) MTA/ Biased Random-Key Genetic Algorithm + Mathematical Model (BRKGA_MM)	MTA/ Iterated Local Search + Mathematical Model (ILS_MM) MTA Simulated annealing + Mathematical Model (SA_MM)

	MTA/Fixed Variable List Algorithm and Clustering Sequence Algorithm + Mathematical Model (FVLA_CSA_MM) MTA Genetic Algorithm + Mathematical Model (GA_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)	

2.4 Material evaluation

All the articles were evaluated and coded according to the holistic framework proposed in Section 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 Results analysis

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 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 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]

3.2 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). 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) 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.
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]
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 3.4. 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 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 4 presents the applied modelling approach and solution techniques in the reviewed works to answer RQ1 and RQ2. The first column in Table 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 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 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. (2017) [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 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]
	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]
	-	Julia	JUMP	Gurobi	MADS	S. Wang et al. [78]
	HA/ BD	NS	AIMMS	CPLEX	MADPCSS	de Kruijff et al. [44]
	HA/ GR	NS	OPL MATLAB	CPLEX	MADPCSS	D. Gupta & Magnusson [26]
	HA/ LF HA/ RF	NS	ILOG CPLEX	CPLEX	MSS	Sillekens et al. [36]
	HA/ LGR	C#	NS	NS	MADS	Fang et al. [91]
	HA/ LPR	NS	NS	CPLEX	MSS	Gaglioppa et al. [53]
	HA/ LPR	NS	GAMS	CPLEX	MSS	Fumero et al. [32]
	HA/ LPR HA/ BM	C#	LINGO	LINGO	MADSS	Zhang et al. [38]
	HA/ NEH	NS	LINGO	LINGO	MADSS	Abdeljaouad et al. [67]
	MA/ GA	NS	NS	NS	MADS	Moon et al. [54]
		C++	NS	CPLEX	MADSS	Cheng et al. [59]
		NS	ILOG CPLEX	CPLEX CP Optimise r	MADSS	Na & Park [62]
	MTA/ GA + MILP	C++	NS	CPLEX	MADPCSS	Motta Toledo et al. [61]
	MA/ MOHSA	NS	MATLAB	NS	MADS	Mohammadi et al. [57]
	MA/GA MA/ SA Hybrid MA/GA + MA/SA	NS	ILOG CPLEX MATLAB	CPLEX	MADPCSS	Aroui et al. [68]
	MA/GA MA/ TS	NS	LINGO-MATLAB	LINGO	MADSS	Ramezanian et al. [39]
	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 Optimize r -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]
	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]

3.4 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 6).

Table 5 summarises the typical objectives used to support decision making in production planning, scheduling and sequencing problems. The objectives were classified according to their

Journal Pre-proof

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 5) to be identified.

Table 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
	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
	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 6

The main objectives of the proposed models.

Ref. / Goals in the objective function	**Costs**	**Time**	**Product**	**Resources**	**Service**	**Sustainability**
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			

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					
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

3.5 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 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 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 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 [100], 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 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	
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

3.6 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 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 Fig. 4).

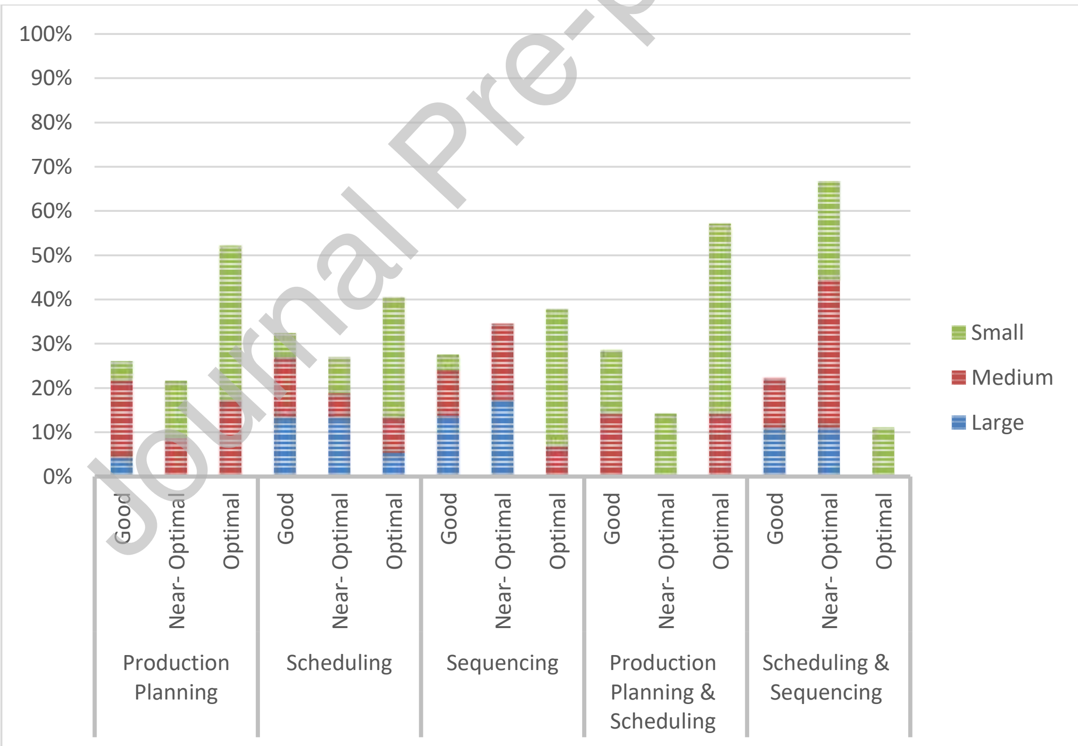

Fig. 4. Distribution of the scale of problems and solution quality.

The application of different types of methods for production planning, scheduling and sequence problems, and the amount of data, provided distinct solutions (see Table 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 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 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	
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	

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 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.

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 [100], 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.

Declaration of Competing Interest

None.

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