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ORIGINAL ARTICLE

Scheduling for Additive Manufacturing: a literature review

Scheduling para Manufatura Aditiva: uma revisão da literatura

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Abstract: Advancements in production technologies and materials have facilitated the use of additive manufacturing (AM) (i.e., 3D printing) in the large-scale production of finished products with high level of customization, simplification of the factory floor, and fast delivery. Production sequencing is a well-established topic in this research area; however, its application to an AM environment suffers from specific issues that are yet to be explored. This paper presents a systematic literature review for mapping the state-of-the-art production sequencing methods in AM and for discussing the content of 26 articles published in magazines between 2017–2020. The main mathematical models, algorithms adopted for their solution, and main characteristics of computational experiments performed in these articles are identified; the results indicate that some characteristics of the problem can still be included in these models, such as the possibility of outsourcing and technology restrictions, which are yet to be explored in the literature. Further, authors observed the need for more robust computational experiments to better evaluate the proposed solutions.

Keywords: Scheduling; Additive manufacturing; Heuristics; Meta-heuristics; Mathematical modeling.

Resumo: Com o avanço das tecnologias de produção e de materiais, hoje é possível utilizar a Manufatura Aditiva (MA), também conhecida como impressão 3D, para a produção em grande escala de produtos acabados, com inúmeras vantagens como alto nível de personalização, simplificação do chão de fábrica e entrega rápida. O sequenciamento da produção, conhecido como Scheduling, é um tema bastante consolidado em sua área de pesquisa, mas sua aplicação dentro de um ambiente de MA enfrenta questões específicas que ainda foram pouco exploradas pelos pesquisadores. No presente artigo, realiza-se uma Revisão Sistemática da Literatura (RSL) para mapear o estado da arte no que tange o sequenciamento da produção em MA, discutindo o conteúdo de 27 artigos publicados em revistas, entre os anos de 2017 à 2021. Foram identificados os principais modelos matemáticos, algoritmos adotados para sua solução e as características principais dos experimentos computacionais realizados. Os resultados mostram que algumas características do problema ainda podem ser incluídas nos modelos, como a possibilidade de terceirização e restrições de tecnologia, que foram pouco exploradas na literatura. Observa-se, ainda, a necessidade de experimentos computacionais mais robustos para uma melhor avaliação das soluções propostas pelos autores.

Palavras-chave: *Scheduling*; Manufatura aditiva; Heurísticas; Meta-heurísticas; Modelagem matemática.

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1 Introduction

Technological advancements in production systems such as additive manufacturing (AM), also known as 3D printing (3DP), have enabled companies to adopt a new production method. This method, which allows the fabrication of pieces with complex geometries within an acceptable time and cost, has attracted the attention of various industries including aerospace, automotive, defense, and health (Li et al., 2017).

In the 1980s, AM was established for rapid prototype development; it was used for creating complex pieces by adding layers of specific types of materials such as plastic, metal, or concrete from a three-dimensional model to produce objects with complex shapes without utilizing any cutting or molding tools (Chergui et al., 2018; Luzon & Khmelnitsky, 2019).

AM technologies have evolved considerably since their inception; it originally focused on the rapid prototyping market, which continues to remain strong. However, a new market has recently emerged because of the significant advances in AM technologies in recent years; this market is geared towards printing finished products for direct consumption (Aloui & Hadj-Hamou, 2021). In Brazil, some companies already offer such a service: e.g., EngiPrinters (2021) provide a service where the clients send their printing projects remotely through the company's website and the printed piece is then delivered to their home.

An analysis of companies that provide 3DP services suggests a set of new production programming challenges. For example, Antón et al. (2020) reported that elements such as cloud manufacturing emerge in addition to others such as multiple machine operation and production order allocation in two-dimensional spaces. Given this context, production programming in AM environments involving multiple clients requires executing production orders for improving performance indicators such as low time and makespan. However, this is not the case when 3D printers are available for low-volume production (e.g., for domestic use or for prototyping in research). This ongoing shift in the production scale in the AM environment is one reason for conducting the present study.

In production engineering, AM simplifies the production process and streamlines the production setup of pieces with diverse characteristics; this provides the main advantage of its use in the industry: the possibility of increasing the mix and personalizing products while maintaining a low production volume. Therefore, several problems faced by traditional manufacturing are overcome; e.g., the need for producing and storing large product lots and managing complex supply chains; this increases firm profitability and customer satisfaction (Luzon & Khmelnitsky, 2019; Ransikarbum et al., 2020; Yilmaz, 2020).

Important questions about planning, programming, and scheduling emerged when attempting to adequately integrate this new technology into a production system once AM became a mature technology or was sufficiently adopted in the industry. Based on the research on AM, several problems related to product and process engineering and production management were analyzed and tackled by researchers (Fera et al., 2018). However, production planning and printing programming and scheduling often remain intuitive and unsystematized by professionals who rely only on their shop floor experience; this results in processes lacking production time improvements and resource optimization (Ransikarbum et al., 2017; Antón et al., 2020). Such difficulties highlight the importance of conducting studies on production process optimization in 3DP environments.

In AM, the scheduling problem addresses some specific issues. The lot-sizing problem considers the geometry of pieces to balance production flexibility with high unit costs of 3DP objects. A considerable amount of processing time and costs may be modified based on characteristics such as height, volume, and area. Further, the use of AM machines with different specifications (such as pre-/ post-processing time, capacity, and cost of materials, among others) affects the scheduling problem. The decision about the best combination and positioning of pieces for printing is considered an NP-hard combinatorial problem (Araujo et al., 2019; Che et al., 2021; Aloui & Hadj-Hamou, 2021; Alicastro et al., 2021).

To the best of our knowledge, the first scientific articles that explore the production scheduling problem in AM using mathematical models and/or proposing solutions were published in 2017 (Li et al., 2017; Ransikarbum et al., 2017). Such articles focused on analyzing the problem mathematically, in addition to testing heuristic solutions and decision support models. The best lot-sizing policy and positioning of pieces for printing regardless of AM technology are defined by combining two extensively studied problems: scheduling problem, considering production lot sizing and the bin packing problem. Therefore, scheduling in AM environments comprises two types of decisions: 1) before printing, the objects are clustered into lots based on a strategy, and 2) these lots are sent to machines based on their printing capacity. The main issue under analysis is whether different combinations of parts with different heights, sizes, and orientations can generate lots with different heights, printing areas, and support structures, which are factors directly affecting the time and cost of the entire process (Li et al., 2017; Ransikarbum et al., 2017; Che et al., 2021).

This scenario becomes even more complex given the increasing use of 3D printers in the production environment on small, medium, or large scales; this creates a high demand for pieces and many AM machines available for work allocation, which are often different from each other in terms of some indicators such as delivery time. Several authors in this area of research have proposed mathematical models for describing these specific cases and fast algorithms to solve the problem by facing these challenges and providing solutions sufficiently fast to allow managers to make their decisions as assertively as possible.

The present study aims at conducting a systematic literature review (SLR) to solve scheduling problems in AM for identifying models most commonly used by authors and their main characteristics, in addition to collecting data on algorithms and on the response and neighborhood exploration structures and understanding how computational experiments are performed and algorithms compared.

This remainder of this manuscript is organized as follows: The method used to select articles for this SLR is described in Section 2. Then, AM technologies and their taxonomy are discussed in Section 3. The content analysis of the 26 articles included in this study is presented in Section 4. Finally, this manuscript ends with the discussion, final considerations, and future perspectives in Sections 5 and 6, respectively.

2 Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) model

The stages of search, selection, and analysis of studies follow the preferred reporting items for systematic reviews and meta-analysis (PRISMA) method proposed by Moher et al. (2009). An article selection flowchart is applied according to this method; it has the following four phases: identification, screening, eligibility, and inclusion. The first step includes defining databases and search strings that will be used. Three databases were selected to search for articles: (1) Engineering Village, was selected because this search platform provides access to the databases of engineering articles and patents (Elsevier, 2020). The databases of (2) Web of Science and (3) SciELO were selected because the index articles of multidisciplinary areas are considered two of the largest and most used databases for bibliometric studies (Marsilio et al., 2011). The search string was defined as “AM” AND “scheduling” because this research aimed at finding studies on the production scheduling problem involving AM technologies.

During the initial search analysis, several studies focusing on only the nesting subproblem were identified, which included decoupling production scheduling from piece positioning (e.g., see Bennell & Oliveira, 2008). Studies exclusively focused on nesting problems were disregarded in the analysis because the present study is focused on the integration between production scheduling and piece positioning.

All articles that included the selected terms in their title, abstract, or keywords were listed by the platforms. In addition, only full articles published in journals were considered in the search. All articles found until August 2021 were included in the search because this is a recent topic in both the industry and the academy.

In the first phase of the PRISMA method, the search for articles in the databases retrieved 65, 44, and 65 articles in Engineering Village, Scopus, and Web of Science, respectively. Among these, 87 articles were duplicated in the three databases. These 87 studies were screened in phase 2 of the PRISMA method by reading their titles and abstracts. In this phase, a total of 51 articles were excluded, and they were classified as "outside the scope (OS):" 28 articles analyzed the AM materials, 14 analyzed specific 3DP technologies without addressing modelling or scheduling problem solutions, 1 article analyzed scheduling problems without relating them to AM technologies, 5 discussed technologies involving multiple AM robots, and 3 focused on the healthcare system, an education support system, and a model for minimizing energy consumption separately.

At the end of the screening and exclusion phase, 36 articles were read in full in phase 3 of the PRISMA method, during which another 9 OS articles were identified and 4 studies focused on the aspects of the Industry 4.0 (I4.0) and Internet of things (IoT), 2 studies reporting risk analysis models in AM environments, and 3 articles addressing maintenance scheduling, simulation models for the analysis of 3DP technologies and a collaborative AM system, separately. Further, the full text of one article was not accessible for reading and was labelled inaccessible (IN). Finally, 26 articles were included for full-length content analysis and included in the review (phase 4 of the PRISMA Method). Figure 1 summarized all stages.

After the screening and selection stages, the remaining 26 articles were subjected to bibliometric analysis towards identifying key characteristics for defining the importance and relevance of AM production scheduling studies within the breadth and scope of this study. The PRISMA methodology checklist applied to this review is available in Appendix A.

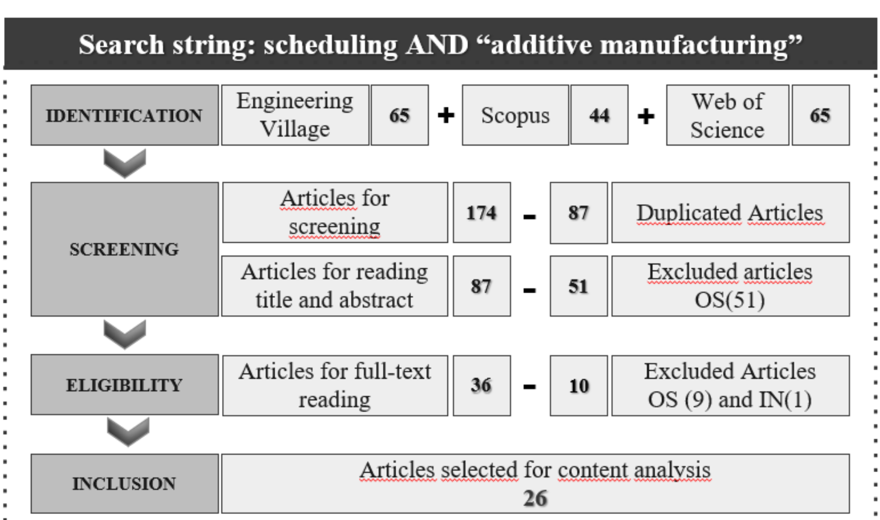

Figure 1. Scheme adopted for SLR, based on Moher et al. (2009). Source: The authors.

Considering the complexity and high number of technologies and advances introduced in AM, 3DP taxonomy is discussed in the next section to familiarize the reader with the terms presented in the content analysis of this review. Further, the findings of the studies require a form of classification. Thus, the present study references studies by Chua et al. (2010), Volpato (2017), and Oh et al. (2020) who characterized AM scheduling problems and their technologies. The elements used to summarize these findings are presented below.

3 AM technologies and taxonomy

AM technologies have evolved over the years, and various types of AM machines have emerged in the market. They comprise a set of different technologies that work with various raw materials.

The first classification, proposed by Chua et al. (2010), divided technologies into liquid, solid, and powder; however, it was insufficient to describe the shaping principles used in production. A standard entitled ISO/ASTM 52900:2015 (ISO, 2016) was created, and the technologies are classified based on the production process. The nomenclature used in the present article is outlined and Table 1 presents the taxonomy of AM technologies based on the standard ISO/ASTM 52900:2015(E) and on the book by Volpato (2017), which classify these technologies, their production principle and some specific applications.

Table 1. Classification of AM technologies.

Classification	Principle	Technologies
Vat polymerization	A liquid photosensitive polymer is selectively curated in a vat by light-activated polymerization.	Stereolithography
Material extrusion	The material is extruded through a beak or orifice and selectively deposited.	Fused deposition modeling
Material jetting	The material is selectively deposited in small drops.	Multi jet printing
Binder jetting	A liquid agglutinating agent is selective deposited to bind powder materials.	Color jet printing
Powder bed fusion	Thermal energy selectively fuses regions in a powder bed.	Selective laser sintering, direct metal laser sintering, selective laser melting, electron beam melting
Sheet lamination	Sheets cut from a material are bound (glued) to form an object.	Laminated object manufacturing, selective deposition lamination
Direct energy deposition	Thermal energy is used to melt materials as they are deposited.	Laser engineered net shaping, direct metal deposition, 3D laser cladding

Source: Adapted from Volpato (2017).

The characteristics of the technologies used that lead to different stages in the production process such as pre- and post-processing stages can directly affect the design of the mathematical models. Based on AM technology, some restrictions for batching the parts must be considered to ensure print quality. For example, printing machines using selective laser sintering (SLS) and binder jetting technology allow stacking parts on the printing platform without damaging their surfaces. In this case, the problem can be understood as a variant of the 3D packaging problem that is considerably more complex than 2D (Wang et al., 2019).

The orientation of parts is a key factor in AM and can affect cost, quality, and time. In some technologies such as those used to produce high-strength plastic materials, orientation has a less significant impact; however, this is not the case in laser-based technologies wherein this characteristic is a crucial factor (Antón et al., 2020).

The taxonomy used in the present research to classify the works selected for the literature review was adapted from the study reported by Oh et al. (2020). The tuple (N_{α}, N_{β}, N_{γ}, N_{δ}, S_{α}, S_{β}, S_{γ}, S_{δ}) is defined wherein "N's" comprises characteristics related to *nesting* and "S's" related to *scheduling*. Therefore, in Section 5 (and in Table 3), the studies will be referenced and classified according to this coding.

The first classification element associated with nesting ($\mathrm{N}_{á}$) defines whether parts will be placed only on the machine printing surface; i.e., all parts will necessarily be in contact with this surface (2D) or "packaged" in a 3DP space, and they will possibly be stacked one above the other.

The second element ($\mathrm{N}_{â}$) corresponds to the possibility of rotating the pieces considered in the nesting algorithm, and these can occur in the A, B, or C directions, and they represent the X, Y and Z axes of the Cartesian plane, respectively. Element $\mathrm{N}_{ã}$ indicates whether the machine build volume is bounded or unbounded, and $\mathrm{N}_{ä}$ shows whether all pieces will enter the full nesting algorithm or only a subset.

Among elements related to the scheduling problem, $\mathrm{S}_{á}$ indicates how the lots scheduled by the machines were sized, and this can result in nesting by an algorithm (nested) and grouping based on the characteristic of interest of the parts (grouped) such as height or volume. The machine build volume can be created based on some parameters by disregarding the parts such as size and volume or they can be provided based on a given structure. Next, $\mathrm{S}_{â}$ describes the types of environments adopted, and this may be single- or parallel-machine or flow shop. The element $\mathrm{S}_{ã}$ indicates the dissimilarity between models related to parallel machines. These characteristics may be discrepant because of location (Lo), size (Si), and process (Pr) parameters. For the restrictions imposed on orders, $\mathrm{S}_{ä}$ indicates whether those properties refer to due date (Du), material type (Ma), or part quality (Qu).

Both the nomenclature on AM technologies and the taxonomy of Oh et al. (2020) are important starting points for the content analysis of the 26 articles selected in the present study.

4 Additive manufacturing scheduling

Authors have approached the AM scheduling problem using various techniques such as mathematical modeling, heuristics, and meta-heuristics. Li et al. (2017) published the first study that used mixed integer modeling for AM; they aimed at minimizing production costs considering the need to print different objects with multiple PBF AM machines. This model focused on grouping objects into batches, called jobs, to build feasible solutions. Subsequently, the model assigned the jobs to machines, which helped minimize production costs. Therefore, the authors simplified the first step of the model by not including a nesting algorithm. The authors implemented their mathematical model through the CPLEX library (CPLEX, 2009) and proposed two heuristics: best-fit (BF) and adapted best-fit (ABF), which showed promising performances in a reasonable computational time.

Li et al. (2017) focused only on 3DP scheduling although they worked with ME technology. Ransikarbum et al. (2017) proposed a mathematical model considering multiple competing objectives, maximizing the load balance of the machines and minimizing total costs, involving printer and part (area x volume x height) costs, among others, and minimizing the total production delay. The authors justified the importance of their multiobjective model based on the main trade-off of AM: reconciling production flexibility characteristic of the high unit costs of the objects.

Araujo et al. (2018) proposed a new taxonomy for packing irregular 3D parts to facilitate the identification of these new problems and adapt the existing literature to better describe the scenario and particularities of 3DP; they did not present a modeling or practical approach. Further, the authors provided and described a new dataset for implementing and evaluating future solution proposals.

In terms of PBF technology, Chergui et al. (2018) analyzed the AM scheduling problem as a composition of two sub-problems: i) allocation of parts in lots; and ii) batch scheduling in AM machines. The authors sorted the parts using the earliest due date (EDD) rule towards minimizing the total delay in an environment of identical parallel machines, and they developed a heuristic comprising a main and secondary algorithm for selecting the next part to avoid increasing the processing time of a temporary job, i.e., any job not yet scheduled on a specific machine when including a new part. Thus, if the print time of the temporary job with the addition of a new part exceeded the minimum expiration date of the parts previously assigned to the print job, then that candidate part would be removed from the list of available parts for that machine.

Dvorak et al. (2018) analyzed the 3DP problem in AM machines equipped with SLM technology; this was the first peer-reviewed article to include multiple objectives in the model towards minimize delays and makespan. In addition to the mathematical model implemented using the CPLEX library, the authors developed hill climbing, simulated annealing (SA), step counting, late acceptance, and Tabu search algorithms for solving 10 problems. The initial responses were constructed randomly, and the methods of exchanging parts and lots were used for neighborhood exploration.

In the study by Gopsill & Hicks (2018), the integrated adoption of nesting and scheduling problems increases the complexity of the model. They authors assessed the influence of the scale effect and of four different production scheduling strategies using first-fit decreasing height (FFDH) as a nesting algorithm to improve the productivity of 3DP machines with ME technology; further, they presented the results of its combination with a genetic algorithm (GA). In addition, they proposed a strategy termed online continuous queue to solve the dynamic scheduling problem for on-demand production.

Thus far, studies reviewed only analyzed parallel machines, whether identical or not. Fera et al. (2018) conducted the first study on the list of articles selected in this review to address the problem in a single AM machine in which parts are grouped based on the construction platform volume towards simultaneously minimizing production delays and costs. Thus, the authors presented a mathematical model and a GA was developed and applied to a small group of generated instances with approximately 30 instances containing between 5 and 30 pieces each. The authors indicated that the GA provided feasible solutions within a reasonable computational time. However, the quality of the solution was not compared with that of other methods.

Luzon & Khmelnitsky (2019) analyzed a single-machine AM scheduling problem, and their mathematical model included a key characteristic in the shop floor operation: failures that may occur during the manufacturing process. The work addressed the dynamic demand of AM scheduling problem towards minimizing the makespan and flow time (total time that the part spends within the manufacturing process). In their mathematical model, they applied the shortest processing time (SPT) sorting rule, developed a simulation model, and determined the best distributions for modeling printer failures and lot sizes that provided the production system with the best performance. Li et al. (2019) considered dynamic demand, and the authors developed a mathematical model for this case along with two heuristics based on different decision-making strategies for printers with GMP technology.

Kucukkoc (2019) was the first peer-reviewed study that modeled the AM scheduling problem considering three different scenarios: a single machine, and identical and nonidentical parallel machines towards minimizing the makespan. The authors performed computational experiments in CPLEX with test data based on the benchmark of the study by Li et al. (2017); they adapted to the characteristics of the aforementioned research. The results showed that the difficulty of finding a solution increased with the size of the problem instance, and the authors solved problems with up to 46 pieces using this approach.

Zhang et al. (2019) developed a heuristic for the scheduling problem using the FFDH strategy and GA for lot scheduling with the following three methods for positioning and machine selection: First-fitting decreasing part-height and random machine selection, random permutation and load balance-based machine selection, and random permutation and random machine selection. Computational experiments were performed to assess the effect on the production system when increasing the number of parts to be printed and of available AM machines, characteristics that were included in their problem instances.

A cloud-based 3DP environment was addressed by Wang et al. (2019) who proposed an intelligent production planning system in AM based on computer vision; they ensured that all parts were packaged in batches and printed as quickly as possible and they met the requirements of a rapid response to orders placed by customers in the cloud. This case study used data from 32 parts with different characteristics; the test results showed the high quality of the packaging solutions.

Some studies found by the systematic review do not directly address the scheduling problem; they are focused on the nesting problem that disregards the step wherein a set of parts (batch) is assigned to AM machines for optimizing production indicators such as in the study by Araujo et al. (2019). In this study, the authors adapted a model termed three-dimensional irregular packing problem for the 3DP scenario which considers irregular shapes in addition to rotating them in three different axes (x, y, and z). They raised the difficulty level of the problem in the first article to add this feature. The authors applied the deepest bottom-left-fill decreasing strategy for nesting and implemented a GA describing in detail the selection, crossover, mutation, and reallocation operators of the population of solutions.

Given the importance of the first stage of the nesting pieces, Oh et al. (2019) assessed the possible effects on Makespan when considering different policies for orientating the parts in a batch, by format, size and number, and only one AM machine of VP technology, which satisfies the scheduling condition defined by the first-in-first-out sorting criterion. Further, the authors considered a dynamic demand and performed experiments to evaluate specific policies for the orientation of the parts, i.e., laying and standing policies, which was aimed at reducing the height of the parts and minimizing their projection on the plane of the printer's base, respectively.

Further, Antón et al. (2020) proposed a solution in the form of an interface implemented in Python by analyzing dynamic demand, and it receives the specifications of parts to be produced and generates the production layout, programming, and scheduling. The authors developed a combinatorial auctions (CA)-based solution to meet the customers' demands in an environment with 3D printers with different technologies and materials.

To this end, Antón et al. (2020) solved the packaging problem in the first stage by maximizing the printing area occupied by a batch of parts, and in the second stage, using a winner determination problem (WDP) for determining batches that need to be produced for achieving the highest possible return. Although authors provided a CA-and WDP-based solution strategy, they did not compare their solution with other algorithms that only exemplifies how they performed their experiments.

Darwish et al. (2020) proposed a 3DP management architecture based on an industrial IoT network that considers a dynamic and workload-intensive environment. The algorithm proposed by the authors showed a complexity of O (nlog(n)), and it was divided into a broker and a cluster manager; it was compared with the first-fit (FF), BF, and best-fit-decreasing algorithms. In addition, Papakostas et al. (2020) addressed dynamic demand and I4.0 and IoT aspects by developing constructive and ordering heuristics to solve the AM online scheduling problem specifically for SLM and DMLS technologies.

Ransikarbum et al. (2020) presented an optimization approach with multiple objectives for scheduling parts in AM considering an environment with nonidentical parallel machines. Its contribution lies in incorporating multiple printing technologies into the problem: ME, SL, and SLS, which includes in its model not only production decisions but also distribution and supply chain supply issues in an integrated manner. Computational experiments were performed by varying the number of parts, types of printers, and distribution locations.

Yilmaz (2020) modelled the AM problem, which considers the supply chain and presents a more complex mathematical model. However, the author employed heuristic and sorting strategies similar to others reviewed here. Rossi & Lanzetta (2020) discussed a hybrid problem integrating planning and scheduling activities as in the study by Yilmaz (2020); it is termed integrated planning and scheduling, together with AM technology.

Fera et al. (2020) provided a new version of the mathematical model with multiple objectives that they had previously proposed in 2018. This introduces some corrections and new features to increase its efficiency in addition to applying the heuristic based on the Tabu search technique; this compares the results with those of the AG implemented in 2018 because the authors used the same test instances in both articles. They concluded that GA is better in terms of computational time; however, TB is better in terms of operational management.

According to Oh et al. (2020), nesting and scheduling problems are treated separately in traditional manufacturing; a disjoint taxonomy for these problems is addressed and a more holistic view of their application is overlooked. A new taxonomy for AM scheduling problems was proposed based on dimensions such as parts, construction, and AM machine from 53 articles reviewed by the authors; they are divided into six other categories that describe and typify the problems in more detail.

Che et al. (2021) focused their research on SLM technology, which treats two stages (nesting and scheduling) in an integrated manner wherein batches are formed and allocated to the machine with the lowest makespan and compatible capacity. In addition to a mixed integer linear programming (MILP) model, the authors presented heuristics for ordering the parts and developed a SA-based metaheuristic with two constructive strategies, BF and FF, and with 11 types of operators for neighborhood exploration produced with 3 basic movements: reallocation, exchange, and division. In addition to applying the operators in the metaheuristic, random local search-based methods were developed towards refining solutions presented by the SA strategy.

In Aloui & Hadj-Hamou (2021), the parts were ordered using the EDD rule, with ties broken by the SPT rule and by the height of the part if the due date and processing time were the same. Furthermore, the authors developed constructive heuristics to solve large-scale cases of the problem. Authors built a data generator for creating instances. A small test problem was generated and solved using exact methods to ensure the validity of the proposed model. Only 15 of the 30 instances were solved with an exact model, which shows the need for fast algorithms to solve large problems.

Alicastro et al. (2021) conducted robust computational experiments to solve an AM scheduling problem, which considers nonidentical parallel machines using SLM technology. The mathematical model developed by the authors was initially proposed by Kucukkoc (2019) and the similarities of the AM scheduling problem with the batch processing machine problem (BPM) are extrapolated. Such a model still lacked an efficient solution implemented in the literature in addition to an exact solution (via mathematical programming). Therefore, the authors developed a metaheuristic termed reinforcement learning iterated local search towards minimizing the makespan, which according to the authors, remains a slightly explored objective in the literature.

Finally, the article by Stittgen & Schleifenbaum (2021) addressed the AM scheduling problem considering the interrelation of performance indicators such as utilization, capacity, and work in the production process; this must be analyzed considering the characteristics of the AM technology. A Monte Carlo simulation model was developed and validated based on data collected on the shop floor of a global AM service provider to assess the impact of configuring a dynamic production environment on these indicators.

The 26 articles qualitatively discussed in this section are summarized in Table 2, which identifies some characteristics relevant to the scope of the more in-depth analysis of AM scheduling problems provided in Section 5. The methodological approach of the study, the number of objective functions, and other features such as whether the studies addressed other links in the supply chain and type of demand are outlined in the chronological order of publication.

Table 2. Summary of the characteristics of the articles analyzed in this review.

Author	Quantitative approach	Single OF	Disregarding the supply chain	Static Demand
Li et al. (2017)	x	x	X	x
Ransikarbum et al. (2017)	x		X	x
Araujo et al. (2018)			X	
Chergui et al. (2018)	x	x	X	x
Dvorak et al. (2018)	x	x	X	x
Gopsill & Hicks (2018)	x	x	X	
Fera et al. (2018)	x		X	x
Luzon & Khmelnitsky (2019)	x		X	
Li et al. (2019)	x		X	
Kucukkoc (2019)	x	x	X	x
Zhang et al. (2019)	x	x	X	x
Wang et al. (2019)	x	x	X	
Araujo et al. (2019)	x	x	X	x
Oh et al. (2019)	x	x	X	x
Antón et al. (2020)	x	x	X	
Darwish et al. (2020)	x	x	X	
Papakostas et al. (2020)	x	x	X	
Ransikarbum et al. (2020)	x			x
Yilmaz (2020)	x	x		x
Rossi & Lanzetta (2020)	x	x		x
Fera et al. (2020)	x		X	x
Oh et al. (2020)			X	
Che et al. (2021)	x	x	X	x
Aloui & Hadj-Hamou (2021)	x	x	X	x
Alicastro et al. (2021)	x	x	X	x
Stittgen & Schleifenbaum (2021)	x		X	

Source: The authors.

The present study reviewed research aimed at identifying solution strategies for AM scheduling problems on cases in which the demand was known prior to its programming and scheduling (static demand) with unique optimization objectives. They exclusively focused on scheduling, while disregarding other links in the supply chain. In addition, only quantitative studies were considered.

5 Discussion

Some characteristics present in the literature on AM scheduling can be listed considering the data presented in the previous section. To this end, Table 3 summarizes key characteristics of the models discussed in the articles based on the taxonomy for AM scheduling problems by Oh et al. (2020). As all studies treated the values N_γ and N_δ as bounded and full, these parameters are not included in the table. Further, the columns referring to technology (T) and OF adopted in each study considered in this review are included in the table. For the content analysis, the authors were listed in an ascending order of publication of the articles.

Table 3. Classification of article by AM model and technology.

Autor	N_α	N_β	S_α	S_β	S_γ	S_δ	T	FO
Li et al. (2017)	-	-	Grouped	PM	Si; Pr	-	PBF	Minimum production costs
Chergui et al. (2018)	2D	C	Nested	PM	-	Du	PBF	Minimum total delay
Dvorak et al. (2018)	2D	C	Nested	PM	Si	Du, Ma	PBF	Minimum makespan
Gopsill & Hicks (2018)	2D	C	Nested	PM	-	-	ME	Maximum productivity indicator
Luzon & Khmelnitsky (2019)	-	-	Grouped	SM	-	-	PBF	Minimum makespan
Kucukkoc (2019)	-	-	Grouped	SM, PM*	Si; Pr	-	PBF	Minimum makespan
Zhang et al. (2019)	2D	C	Nested	PM	-	-	VP	Minimum makespan
Araujo et al. (2019)	3D	ABC	Nested	PM	-	-	PBF	Minimum construction height
Che et al. (2021)	2D	ABC	Nested	PM	Si; Pr	-	SLM	Minimum makespan
Aloui & Hadj-Hamou (2021)	2D	N/A	Nested	PM	Si; Pr	Du	PBF, MJF	Minimum total delay
Alicastro et al. (2021)	2D	C	Nested	PM	Si; Pr	-	SLM	Minimum makespan

*The author proposes three distinct models: one with a single machine, an identical parallel machine, and nonidentical parallel machine. Source: The authors.

The results indicate that some researchers report missing observations in the first two elements of the tuple because they are related to the characteristics of the executed nesting algorithms; in these particular cases, the parts were grouped into lots.

The first step can be defined through a nesting algorithm or by merely grouping the parts according to some criterion (similarity, area, and delivery time, among others); the AM scheduling problem can be divided into two sub-problems: i) allocation of parts in batches and ii) allocation of batches in machines. Table 3 indicates that only three authors used grouping to form batches, approximately 27%. Therefore, the solution of a nesting algorithm for the prior formation of batches of parts is an important characteristic. According to some authors, solving the scheduling problem in this way can enhance the final results (Aloui & Hadj-Hamou, 2021; Che et al., 2021).

However, the dimension ($N_{á}$) and rotation ($N_{â}$) characteristics are presented and significantly impact the complexity of the algorithm when the models include a nesting algorithm to create part lots. Araujo et al. (2019) researched a 3D positioning problem with irregular parts; however, despite representing important cases in AM, many authors simplify the problem for 2D positioning as observed, both by using factors of specific technologies that prevent stacking parts and simplifying mathematical models and algorithms. The possibility of allocating parts in three dimensions can improve objective function results by allowing the allocation of more parts in the print region; however, it significantly increases the complexity of mathematical models and algorithms. Authors tend to simplify the rotation of parts $N_{â}$ by adopting only the rotation on the Z axis.

The characteristics of the machines significantly affect the models and constraints of the different environments and scheduling objectives. Column $S_{â}$ shows that the most working conditions referred to environments with parallel machines, which accounts for approximately 90% of the studies. Among these studies, only four studies analyzed environments with identical parallel machines. The dissimilarity of nonidentical machines is shown in column $S_{ä}$, and it highlights that most machines differ in size and parameters. Further, only two research groups tackle a single-machine environment.

The most prevalent environment in Table 3 was analyzed in the study by Che et al. (2021), who designated the production scheduling problem of AM as unrelated parallel AM machine scheduling problem, derived from the BPM scheduling problem. Such a manufacturing environment is composed of multiple AM machines with different sizes, capacities, and configuration parameters, among others.

Completing the tuple of scheduling characteristics, the $S_{ã}$ column outlines studies containing objective function constraints that show studies aimed at minimizing delays present the due dates (Du) constraint. A key point related to the study by Dvorak et al. (2018) is that although its objective function was makespan minimization, the model contained light constraints for minimizing the number of delayed due jobs and the materials (Ma) constraint for maximizing the total printing area while simultaneously addressing the constraints of the materials.

Numerous AM technologies are available on the market; however, most articles reviewed here address only one technology at a time, except for the study by Aloui & Hadj-Hamou (2021). In addition, PBF is the technology most commonly used in the articles, in approximately 64% studies, and it is popular in the production of metal parts. However, different technologies directly affect the pre- and post-processing stages of parts and the setup of the 3D printers. Such particularities translate into differences in the mathematical models developed by each research group as a function of the AM technology.

Table 3 indicates that approximately 54% of the articles selected for review aimed at minimizing makespan, and that the objective function of 18% of the studies consisted of minimizing total delays. Therefore, it demonstrated compliance with more traditional minimization objectives of scheduling research.

Table 4 presents the characteristics of the solutions by focusing on the algorithms to grasp the main approaches, their limitations, and similarities. Thus, the first column identifies the author and year of publication of the article in the chronological order. The second column outlines the solution strategies for solving the AM scheduling problem implemented by the authors, with most studies developing their own mathematical models because only two studies adopted models from other authors (Gopsill & Hicks, 2018; Araujo et al., 2019). Among the fast algorithms (column 2), heuristics were developed in approximately 45% studies; however, two studies failed to present algorithm proposals for solving the problem and they developed only mathematical models (Luzon & Khmelnitsky, 2019; Kucukkoc, 2019). Column number in Table 4 reveals the data structures used to represent the solutions to the problem at hand.

Table 4. Classification of articles by computational experiment.

Authors	Solution strategies	Response data structure	Sorting strategies	Constructive heuristics	Neighborhood exploration	Comparison of algorithms	Number of Instances	Data
Li et al. (2017)	Mat. Mod. and Heuristic	N/A	N/A	BF and ABF	N/A	Execution Time and Objective Value	42	Generated
Chergui et al. (2018)	Mat. Mod. and Heuristic	N/A	EDD	Custom heuristic	N/A	N/A	27	Generated
Dvorak et al. (2018)	Mat. Mod., AS, TS, HS, SC and TS	N/A	N/A	Random	Yes	N/A	10	Generated
Gopsill & Hicks (2018)	FFDH + GA	N/A	DH	FFDH	N/A	Simulation	N/A	N/A
Luzon & Khmelnitsky (2019)	Mat. Mod.	N/A	SPT	N/A	N/A	Simulation	N/A	N/A
Kucukkoc (2019)	Mat. Mod.	N/A	N/A	N/A	N/A	N/A	42	Benchmark
Zhang et al. (2019)	Mat. Mod., Heuristic and GA	Vectors and Coordinates	DH	FFDH	Yes	Wilcoxon	14	Benchmark (Cited)
Araujo et al. (2019)	Brute Force, GA and Heuristic	Vectors and Coordinates	DH	Random	Yes	Objective Value means	3	Generated (Online)
Che et al. (2021)	Mat. Mod. and SA	Skyline (x, y, z, l1, l2)	SPT, DH, DL, DW, DA and DV	BF and FF	Yes	Execution Time and Objective Value	140	Generated (Online)
Aloui & Hadj-Hamou (2021)	Mat. Mod. and Heuristic	Vectors	EDD, SPT, DH	Custom heuristic	N/A	Execution Time and Objective Value	30	Generated
Alicastro et al. (2021)	Mat. Mod. e ILS	Vectors	DH	NFDH, FFDH E BFDH	Yes	Execution Time and Objective Value	128	Benchmark and generated (Online)

Source: The authors.

The first six studies failed to identify these structures in detail; this is represented by the argument "*Not Available*" ("N/A") that indicates this information could not be found in these articles. As the topic matured over the years, authors began to describe this structure in their articles, most of whom used the response structure based on vectors and coordinates. Only Che et al. (2021) described a slightly more complex and detailed structure termed “Skyline.” In studies that only analyzed scheduling, the response structures were determined by vectors of integers scheduling batches on available machines; however, the positioning of the parts required building data structures to store the coordinates of these parts within the printing space. The set of sorting rules and constructive heuristics applied correspond to a mixture of strategies used for scheduling and bin packing problems. The sorting strategies applied to the articles were outlined in column four, and they comprise the following rules: EDD, SPT, decreasing height (DH), decreasing length (DL), decreasing width (DW), decreasing area (DA), and decreasing volume (DV).

DH is the most commonly used sorting strategy, and it is found in approximately 54% of the studies. In addition, only Che et al. (2021) and Aloui & Hadj-Hamou (2021) used more than one sorting strategy.

Column five identifies constructive heuristics, i.e., how the initial responses of the algorithms were created. Based on these articles, they can be classified as BF, ABF, FFDH, FF, next-fit decreasing height (NFDH), custom heuristics, or random. Luzon & Khmelnitsky (2019) and Kucukkoc (2019) did not describe how they developed those heuristics. Two strategies stood out: FFDH (27%), which first sorts the pieces from highest to lowest and then fits them into the first bin with enough space, and BF (18%), which arranges the pieces within the printing space to fill as much available area as possible.

Further, the articles were evaluated based on whether they applied neighborhood exploration to enhance the results of the algorithms developed based on exchange, insertion, and removal movements between both parts and production batches. Some movements were analyzed for creating, dividing, combining, and deleting batches during the searching process for optimizing different objectives. The information contained in the sixth column of Table 4 shows that approximately 45% of the research groups completed this important step for refining the answers.

The solutions proposed in AM scheduling studies must be compared and evaluated in some way because they aim at solving a combinatory problem. Column seven shows that most studies used two variables for this comparison: execution time and objective function value. Execution time refers to the time taken by a computer to find a solution to the combinatorial problem. The search space increases exponentially with the number of parts requiring scheduling because AM scheduling problems are NP-hard. Many authors developed mathematical models subjected to exact algorithms for proving the optimal answer such as IBM’s CPLEX Optimization Studio. Although these algorithms demand long execution times and memory to provide such a proof, they are used to validate the results of other algorithms such as heuristics and meta heuristics. Thus, the response quality is evaluated based on the objective function values. For maximization problems, higher values are considered to be better for objective function performance; for minimization problems, lower values are considered better.

Assessing the robustness of computational experiments requires determining whether the studies used good samples of problems. Column eight displays the number of instances, and column nine shows whether these data were generated or retrieved from other articles (benchmark) and if they are available to the reader. Only Alicastro et al. (2021) and Che et al. (2021) used large samples; however, these samples are considered too small to represent reality. Most authors used a generator to create their dataset (approximately 63% articles), and only a few of them make these data available online.

The limitations in comparisons between algorithms were noted. The literature is extremely recent, and most researchers have conducted normative research aimed at developing new optimization models adapted to AM technology, which is experiencing an enormous growth. Some researchers focused on numerical exemplification of their models, and they performed experiments with very limited datasets and by applying only CPLEX to identify optimal solutions for small instances. Among them, the study by Che et al. (2021) has gained interest because they use a supercomputer to solve larger instances.

6 Final considerations and future perspectives

This study reviewed the literature on AM scheduling to understand how researchers in the area are solving this problem given the increasing use of 3D printers in production environments and the need to ensure the competitive performance of companies in this setting.

Although many studies proposed mathematical models for the problem, most do not include technological constraints intrinsic to each AM technology; this impairs their representation of reality. Further, the models must also be improved to keep up with the constant advancements in AM technologies.

The AM scheduling problem is tackled using many approaches in two different stages: first, by sorting pieces into lots using a nesting algorithm, and subsequently, by scheduling those lots to 3DP machines. Some authors propose applying these two stages of the scheduling problem in an integrated model, which can further increase its complexity.

This review indicated that some characteristics of the problem can be simplified in the models to reduce their complexity without losing the quality of the solutions, e.g., considering positioning only in two dimensions. In this case, it may not be allowed to stack parts because of the technological issues inherent to the type of AM technology. Other common simplifications include allowing parts to be rotated only on the C axis and considering parts with regular shapes.

Various implementations of mathematical models for validating other algorithms were identified; however, with few heuristics versus heuristics or meta-heuristics versus meta heuristics comparisons. There is room for a more elaborate comparative analysis, which involves algorithms similar to each other and includes comparisons on tuning strategies.

The analysis of studies selected in this SLR on quantitative models and solution strategies suggests that the literature on this topic is extremely recent. Both the implementation of a heuristic adaptation and the development of hybrid strategies between enumerative and heuristic algorithms, in addition to meta-heuristics, represent wide knowledge gaps that should be bridged in future research efforts aimed at developing fast algorithms for AM scheduling problems.

Thus, this study presented the following research avenues (i) in exact methods, which include mathematical formulations that generate more adequate bounds in addition to decomposition methods and MIP-Heuristics; and (ii) in heuristics, which improve and introduce new methods for AM scheduling. Further, empirical studies on real AM environments must be conducted to indicate the restrictions and characteristics of such environments.

Finally, although the present study only considered articles on integrated production programming with nesting decisions, a similar analysis should be conducted considering only the nesting subproblem.

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Appendix A. PRISMA 2009 Checklist.

Topic	Item no.	Checklist item	Reported on page #
		TITLE	
Title	1	Identify the article as a systematic review, meta-analysis, or both.	Page 1
		ABSTRACT	
Structured abstract	2	Present a structured summary including, if applicable: basic context of the scientific work (theoretical framework), objectives, data source, eligibility criteria, participants, interventions, summary of the methods, study evaluation; transparency of the study methods (critical evaluation), results, limitations, conclusions and implications of the main findings; and systematic review registration number.	Page 1
		INTRODUCTION	
Rationale	3	Describe the rationale for the review in the context of the state-of-the-art.	The increasing use of 3D printers in the production environment on small, medium, or large scales has increased the complexity and made it necessary to address the high demands for pieces and AM machines for work allocation. These demands often differ because of some indicators such as delivery time. Various authors in this area of research have proposed mathematical models to describe these specific cases and fast algorithms to solve the problem to face such challenges and aid managers in making decisions as assertively as possible quickly.
Objectives	4	Provide an explicit statement about the issues addressed regarding participants, interventions, comparisons, outcomes, and study design (PICOS).	Page 4: "The present study aims at conducting a systematic literature review (SLR) to solve scheduling problems in AM for identifying models most commonly used by authors and their main characteristics, in addition to collecting data on algorithms and on the response and neighborhood exploration structures and understanding how computational experiments are performed and algorithms compared."
		METHODS	
Protocol and registration	5	Indicate whether a review protocol was followed, if and where this protocol can be accessed (for example, e-mail address), and, if available, provide information about the review record, including the registration number	Not applicable
Eligibility criteria	6	Specify study characteristics (for example, PEAKS, extent of follow-up) and reporting characteristics (for example, publication interval (years), language, whether published) used as eligibility criteria, providing a justification.	Page 5: "(...) this research aimed at finding studies on the production scheduling problem involving AM technologies. During the initial search analysis, several studies focusing on only the nesting subproblem were identified, which included decoupling production scheduling from piece positioning (for example, see Bennell & Oliveira, 2008). Studies exclusively focused on nesting problems were disregarded in the analysis because the present study is focused on the integration between production scheduling and piece positioning. All articles that included the selected terms in their title, abstract, or keywords were listed by the platforms. In addition, only full articles published in journals were considered in the search (...)"
Sources of information	7	Describe all sources of information in the search (for example, database with dates of coverage, contact with authors to identify additional studies) and date of the last search.	Page 5: "Three databases were selected to search for articles: (1) Engineering Village, was selected because this search platform provides access to the databases of engineering articles and patents (Elsevier, 2020). The databases of (2) Web of Science and (3) SciELO were selected because the index articles of multidisciplinary areas are considered two of the largest and most used databases for bibliometric studies (Marsilio et al., 2011). (...) All articles found until August 2021 were included in the search because this is a recent topic in both the industry and the academy."

Appendix A. Continued…

Topic	Item no.	Checklist item	Reported on page #
		METHODS	
Search	8	Present the complete electronic search strategy for at le ast one database, including the limits used so that it can be repeated.	Page 5: “additive manufacturing” AND “scheduling”
Study selection	9	Introduce the study selection process (that is, search, eligibility, those included in the systematic review, and, if applicable, those included in the meta-analysis).	Page 5-6
Data collection process	10	Describe the method for extracting data from articles (for example, pilot, independent, and duplicate search) and all processes for gathering and confirming data from studies.	Not applicable
List of data	11	List and define all variables retrieved from the data (for example, PEAKS, funding sources) and any assumptions or simplifications made.	Not applicable
Risk of bias in each study	12	Describe the methods used to assess the risk of bias in each study (including specifying whether the risk was assessed during the study or at the outcome level), and how this information was used in data analysis.	Not applicable
Summary measures	13	Define key measures for summarizing results (for example, relative risk, and mean difference).	Not applicable
Synthesis of results	14	Describe methods for data analysis and combination of study results, if performed, including consistency measures (for example, I2) for each meta-analysis.	Not applicable
Risk of bias between studies	15	Specify any assessment of the risk of bias that may affect cumulative evidence (for example publication bias and selective reporting across studies)	Not applicable
Additional analyses	16	Describe additional analysis methods (for example, sensitivity or subgroup analysis, and meta-regression), if performed, indicating which were pre-specified.	Not applicable
		RESULTS	
Study selection	17	Present the numbers of studies screened, evaluated for eligibility and included in the review and the reasons for excluding a study at each stage, preferably via a flowchart.	Page 5: Figure 1
Study characteristics	18	For each study, present characteristics for data extraction (for example, study size, PEAKS, follow-up period) and present the citations.	Not applicable
Risk of bias between studies	19	Present data on the risk of bias in each study and, if available, any assessment of outcomes (see item 12).	Not applicable
Results from individual studies	20	For all considered outcomes (benefits or risks), present for each study: (a) a simple summary of data for each intervention group and (b) estimated effects and confidence intervals, preferably using forest plots.	Not applicable
Synthesis of results	21	Present results for each meta-analysis performed, including confidence intervals and consistency measures.	Not applicable
Risk of bias between studies	22	Present the results of the assessment of the risk of bias between studies (see item 15).	Not applicable
Additional analyses	23	Present results of additional analyses, if performed (for example, sensitivity analysis or subgroups, meta-regression [see item 16]).	Not applicable

Appendix A. Continued…

Topic	Item no.	Checklist item	Reported on page #
		DISCUSSION	
Evidence summary	24	Summarize the main results, including the strength of evidence for each result; consider its rele vance to key groups (for example, healthcare professionals, users and policymakers).	Page 15: Table 3; Page 20: Table 4
Limitations	25	Discuss limitations at the study and outcome (for example, risk of bias) and review (for example, incomplete identification of research studies, reporting of bias) levels.	Not applicable
Conclusions	26	Present the general interpretation of the results in the context of other evidence and implications for future research.	Pages 23–24
		FUNDING	
Funding	27	Describe funding sources for the systematic review and other support (for example, data), and the role of funders in the systematic review.	The São Paulo Research Foundation (*Fundação de Amparo à Pesquisa do Estado de São Paulo* – FAPESP) - usually included in the list of journals as FAPESP, in Portuguese grant number #2019/12023-1 National Council for Scientific and Technological Development (*Conselho Nacional de Desenvolvimento Científico e Tecnológico* – CNPq) - Grant 405702/2021-3