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Review

Scheduling in cloud manufacturing systems: Recent systematic literature review

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Abstract: Cloud Manufacturing (CMfg) is a novel production paradigm that benefits from Cloud Computing in order to develop manufacturing systems linked by the cloud. These systems, based on virtual platforms, allow direct linkage between customers and suppliers of manufacturing services, regardless of geographical distance. In this way, CMfg can expand both markets for producers, and suppliers for customers. However, these linkages imply a new challenge for production planning and decision-making process, especially in Scheduling. In this paper, a systematic literature review of articles addressing scheduling in Cloud Manufacturing environments is carried out. The review takes as its starting point a seminal study published in 2019, in which all problem features are described in detail. We pay special attention to the optimization methods and problem-solving strategies that have been suggested in CMfg scheduling. From the review carried out, we can assert that CMfg is a topic of growing interest within the scientific community. We also conclude that the methods based on bio-inspired metaheuristics are by far the most widely used (they represent more than 50% of the articles found). On the other hand, we suggest some lines for future research to further consolidate this field. In particular, we want to highlight the multi-objective approach, since due to the nature of the problem and the production paradigm, the optimization objectives involved are generally in conflict. In addition, decentralized approaches such as those based on game theory are promising lines for future research.

Keywords: cloud manufacturing; scheduling; literature review; Industry 4.0; Internet of Things; cyber-physical systems; optimization; multi-objective; cloud computing

1. Introduction

The development of Internet of Things (IoT) has generated an unprecedented technological revolution, allowing the connection of different elements and systems with each other, which was previously unimaginable [1]. One of the most outstanding results of this technology is *Cloud Computing*, where the possibility of connecting elements and systems transcends physical proximity, and enable to connect very distant elements through the cloud [2, 3]. This linkage through the cloud provides the necessary support to generate new relationships between previously unrelated agents [4]. From these links, these agents can coordinate and manage their activity jointly, achieving a synergy with their capacities and resources, that provide skills and competencies that none of the agents had separately. This same idea is the basis for the concept of *Cloud Manufaturing* [5].

Cloud Manufacturing (CMfg) is a manufacturing paradigm created from the advantages of Cloud Computing [5,6]. In Cloud Manufacturing, the production or manufacturing services and the customers who demand these services are linked by a virtual platform in the cloud [7]. In this way, customers have access to a growing number of manufacturing service suppliers, while service suppliers, for their part, have access to a larger number of customers than would be available only by their own means [8]. The CMfg-based manufacturing model takes advantage of the possibility of accessing, through the cloud, to a set of distributed or diverse production resources that can be grouped on demand [9]. This possibility of grouping resources on demand enables the possibility of generating production chains that share resources from more than one production service supplier. Therefore, production processes can be carried out in different geographical locations [10]. This flexibility in the production configurations considerably reduces the costs of the life cycle of the products (one manufacturer does not have to develop all the production technology), as well as the optimal allocation of service and service orders [11]. CMfg allows working as a connected network of resource suppliers, with ubiquitous access and great capacity to virtualize those resources. This ability to virtualize productive resources is enhanced by the incorporation of cyber-physical systems (CPS) and Industry 4.0 technologies [12, 13]. CPS and Industry 4.0 technologies allow deep digitization of production resources, enabling access to shop floor information in real time [14, 15]. This real-time information notably improves decision-making capacity about the production system, especially those related to production planning [16–18]. Among the planning problems, the scheduling problem takes on special relevance, since it is a computationally complex problem [19], and which contemplates a very short planning horizon [20]. Therefore, the CPS allow to have more precise information on the real state of the shop floor, as well as to be able to implement and execute the schedule more agilely, which results in a more agile and controlled production system [21, 22]. CMfg benefits from CPS and Industry 4.0, being able to have information on the status of production (for example, the workload in process), but also being able to remotely control physical processes [7, 23].

Taking into account the aforementioned description, it is natural to study those scheduling problems that emerge from CMfg environments, in which the distributed resources, and the possibility to group them with great flexibility, entails a non-trivial problem of coordination and synchronization of activities [24]. In addition, given the nature of CMfg that allows the system to scale quickly (following a *pay-as-you-go* logic), the complexity of the scheduling problem embedded within CMfg also grows rapidly [25]. In the article of Liu et al. [11], an in-depth study is developed on the different implications that a paradigm such as CMfg has to solve the related scheduling problem. Among the numerous contributions of [11], the large number of new features that must be considered to solve scheduling in CMfg systems stands out, compared to more traditional areas of scheduling study. In that work, the authors compile and analyze the characteristics and properties of this new scheduling problem. From Liu et al. the amount of papers that address scheduling problems in CMfg has grown considerably, and they have been consolidating and deepening the topic. In those papers about scheduling on CMfg prior to Liu et al., the authors had to explain in detail the characteristics of CMfg, and discuss the reasons for studying this problem. On the other hand, later papers are based on the compilation made by Liu et al. [11]. Thus, these new papers delve into the different approaches to solve the problem [26], rather than discussing the features of CMfg. In other words, once the problem have been clearly defined, it is easy for the scientific community to focus its efforts on addressing the idea of *how to solve that problem.* Therefore, papers after Liu et al., focus mainly on the scheduling problem emerged in CMfg. This modality of proposing and contrasting different optimization methods and approaches is a growing trend in the CMfg scheduling literature for the most recent years [27]. This trend confirms that the study of the problem has begun to mature.

The contribution of this paper is aligned with the last idea stated above. The main objective of this work is to review all the papers that were published after [11], and to make a complete review of the literature. This review is particularly oriented towards the optimization approaches used to solve Scheduling in CMfg. This review proposes to identify which have been the most used optimization methods, as well as the characteristics of the problems addressed, such as objectives or particular restrictions. Thus, the goal of this review is to contribute to the consolidation of this research line within the problems of Cloud Manufacturing, as well as those of Scheduling. To do this, a systematic review of the literature is proposed [28], together with an analysis and discussion of the main conclusions and results. In this sense, we suggest future research lines that will serve as a guide for future researchers.

The rest of the paper is organized as follows. Section 2 explains the review methodology used. In Section 3, the in-depth review of all selected works is shown. In Section 4 future lines of research are presented, while in Section 5 the main conclusions of this literature review are provided.

2. Systematic literature review

We present in this section the review of the literature carried out for Scheduling problems in Cloud Manufacturing. The objective of this survey is to analyze and demonstrate the growing interest of the scientific community in the subject. The review methodology *Systematic Literature review* is used, as it provides a suitable methodology for approaching the literature in an organized and efficient way [28]. In addition, this allows the presented results can be reproduced in the future [29].

As mentioned in the introduction section of this paper, we attempt to contribute from the work of [11], in which the literature about CMfg is reviewed from 2012 to February 5, 2018. In our case, the review consider those works after that date. Therefore, we consider the period of time between 2018 February 6, and 2020 July 6, for the execution of the queries in the selected databases.

2.1. Methodology

In order to perform a systematic review, a repeatable and verifiable process must be defined [29]. To do this, we choose [28] and [30] as a basis, and develop the following procedure for the systematic review presented here:

1. Define literature classification criteria considering databases or collections on which the search will be carried out.
2. Consolidation of the results obtained from the searches according to each of the criteria in the different collections.
3. Consolidation of the results obtained considering all the databases consulted.
4. Elimination of duplicates, indicating the times that the publication has appeared in the different searches.
5. Reading of Titles and Abstracts for initial classification of publications according to the classification defined in step 1.
6. Elimination of publications NOT related to the subject discussed.
7. Deep reading of those publications that generated doubts regarding their relationship with the topic and then classify or discard it.

2.2. *Implementation of the systematic review*

The implementation of a systematic literature review begins by defining the criteria to classify the literature according to certain search objectives. To classify the literature, we consider those elements or basic concepts related to scheduling in CMfg environments, defining the following categories or classifications: *Cloud manufacturing AND scheduling OR Cloud-based Manufacturing AND scheduling*. From these categories, several searches were performed in different well-known databases of scientific publications. In addition, certain rules were established in order to guide the search process. The search rules are described below:

- The search focus on articles and conference proceedings.
- The electronic databases (collections) considered for the search are:
  - Scopus
  - IEEE
  - Science Direct
- Search at each collection must be carried out looking for the established categories.
- For all searches, the terms: *cloud manufacturing* or *cloud-based manufacturing*, or their combination, are required in the title, abstract or keywords.
- In turn, it is required that at least one of the terms of the categories used, or a combination of them, is present in the title, abstract or keywords.

The diagram of Figure 1 illustrates the process of searching and filtering performed. The different criteria applied for filtering searches are shown in the first stages on the left side of Figure 1. As a result, a set of 128 papers is obtained. This set of works is then submitted to the classification stage (box labeled "Classify the articles based on reviewing the abstract of the article" in Figure 1). From that stage onwards, each one of the papers is analyzed in detail in order to determine whether or not it really corresponds to a scheduling problem in CMfg.

Consolidation. We note that some of the 128 works obtained may be duplicate as multiple classifications and/or collections are used. Therefore, a consolidation step must be carried out in order to eliminate duplicated works. As a result, a set of 102 papers is considered for the future steps of the process.

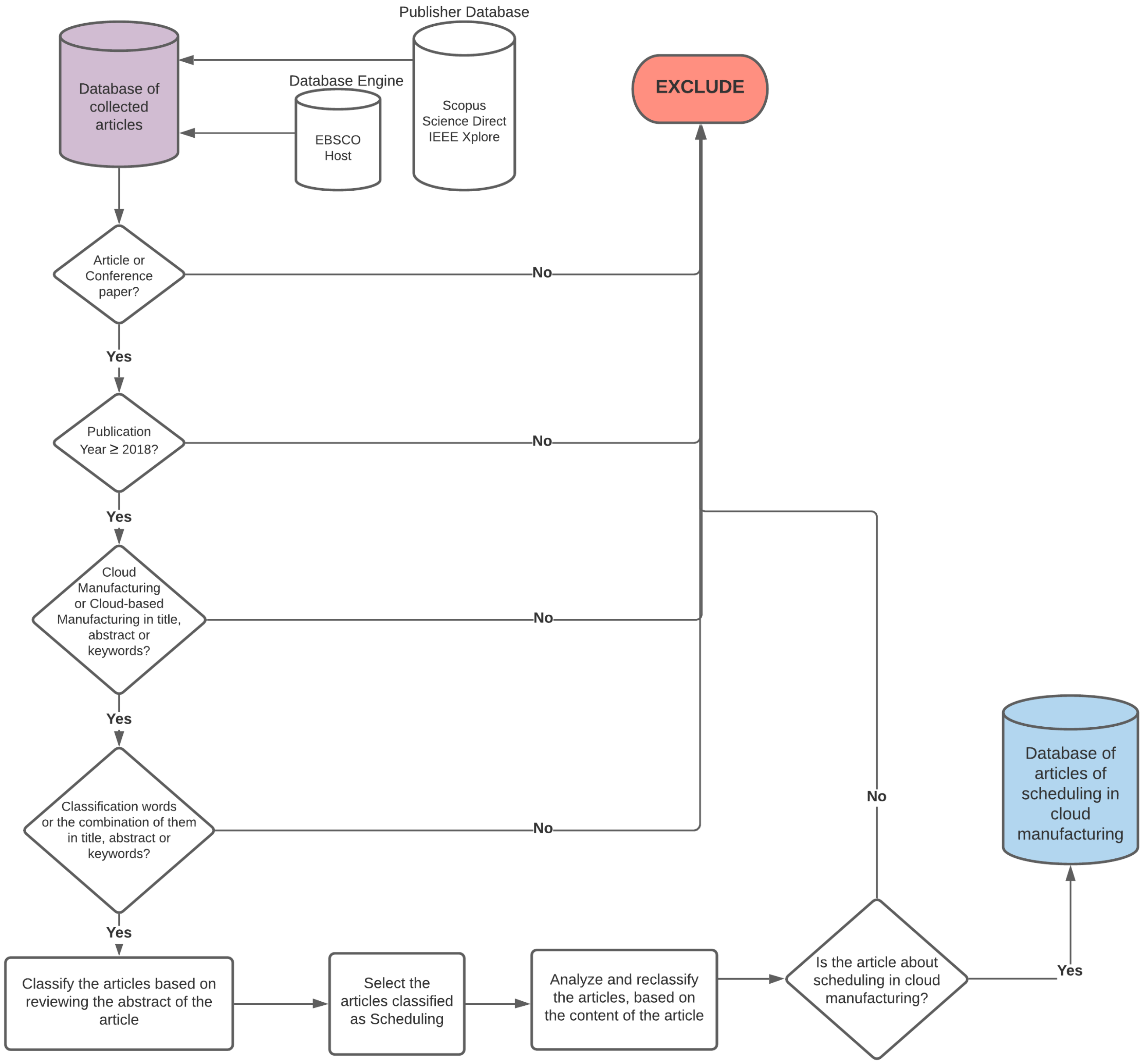


Figure 1. Implementation of Systematic Review process.

Initial classification. A first stage of classification is carried out on the set of works obtained as a result of the consolidation stage, in order to reject those works that should not belong to the set. The classification is applied on the content of the title and abstract of each work. The result of this stage is a set of 59 papers.

Final classification. Once the initial classification of the papers is finished, we analyze the content of those papers for which it has not been possible to determine until now whether they should be taken into account or not for the review process. As a result of this final classification stage, a final set of 47 papers is obtained for the literature review presented in Section 3.

3. Literature review

As mentioned in Section 2, a systematic literature review was conducted for scheduling problems in CMfg environments. The objective of that review is to analyze the evolution in the study of scheduling problems in CMfg after Liu et al. [11]. To do this, we present below a classification of the works according to the approach and/or resolution method used by the authors to address the problem.

3.1. Exact approaches

In this first stage of the review, we review all the papers found that make use of exact resolution methods. The first work that we found within this group is Delaram et al. [31]. The authors discuss the analogy between tasks scheduling in cloud computing and cloud manufacturing. A linear mixed-integer programming (MILP) formulation is proposed, with the aim to minimize logistics and production costs. Some illustrative cases are solved using LINGO. Suma and Murugesan [32] also address a problem through a MILP approach, but in this case, in addition to logistics and production costs, both production and transfer times are considered in the objective function. To solve the problem they use a Min-Max approach. In Vahedi et al. [33], a multi-objective problem is addressed using a ϵ-constraint method. The particularity of the problem studied is that it allows the rejection or acceptance of jobs by the service suppliers. In addition, the prices and produced quantities are established in order of equalizing the profits along all the producers associated with the CMfg platform.

Zhang et al. [34] suggest a process-by-stages approach for the assignment problem of tasks to producers. In the first stage, the production process is planned, either by a multi-agent system or by simple proximity, and in a second stage, the scheduling is carried out. In this case, the scheduling is done using Constraint Programming as the resolution method. Akbaripour et al. [24] tackle a scheduling problem with time windows for the availability of productive resources. To solve the problem of transportation and production of customer orders, the authors propose a MILP model. The model seeks to minimize production and transportation costs, as well as production and transportation times, while also trying to maximize the quality of service used for production. They solve the problem using CPLEX. Other approach is to consider different levels of decision, in which the decision of one player is linked to the decision of another one. Wang et al. [35] is an example of this approach. In their work, the authors propose a multi-agent structure, where service providers (short-term agents) optimize their performance linked to a hierarchical agent with priority with long-term objectives. However, the hierarchical agent can optimize its performance measure as long as the objective function of the rest of the short-term agents yield within certain limits. Different problems and configurations of the cloud manufacturing problem are analyzed, as well as different objective functions (total completion time and the weighted number of late jobs). In addition, the authors study the complexity of the different problems proposed, and present resolution methods for some of them.

3.2. Game Theory based approach

A widely used approach for decision-making problems in CMfg is Game Theory. The main advantage of this approach is that it allows the decision-making process to be decentralized so that customers and suppliers of production resources directly coordinate their activity. In Liu et al. [36] the system under study is modeled as a multi-agent system, in which the different agents negotiate and resolve the decision problems involved in CMfg. To do this, first, customer orders must be broken down into subtasks in order to be able to make the corresponding matching between subtasks and productive resources. In Xiao et al. [37], also a decentralized problem is analyzed but considering the customer's perspective. The customer establishes his payments in order to minimize total production times, total production costs, and improving reliability. To find Nash equilibria, a Biogeography-based optimization algorithm is used. Chen et al. [38] suggest a cooperative game approach, in which customers seek to obtain resources to produce their orders. Initially, the allocation of clients to resources is done centrally, and then, in a second stage, collaborative games are proposed with the aim to improve the initial allocation. The authors demonstrate that this problem is NP-hard. Finally, the authors propose dynamic programming algorithms to solve some of the problems proposed.

Another type of problem that can be addressed with game theory is the case of incomplete information, as in Liu et al. [39]. In this work, the authors propose a decision mechanism based on a double auction. These auctions are held between the service applicant (customer) and the service provider (producer). The mechanism ensures that the services finally assigned meet the quality, time, and cost preferences defined by the clients. Another approach to address the problem is to consider a non-cooperative public goods game model as in Bai et al. [40]. This approach allows us to converge towards an optimal schedule more efficiently than other methods, such as Genetic Algorithm (GA). Another strategy is to consider biddings as in Liu et al. [41]. The objective of this work is to maximize the overall benefit of all participants. In the case of decomposing the production tasks into sub-tasks, the bidding method is also applied. The authors' results make it possible to ensure that the proposed approach efficiently solves the problem, as well as to ensure trust and fairness among the participants.

3.3. Bio-inspired metaheuristics

Metaheuristics, and in particular those bio-inspired, are among the most widely used methods to solve scheduling problems [20], even in the context of CMfg [11]. Zhou et al. [42] address an additive manufacturing system (3D printing) acting in a CMfg mode. For this system, a large set of geographically distributed print service providers can benefit from the CMfg platform. A transaction model approach is proposed by the authors to match customer specifications (material requirements, precision, costs, quality, etc.) with the suppliers capabilities. The scheduling problem arising from the operations required is solved by means of a Genetic Algorithm (GA) procedure. In Simeone et al. [43] a sheet metal cutting problem is considered. The study focuses on the problem of matching suppliers capabilities with customers needs in such a way that the use of resources is optimized. Another example of sheet metal manufacturing is found in Helo et al. [44]. This work addresses a scheduling problem for several geographically distributed service providers, solving the problem centrally. As a result of this centralized approach, the CMfg platform offers scheduling as a service. To tackle the optimization problem a GA approach is used. Suma and Murugesan [45], suggest an Artificial Immune Algorithm based-on procedure for solving the Cmfg scheduling problem, minimizing both costs and workload of suppliers with robotized services. Zhou et al. [46] consider the scheduling problem of a CMfg characterized by highly customized tasks. The problem is modelled by means of a directed graph that allows assigning and sequencing tasks taking into account the customer preferences. To solve the problem a GA approach is used. In Yuan et al. [47] a merged approach of GA and Ant Colony Optimization (ACO) is proposed for solving the scheduling problem in a CMfg platform. Four different metrics are considered to solve the assignment problem to each service provider: time of delivery, cost, quality and capability. We note that the later criterion summarizes information about the provider's general capacity, including percentages of waste, failure rate and collaboration capacity, among others. He et al. [48] introduce a service provider selection method that incorporates customer preferences into the decision process to include costs, time of delivery, quality and environment considerations. To solve this multi-objective optimization problem the authors develop a GA based on procedure. In Jafarnejad Ghomi et al. [49], the allocation and scheduling problem is addressed also considering a GA for a multi-objective optimization approach. The workload among different suppliers is considered in addition to the objectives aforementioned. A well-known approach to face multi-objective problems is the Analytical Hierarchy Process (AHP). This approach is used in Hu et al. [50] to solve a scheduling problem with five different objectives: workload, efficiency, resources, reliability, and IoT capability. These five objectives are weighted according to the AHP approach, and optimized using a Chaos Optimization Algorithm based-on procedure. Zhang et al. [51] exploit a fuzzy variant of the AHP to address a scheduling problem in CMfg for optimizing the time, cost, quality and use of the services. A Firefly Algorithm (FA) based-on procedure is suggested to solve the problem. Also Zhang et al. [52] make use of a fuzzy variant of AHP to solve a scheduling problem in CMfg that includes conflict of interests among customers, service providers and CMfg platform owners.

A distinctive feature of CMfg is that the manufacturing environment is highly dynamic, as customer needs and availabilities from service providers can change in the short term. To face this dynamism, Elgendy et al. [53] propose a modified GA that allows them to solve the problem efficiently. In Du et al. [54], a multi-objective optimization problem to minimize makespan, cost and workload is addressed. To solve the problem the authors propose a hybrid method based on Cat Swarm Optimization (CSO) and FA. Zhang et al. [55] consider the scheduling problem from a flexible production job-shop configuration. To solve the problem, the authors propose an ACO based-on procedure. In Li et al. [56] an ACO approach is also used for solving the problem, but in a multi-objective version (MACO). The objectives to be minimized involve times and costs related to setup, processing and transfer of tasks. The results obtained from the numerical experiments carried out by the authors show that MACO outperforms NSGA-II for the problem under consideration. Jafarnejad Ghomi et al. [57] suggest a Queuing Systems formulation to optimize the workload and transport times of a CMfg scheduling problem. A Particle Swarm Optimization (PSO) algorithm is suggested for solving the problem. Li and Luo [58] consider a job shop scheduling problem for CMfg platforms, with the objective to minimize the penalty of delayed jobs. To solve the problem a GA based-on procedure is proposed. In Shi et al. [59] a CMfg scheduling problem is addressed, to minimize both cost and production times. A solving procedure is suggested based on Bat Algorithms and Cellular Automata. Lin et al. [26], propose a model that integrates the allocation and scheduling decisions in CMfg. The problem considers simultaneously the minimization of production times, rental and transportation costs. To solve this multi-objective problem the authors make use of the decomposition-based multi-objective evolutionary algorithm (MOEA/D) approach. More recently, Yuanjun et al. [60] study the performance of six different metaheuristics for multi-objective scheduling problems in CMfg. From the numerical experiments carried out they conclude that integrated scheduling can lead to more effective solutions than the traditional step-by-step decision scheme. Another multi-objective scheduling problem is addressed in Fazeli et al. [61]. The criteria to be optimized in this work are the total service times, costs, quality of service and the availability of providers. To solve the problem, assembled methods are suggested, based on GA, PSO and Social Spider Optimization (SSO).

Scheduling problems in CMfg are not exempt from facing uncertainties inherent to the production processes. In this sense, Ding et al. [62]) study a scheduling problem where service providers are subject to accidental interruptions. The problem considered in [62] includes as optimization metrics the fitness, robustness and stability of the system. Robustness and stability are used to measure the impact of unplanned interruptions on system performance, while fitness to measure the traditional criteria such as time, cost, and reliability. To solve the problem, the authors suggest a 2-stage procedure based on GA. Four different scheduling problems with uncertainty are addressed in Li et al. [63], using a fuzzy approach and ACO algorithms.

3.4. Machine learning and Artificial intelligence

This subsection analyzes the articles that have used methods based on Machine Learning or Artificial Intelligence. This subsection clearly shows the speed of growth in the study of scheduling problems in CMfg. Until the review of [11] there are practically no papers based on these approaches, while from that review to the moment, there have been several publications in this field. As the first contribution in this line is Liu et al. [25], where the same authors as in [11], propose an exploratory study on the subject. In [25], a deep reinforcement learning (DRL) based approach is proposed, which combines the benefits of deep learning with reinforcement learning. The work develops a framework where the different scheduling problems in CMfg environments can be solved from DRL. This approach would automatically extract high-level characteristics of tasks and resources, as well as the learning inherent in scheduling patterns, rules, and approaches. In Chen et al. [64], the objective is to minimize the makespan and the total traveled distance. To obtain non-dominated solutions, the authors develop an agent system that makes decisions using the method of Reinforcement Learning based Assigning Policy (RLAP). Under the RLAP approach, tasks are assigned to each agent, which allows to solve problems with dynamic features. Dong et al. [65] suggests a Deep-Q-Network (DQN) method for the task assignment problem, which includes a classification of the tasks and the current status of the process. The proposed method is compared against other classical resolution heuristics proposed to minimize the makespan. The numerical experiments show the benefits of DQN when surpassing the other methods. An application based on Artificial Neural Networks (ANN) can be found in Zhu et al. [27]. A multi-user demand problem and the resource allocation problem are presented as a multi-objective optimization problem. This multi-objective problem seeks to minimize operating time, maximizing the use of resources, and minimizing general expenses. The authors transform the multi-objective problem into a reinforcement learning (RL) problem and solve using ANN. In Morariu et al. [66] , recurrent neural networks (RNN) are applied. In this case, the authors use the RNN to generate a predictor of future scenarios and thus obtain the schedule. To do this, the providers of productive resources provide information in real-time, about the current state of the production process. This information is then filtered and processed by RNN, to estimate the near-future scenario, and this feeds the optimizer that determines the schedule.

3.5. Heterogeneous approaches

Finally, we present below some works that contribute to scheduling in CMfg, but that due to their specific characteristics do not fall into any of the previous sections (or if they do, it would be in more than one of them). Therefore, these works are analyzed individually in this subsection.

The first work of this group is Zhou et al. [67]. In this work, the authors propose a model based on Discrete Events Simulation (DES). Based on this approach, the authors study the dynamic relationships that occur between the different elements of the CMfg system (providers, customers and owners of the platform). Different numerical experiments are reported, with variations in the values of demand and resources, since the authors claim that this kind of study will be important for future dynamic developments of CMfg.

In line with the previous work, Zhou et al. [68] also propose an analysis of the events present in a CMfg environment. However, in this work, the authors go one step further and develop heuristic methods for sequencing tasks (*event-triggered dynamic scheduling*). The proposed heuristic is based on determining those events that require or not the activation of a new operation. In this way, the proposed heuristic is able to achieve better results than other existing heuristics.

A highly customized method for scheduling problems in CMfg is proposed by He et al. [69]. The authors consider a problem similar to that of [48] but using a different allocation approach. In this case, the resolution method is based on a heuristic to solve the scheduling by analyzing the job priorities. Jobs with the same priority are managed in such a way that they are all optimized simultaneously.

In Additive Manufacturing environments, the assignment of tasks to the right supplier, is a key element for solving scheduling problems in CMfg. In this sense, Wang et al. [70] propose a special method based on computer vision algorithms. Thus, the form factors and dimensions of the tasks commissioned by clients can be matched with the correct supplier. The planning of the operations is based on the results of the computer vision algorithms.

The last of the miscellaneous works, Zhou et al. [71], especially analyzes the impact of implicit logistics services in a CMfg system. First, a set of pre-selected manufacturing service providers is generated. Thus, tasks can be assigned considering logistics efficiency. To achieve efficiency in the logistics service, a heuristic method is used that is based on the distance between customers and suppliers.

4. Discussion and future research lines

In this section, the review carried out is analyzed in general terms. Based on this analysis, some future research lines are identified and discussed. To facilitate the explanations, we use the same classification that for the resolution methods presented in Section 3.

4.1. Review results discussion

As a first summary of the performed review, Figure 2 is presented. This figure shows the representativeness of each of the methods used to solve Scheduling problems in CMfg in terms of percentages of the total reviewed papers.

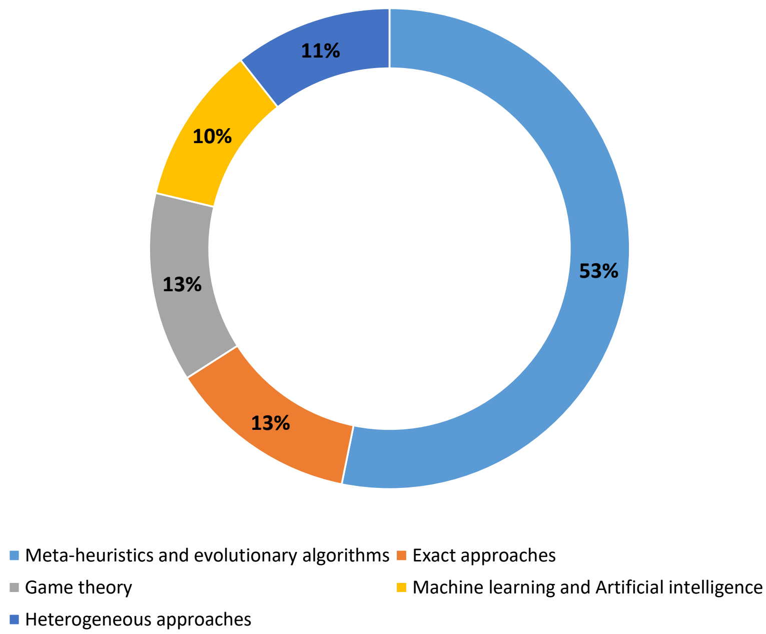


Figure 2. Resolution approaches used for Scheduling in Cloud Manufacturing (CMfg).

Exact approaches. These types of approaches represent 13% of the articles reviewed, as can be seen in Figure 2. Within the reviewed papers it is interesting to note that, when studying the problem with exact approaches, the structural analysis of the problem and its behavior take on another depth. In spite of the complexity of the problem, certain methods and strategies are proposed to optimally solve the problem under particular assumptions, [35]. On the other hand, the study of the problem in a exactly manner can provide new insights about how the complexity scales as the problem size increases. We note that in a cloud-based paradigm, the *pay-as-you-go* criterion can make the system grows considerably in a very short time. This may cause a considerable pressure on the CMfg platform, as it must ensure the quality of service between customers and suppliers.

Game theory approaches. Based on the review of articles related to game theory, the models and results achieved are very interesting and promising. Naturally, game theory allows solving a decision problem in a decentralized and efficient way, in which each player obtains the best possible result for the scenario faced. Although the CMfg scheduling study is very recent, there is clear evidence (13% of the works reviewed use this approach) that it is a more than an adequate approach to address this problem.

Bio-inspired metaheuristics. Metaheuristics based-on procedures have been widely the most suggested method to solve scheduling problems in CMfg, representing more than 50% of the reviewed articles. The main argument for this percentage may be the computational complexity of scheduling problems, where in many cases they are NP-complete [19]. In addition, the problem of matching or assigning each customer's order to each service supplier must be solved [5], which increases the difficulty of resolution. Considering the versatility of bio-inspired metaheuristics to address combinatorial optimization problems, they are an excellent option for the problems considered in this present paper. In this sense, a large number of the reviewed papers about metaheuristics make use of GA to solve the problem. GA can be considered as one of the most general methods of the bio-inspired metaheuristic approach. Thus, it would be concluded that there is still a lot of room for the design of more tailored bio-inspired metaheuristics.

Machine learning and Artificial intelligence. The last group of works presented in this review about scheduling in CMfg, are those based on the approaches of Machine learning and Artificial Intelligence. These resolution methods have exploded in recent years, extending their capabilities and applications to areas that have never been thought of from that perspective [72]. Past CMfg reviews have found no articles about it, as mentioned by [25]. Considering all the groups of the works reviewed, this is the smallest, representing 10% of the total. However, those articles have shown that these approaches can be valuable to address preference-driven allocation problems.

4.2. Future research lines

Scheduling in Cloud Manufacturing is a topic of growing interest in the scientific community, where notable contributions have been made in modelling and solving related problems. However, we believe that there is still a long way to go to reach the maturity that scheduling has achieved in other fields. With this idea in mind, we provide below certain directions for future research. We note that the proposed lines for future research are based on those works considered for the systematic review presented in Section 3, with special emphasis on the optimization approaches used. For those readers interested in other topics of CMfg such as task decomposition or matching, we direct to [11].

(1) Multi-objective optimization. As a first research line, it is proposed to deepen the study of multi-objective problems. Multi-objective problems emerge when there are conflicting objectives acting simultaneously. Therefore, you cannot improve the performance obtained in one objective without negatively affecting another of the objectives [73]. In this sense, an environment like CMfg is a natural environment for the exploration of this type of problem, in which different agents participate with different (and not infrequently, conflicting) objectives. On the other hand, the review of the literature evidenced this need to study the problem from a multi-objective perspective. Especially in the works that used metaheuristics, the vast majority dealt with a multi-objective version of the problem. For many cases, the multi-objective function involves minimizing costs and production times. This poses a conflictive situation by nature, since to accelerate production (and thus reduce times) it is necessary to increase the amount of resources allocated (increased costs). This situation is accentuated if the quality of the production service is considered.

A first approach for multi-objective optimization problem is to transform it in a single-objective problem, for example by applying some weighted sum method on the different objectives. In this sense, articles were found that used AHP to develop this weighting sum in a realistic and relevant way for decision makers [50], or sequentially solving single-objective problems using the ϵ -constraints [33] method. Beyond the validity and the contribution of these approaches, there were few cases in which the set of Pareto Optimal solutions was studied. In this sense, some articles that have worked on this set of solutions were detected ([56], [26], [60]). However, further analysis of non-dominated solutions will be really valuable for Scheduling in CMfg, because it will allow to delve into the structure of the problem and help to understand the impact of the different variants of the problem. To face this problem, it can be concluded that the use of bio-inspired metaheuristics is the main way forward. This is supported by the literature review presented here, since more than 50% of the articles base their optimization process on these methods.

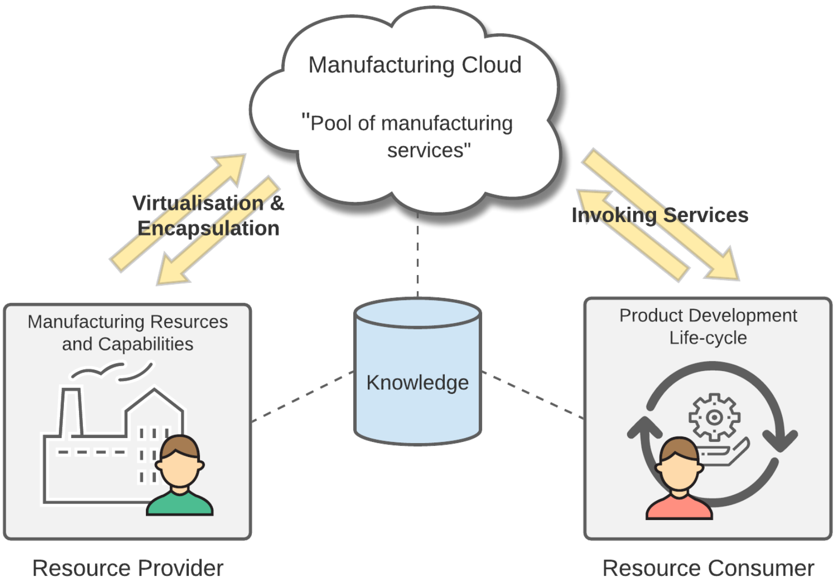
(2) Descentralized decision methods. Another line of research that will contribute to the scientific development of Scheduling in CMfg is the analysis of decentralized decision methods. The opportunity to develop methods that facilitate the free action of the platform participants, both customers and service suppliers, will contribute to improve the development of CMfg as a business model. A clear example was found in this review in those works that have developed resolution models based on game theory. Considering the reviewed works as starting points, it will be interesting to deepen the study of game theory problems with incomplete information, where the participants do not know the rest of the participants and mechanisms must be developed that allow convergence to equilibrium. In this way, scenarios with increasing numbers of participants can be represented, aligned with the pay-as-you-go logic of CMfg.

(3) Model Business approaches. Given the impact of scheduling optimization on the costs and benefits of each participant, it is important to study the business models that allow CMfg participants to directly relate the decisions made with their business goals. Although the business model strategy exceeds the Scheduling optimization problem in CMfg, the truth is that the CMfg service level will depend directly on the production scheduling [11], either in delivery times or in the quality of products. We observed that the business model appears to have a greater impact on CMfg scheduling problems than on other traditional manufacturing paradigms, as most of the reviewed papers consider the minimization of the costs involved. In addition, for those articles that addressed the problem in a multi-objective way in CMfg, the costs always appear as one of the optimization objectives. Therefore, as the quality of a schedule in CMfg depend largely on its costs, we can conclude that the relationship between scheduling and business model is much closer for CMfg than for other paradigms. Business model should be studied from the perspective of the CMfg platform owner, in order to ensure fairness for both customers and resource providers.

(4) Analytics and Machine Learning. CMfg must provide information to both customers and service providers. Information can be originated from the counterpart (customers to suppliers and viceversa), or even from records of past transactions. Therefore, the CMfg platform, by acting as a hub for linking the participants of a manufacturing process, can access to valuable information for the study of scheduling. In particular, based on the information on profiles, preferences and previous decisions, the CMfg platform can greatly help to obtain an optimal schedule. In addition, this kind of information can help to fine-tune the system by evaluating possible future scenarios, as proposed by [66]. The alternative of real-time information opens the door to the dynamic scheduling problems in CMfg, as it is highlighted by [11]. Being able to have direct and real-time information about the involved systems reduce the possibility of unexpected events that usually trigger rescheduling processes [13,74]. However, to capitalize the available information into a specific benefit for scheduling, efficient and agile methods must be developed for processing and interpreting the information.

(5) Exact Approaches. Although the difficulty of scheduling problems is a natural obstacle to exact method-based resolution procedures, they can provide critical and analytical insight that many other methods do not. A clear example is provided by [24], in which some MILP models are proposed for the study of scheduling in CMfg. In addition, approaches based on constraint programming [34] or dynamic programming [35] are promising. On the other hand, the study of the order of complexity of this type of problems also contributes significantly to the development of the topic. For all those mentioned above, the approaches based on exact methods stand out as a line of research.

(6) Some technologies considerations. Cloud Manufacturing proposes a direct interconnection between suppliers of manufacturing services and customers through a platform, as shown in Figure 3. However, as it is argued at the beginning of the paper, this direct interconnection is essentially due to the advancement of information technologies. Therefore, it is reasonable to foresee that this production paradigm could be affected by future developments in information technologies. For instance, we would like to highlight some advances in Fog Computing that we believe will affect CMfg in the near future [75]. Fog Computing is an architecture that seeks to concentrate most of the storage, processing and communication in the devices that are at the edge of the network [76]. This makes it possible to migrate from a total centralization of the data flow and its processing in a central server or service provider (i.e. cloud computing) to an intermediate layer between the physical devices and the cloud hub [77]. This migration reduces network requirements as well as improves system security by preventing data from leaving the production system [78]. In addition, the Fog layer significantly improves the response speed required by connected systems, which, in turn, reduces network latency and allows task queues to be processed locally [79]. There are already various methods and developments that enable scaling the Fog nodes required by the network according to requirements, ensuring an agreed level and quality of service [76, 80, 81]. All these features mentioned above, allow us to conclude that Fog Computing will impact CMfg soon, since they improve the capabilities of the network systems that support the central idea of this production paradigm.



Manufacturing diagram.pdf

Figure 3. Cloud Manufacturing basic diagram.

5. Conclusions

Scheduling in Cloud Manufacturing is a central theme for the development and promotion of Cloud Manufacturing as a manufacturing system. Although it is a subject with very little history compared to other scheduling subjects, very valuable advances have already been made, such as the identification of different problem areas, as well as components of solving planning in a distributed manufacturing environment like the one proposed by CMfg. Here we show that on the basis of these structural advances, more and more papers have appeared in the literature that suggest different methods and approaches to solve the problem. We want to highlight that the most common proposed resolution methods are those based on bio-inspired metaheuristics. In particular, we found that Genetic Algorithm is the main solving method used to solve the problem.

Another conclusion that we can draw from the literature review is that the scheduling in CMfg, except for a few exceptions, should be approached from a multi-objective perspective. The main argument for this observation is that the different participants of the system, i.e. clients and service suppliers, have conflicting objectives that must be considered simultaneously to ensure the sustainability of the CMfg platform. Also from the literature review, it was identified that the development achieved is far from taking advantage of the full potential that areas such as multi-objective optimization can contribute, particularly in the implementation of multi-objective evolutionary algorithms.

Finally, we propose and discuss certain lines for future research, with the aim of further strengthening the study of Scheduling in CMfg. Some of these proposals attempt to take advantage of developments in other fields of scheduling. Therefore, they could result in fairly straightforward applications of those methods in the novel paradigm of CMfg.

Conflict of interest

The authors declare there is no conflict of interest.

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