A Systematic Literature Review About Multi-objective Optimization for Distributed Manufacturing Scheduling in the Industry 4.0

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Abstract. Multi-objective optimization problems are frequent in many engineering problems, namely in distributed manufacturing scheduling. In the current Industry 4.0 this kind of problems are becoming even more complex, due to the increase in data sets arising from the industry, thus requiring appropriate methods to solve them, in real time. In this paper, the results of a Systematic Literature Review are presented to reveal the state of the art in this scientific domain and identify the main research gaps in the current digitalization era. The results obtained allow to realize the importance of the multi-objective optimization approaches. Typically, when addressing large scale real problems, the existence of many objectives usually benefits with the establishment of some level of trade-off between objectives. In this paper, a summarized description and analysis is presented, related to several main issues arising currently in companies requiring the application of multi-objective optimization based distributed scheduling, for enabling them to fulfill requisites imposed by the Industry 4.0. In this context, issues related to energy consumption, among other customer-oriented objectives are focused to enable properly support decision-making through the analysis of a set of 33 main publications.

Keywords: Multi-objective optimization · Distributed manufacturing scheduling · Industry 4.0 · Decision-making support

1 Introduction

In this paper, a summarized description and analysis of the main results obtained through the application of a Systematic Literature Review (SLR), a widely used and well-known methodology currently used [1], is carried out. SLR is an important research methodology, consisting not only of a simple text review on a given subject, but rather, on an approach that also permits answering several research questions, properly formulated. Thus, it is a "methodology that allows not only to locate contents or existing studies, through the selection and evaluation of different contributions, but also to analyze and synthesize data, duly organized, by themes, in order to report them properly and to

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highlight relevant contents". Thus, this methodology allows the extraction of important conclusions, in a clear and well-structured way, with the purpose of showing some new evidence, about something, or in some way, that has not yet been explored [2]. In this sense, a SLR on multi-objective optimization for solving distributed manufacturing scheduling problems in the context of the Industry 4.0 or I4.0, for short, is focused in this study. Scientific publications, related to various issues, that apply multi-objective optimization to real problems in industry, namely, regarding its transition to the I4, are analyzed. In this context, energy consumption in industry, customer criteria satisfaction, among other objectives and issues that arise in the context of multi-objective optimization in solving industrial problems are explored to properly support the decision-making process. A total of 33 publications were deeply studied.

Optimization refers to finding one or more solutions that correspond to extreme values or compromises of one or more objectives. Multi-objective optimization (MOO) involves a problem solving in which an optimal optimization of multiple conflicting objectives is intended to be achieved. Objectives are in conflict if there are trade-offs or compromises between these objectives, that is, if there is no single feasible solution that is optimal for all objectives [3]. These problems with two or three conflicting objectives are usually called multi-objective optimization problems (MOOP). These are different from single-objective optimization problems, which are simpler in terms of complexity and demand from the decision maker [4]. Problems with more than three objectives conflicting with each other, known as many-objective problems, are very difficult to solve but are common in almost all areas of knowledge and usually [5].

In the I4.0, many difficulties have been encountered, namely related to the multi-objective nature of many scheduling problems that involve conflicting objectives. Frequently, decision-making based on multi-criteria or multi-objective approaches has been adopted to address these problems at a more real scale, therefore, complex, because they are critical problems to be solved, requiring a proper decision support process, based on an analysis of the various existing alternatives [6]. In most cases, solving multi-criteria decision-making problems is focused on finding solutions for a given set of alternatives [7]. However, every Pareto optimal solution is an equally acceptable solution to a multi-objective optimization problem. Therefore, in the process of choosing a single preferred solution among all alternatives can be a difficult task due to a high cognitive effort required [8].

On the other hand, the manufacturing scheduling (MS) problem is an optimization problem in which several tasks are assigned to machines, organized in a certain way, in a production system, at given instants, while trying to optimize objectives, such as makespan, cost or load balancing, among others [9, 10]. In the context of I4.0, scheduling or MS can be aided or achieved through an AI-based approach, namely for solving distributed manufacturing scheduling (DMS) problems. Such an approach, combined with other emerging production technologies that enhance mass customization, through the current cyber-physical systems (CPS), underlying the I4.0, allow an innovative approach in production [11]. Through the use of a DMS approach, it is expected to achieve several advantages, namely the reduction of production time, while aiming to meet product delivery times, among other performance measures to be optimized.

With the advent of the I4.0, there has been an increasing need to handle large volumes of varied data and in many of these cases these are problems with many conflicting objectives, a fact that further increases the complexity of the problems, making it even more difficult to be solved, particularly in terms of optimization. Thus, difficult decision-making processes in real production environments emerge in this context. The transformation of data into information or knowledge has been fundamental in several areas of engineering to support decision-making, including in more complex contexts, given the existence of many alternative scenarios, with a large number of solutions [5].

In this paper, it is intended to present the results of a SLR, about multi-objective optimization as a tool to support decision-making in solving MOOP, occurring in the context of DMS, currently, in the I4.0 era. Therefore, the aim is to identify gaps and opportunities for research in this scientific domain.

This paper is structured as follows. In Sect. 2, the SLR methodology is briefly described. Section 3 presents the results and a deeper analysis of a main set of 33 publications found. Finally, in Sect. 4, the main conclusions are addressed, along with some planed future work.

2 Methodology

In this research, the SLR methodology is used. SLR is a systematic method and, which should be comprehensive and reproducible, in order to better identify, assess and synthesize existing works, with a greater or lesser degree of complexity, proceeding to their registration and that have been produced by a researcher, a professional or simply a scholar [1, 2, 12]. SLR, in addition to allowing to contribute to the development of theory, also allows to facilitate the interpretation of existing contributions, through complements and extensions of research areas.

SLR uses a pre-planned research strategy, and this type of review is intended to answer specific research questions about existing studies [2]. In this work the following research questions were formulated:

- RQ1: Is MOO being applied to solve DMS problems in the current I4.0 era?
- RQ2: What are the main issues that arise when studding MOO-DMS in the I4.0?
- RQ3: What else can be further explored for solving MOO-DMS problems?

To answer these research questions, in this work, the SLR methodology by [13] was adopted. This methodology is illustrated in Fig. 1 and involves the following three main steps: (i) Input, (ii) Processing and (iii) Output.

Further to this adaptation, it was also applied the proposals of [1] and [2].

In the input phase (1), the objectives of the search are defined, the search terms are identified, and the keywords for the subject under study are selected, as well as the platforms where the different materials to be studied can be searched. After the selection of the research platforms, it is necessary that the input is adequate and with quality, thus promoting quality output (3).

The processing phase (2) is where the whole process is done in order to obtain a desired result. Such processing includes five steps, from planning to the last step, which

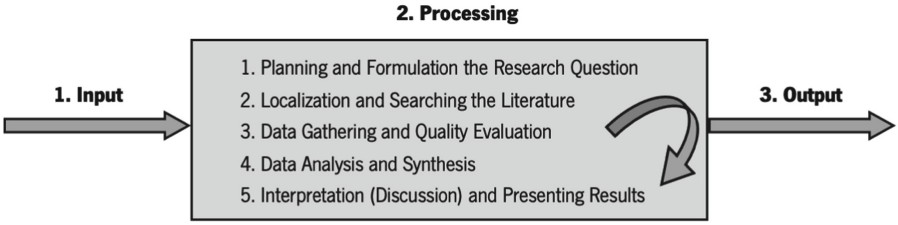

Fig. 1. Stages of the literature review (adapted from [13]).

serve as the basis for presenting the results of the research, and these steps can be, iteratively, restarted if necessary [13]. Typically, this phase encompasses all or most of the following steps [2, 13]: (1) Planning and Formulating the Research Question; (2) Locating and Searching the Literature; (3) Data Collection and Quality Assessment; (4) Data Analysis and Synthesis; (5) Interpretation (Discussion) and Result Presentation.

The first step of this phase is related to the planning and formulation of research questions in order to guide the SLR. The second stage is associated with locating and searching the literature. In this paper, the Scopus[1] and Web of Science[2] (WOS) platforms were used, and to complement the b-on[3] Portuguese library platform. The b-on provides access to the full text of papers, in several indexed scientific journals, within the Portuguese academic community.

The research was carried out in the time span from 2010 to 2022. Table 1 presents the search platforms used, the search terms, as well as the results obtained. The following keywords or search terms were applied according to the specificity of each search platform: "multiobjective optimization OR multi-objective optimization", "distributed scheduling", "industry 4.0" and "manufacturing". The results are presented in two parts: without filtering and refining the search. In total, without filters and using only the search terms, 615 articles were obtained. By further refining the search, by applying the other search options, it was possible to reduce the search to a total of 74 articles. For the b-on platform, in the first part, the search term is applied without any search option and without any filter applied, presenting 230 articles as the search result. In the second part, search options are also applied, thus refining, and restricting the focus of the search and resulting in only 46 articles remaining for analysis. For the Scopus platform, 282 articles were identified using the search terms alone. After applying the search options, 12 articles were obtained. Finally, for the WOS platform, 103 articles were found in the first part, and with the search options applied and considering only the articles with open access, the output was reduced to 16 articles.

The third stage, data collection and quality assessment, is related directly with the collection of literature in the different platforms. It is in this stage that the inclusion and exclusion criteria were defined. The exclusion criteria were chosen based on the research objectives and defined keywords. Some search terms were applied only to the

[1] https://www.scopus.com.
[2] https://www.webofscience.com.
[3] https://www.b-on.pt.

Table 1. Search terms.

Platform	Search terms	Total without search options	Search options		Last execution by	
			Limiters	Expanders	Screen and search	Results with search options
B-On	AB (multiobjective optimization OR (multi-objective optimization)) AND TX distributed scheduling AND TX industry 4.0 AND TX manufacturing	230	Full Text; Peer Reviewed; Publication Date: 2010.01–2022.02; Research areas: Science, Applied Sciences, Engineering, Computer Science, Mathematics, Technology, Information Technology	Search also in the full text of the articles; Apply equivalent subjects	Advanced search	46
Scopus	(TITLE-ABS-KEY (multiobjective AND optimization) AND ALL (distributed scheduling) AND TITLE-ABS-KEY (industry 4.0) AND ALL (manufacturing))	282	Publication Date: 2010.01–2022.02; Research areas: Engineering, Computer Science, Business, Management and Accounting, Decision Sciences,	N/A	Advanced search	12
Web of Science	Multiobjective optimization OR multi-objective optimization (Title) and distributed scheduling (Topic)	103	Publication Date: 2010.01–2022.02; Research areas: Computer Science Information Systems, Engineering Electrical Electronic, Telecommunications, Computer Science Software Engineering, Computer Science Artificial Intelligence, Mathematics Interdisciplinary Applications, Computer Science Theory Methods, Engineering Multidisciplinary, Multidisciplinary Sciences, Operations Research Management Science; Open Access Articles		Advanced search	16

title and others to the abstract or the entire text of the article. Articles that were not peer-reviewed were excluded. Finally, as an inclusion factor only articles written in English were considered, with full text available, limitation of search time between 2010 and 2022, resulting in a reduction in the number of articles to 46, 12 and 16 for the b-on, Scopus and WoS platforms, respectively, as mentioned before and presented in Table 1.

The data analysis and synthesis are the fourth stage. This phase was performed by categorizing by title, year of publication, publisher as well as reading the abstracts of the selected articles, as summarized in the Fig. 2. Reading the abstracts allowed to understand the subject addressed in the article. Those articles related to the industry were included and those articles outside the industry context were excluded. Finally, in the fifth stage (Interpretation (Discussion) and Result Presentation), a summary of each selected article was done. Overall, 615 documents were identified on the three search platforms, only 33 are within the scope of this study, as shown in Fig. 2.

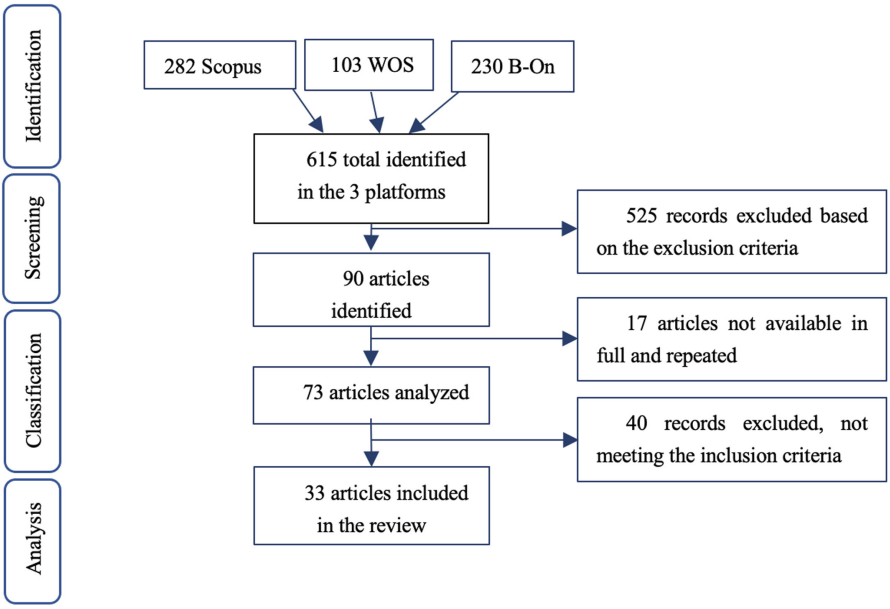

Fig. 2. Summary of the article selection process (adapted from [14]).

In this sense, Table 2 presents the summary of the processing phase, where it is presented what was applied, the inclusion and exclusion criteria, among others.

The output phase is the last of the three phases. It is the phase where the results of the research process are presented. In a succinct way, a discussion about the subject under study is described. In this phase, the content of materials of great interest to the research in focus is presented, eliminating materials of little interest to the study.

Table 2. Summary of the research phases.

Phases of the review	Description
(1) Planning and Formulating the Research Question	- What are the most studied issues when it comes to multi-objective optimization in distributed manufacturing scheduling in the I4.0 era? - Is multi-objective optimization in the I4.0 era applied to distributed manufacturing scheduling problems? - What contributions already exist to aid decision making applied to multi-objective optimization in distributed manufacturing scheduling problems? - What else can be explored that is yet to be explored in multi-objective optimization in distributed manufacturing scheduling problems?
(2) Localization and Literature Search	Scopus, Web of Science, B-On, search time interval: 2010–01/3–2022 considered keywords: multi-objective optimization, distributed scheduling, industry 4.0, decision-making
(3) Data Collection and Quality Assessment	Exclusion: Not peer reviewed, not industry related, article not complete, article not available Inclusion: any MOO subject in industry, academic articles, only written in English, research time limitation between 2010 and 2022 Total articles: 33
(4) Data Analysis and Synthesis	Excel was used to organize and categorize the subjects of the articles according to the keywords, the subject of the article, the year of publication, and also the publisher
(5) Interpretation (Discussion) and Result Presentation	Interpretation on the use of multi-objective optimization in distributed manufacturing scheduling problems in the Industry 4.0, based on the survey of the literature done in order to answer the formulated research questions

3 Results and Discussion

As already mentioned in the previous sections, from the results obtained, 33 articles were considered that met the conditions set to answer the research questions. The characteristics of these selected articles were analyzed. All selected articles were organized in an Excel file to facilitate quantitative analysis, information such as year of publication, publishers, keywords, as well as the number of citations.

An important aspect to consider is the year of publication. In this sense, Fig. 3a presents the number of publications per year, within the scope of the subject under

research. In this figure, it is represented the publications in the time interval between January 2010 and March 2022. Through this figure, it is possible to observe the variation of publications per year, showing that in the first four years there is no article among the 33 presented, and having been reached in 2020 the highest number of publications, with a total of 10 publications, and in the last year there is not a large number of publications because it refers to only three months. Although, it can be observed that the research about the subject under study is growing. On the other hand, it can be seen that the 33 articles are from different publishers, being the publisher with the largest number of articles the Taylor & Francis Ltd and Elsevier, both with 7 articles, followed by 6 articles from Springer and the remaining 5 from different publishers, as illustrated in Fig. 3b.

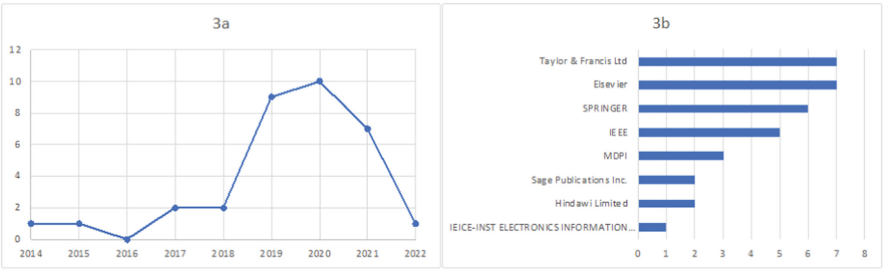

Fig. 3. (a) Number of articles per year. (b) Publishers of the articles.

In the context of multi-objective optimization, several topics are addressed, but when referring to distributed manufacturing scheduling problems it comes out that this subject has not been fully addressed, but still on a small scale, which decreases even more when referring to problems occurring in the I4.0. Since this topic is quite recent, the goal of this work is pertinent to identify different multi-objective optimization problems applied to manufacturing scheduling problems in the I4.0 context. Based on the review carried out, it can be concluded that currently problems that associate these three topics are still little explored, because as it can be seen, in different collected materials only six articles address two topics (Multi-objective Optimization and Scheduling) while only two address all three topics (Multi-objective Optimization, Scheduling and Industry 4.0).

The results are summarized in Table 3, where the 33 articles are classified. In this sense, the crossing of the topics using the following keywords are presented: Multiobjective Optimization, Scheduling and Industry 4.0, identified in the title, keywords or abstract of the articles.

3.1 Multi-objective Algorithms in Industry

Based on the reading of the selected articles, it can be realized that the I4.0 is accepted in the manufacturing industry as it guides an innovative and promising production paradigm. A new feature of I4.0-based manufacturing systems is the application of advanced, intelligent machines that have communication, self-optimization, and self-training capabilities [17]. In [17] a production flow program considering multiple objectives is investigated. An integer mixed programming model was formulated by the

Table 3. Keyword crossing.

Criteria	Keywords	Reference
Multi-objective optimization	Multi-objective, multicriteria	[15–34]
Scheduling	Programing	[15, 17, 18, 21, 25, 27, 29, 32, 35–40]
Industry 4.0	I4.0, industry, manufacturing	[17, 18, 23, 28, 39, 41–44]
Multi-objective optimization & scheduling	—	[15, 17, 18, 21, 25, 27, 29]
Multi-objective optimization & Industry 4.0	—	[17, 18, 23, 28]
Scheduling & Industry 4.0	—	[17, 18, 39]
Multi-objective optimization & scheduling & Industry 4.0	—	[17, 18]

authors and solved by a fireworks algorithm developed and designed with specific strategies, such as spark burst procedure. Simulation experiments were conducted by the authors on a set of test problems, and their experimental results demonstrated that their model and the proposed algorithm achieved satisfactory performance when compared with some state-of-the-art multi-objective optimization algorithms [17].

In view of the growth in data volume and with many dimensions motivated by the emergence of the I4.0, the need for using artificial intelligence (AI) technologies for this complex data analysis is also growing [28]. To address these aforementioned problems, in [28] it is proposed a multi-objective evolutionary algorithm based on decomposition with adaptive exploration. Through dynamic exploration and joint exploration, their proposed algorithm improved the global search capability as well as the diversity of the solutions found by the algorithm.

In [26] several multi-objective meta-heuristic optimization algorithms to generate Pareto optimal solutions for micro-turning and micro-milling applications are used. A comparative study was conducted by the authors to evaluate the performance of the non-dominated sorting genetic algorithm II (NSGA-II), multi-objective lion ant optimization (MOALO) and multi-objective dragonfly optimization (MODA).

A new efficient 2-stage NSGA-II algorithm was proposed in [16] and the results compared with the original NSGA-II algorithm. The authors report that the performance of the 2-stage NSGA-II algorithm was significantly superior to that of the original NSGA-II algorithm.

The optimization of task scheduling in a distributed heterogeneous computing environment is a difficult non-linear multi-objective problem. It plays an important role in decreasing the service response time and cost and also in increasing the quality of service [35]. In [35], the authors consider four conflicting objectives with each

other, namely for minimizing task transfer time, task execution course, energy consumption and task queue length. They developed a comprehensive multi-objective optimization model for task scheduling, allowing to reduce the costs from both customer's and supplier's point of view. Their model was assessed by applying two evolutionary multi-objective algorithms: Multi-Objective Particle Swarm Optimization (MOPSO) and Multi-Objective Genetic Algorithm (MOGA). The simulation results showed that the proposed model provided optimal trade-off solutions among the four conflicting objectives, thus significantly reducing the response time of the improvisational work (makespan).

3.2 Energy Consumption in Industry

In general, the operation of industrial systems requires the consumption of energy for the operation of various machines. Energy efficient production scheduling is an area that has attracted attention from researchers due to the massive energy consumption of the manufacturing process [27]. In this regard, in [27], the authors presented a study of an energy-efficient production job scheduling problem with sequence-dependent setup time with the goal of minimizing the production time, total delay and total energy consumption, simultaneously. In [20], a multi-objective optimization method for wind and thermal power systems is proposed. The wind speed in the wind farm is considered as the decision variable and the minimization of fuel costs and emission costs of the thermal power unit as objectives.

Nowadays, with the emergence of the I4.0, it is evident the increase in energy consumption necessary to be compatible with the new technologies used by the fourth industrial revolution. In recent years, attention to energy conservation has been increasing for manufacturing activities and especially for energy-intensive industries [40]. A multi-objective optimization algorithm to improve productivity and reduce costs and energy consumption of autonomous industrial processes was presented in [23], in order to achieve sustainable growth. The analyses were done in an assembly-line production with robotic cells and subsequent material handling systems thus using autonomous guided vehicles (AGVs) as an internal conveyor. In [44] it is also presented a solution approach for multi-objective optimization in vehicle-based automated storage systems. These systems over traditional systems have great advantages since they have a flexible travel pattern of autonomous vehicles, thus allowing the number of vehicles in the system to be varied based on the demand for alternatives [44].

Optimizing the production schedule to be more energy efficient while meeting production goals is a difficult task [24]. Therefore, how to schedule and distribute production tasks to meet production goals while making the best use of the ever fluctuating energy market prices and availability of locally installed energy sources? [24]. Accordingly, a generic algorithm was presented in [24] for optimizing production schedules in terms of energy consumption, peak consumption reduction and makespan, which considers that tasks can be performed in different ways, having different characteristics.

Another approach to energy consumption in industry was presented in [22]. These authors presented a multi-objective stochastic optimization algorithm to analyze energy consumption, construction period, and demonstrated its benefits in the construction process, considering random events.

Multi-robotic services are commonly used to increase the efficiency of I4.0 application, including emergency management in smart factories. The workflow of robotic services consists of data-intensive tasks that are sensitive to computation-intensive delays. When multiple robots in a cloud instance work collaboratively, the optimal resource allocation for the robotic workflow tasks becomes a challenging problem. Because the tasks are interdependent, inconveniences in data exchange between local robots and the remote cloud degrades the quality of services [41]. In their study, these authors addressed the simultaneous optimization of the makespan, energy consumption, and cost while allocating resources for robot workflow tasks. On the other hand, in [30] some problems are described considering the design and line balance of mixed-model disassembly with multi-robotic workstations under uncertainty. The tasks of different models are executed simultaneously by the robots that have different disassembly capabilities. The robots have unidentified task times and energy consumption. The processing times of the tasks are assumed to be interval numbers when considering the uncertainties in the disassembly process. A mixed-integer mathematical programming model to minimize the cycle time, workstation energy cycle and total energy consumption is proposed.

3.3 Planning on Production Lines

Manufacturing process scheduling is a complex process and in the context of the I4.0 it becomes even more complex. Meta-heuristics help to solve these complex problems, despite requiring greater computational power. The use of high-performance architectures present in cloud computing and edge computing, can support the development of better meta-heuristics allowing to deal with complex problems of I4.0 [39]. In this sense, a literature review is presented in [39], providing an overview of meta-heuristics for activity scheduling. Logistics and supply chain systems (SCS) are important parts in industrial systems [43]. In this paper, the author collects and analyses papers that explore several problems in logistics and SCS. Different important approaches that can be found in logistics and SCS are presented, considering game theories, meta-heuristics, multi-objective optimization, robust control, and fuzzy sets.

An approach for cloud-based distributed optimization for factory process scheduling and planning was presented in [42]. The authors proposed three approaches for dynamically managing subpopulation creation and elimination developed by a multi-objective algorithm. In [19] it is also addressed the Distributed Hybrid Flow Shop Scheduling Problem with Multiprocessor Tasks, by considering two objectives simultaneously (the makespan and the total energy consumption). The problem was divided into three subproblems: task assignment between factories, task sequence in each factory, and machine assignment for each task. They then formulated a mixed interlinear programming model and proposed a Novel Multi-Objective Evolutionary Algorithm based on Decomposition (NMOEA/D). In [32] two problems that include schedule assignment (in cases of identical part production) and part sequencing (in cases of different part production) are modeled. The first model was used to minimize cycle time and operating cost, and the second to minimize both the mean and standard deviation of total production cost as well as cycle times. A simulation-based mathematical modeling and optimization method was presented to schedule, assign similar parts, and plot the optimal sequence of different parts in [33]. These authors proposed an optimization method based on data analysis for

enriched distributed process planning while considering machine tool selection, cutting tool selection, and machining condition determination.

Due to stochastic uncertainty, the problems of scheduling semiconductor manufacturing systems with the goal of optimizing classical performance indices tend to be increasingly complicated [36]. In [31], the problem of scheduling a semiconductor manufacturing system with uncertain processing times was addressed.

The proposal involved a three-phase multi-objective optimization approach, which enabled to collaboratively optimize performance indices and their robustness measures. Furthermore, in [37] an integrated scheduling problem in a distributed manufacturing system is investigated. A multi-objective stochastic model considering two scheduling criteria as well as operation process uncertainties. A multi-objective brain storm optimization algorithm was developed, and the proposed model demonstrated promising experimental results when compared with two state-of-the-art multi-objective algorithms [37].

In recent years, due to the vast applications in production systems, hybrid flow scheduling problems have gained increasing attention. Most previous studies assume that the job processing times are deterministic and constant [29]. In [29] a stochastic hybrid flow planning problem for minimizing markespan and total delay is described.

With the emergence of cloud computing technologies, services with the same functionalities and different non-functionalities occur in the cloud manufacturing system. Therefore, optimizing the composition of manufacturing services become increasingly important in meeting customer demands. This issue involves multi-objective optimization [31]. A new manufacturing service composition model based on service quality, as well as considerations of crowdsourcing and service correlation, was proposed in [31]. Due to the e-commerce development and growth, warehouse logistics has also been facing emerging challenges in ways that include more order batches and shorter order processing cycles. Therefore, intelligent warehouse systems using autonomous robots for automated storage and intelligent order scheduling are becoming dominant [25]. Accordingly, in [25] a multi-robot cooperative scheduling system in intelligent warehouse is proposed. The cooperative multi-robot scheduling system of intelligent storage aims to drive many robots in an intelligent warehouse to perform distributed tasks in an optimal manner (e.g., in time saving and energy conservation).

There is currently great attention on Cloud Manufacturing (CMfg) as a new service-oriented manufacturing paradigm. To integrate activities and services through a CMfg, two important issues to facilitate the success of CMfg are Service Load Balancing and Transport Optimization [38]. In this regard, a new queuing network for parallel scheduling of multiple processes and customer orders to be supplied is developed in [38].

Service oriented systems based on customer order as well as metrics related to cost and time are important for the success of a cloud manufacturing system [18]. Another important aspect is establishing equity among factories with cloud systems to obtain benefits according to capacity. On the other hand, is also relevant to establish equity among customers who order products based on their preferences. In this regard, in [18] a multi-objective mathematical model capable of considering both customers and

service factories and the equity between them is developed. This model is able to simultaneously assist the decision maker regarding rejecting or accepting customer orders, assigning jobs to machines, determining a price for each job as well as scheduling work on the machines. Meanwhile, in [15] a Multi-objective Genetic Algorithm Optimization (GMOA) is proposed to solve flexible ordering problems for a medium-scale screw factory. New smart manufacturing technology facilitates the interconnection of process planning data as well as purchasing scheduling and optimizing the integration of different manufacturing processes [21]. A multi-objective optimization integrated process planning and scheduling with uncertain processing time and date is addressed in [21].

Sustainability has been widely studied in the industrial area, so end-of-life product recovery is an active way to achieve sustainable manufacturing, while extending producer responsibility to closed-loop product service. This is still a challenge to provide flexible and intelligent recovery plans for industrial equipment at different product service periods [34]. However, in [34] the intelligent recovery decision making problem is addressed. The authors proposed a system framework for the implementation of intelligent end-of-life product recovery management based on product state monitoring. Multi-objective optimization models are formulated to identify the age-dependent recovery roadmap that best matches the product condition and meets business objectives. Recovery profits and energy performance are optimized in the models to achieve more environmentally friendly recovery.

4 Conclusions

In this paper, a SLR concerning multi-objective optimization approaches for distributed manufacturing scheduling problems in the I4.0 era was presented. Based on the results obtained, a study considering a set of 33 articles collected from different platforms (Web of Science, Scopus and b-on) was conducted. A careful analysis of these results was performed, six articles emerged as the most relevant for answering the research questions raised in this work.

Moreover, it can be concluded that research about this subject has been growing in recent years, as could be seen through a graph showing the number of publications per year. It was also possible to identify several issues regarding multi-objective optimization in distributed manufacturing scheduling problems in the I4.0 era. There are concerns on reducing energy consumption, along with logistics and supply chain systems issues, that are modeled as multi-objective problems and solved through multi-objective optimization algorithms, namely for production flow scheduling. As response to RQ1, this study shows that there are some recent applications of multi-objective approaches to solve DMS problems. However, this is an area that is starting to grow and, since the large amount of data available in this I4.0 era, it is expected to see in near future new relevant developments.

The recent features of scheduling job shop problems (JSP) in the I4.0 are highlighted as distributed intelligent scheduling in contrast to traditional centralized scheduling. In terms of RQ2, one of the future trends of the JSP scheduling in the I4.0 should be in the development and use of different kind of approaches, namely based on AI, such as intelligent agents. In situations where the traditional centralized workshop scheduling is transformed into the distributed intelligent scheduling, it can significantly reduce

the computational workload and the system will become more flexible and agile [11]. In this sense, it can also be said that the I4.0 is already being accepted in the manufacturing industry, as it guides an innovative and promising production paradigm to be further explored. A new and fundamental feature of I4.0-based manufacturing systems is the application of advanced, intelligent machines that have communication, self-optimization, and self-training capabilities [17].

Also, in the context of the I4.0 manufacturing scheduling can be further supported or better achieved through the use of different kind of approaches, namely on AI, and for solving distributed manufacturing scheduling problems. Such approaches, conciliated with other emerging production technologies that enhance mass customization, through the current cyber-physical systems underlying the I4.0, and thus allowing to reach an innovative approach in production [11]. Through the use of a distributed MS approaches, several advantages are expected to be achieved, namely the reduction of production time, while aiming to meet product delivery deadlines, among other performance measures to be optimized. Several algorithms have been applied and proposed to solve multi-objective optimization problems, in the manufacturing scheduling domain, namely in distributed manufacturing scheduling. Based on this review, it was also found that multi-objective optimization is being used in the I4.0 to optimize energy consumption associated to the operation of new technologies. The increasing advances in technology, associated with intelligent manufacturing systems in the I4.0 has been reflected by growing energy requirements. This can be an important feature in near future as well as environmental issues.

There are multiple issues that can be further explored concerning RQ3. In terms of future work, the use of multi-objective optimization approaches and methods to solve distributed manufacturing scheduling problems, in the context of the I4.0 should be further explored. These kind of scheduling problems should continue to be oriented to the current requirements imposed by the I4.0, as they do remain underexplored. Therefore, it is thought to be a rather vast area, and therefore, of great interest to continue to be explored, through the application of multi-objective optimization approaches, by considering diverse kind of internal and external performance measures of companies.

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