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Scheduling in the industry 4.0: a systematic literature review

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Industry 4.0 is characterised for being a new way of organising the supply chains, coordinating smart factories that should be capable of a higher adaptivity, making them more responsive to a continuously changing demand. This paper presents a Systematic Literature Review (SLR) with three main objectives. First, to identify in the literature on Industry 4.0, the need for new job scheduling methods for the factories of the digital era. Second, to identify in the literature of scheduling, which of these issues have been accomplished and what are the most critical gaps. Third, to propose a new research agenda on scheduling methodology, that fulfils the needs of scheduling in the field of Industry 4.0. The results show that literature related to the subject of study is rapidly growing and the needs of new methods for job scheduling in the digital factories concern two main ideas. First, the need to create and implement a digital architecture where data can be appropriately processed and second, the need of giving a decentralised machine scheduling solution inside such a framework. Although we can find some studies on small production lines, research with practical results remains scarce in the literature to date.

Keywords: Industry 4.0; Job Shop Scheduling; Systematic literature review; Smart factory; Cyber-physical systems

1. Introduction

Industry 4.0 or the fourth industrial revolution, has recently started. Its development will be settled during the second and third decades of the XXI siècle. It is characterised for being a new way of organising the supply chains, coordinating several smart factories that should be capable of a higher adaptivity, making them more responsive to a continuously changing demand. In this context, scheduling systems must, in addition to the more efficient allocation of resources, promote the synchronisation of the tasks performed by the autonomous agents that make up these systems.

Two main challenges to achieve its potential are, first, answering how should the information from production be gathered and processed. In other words, how should the data flow through the production system? And second, considering the data is affordable on a real-time basis, what efficient scheduling methods can be applied to find effective solutions? The interest in developing such flexible, dynamic and robust systems, remains in the volatile demand scenario of our times (Mourtzis & Vlachou, 2018).

Now, these goals seem to be affordable due to the new technologies that are being introduced into the production process. Those new technologies that will surely have a significant impact in our economies are known as the five driving forces for smart distributed scheduling in Industry 4.0: internet of things (IoT), cyber-physical systems, smart factory, deep learning and self-decision (Rossit et al., 2018).

All these technologies combined allows production activity control to gather and use in real-time information to manage production processes in the shop floor. The problem that remains is how to decide on the priorities and allocation of resources to achieve de desired performance of the production system.

Recent studies have been carried out to adapt some of the well-known job shop scheduling methods to the perspectives of Industry 4.0 (Zhang et al., 2019), while others have been working the new concept "smart scheduling" (Rossit et al., 2018), directly related to smart factories. Nevertheless, most of those studies are theoretical; not many of them are real case studies. The three main objectives of this article are, first to identify in the literature of Industry 4.0, the needs of new methods for job scheduling in the new digital era factories. Second, to identify in the literature of scheduling what issues have been accomplished and what are the most critical gaps about those needs, and third to summarise these issues and propose a new research agenda on scheduling methodology, that fulfils the needs of scheduling in the field of Industry 4.0.

A Systematic Literature Review (SLR) will be carried out to achieve these objectives, screening the papers that approach the scheduling problems under the context of the new digital age production systems.

This article is structured as follows. In Section 2, the background of Industry 4.0 and Machine Scheduling will be introduced. In Section 3, the methodology applied to search in the literature will be described, while in Section 4, the results will be shown and discussed. Final remarks in Section 5 will conclude the document.

2. Background

2.1 Industry 4.0

The main difference between Industry 4.0 and its predecessor is that, instead of the traditional hierarchical and centralised structures, it exhibits schemes in which autonomous agents interact in decentralised architectures (Rossit et al., 2018). These autonomous agents are supposed to take autonomous decisions, according to all the continuously changing information gathered from all other autonomous agents, new jobs that entered the system or even cancelled jobs that have already been scheduled and they are at the half-way process. There are 5 relevant concepts that can be combined to achieve this goal: *Internet of things (IoT), Cyber-Physical systems, smart factory, deep learning and self-decision.*

Cyber-Physical systems integrate the computer process and the physical real process. It is based on the virtualisation of the physical system. In cyber-physical systems, physical and software components are deeply related to interacting with each *other* in a lot of ways that change with context. Of course, this technology needs significant computational resources, such as processing capability and local storage, and multiple sensory input/output devices.

Internet of things (IoT) is the extension of internet connectivity into physical devices and every-day objects. IoT technology can link jobs, machines, tools, vehicles, robots and people through all the production system. By using all this linking information, "big" data are generated, providing them in real time information all over the factories. In other words, this technology will be applied to know the state and behaviour of all the jobs and resources that are being carried out through all the production system. It is a gathering and supplier information technology.

Smart Factory is the name used to refer to those factories that integrate smart agents through their production system. It is the result of applying the combination of Cyber-Physical Systems and IoT in a factory. They are characterised by the fact that scheduling decisions are no longer taken centrally, like most traditional factories. The decision-making is decentralised, it will result from the smart agents that will take self-decisions by continuously processing data collected through the CPS and the IoT. Smart factories on the basis of collaborative cyber-physical production systems represent a future form of industrial networks (Ivanov et al., 2016).

Deep learning is a subfield of artificial intelligence concerned with algorithms inspired by the structure and function of the human brain called artificial neural networks. The ability of these algorithms to process a large volume of data to extract meaningful information purely using the computational capabilities of existing von Neumann computing architecture makes these attractive for solving various Artificial Intelligence (AI) problems (James & Bakambekova, 2019). Deep learning is a learning technique that learns features and tasks, directly from data. Data can be, images, text or sound. The main advantage of using this technology is that the more data is gathered, the more efficient this tool becomes.

Self-decision is the autonomy that smart agents should have to take a decision by themselves. Those decisions are based on the information that is generated by all other smart agents that integrate the Cyber-Physical Production System. This technology is what enables a smart factory to perform decentralised scheduling. The ability of CPPS to carry out a wide spectrum of activities, ranging from the physical operations of production to planning, evaluating and managing the entire production process, will have an impact on decision-making activities in the area of industrial planning and control (Rossit et al., 2018). Self-decision can be learned through deep learning technologies or can be programmed using the Tolerance Scheduling Methods (Rossit et al., 2018).

2.2 Machine Scheduling

Production scheduling assigns capacity constrained resources, which are normally machines that can do some specific tasks, to a set of jobs that need to be accomplished. This process of allocating and sequencing the jobs in each machine is done under some natural circumstances that transform some of the at first possible solutions into non-feasible ones. Those natural circumstances such as the fact that one machine can only process one job at a time or, once a job is started in a machine the job needs to be ended before another job is started or even the fact of having to prepare a specific machine setup for each family of jobs, are known as constraints. The aim of machine scheduling is to find a schedule of the jobs to be processed on machines in a way that optimizes some performance measures without violating any of the stated constraints (Abedinnia et al.,2017).

More rigorously, as (Graham et al., 1979) state, we consider that n jobs Jj, (j = 1 , . . . , n) have to be processed on m machines Mi(i = 1, . . . , m). Throughout, we assume that each machine can process at most one job at a time and that each job can be Different goals and constraints that yield a wide variety of scheduling problems are reflected by a 3-field problem classification $\alpha/ \beta/ \gamma$. The α field describes the machine environment and contains just one entry. The β field provides details of processing characteristics and constraints and may contain no entry at all, a single entry, or multiple entries. The γ field describes the objective to be minimized and often contains a single entry (Pinedo, 2008).

Following the previous notation, many variants of scheduling problems can be formulated. First, scheduling problems can be classified into Static or Dynamic Scheduling Problems. Static problems consider that the jobs are all available at the time zero. Dynamic problems consider that new jobs arrive at the system over time (Vieira et al., 2003).

Secondly, scheduling models can be classified into deterministic or stochastic. On the one hand, deterministic models consider that all variables considered in the formulation of the problem such as processing times, setup times, due dates etc, are determined and have a unique value. On the other hand, stochastic models consider that at least one of these variables is random, for example, the processing time of a job may be characterized by a normal distribution with a given mean and standard deviation. This implies that the solution to the problem must consider a stochastic approach and also that the results should be interpreted statistically. Stochastic scheduling problems turn to be hard to solve in relation to their deterministic counterpart (Baker & Trietsch, 2009).

Thirdly, the configuration of the machine shop. Problems can be classified into single or multiple stages. In the first case, jobs require only a single operation. In the second, each job needs multiple operations on different machines. Additionally, the environment may have a single machine for each operation type or more than one machine of a given type. Thus, we would have four basic configurations: single machine (one stage), parallel machines (single stage, with alternative machines), flow shop (serial multistage, each stage with a single machine) and job shop (multistage, each job with a specific routing). More configurations are possible by combining these basic ones, for example, a flexible flow shop wherein at least in one stage, there is more than one machine (Pinedo, 2008).

Many solving methods have been proposed to find solutions to scheduling problems. Exact methods, capable of finding the optimal solution, are used for small problems of less computational complexity. However, most of the scheduling literature problems fall into what is called NP-hard problems that hamper the use of exact methods. This has led to a tremendous effort from the scientific community on researching effective algorithms that can find a near optimal solution, known as approximate methods, formed by heuristic and meta-heuristic methods. (Garey et al., 1976).

3. Methodology

In order to accomplish the three main objectives of this paper, previously stated in Section 1, a Systematic Literature Review was carried out. By following this methodology, we expect, first to identify in the literature of Industry 4.0 the needs of new methods for job scheduling for the new digital era factories. Second, to identify in the literature of Scheduling what issues have been accomplished and what are the most important gaps in relation to those needs. Third to summarise an agenda of what new scheduling approaches should be researched in the near future, to efficiently fulfil the needs of scheduling in the field of Industry 4.0.

A Systematic Literature Review (SLR) is an important research endeavour by itself and not merely a review of previous writings (Thomé et al., 2016). SLR differs from narrative reviews by adopting a more rigorous and well-defined review process (Cronin et al., 2008). The research will follow the eight steps approach proposed by Thomé et al. (2016). The eight steps are: (i) planning and formulating the problem; (ii) searching the literature; (iii) data gathering; (iv) quality evaluation; (v) data analysis and synthesis; (vi) interpretation; (vii) presenting results; and (viii) updating the review.

We collected the articles by using the database Scopus, considered one of the most relevant databases of peer-reviewed literature from scientific journals, books and conference proceedings. Some exclusion criteria were applied to define the database of our article. Conference papers and book chapters were excluded. Only articles in English were included. Since the intersection of both subjects, Industry 4.0 and Scheduling, seems relatively recent, no exclusion criterion for the year of publication was applied.

We discussed beforehand some articles related to scheduling and Industry 4.0. From this discussion, relevant issues and methods were identified and a set of keywords was proposed. They can be divided into two classes related to:

(1) Industry 4.0
(2) Machine Scheduling

After trying some keywords combinations in the Scopus database, the final used keywords were:

TITLE-ABS-KEY (“industry 4.0” OR "smart factory" AND "scheduling") AND (LIMIT TO (SRCTYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (DOCTYPE , "ar"))

As observed, the related words to Industry 4.0 used were “Industry 4.0” and “Smart Factory” while “Scheduling” was the only keyword used related to Machine Scheduling. The research was applied to Title, Abstract and keywords of the Scopus database. Some filters where applied: (SRCTYPE,"j") to only include journals, (LANGUAGE,"English") to exclude documents that were not written in English and (DOCTYPE,"ar") to only include documents considered journal by the Scopus database. The keywords applied were not very restrictive, with the intention of not excluding important papers into the intersection of both fields of study.

A total of 61 scientific papers were obtained as a result of the search in Scopus with the keywords selected. To test the relevance of the collected papers, an abstract, introduction and conclusion analysis of the 61 papers was carried out. Papers not directly related to Scheduling or Industry 4.0 were excluded. A somewhat more complicated analysis was to identify whether the article effectively addressed both scheduling and Industry 4.0. More specifically, we confronted the introduction and conclusion, checking for consistency in approaching the two themes in the two sections. The review process was interactive; the discrepancies were debated until consensus was reached.

On the one hand, we remarked that articles focusing on Machine Scheduling are generally characterised for presenting one or more problems and some scheduling algorithms to solve them.

Their objective usually remains in proving that, for a well-defined problem, the newly proposed algorithms perform better than others available in scheduling literature. They mention some Industry 4.0 concepts, but they do not deepen it.

On the other hand, articles focusing on Industry 4.0 are generally characterised for defining how the information should flow in the Smart Factory. It discusses where, when and how the data should be gathered, processed and delivered so that the agents can take decisions by itself. They tend to present Scheduling as an important part of this system; however, no greater detail of it is given.

As the keywords applied were not very restrictive, a total of 31 papers were excluded during this content review process. In the end, 30 papers were considered as valid. These 30 papers were used for the bibliometric analysis to explore the evolution of current research in the intersection of Industry 4.0 and Scheduling fields. The final database is shown in Table 1.

[Table 1 about here.]

Then we did a complete reading of the five most cited articles from the final database ([1], [2], [8], [14], [17]) to look for some distinguishing characteristics. From this analysis, we classified the methodology adopted in each of the papers and questions were refined and systematically answered for each of the read papers, with the idea of synthesizing and emphasising the relevant information in Section 4. A total of six methods and six questions were applied. The 6 applied methods are summarised below:

M1: Practical / Survey: Articles in which the researcher collects data through a previously designed questionnaire, without modifying the environment or the phenomenon where the information is collected either to deliver it in the form of a triptych, graph or table.

M2: Literature review: Articles characterised for reviewing existing scientific literature, analysing it looking for gaps in the literature and proposing new agendas to future research.

M3: Theoretical/Experimental: Articles that formulate a model or/and a solving algorithm method. However, in those articles, the model or algorithm is not validated in practice.

M4: Practical / Case Study: Articles that propose a model or/and an algorithm that is tested in a real production system.

M5: Practical/Simulation: Articles in which the authors prove their model by simulations, often comparing the results with other well-known methods that are also simulated.

M6: Theoretical/Qualitative: Articles that present a qualitative theoretical model in which the general ideas, conditions or physical machines should work. They are often related to how to integrate an Information System, without verifying it in a real case study.

The 6 refined questions are:

Question 1: Does the scheduling system meet the specific needs of Industry 4.0? If so, which ones?

Question 2: Does the scheduling system depend on technologies related to Industry 4.0? If so, which ones?

Question 3: What distinguishes the considered scheduling system from the traditional ones?

Question 4: Do the authors discuss the limitations of the scheduling system in Smart Factories? If yes, which ones?

Question 5: Do the authors discuss the potential of the scheduling system in Smart Factories? If yes, which ones?

Question 6: Do the authors point out the needs for further studies in Smart Scheduling? If so, which ones?

Afterwards, a full reading of the remaining 25 papers was performed. The described steps of the methodology explained in this section are summarized in Figure 1.

[Figure 1 about here.]

4. Results

4.1 Descriptive analysis

The 30 papers that were analysed come from a total of 21 different scientific journals, as seen in *Table 2.* The IEEE Transactions on Industrial Informatics is the one that has the most papers (5), followed by International Journal of Production Research (3) and by International Journal of Computer Integrated Manufacturing (3). We highlight first, that the journals listed are relevant, all having a Journal Citation Index ranging from 0.050 to 9.270. Second, the articles are distributed by a large number of journals from Mechanical and Production Engineering communities, which shows a broad interest in the subject.

[Table 2 about here.]

As presented in the preceding section, the research of the papers did not limit the publication year. However, only papers dating from 2015 to now, integrate the final database. This fact proves that the studies that consider both Machine Scheduling and Industry 4.0 are new in scientific research. As shown in Figure 2, there was only one article published in 2015, three articles published in 2016, seven articles published in 2017, nine articles published in 2018 and ten articles during the first four months of 2019, as the literature research was performed the 3th May of 2019. Considering that the rate of publishes will be constant, 30 papers are estimated to be published during this year. This fact proves that the interest in studying the interface between Machine Scheduling and Industry 4.0 is rapidly growing.

[Figure 2 about here.]

Afterwards, the selected papers were classified by their methodologies into Practical / Survey (M1), Literature Review (M2), Theoretical/Experimental (M3), Practical / Case Study (M4), Practical/Simulation Study (M5) and Theoretical/Qualitative (M6), as shown in Table 3. Some articles used more than one such methodology.

[Table 3 about here.]

As observed, the most used methodologies are (M3) and (M6), being used 14 and 15 times, respectively. Most of the articles present or study a model, and to do so, they usually have to choose between one of those two alternatives to describe the problem in detail. Once the problem is stated, most of the articles try their proposed model by using (M4) or (M5). To prove the article's findings (M4) and (M5) has been applied 13 and 12 times, respectively. Regarding (M4), it is essential to remark that studies carried out in a real production system usually investigate small application cases, giving evidence that the model can be applied in a real situation. Apart from the articles that present or study a scheduling model, two Literature Reviews were done, [11] and [21], and a Survey, [8], which also reviews several other papers from the studied topic.

4.2 Analysis of contents

Having finished the descriptive analysis, we now intend to give an overview of the information gathered after a complete reading of each article in the database, guided by the six questions formulated in section 3 - Methodology.

Two main trends have been identified among the analysed papers. There is a group of researchers that aim to create a framework or architecture where information related to machine scheduling can be gathered, stocked and processed. These papers focus on answering how to collect data, to where and how should this data be sent. The second group focuses more on giving a decentralised machine scheduling solution assuming a suitable information system architecture is available. Similar to what [21] proposed, one issue is the management of real-time information, and the other is the decentralisation of decision-making. There is one thing in common between both of them, the core principle of smart manufacturing is connecting of people, data, and things through the adoption of the Internet of Things (IoT) [12].

Starting with the first group, the study carried out by [1] proposes a 3-layer architecture with the adoption of appropriate technologies of Industry 4.0, such as SDIN technology, D2D, NB-IoT, 3GPP, 5G. Apart from the proposed architecture, the authors present an ontology-based scheduling mechanism. Its viability is tested through a real production system, more specifically, in a candy packaging line, achieving better results than a traditional model.

In article [9], a 4-layer architecture is proposed. These layers are named as resource layer, knowledge layer, rule layer and the data layer. Similar to [1], [9] offers an ontology-based scheduling mechanism. Then the viability of it is tested through the same candy packaging line used in [1], and the results show utilisation rate is improved, and simultaneously, the energy consumption is reduced. The main limitation was the impact of network bandwidth requirement on the system [9].

In article [17], a resource sharing-based framework (RSBF) is developed to enable flexible modelling of a wide range of CPSs, with a specific focus on resource sharing. RSBF has the objective of maximising CPS utility through decentralised control. RSBF constitutes the first implementation considering social welfare metrics for effective decision-making on resource allocation in CPSs. The authors discuss the viability through a case study, showing that process time can be highly reduced while achieving a nearly optimal solution. Furthermore, promising results indicate that RSBF is flexible and adaptable and can, therefore, be used in different CPS domains [17].

In article [7] a Hierarchical Data Transmission Framework for Industrial Wireless Sensor and Actuator Networks is proposed. That aims to be a hybrid model, trying to take profit of advantages of both centralised and decentralised architectures. Distributed data transmission schemes, which are scalable and flexible, are suitable for handling large-sized and unpredictable communications. However, they are incapable of optimising real-time performance and reliability based on local information. By contrast, centralised data transmission schemes can rely on global information to improve the two performances measures.

After discussing some new data frameworks, we now continue to the second group, the one that focuses on giving a scheduling solution once the framework is created.

One of the observed solutions is the possibility of creating a digital twin. A digital twin can be defined as an integrated virtual model of a real-world system containing all of its physical information and functional units [22]. In article [22], the design and implementation of a digital twin application for a connected micro smart factory are proposed, differing from other digital twin studies that concentrate on the management of only a single machine. Results show accurate information synchronisation between a manufacturing element in the physical world and digital twin. The same results were obtained for the same experiments performed on other plants and robots with a 100% match rate. The research results were validated by implementing the digital twin concept in a shop of 3D printers.

Article [12] presents a cloud-assisted self-organised architecture (CASOA) is presented comprising smart agents and cloud to communicate and negotiate through networks. CASOA consists of four types of primary agents: suggestion agents, product agents, machining agents, and conveying agents. The agents use suitable communication methods to exchange their reasoning information based on their body of knowledge [12]. An experiment was conducted by using several plants and network devices to verify the proposed architecture with respect to its dynamic scheduling method. Results show that the presented architecture can be easily deployed to build smart manufacturing system and can improve the robustness of the manufacturing system when dealing with mixed multi-product tasks.

Article [26] proposes an “Entity model” that simulates the physical manufacturing system. An entity model of a manufacturing system is a highly customised copy of the production line. The viability is discussed through the modelling of an "Entity Model". However, there are some limitations: the "Entity Model" cannot synchronise all the movements of the physical system because they are continuous, and the simulation works with discretisation [26].

In article [18], Anarchic Manufacturing is studied. The paper aims to explore purely distributed systems, with no central control or oversight. ‘Anarchy’ in manufacturing is defined as a heterarchical distributed structure where decision-making authority and autonomy is at the lowest level between system elements. Through simulations, they proved that hierarchical systems are not less flexible than anarchical systems. However, the anarchical system does not need complete information at any single point in the system, while the centralised system does; this can provide an advantage in naturally distributed scenarios [18].

In article [24], authors developed a mathematical model and a black hole and floral pollination algorithms-based optimisation method, which makes it possible to optimise the in-plant supply of a cyber-physical production environment called “matrix production”. More generally, this paper focused on the mathematical modelling of the supply to in-plant matrix production cells including a time frame, capacities, energy consumption, and emissions. Finally, the paper shows and discusses the impact of optimisation on the performance of the system [24].

Article [27] proposes a Decision Support System (DSS) for dynamic job-shop scheduling using simulation and real-time data. DSS continuously monitors operations, seeks opportunities to improve the shop schedule performance, formulates better processing sequences and implements them, by considering real-time data gathered from the shop [27]. The viability is tested through simulations running in Arena, and the results obtained from them show that the DSS improves the system performance by increasing workstation utilisation and decreasing both the number of tardy jobs and the amount of waiting time among the rules considered in the study.

Besides the two main trends previously discussed, some articles consider the idea of using the Industry 4.0 concepts to develop innovative management practices. One of those ideas refers to the optimisation of machines maintenance schedule, combining it with the shop scheduling of jobs.

An example of it is article [10], which proposes a cloud-based cyber-physical system for adaptive shop-floor scheduling and condition-based maintenance. The proposed method is applied and validated in a real case study from a high-precision mould-making industry. Some ideas to improve the proposed model are to use captured data from the monitoring system to predict energy consumption as well considering the available time for predictive maintenance [10].

Directly related to maintenance scheduling, article [15] studies statistical and artificial intelligence-based approaches which predict the remaining life of the components and make accurate maintenance planning decisions. However, the major challenge lies in the fact that most of the existing factories do not have their entire set of manufacturing equipment equipped with conditions monitoring devices.

Introducing an economic parameter directly related to energy price fluctuation, article [3] proposes an energy-aware load balancing and scheduling (ELBS) method based on fog computing. Fog computing, considered as a new decentralised computing trend of cloud architecture, is one of challenging industry topics for IoT [3]. The viability of this model is tested through a real production system.

Another application of the high availability of the information of an entire production system is presented in article [13] in the context of product remanufacturing.". The authors develop a data-driven simulation approach to predict material flow behaviour within the remanufacturing shop, by utilising data from digital manufacturing systems (i.e. databases, traceability systems, process plans) to update and automatically modify the simulation constructs to reflect the real world or planned system [13].

Being aware that most of the technologies are nowadays unaffordable for most of the industrial environments around the world, article [29] proposes Industry 3.5 as an intermediate step between existing Industry 3.0 and to-be Industry 4.0, in which digital decision making, big data analytics, and manufacturing intelligence are integrated to empower smart production with disruptive innovations that can be realized in existing industrial infrastructure.

5. Conclusions

In this paper, we present a Systematic Literature Review on machine scheduling in Industry 4.0. A total of 30 scientific articles were surveyed, classified and analysed. After the analysis of the articles, we conclude that the needs of new methods for machine scheduling in the new digital era are concerned with the two following main ideas.

First, the need to create and implement a digital architecture where data can flow properly through a real industrial production environment. Several information architectures to manage real-time data are being proposed. Those frameworks generally consist of a few layers which are in charge of gathering, stocking and processing the information into a Smart Factory. However, the number of layers and the interaction among them usually depends on the nature of the work and tasks that need to be performed in a Smart Factory. Therefore, there is still no unified framework that could include all production systems.

Second, there is a need to provide a decentralised machine scheduling solution once the framework is created. Several decentralised scheduling solutions have been proposed. Some of them focus on creating a scheduling method based on the autonomy of jobs to decide where and when their tasks should be carried out, while others focus on creating a scheduling method based on the communication between smart agents. Those scheduling methods consider dynamic information and are usually tested by introducing some disruptive events in the simulations to validate their flexibility, which results to be better than centralised machine scheduling solutions. Furthermore, the computing workload is reduced when opting for a decentralised solution.

Finally, we emphasize that, among the 30 articles reviewed, it can be seen that practical articles are very few. Some studies in small productions lines have been carried out. The capacity to deal with the vast amount of data generated by a Smart Factory and taking decentralised scheduling decisions by using this information remains as an unsolved problem.

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List of Figures

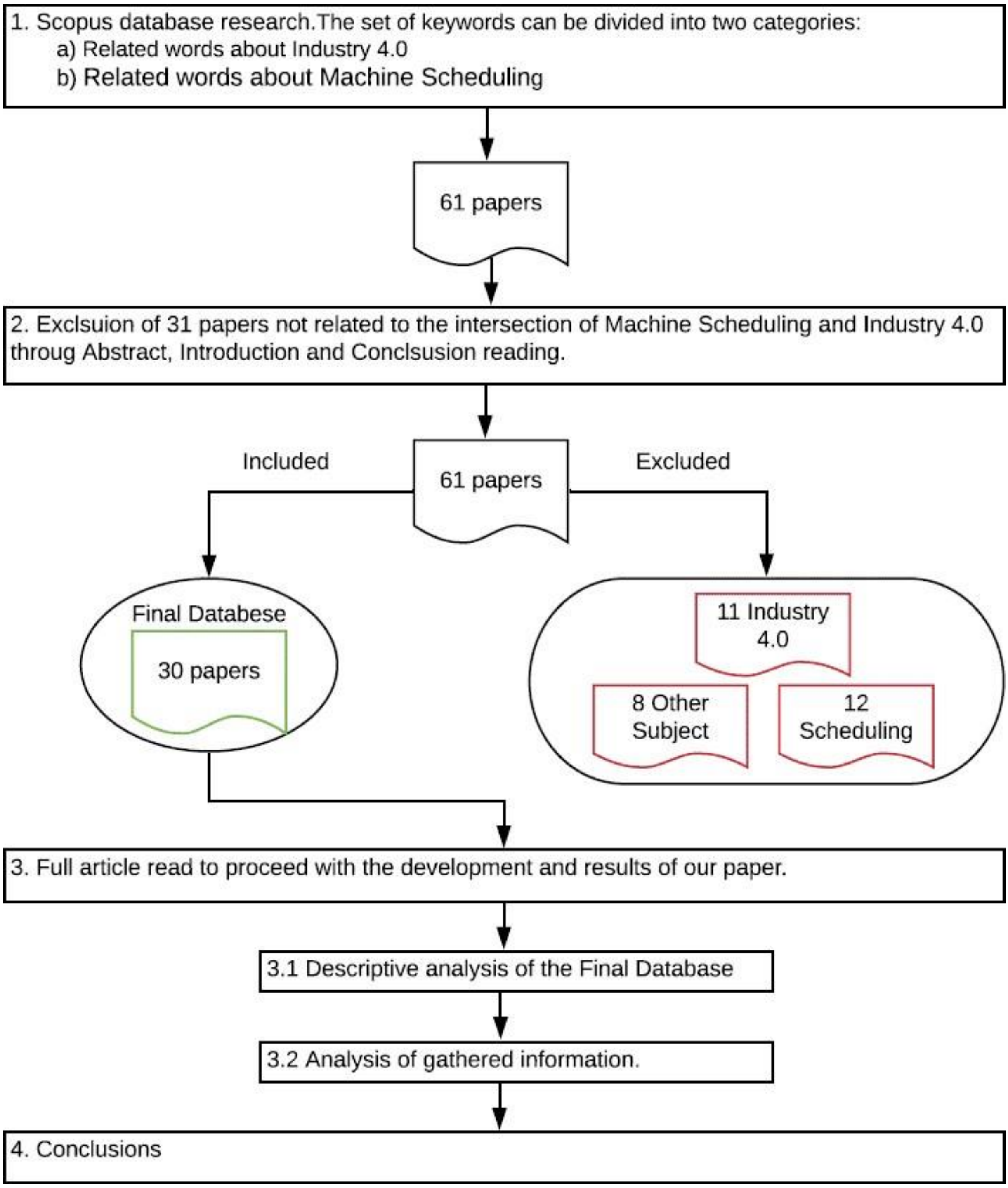

Figure 1. The methodology applied for the Systematic Literature Review

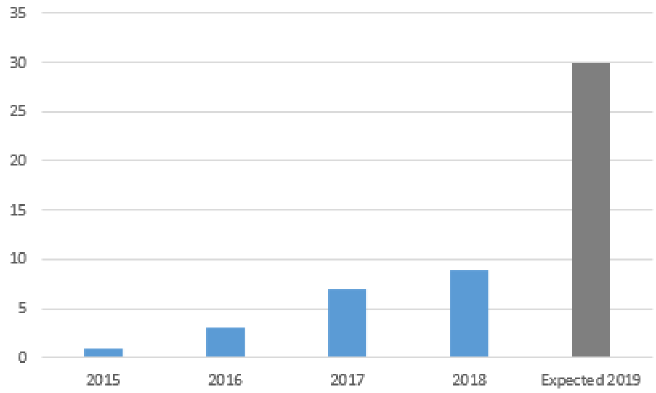

Figure 2. Publications per year

List of Tables

Table 1. Final database of articles

[1] (Wan, Chen, Imran, et al., 2018)	[16] (Wang & Li, 2019)
[2] (C. C. Lin, Deng, Chen, & Chen, 2016)	[17] (A. Nayak et al., 2016)
[3] (Wan, Chen, Wang, et al., 2018)	[18] (Ma, Nassehi, & Snider, 2019)
[4] (Chekired, Khoukhi, & Mouftah, 2018)	[19] (Saif et al., 2019)
[5] (N. G. Nayak, Durr, & Rothermel, 2018)	[20] (P. Lin et al., 2018)
[6] (Wan et al., 2019)	[21] (Rossit, Tohmé, & Frutos, 2019)
[7] (Jin et al., 2017)	[22] (Park et al., 2019)
[8] (Zhan et al., 2015)	[23] (Lee & Chung, 2016)
[9] (Wan, Yin, et al., 2018)	[24] (Bányai et al., 2019)
[10] (Mourtzis & Vlachou, 2018)	[25] (Xu & Chen, 2018)
[11] (Zhang et al., 2019)	[26] (Zhu, Qiao, & Cao, 2017)
[12] (Tang, Li, Wang, & Dong, 2017)	[27] (Turker et al., 2019)
[13] (Goodall, Sharpe, & West, 2019)	[28] (Pei, Tong, He, & Li, 2017)
[14] (Tao et al., 2017)	[29] (Chien, Hong, & Guo, 2017)
[15] (Upasani et al., 2017)	[30] (Iannino et al., 2018)

Table 2. List of journals and respective papers

Journal	Articles
ACM Computing Surveys	[8]
Advances in Mechanical Engineering	[26]
Applied Sciences (Switzerland)	[24]
Computers and Industrial Engineering	[15]
Computers in Industry	[13]
IEEE Access	[12]
IEEE Communications Magazine	[1], [2]
IEEE Transactions on Industrial Informatics	[3],[4],[5],[6],[7]
IEEE/ASME Transactions on Mechatronics	[9]
International Journal of Computer Integrated Manufacturing	[20],[21][22]
International Journal of Distributed Sensor Networks	[23]
International Journal of Production Research	[17],[18],[19]
International Journal of Simulation: Systems, Science and Technology	[30]
Journal of Intelligent Manufacturing	[11]
Journal of Manufacturing Systems	[10]
Journal of the Chinese Institute of Engineers	[29]
Mathematics	[27]
Mechanika	[28]
Proceedings of the Institution of Mechanical Engineers	[25]
Robotics and Computer-Integrated Manufacturing	[14]
Sensors (Switzerland)	[16]

Table 3. Methodologies applied in each article of the final database

Article	M1	M2	M3	M4	M5	M6
[8]	X					
[11]		X				
[21]		X				
[5]			X			
[15]			X			
[3]			X	X		
[6]			X	X		
[9]			X	X		
[12]			X	X		
[19]			X	X		
[24]			X	X		
[7]			X		X	
[16]			X		X	
[20]			X		X	
[22]			X	X	X	
[25]						X
[28]						X
[30]						X
[1]				X		X
[14]				X		X
[17]				X		X
[10]			X	X		X
[13]					X	X
[18]					X	X
[23]					X	X
[26]					X	X
[27]					X	X
[4]			X		X	X
[2]				X	X	X
[29]				X	X	X
Total	1	2	14	13	12	15