Journal of Manufacturing Systems 61 (2021) 265–287

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Smart manufacturing scheduling: A literature review

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ARTICLE INFO

Keywords:
Smart manufacturing
Scheduling
Digital twin
Zero-defect manufacturing
Industry 4.0

ABSTRACT

Within the scheduling framework, the potential of digital twin (DT) technology, based on virtualisation and intelligent algorithms to simulate and optimise manufacturing, enables an interaction with processes and modifies their course of action in time synchrony in the event of disruptive events. This is a valuable capability for automating scheduling and confers it autonomy. Automatic and autonomous scheduling management can be encouraged by promoting the elimination of disruptions due to the appearance of defects, regardless of their origin. Hence the zero-defect manufacturing (ZDM) management model oriented towards zero-disturbance and zero-disruption objectives has barely been studied. Both strategies combine the optimisation of production processes by implementing DTs and promoting ZDM objectives to facilitate the modelling of automatic and autonomous scheduling systems. In this context, this particular vision of the scheduling process is called smart manufacturing scheduling (SMS). The aim of this paper is to review the existing scientific literature on the scheduling problem that considers the DT technology approach and the ZDM model to achieve self-management and reduce or eliminate the need for human intervention. Specifically, 68 research articles were identified and analysed. The main results of this paper are to: (i) find methodological trends to approach SMS models, where three trends were identified; i.e. using DT technology and the ZDM model, utilising other enabling digital technologies and incorporating inherent SMS capabilities into scheduling; (ii) present the main SMS alignment axes of each methodological trend; (iii) provide a map to classify the literature that comes the closest to the SMS concept; (iv) discuss the main findings and research gaps identified by this study. Finally, managerial implications and opportunities for further research are identified.

1. Introduction

The supply chain is a heterogeneous multi-objective environment in which various entities with different roles are hierarchically organised to form multitiered networks to develop processes of disparate natures in many stages and locations. With such complexity, the adequacy and suitability of planning processes are key to successfully face the supply chain management challenge [1]. Therefore, a supply chain's digital transformation process must also be oriented towards the digitisation of production planning processes [2], among them scheduling. According to Pinedo [3], scheduling is regularly used in industrial and service companies to allocate resources to tasks during specific time periods to optimise one objective or more. Initially, it is worth highlighting the contributions made to the scheduling theory by Gantt, Knoeppel and Coes [4]. However, since the 1970s, publications have significantly increased [5], possibly due to the influence of works like those of Conway et al. [6] or Baker [7] and, more recently, by initiatives like Industry 4.0 [8] or equivalent production models, such as smart manufacturing. The diversity of approaches to the scheduling theory in the scientific literature reflects the rapid evolution of its environment, mainly due to the continuous emergence and availability of new technologies, which provide opportunities to move towards new frameworks and models that can change the traditional paradigms of production planning and scheduling [9].

One of these new technologies is the digital twin (DT), which was originally conceived as a means to improve the performance of physical entities by leveraging computational techniques enabled through virtual replication [10]. However, its evolution has allowed production processes or, more specifically in our case, scheduling, to be also subject to reproduction in virtual space (twinning) to obtain the same benefits [11]: reducing costs, time or risks; improving efficiency, reliability or flexibility; supporting the management of complexity [10]. It should also be noted that traditional enterprise resource planning (ERP) systems perform poorly at the operational level [12]. Compared to pure

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https://doi.org/10.1016/j.jmsy.2021.09.011
Received 30 July 2021; Received in revised form 14 September 2021; Accepted 14 September 2021

simulations, the aim of implementing the DT is dynamic optimisation, which allows real-time reflections of physical entities, an interaction between physical and virtual spaces, and the system's automatic evolution [13].

The goal of enabling a scheduling system to self-manage automatically and autonomously requires an action by the system itself. However, an automatic system's performance also depends on the characteristics of the environment to be controlled [14]. Thus the system's correct operation is favoured when the process to be controlled is stationary or quasistatic, while control is hindered or at-risk when the process' dynamism is marked and transient phenomena are numerous. This is the case in industrial production, where solutions can quickly become unfeasible because of their stochastic nature and the uncertainty generated by machine breakdowns, waste rates, delivery delays, among others [15], along with the arrival of new orders or cancellations. Therefore, scheduling automation will not be based only on an endogenous strategy, which guides action exclusively towards system transformation for automation. Such a policy, like an integral one, must also be based on an exogenous strategy [14], i.e. also acting on the environment and its variability, on the number of disturbances of the process being controlled, the size of these disturbances and their disruptive potential. More concretely, the possible disturbances in the real highly stochastic environment of the machine shop are numerous and range from the arrival of new orders or preventive maintenance operations, which are desirable or foreseeable events, respectively, to the cancellation of orders, defective production, stockouts, machine breakdowns, among others [16], which are rather unpredictable events with generally negative implications. In this uncertain context, ZDM is a strategy followed to minimise, mitigate or eliminate failures and defects during the production process. It is based on evidence that they will always exist, and will eventually impact production and its output, but by admitting that: (i) faults and defects can be detected and minimised more quickly online; (ii) any production output that deviates from specification should not be allowed to move on to the next step in the value chain or, eventually, to an end customer [17]. For Halpin [18], the zero defect model is a management tool that aims to reduce defects through prevention. It intends to motivate people to prevent making mistakes by developing a constant conscious desire to do their job right the first time. With the evolution of production environment, this approach has also evolved and deploys functions other than prevention, such as detection, repair and prediction [19]. In fact other philosophies, such as lean manufacturing, six sigma, lean six sigma, total quality management and constraint theory, share a part of the objectives and benefits of ZDM by addressing three ZDM functions: detect, repair and prevent. However, prediction is an exclusive aspect of ZDM that is absent in ese other philosophies, which do not learn from defects, but rather eliminate them. Thus to improve the future, these other philosophies analyse the past by losing valuable information from the present and generating an inertia between the occurrence of events and the identification of necessary improvements, while ZDM uses real-time data to prevent defects [20], a characteristic that distinguishes ZDM from other management models and guides operations management (OM) towards smart manufacturing scheduling (SMS). On the other hand, while some approaches to the ZDM strategy focus on product and process defects, e.g., mainly linking product defects with quality control, and process defects with maintenance and the health of production means [21], other approaches extend the scope of ZDM to also process parameter monitoring, collaborative production, data management, production reconfiguration and reorganisation, and production rescheduling [22].This is an approach that brings the ZDM model closer to the aforementioned complementary exogenous strategy to act on the production environment and its variability, and to control those disturbances that directly or indirectly impact the scheduling process and hinder its automation. In addition, ZDM can be seen as a new standard from the sustainability perspective for those companies whose management is oriented towards more eco-friendly and efficient production [21],because addressing the elimination of defective products and processes indirectly implies posing waste elimination.

The term SMS has been scarcely addressed in the literature. In most cases [23–27], the expression arises from adding the attribute smart to manufacturing scheduling as a simple qualifier without denoting greater intentions. On the contrary in [28,29] this expression comes from the conjunction of smart manufacturing as an environment defined by the application of Industry 4.0 technologies with scheduling to point towards a new conceptual space, but without providing a definition of SMS. Thus Zhou et al. [28] make use of SMS, in contrast to traditional job shop scheduling, by highlighting its bigger number of tasks and services, dynamic state and uncertainty in their research into dynamic scheduling based on deep reinforcement learning (DRL), while Rossit and Tohmé [29] introduce it descriptively as a paradigm by providing some of its features, such as the requirement for decentralization, collaboration and information exchange in real time. Yet as far as we know, there is no previous definition of SMS. Here SMS is defined as fostering ZDM objectives oriented towards zero-disturbance and zero-disruption to optimise production processes by implementing DTs in order to facilitate the modelling of automatic and autonomous scheduling systems. Moreover, we do not identify another state of the art by addressing scheduling, DT and ZDM.

This article aims to present a systematic literature review of the scientific publications in which a partial or complete relation is established among Industry 4.0, scheduling, the DT and ZDM concepts regardless of their focus, but by placing an emphasis on those oriented towards an automatic and autonomous shop floor scheduling model synchronised in real time with physical processes. The main contributions of this article are to: (i) classify the 68 reviewed papers according to the conceptual scheme from which the topic is tackled, i.e. Industry 4.0, scheduling, the DT and/or ZDM; (ii) identify their main objectives, contributions and limitations; (iii) delve into the role played by concepts scheduling, the DT and ZDM in the selected literature from a technological perspective; (iv) address an automatic and autonomous shop floor scheduling model synchronised in real time with physical processes from the main methodological trends, which are oriented to apply DT technology and the ZDM management model, using one of the main Industry 4.0 enabling technologies, and/or provide scheduling systems with capabilities inherent to SMS; (v) present the main SMS alignment axes provided by the reviewed literature for each methodological trend; (vi) propose a map, based on these methodological trends and their SMS alignment axes, with which to frame the reviewed literature that come the closest to the SMS concept; (vii) discuss the main findings and research gaps in this research work.

The rest of the article is structured as follows. Section 2 introduces the literature review methodology. Section 3 presents the literature review by describing the main findings based on thematic, content and taxonomic analyses. Section 4 discusses the main findings and research gaps of the literature that comes the closest to the SMS concept. Section 5 concludes and identifies future research lines.

2. Review methodology

Here we explore the intersection in the state of the art among: (i) the scheduling process; (ii) the DT enabling technology; (iii) the ZDM management model; and (iv) the conceptual spaces resulting from the intersection of two of the three previous sets. Therefore, the present framework considers conceptual, descriptive, experimental or exploratory research approaches in which: (i) the association of the three concepts occurs (space 1 = scheduling ∩ DT ∩ ZDM); (ii) the scheduling process is assisted by DT technology (space 2 = scheduling ∩ DT); (iii) the scheduling process is associated with the ZDM model (space 3 = scheduling ∩ ZDM) (Fig. 1). Of these sets of approaches, those oriented towards enabling the scheduling system to a greater or lesser extent for automatic and autonomous management acquire a special value.

In the digital transformation space represented by the supply chain

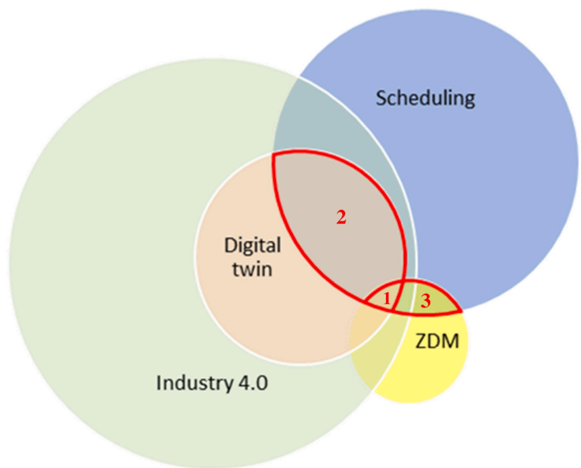

Fig. 1. Research framework.

4.0 metamodel [2], the intersection among the three main concepts addressed in this state of the art, i.e. scheduling, the DT and ZDM (space 1), with approaches oriented towards automatic and autonomous scheduling management, would correspond mainly to a digital transformation strategy represented by the issues highlighted in Table 1.

A literature review is a systematic, explicit and reproducible method for identifying, evaluating and synthesising the existing body of completed and recorded works produced by researchers, scholars and practitioners [30] on a specific topic; or, in short, a scholarly synthesis of the contents of the scholarly studies on the aforementioned topic [31]. Here the methodology used for the literature review was a simplification and adaptation of the step-by-step approach of Thomé et al. [32] for the specific case of research in the OM field. This methodology comprises the following steps: (i) problem formulation; (ii) literature search; (iii) literature collection; (iv) quality assessment; (v) analysis and synthesis; (vi) interpretation; (vii) presenting the results. Fig. 2 graphically represents the sequence of actions performed during the literature search, collection and quality assessment part of the process, the analysis and synthesis.

The study was conducted according to the following seven initial decisions: (i) semantic fields for the literature search; (ii) databases used; (iii) fields of each document on which to perform searches; (iv) consultation dates and time periods to explore; (v) document typologies; (vi) subject areas; (vii) language of documents (English and Spanish). The four semantic fields on which the literature search was based were: (i) field 1: "Industry 4.0"; (ii) field 2: "scheduling"; (iii) field 3: "digital twin"; (iv) field 4: "zero-defects". Each semantic field is made up of the keywords selected after checking their relevance through individual searches. The keywords making up the semantic fields present some differences depending on the database used and its query system. The following five used databases were considered: (i) Scopus; (ii) Web of Science; (iii) ScienceDirect; (iv) Pro Quest; (v) IEEE Xplore. They were used during a sequential process, in which the search results were initially obtained from Scopus and, subsequently, the other four databases were used to complement, in the indicated sequence, the initial Scopus results using the automatic duplicate discard utility of the JabRef tool. By this procedure, Scopus was the source of 83.5 % of the search result documents, while 6.6 % came from Web of Science, 5.5 % from Science Direct, 3.3 % from Pro Quest and 1.1 % from IEEE Xplore. The Scopus, Web of Science and Pro Quest databases allowed the most flexible searches because, on the one hand, they do not limit the number of keywords in a search field and, on the other hand, they allow the use of wildcards to complement character strings. For these reasons, all the keywords in each semantic field coincided in these three databases. In contrast, ScienceDirect does not allow wildcards to be used and limits the number of Boolean connectors to 8, whereas IEEE Xplore does not allow to use more than 6 wildcards and 50 keywords in each query string, which leads to some variations in the components of each semantic field. Appendix B details the keywords selected in each semantic field for each database used in the study.

The search fields for each paper were the title, abstract and keywords specified by the author/s in papers, with variations depending on the database: (i) with Scopus, the tag combination was TITLE-ABS-KEY; (ii) in Web of Science, tags TI-AB-AK were used; (iii) with ScienceDirect, the advanced search field "Title, abstract or author-specified keywords" was applied; (iv) as there is no search field for author-specified keywords in Pro Quest, the query was limited to the advanced search options for our keywords in "Document Title - TI" and "Abstract - AB"; finally, (v) with IEEE Xplore, the advanced search options were "Document Title", "Abstract" and "Author Keywords".

The consultation dates were: (i) Scopus and Web of Science, 22 February 2021; (ii) ScienceDirect and Pro Quest, 23 February 2021; (iii) IEEE Xplore, 24 February 2021. In relation to the exploration period, all the papers published after 2010 were considered, which roughly coincided with the emergence of the Industry 4.0 initiative. In Scopus and Web of Science, a time window was considered between 1 January 2011 and the consultation date. For queries in ScienceDirect and IEEE Xplore, the 2011–2021 period was set, with the only difference being due to the different query date. In contrast, Pro Quest the filtering option "Last 10 years" was chosen, which is offered after the advanced search without setting a period, and therefore covered the period from 24 February 2011 to 23 February 2021.

The two document types considered in the literature collection were basically journal articles and conference proceedings, albeit with the variations of each database. With Scopus, the scope of the search was limited by tags "article", "review", "conference paper" and "conference review". In Web of Science, the results were refined by selecting types "article", "review" and "proceedings paper". With ScienceDirect, the results were refined using types "research articles" and "review articles". In the Pro Quest query, "article", "literature review" and "conference proceeding" were selected. Finally, in the IEEE Xplore advanced search, the refinement options of "conferences" and "journals" were selected.

Regarding the refinement of searches for documents per subject area, in Scopus the search was limited to subject areas of "engineering", "computer science", "business, management and accounting", "decision sciences", and "multidisciplinary". In Web of Science, the search was refined by selecting papers from categories "management", "engineering manufacturing", "industrial engineering", "engineering multidisciplinary", "automation control systems", "computer science systems", "computer science theory methods", "computer science artificial intelligence", "computer science interdisciplinary applications", "computer science cybernetics", and "operation research management science". In

Table 1
Conceptual space 1 (scheduling ∩ DT ∩ ZDM) in supply chain 4.0. Source: Based on Serrano et al [2].

OM process	Industry 4.0 design principle	Technology category and enabling technology
Job scheduling	Technology Intelligence Virtualisation Decentralised decision making Real-time action ability	Software-based technical assistance: Algorithms Technical assistance in interface: DT Technical assistance in data management and decision making: Optimisation Associated with management models: ZDM

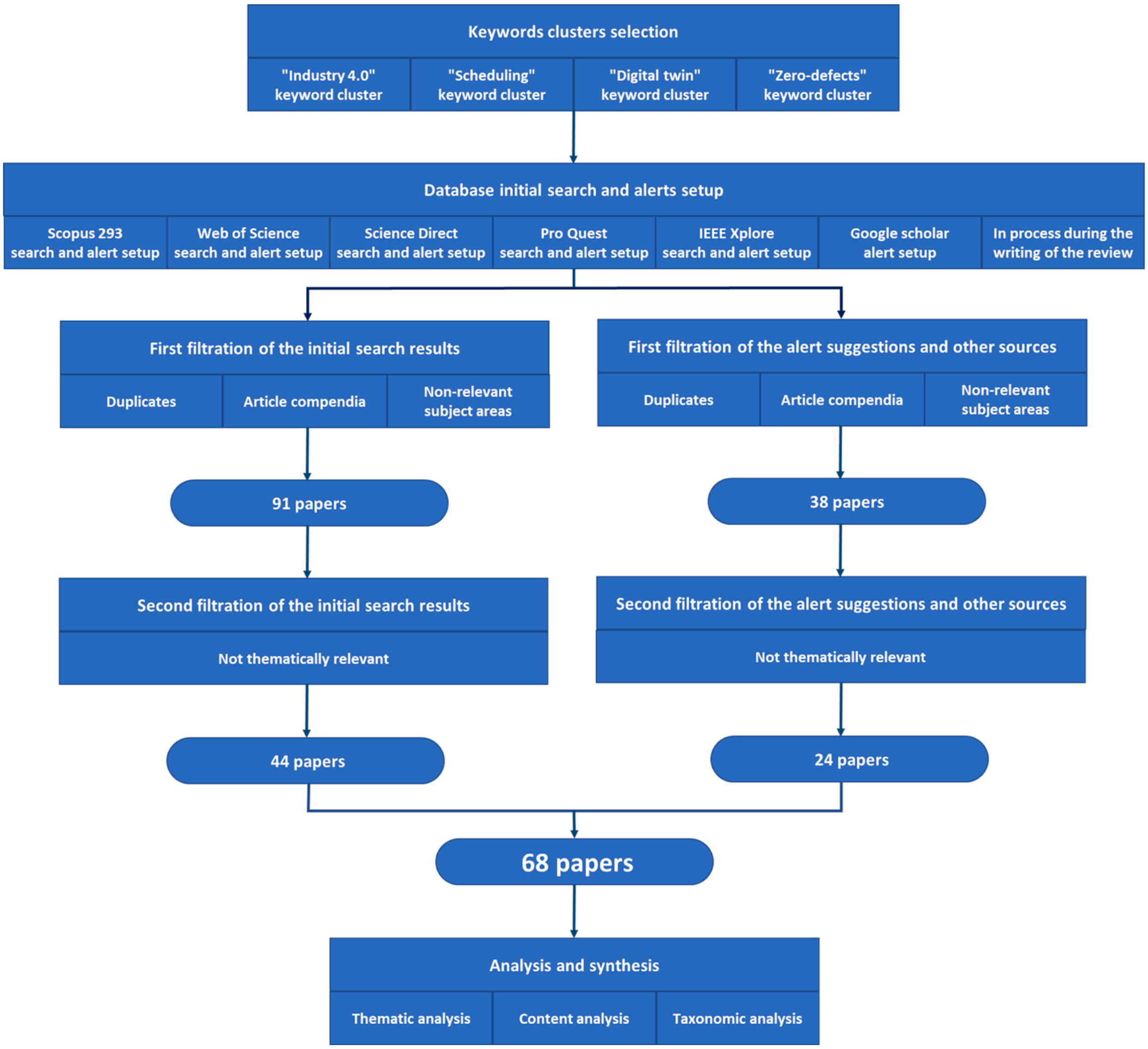

Fig. 2. Searches, collection, quality evaluation, analysis and synthesis methodology diagram.

ScienceDirect, "engineering", "decision sciences" and "computer science" were selected. For Pro Quest and IEEE Xplore, this type of filtering was not possible because the application did not support it.

Given the complexity and magnitude of the queries to be done and to simplify them, a decision was made to divide them up and formulate them individually for all four studied semantic fields (Industry 4.0, scheduling, the DT, zero-defects) to subsequently combine their results. In this way, it was also possible to obtain information from not only the integral combination "field 1" AND "field 2" AND "field 3" AND "field 4", but also from the partial combinations of semantic fields, i.e. those that relate only two or three fields and that, despite representing partially coinciding approaches, are relevant to the research: (i) "field 2" AND "field 3" AND "field 4" ("scheduling" AND "digital twin" AND "zero defects"), considering that employing an Industry 4.0 enabling technology like the DT is implicit in this. Therefore, it is a query that practically coincides with the integral combination: (ii) "field 1" AND "field 2" AND "field 3" ("Industry 4.0" AND "scheduling" AND "digital twin"); (iii) "field 2" AND "field 3" ("scheduling" AND "digital twin"); (iv) "field 1" AND "field 2" AND "field 4" ("Industry 4.0" AND "scheduling" AND "zero defects"); (v) "field 2" AND "field 4" ("scheduling" AND "zero defects"). The details of the search strings for each field are provided in Appendix C. In ScienceDirect, the inherent limitations of the search tool did not allow the combination of complete individual fields. So queries were made directly for each indicated combination, but by limiting the number of keywords to the eight Boolean connectors allowed by the application.

Apart from automatically removal duplicates during the sequential export to JabRef of the search results in each database, the obtained documents as a whole were subjected to a first manual filtering consisting of: (i) discarding duplicate documents not previously discarded by JabRef; (ii) discarding conference proceedings abstracts; (iii) discarding articles in which the used keywords had a different meaning to that of the indicated framework, e.g., "DNA sequencing" or "hospital scheduling"; (iv) documents whose research topic differed from that of the present research, and are listed in Appendix D. This gave 91 documents. In addition, periodic alerts were set in the five databases for: (i) the combined queries of "field 2" AND "field 3"; and (ii) the combined queries of "field 2" AND "field 4". In this way, and by using the same criteria to filter the results, 38 additional documents were collected until the time of writing, which gave 129 collected documents (Fig. 3). Subsequently, a filtering process was carried out by reading the content and performing a first analysis of the 129 preselected documents, which consisted of discarding: (i) those that represented academic contributions with no correspondence to the research framework; (ii) those documents that did not combine at least two of the semantic fields defined in the present research. After this filtering process, 68 documents were finally selected (Fig. 3), a list of which is provided in Table 2.

The oldest selected document dates from 2014, and the second oldest from 2016. It is worth mentioning that: (i) the scientific publications on the Industry 4.0 paradigm date back to 2013 [8]; (ii) 95% of the publications on DT technology emerged during the 3-year period from 2018

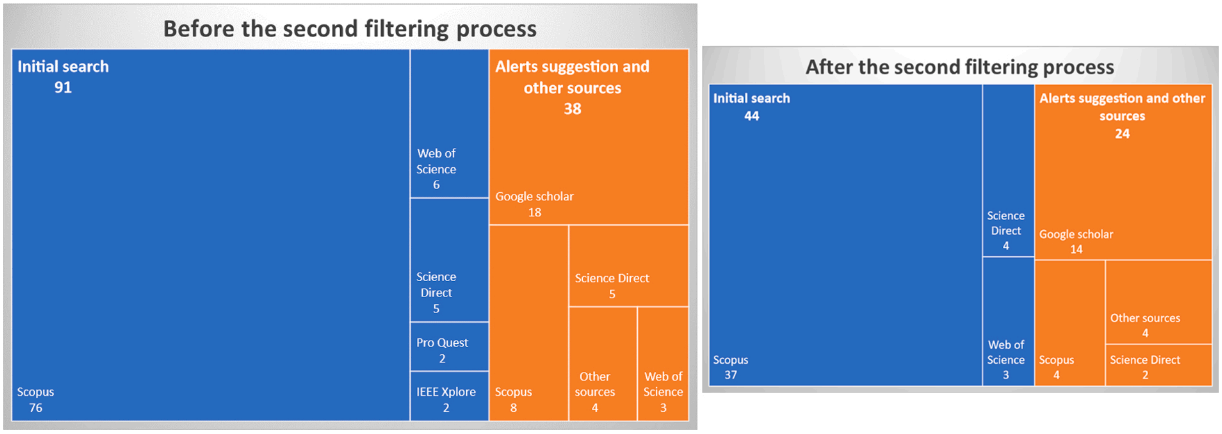

Fig. 3. Results of the search sources.

to 2020, and 5% were produced since its inception to 2017 [5]; and (iii) publications on ZDM rarely exceeded 10 per year until 2014, from which time they have significantly increased year after year [21]. Thus the knowledge fields making up the established framework attracted academic interest after the first half of the explored decade (Fig. 4). The papers dated 2020 account for more than 50 % of all the papers in the reviewed literature.

Of the collected 68 documents, 34 were scientific articles published in indexed journals and 34 were conference proceedings (Fig. 5). Of the articles published in indexed journals, the nine publications in the Journal of Manufacturing Systems stood out for accounting for more than 25 % of the selected articles, followed at a distance by IEEE Access, International Journal of Advanced Manufacturing Technology, International Journal of Computer Integrated Manufacturing and International Journal of Production Research, which with two publications each account for almost another 25 % of the articles published in indexed journals.

Regarding the number of authors and entities that have made a major contribution to the literature review, the following figures are worth mentioning: (i) 231 authors participated in the publication of the 68 papers; (ii) these authors are affiliated to 98 institutions or companies; (iii) these institutions or companies have 27 different nationalities; (iv) of all these institutions and companies, those belonging to the People's Republic of China (67 authors, 18 papers), the USA (35 authors, 10 papers) and the Swiss Confederation (17 authors, 10 papers) hosted 52 % of the authors and 47 % of the scientific output; (v) 85 institutions have participated in the publication of one single paper, 10 institutions in two papers, two institutions in three papers, and one institution, the École Polytechnique Fédérale de Lausanne, participated in up to eight papers; (vi) of the 231 authors, the vast majority participated in the publication of one or two papers, six participated in three each, and one first author from the École Polytechnique Fédérale de Lausanne, Foivos Psarommatis published up to seven papers. Figs. 6–8 and Table 3 detail this information.

3. Literature review

Here the selected articles are reviewed through a thematic, content and taxonomic analysis.

3.1. Thematic analysis

Based on the keywords of the reviewed research articles, a map of co-occurring topics was drawn up using the VOSviewer v.1.6.16 tool, where the concepts present in the literature review with more than five occurrences can be viewed, as well as their dimension and interrelations (Fig. 9).

The most widely used topic in the literature review was the DT, which heads a cluster (in red in Fig. 9) that groups together Industry 4.0, smart manufacturing, and cyber-physical systems (CPS). A second cluster (green) relates optimisation and simulation, in which the authors' use of genetic algorithms, scheduling algorithms and real-time control as keywords stands out. The third cluster (yellow) focuses on production control, production scheduling and decision making, and is associated with concepts like intelligent manufacturing and machine learning (ML). The fourth and last cluster (blue) is generated from the scheduling concept which, in the literature review, is associated mainly with artificial intelligence (AI), real-time systems, job-shop scheduling and ZDM.

The DT played a central role in the reviewed literature and presented a relatively large number of co-occurrences with practically all the other concepts (Fig. 10). This was not the case for ZDM, with a more limited number of co-occurrences, but with a connection to the other main framework concepts: Industry 4.0, scheduling and the DT. ZDM also presented several relations with the concepts AI, process control and real-time systems, which is interesting because of the value that this research gave to approaches oriented towards a real-time automatic and autonomous scheduling management.

3.2. Content analysis

The first step of the content and taxonomic analysis of the literature review, generally, consisted of:

- Identifying the research methodology, i.e. (C) conceptual, (D) descriptive, (E) empirical, (ECS) exploratory cross-sectional and (EL) exploratory longitudinal.
- Indicating the industrial sector in which research was conducted.
- Classifying the documents based on the conceptual schemes used within the framework of this research, i.e. (DT-ZDM-S) the DT-enabling ZDM-based scheduling, (DT-S) DT-enabling scheduling, (ZDM-S) ZDM-based scheduling and (O) other relevant schemes.
- Detailing the objective of the document.
- Detailing experiments or case studies, if any.
- Detailing the main contributions and limitations of the reviewed literature.

Appendix E presents the results of this first content analysis and the following figures are worth noting: (i) The majority of the research methodology is experimental, with 53 of 68 (78 %), which indicates that most of the reviewed documents contained research results in an advanced stage and were, therefore, empirically validated; (ii) exploratory research methodologies were not a trend (only 1), which could be related to the fact that DT technology continues to be a topic that is

Table 2
Selected literature.

	Author/s	Document title
1	Barni et al., 2020 [33]	Digital twin-based optimization of a manufacturing execution system to handle high degrees of customer specifications.
2	Borangiu et al., 2020a [34]	Smart manufacturing control with cloud-embedded digital twins.
3	Borangiu et al., 2020b [35]	Digital transformation of manufacturing. Industry of the future with cyber-physical production systems.
4	De Modesti et al., 2020 [36]	Production planning and scheduling using machine learning and data science processes.
5	Debevec and Herakovic, 2019 [37]	Digital twin of unique type of production for innovative training of production specialists.
6	Dobler et al., 2020 [38]	Supporting SMEs in the Lake Constance region in the implementation of cyber-physical systems: Framework and demonstrator.
7	Dreyfus and Kyritsis, 2018 [39]	A framework based on predictive maintenance, zero-defect manufacturing and scheduling under uncertainty tools, to optimize production capacities of high-end quality products.
8	Fang et al., 2019 [40]	Digital-twin-based job shop scheduling toward smart manufacturing.
9	Feldt et al., 2020 [41]	Digital twin: Revealing potentials of real-time autonomous decisions at a manufacturing company.
10	Ferrario et al., 2019 [42]	A multipurpose small-scale smart factory for educational and research activities.
11	Gaikwad et al., 2020 [43]	Toward the digital twin of additive manufacturing: Integrating thermal simulations, sensing, and analytics to detect process faults.
12	Gorodetsky et al., 2019 [44]	The framework for designing autonomous cyber-physical multi-agent systems for adaptive resource management.
13	Graessler and Poehler, 2020 [45]	Integration of a digital twin as human representation in a scheduling procedure of a cyber-physical production system.
14	Gramegna et al., 2020 [46]	Smart factory competitiveness based on real time monitoring and quality predictive model applied to multi-stages production lines.
15	Guo et al., 2020 [47]	Graduation Intelligent Manufacturing System (GiMS): an Industry 4.0 paradigm for production and operations management.
16	Hu et al., 2020a [48]	Petri-net-based dynamic scheduling of flexible manufacturing system via deep reinforcement learning with graph convolutional network.
17	Hu et al., 2020b [49]	Study on the application of digital twin technology in complex electronic equipment.
18	Jiang et al., 2020 [50]	How to model and implement connections between physical and virtual models for digital twin application.
19	Kang et al., 2019 [51]	Design and implementation of runtime verification framework for cyber-physical production systems.
20	Latif and Starly, 2020 [52]	A simulation algorithm of a digital twin for manual assembly process.
21	Li et al., 2020 [53]	Framework for manufacturing-tasks semantic modelling and manufacturing-resource recommendation for digital twin shopfloor.
22	Lin and Low, 2020 [54]	Concept design of a system architecture for a manufacturing cyber-physical digital twin system.
23	Lindström et al, 2020 [17]	An initial model for zero defect manufacturing.
24	Liu et al, 2020b [55]	Intelligent scheduling of a feature-process-machine tool super network based on digital twin workshop.
25	Ma et al., 2020 [56]	A digital twin-driven production management system for production workshop.
26	Maitreesorasuntee et al., 2020 [57]	A steel tube production planning and scheduling with product-dependent changeover time using digital twin.
27	Majdzik et al., 2021 [58]	(IMS2019) Integrated fault-tolerant control of assembly and automated guided vehicle-based transportation layers.
28	Moyne et al., 2020 [59]	A requirements-driven digital twin framework: Specification and opportunities.
29	Negri et al., 2019 [60]	A digital twin-based scheduling framework including equipment health index and genetic algorithms.
30	Negri et al., 2020 [61]	Field-synchronized digital twin framework for production scheduling with uncertainty.
31	Papacharalampopoulos et al., 2020 [62]	Towards a digital twin for manufacturing processes: Applicability on laser welding.
32	Paprocka et al., 2014 [63]	A production scheduling model with maintenance.
33	Park et al., 2019 [64]	Design and implementation of a digital twin application for a connected micro smart factory.
34	Pinon et al., 2018 [65]	Enabling the digital factory through the integration of data-driven and simulation models.
35	Preuveneers et al., 2018 [66]	Robust digital twin compositions for Industry 4.0 smart manufacturing systems.
36	Psarommatis and Kiritsis, 2018 [19]	A scheduling tool for achieving zero defect manufacturing (ZDM): A conceptual framework.
37	Psarommatis and Kiritsis, 2021 [67]	A hybrid decision support system for automating decision making in the event of defects in the zero defect manufacturing era.
38	Psarommatis et al., 2020a [68]	Improved heuristics algorithms for re-scheduling flexible job shops in the era of zero-defect manufacturing.
39	Psarommatis et al., 2020b [69]	A two-layer criteria evaluation approach for re-scheduling efficiently semi-automated assembly lines with high number of rush orders.
40	Psarommatis et al., 2020c [70]	A computational method for identifying the optimum buffer size in the era of zero-defect manufacturing.
41	Psarommatis et al., 2020d [71]	Identification of the critical reaction times for re-scheduling flexible job shops for different types of unexpected events.
42	Psarommatis, 2021 [72]	A generic methodology and a digital twin for zero defect manufacturing (ZDM) performance mapping towards design for ZDM.
43	Reichardt et al., 2021 [73]	Procedure model for the development and launch of intelligent assistance systems.
44	Saad et al., 2021 [74]	Smart production planning and control: Technology readiness assessment.
45	Santos et al., 2019 [75]	Industrial IoT integrated with simulation - A digital twin approach to support real-time decision making.
46	Schmidt et al., 2021 [76]	Novel robotic cell architecture for zero defect intelligent deburring.
47	Schuh and Blum, 2016 [77]	Design of a data structure for the order processing as a basis for data analytics methods.
48	Serrano et al., 2021a [5]	Digital twin enabling intelligent scheduling in ZDM environments: an overview.
49	Serrano et al., 2021b [16]	Smart Digital Twin for ZDM-based job-shop scheduling.
50	Serrano et al., 2021c [78]	Digital twin for a zero-defect operations planning in supply chain 4.0.
51	Shao and Kibira, 2018 [79]	Digital manufacturing: Requirements and challenges for implementing digital surrogates.
52	Smith and Nicksic, 2020 [80]	Improving factory scheduling with statistical analysis of automatically calculated throughput.
53	Tao and Zhang, 2017 [81]	

(continued on next page)

Table 2 (*continued*)

	Author/s	Document title
		Digital twin shopfloor: A new shop-floor paradigm towards smart manufacturing.
54	Vachálek et al., 2017 [82]	The digital twin of an industrial production line within the industry 4.0 concept.
55	Vijayan et al., 2020 [83]	Simulation-based decision framework for hybrid layout production systems under disruptions.
56	Villalonga et al., 2021 [84]	A decision-making framework for dynamic scheduling of cyber-physical production systems based on digital twins.
57	Wang and Wu, 2020 [85]	Model construction of planning and scheduling system based on digital twin.
58	Wang et al., 2020 [86]	Digital twin design for real-time monitoring- a case study of die cutting machine.
59	Xia et al., 2020 [13]	A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence.
60	Xu and Xie, 2021 [87]	Dynamic production scheduling of digital twin job-shop based on edge computing.
61	Yan et al., 2021 [88]	Research on flexible job shop scheduling under finite transportation conditions for digital twin workshop.
62	Yu et al., 2021 [89]	Job shop scheduling based on digital twin technology: A survey and an intelligent platform.
63	Zhang et al., 2019 [90]	Digital twin-driven cyber-physical production system towards smart shopfloor.
64	Zhang et al., 2020a [91]	Digital twin system design for dual-manipulator cooperation unit.
65	Zhang et al., 2020b [92]	Digital twin enhanced dynamic job-shop scheduling.
66	Zhang et al., 2021 [93]	Bi-level dynamic scheduling architecture based on service unit digital twin agents.
67	Zhou et al., 2020 [94]	Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing.
68	Zupan et al., 2018 [95]	Local search with discrete event simulation for the job shop scheduling problem.

addressed by more academics than companies, and is still far from being widely used in business practice. This situation also occurs, albeit on a smaller scale, with the ZDM management model; (iii) 90 % of the documents (61 documents) were cross-sectoral nature. This lack of sectoral specialisation in the research indicates, once again, that it is a scarcely addressed framework in the business sphere; (iv) as regards the conceptual frameworks with which the documents in the literature reviewed were aligned, six corresponded to the DT-ZDM-S framework, 37 to the DT-S partial framework, eight to the ZDM-S partial framework and 17 derive from these frameworks (framework O), but maintain some relevance for the framework. It should be noted that five of the DT-S and ZDM-S papers provided additional schemes that could also be classified as O-schemes, which were identified as DT-S/O and ZDM-S/O. It can be deduced that the authors' tendency to investigate solutions for scheduling issues based on DT technology was more pronounced than their study of scheduling in ZDM environments, but the latter tendency was not negligible as several authors opted for this research line. Contributions to the ZDM-DT-S framework were still only a few in terms of number of publications, but the five papers addressing involved three authors and were published in 2020 and 2021. These details indicate that this is a recent topic still to be explored. It is worth highlighting publication [96] which, despite not being included in the literature review for being a doctoral thesis, addresses the ZDM-DT-S approach. It focused on quality control and the four ZDM strategies (i.e. detection, prediction, prevention, repair), and the DT, which replicates the scheduling process and is used to: firstly investigate the possible ZDM alternatives available among these three strategies; to secondly conclude which quality control configuration was the most suitable.

Figs. 11–13 graphically represent the information related to this first step of the content analysis of the literature review.

Starting with the six variants of conceptual approaches, i.e. ZDM-DT-S, DT-S, DT-S/O, ZDM-S, ZDM-S/O and O, detected in the reviewed literature (Fig. 13), a content analysis was carried out for each main concept involved: (i) scheduling for the ZDM-DT-S, DT-S, DT-S/O, ZDM-S and ZDM-S/O schemes (Appendix F); (ii) the DT for the ZDM-DT-S, DT-S, DT-S/O schemes, plus those O schemes in which DT technology was considered (Appendix G); (iii) ZDM in the ZDM-DT-S, ZDM-S and ZDM-S/O schemes, plus those O schemes in which the ZDM management model was considered (Appendix H).

The analysis done of the scheduling process in each reviewed work, and set out in Appendix F, consisted of:

- Detailing the role played by the scheduling issue.
- Determining the product typology from the point of view of the number of catalogue items and component levels making up the final product; i.e. (SISL) single-item and single-level, (SIML) single-item and multilevel, (MISL), multi-item and multilevel, and (MIML) multi-item and multilevel.
- Classifying the workshop typology; i.e. (SM) single-machine, (PM) parallel-machine, (FS) flow-shop, (FFS) flexible flow-shop, (JS) job shop, (FJS) flexible job shop, (OS) open shop; (CPA) complex product assembly.
- Identifying the type of task delivery flow by distinguishing cases in which the sequence of tasks remained unchanged from t = 0 to the end, or with static flow (S), from cases in which new tasks could be introduced at any time and, thus, required rescheduling to be triggered, or with dynamic flow (D).

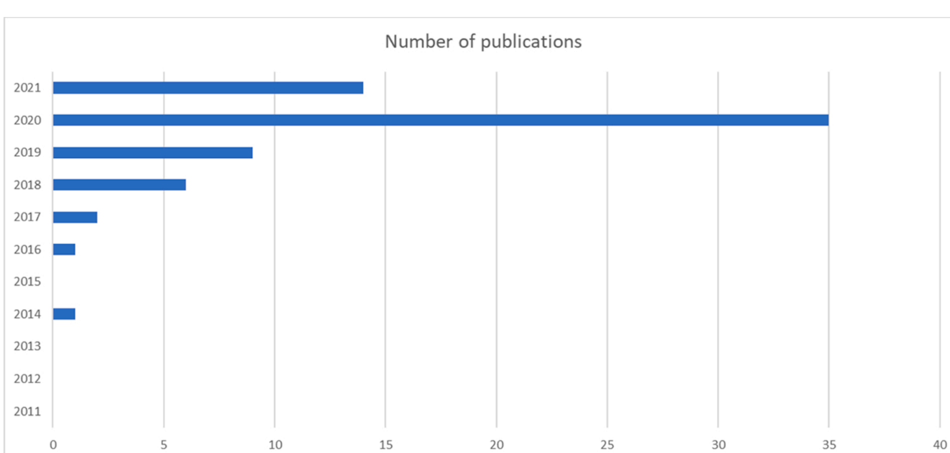

Fig. 4. Annual distribution of publications.

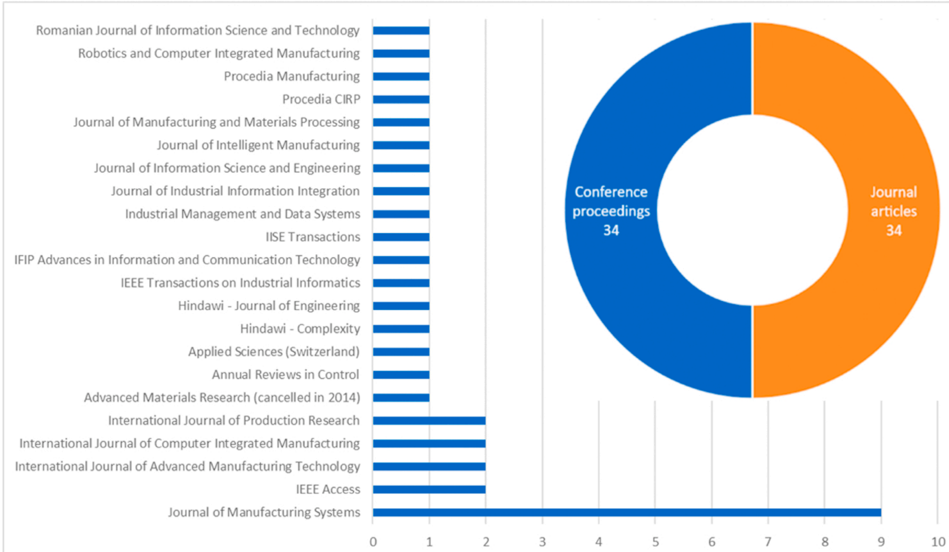

Fig. 5. Document types and articles per journal.

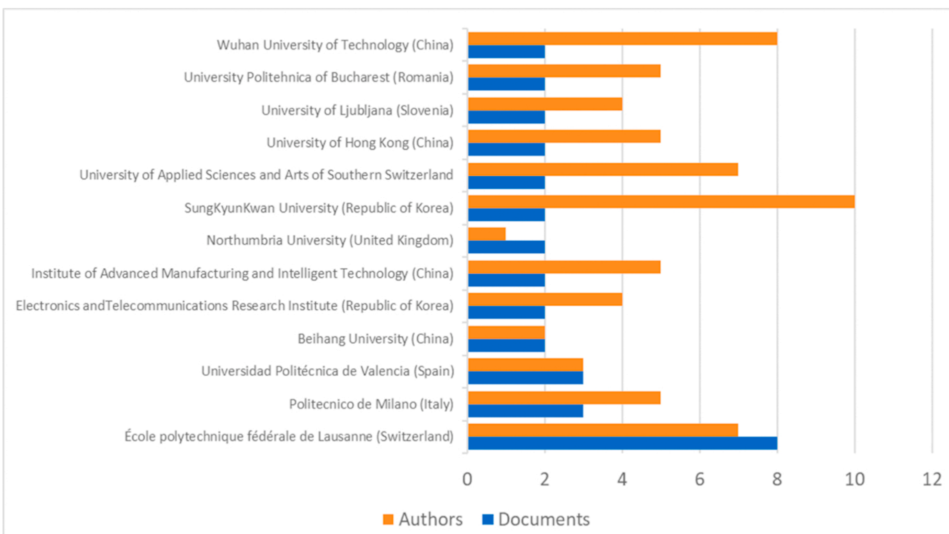

Fig. 6. Institutions with the most active role in the literature review.

- Indicating the approach given to the objective function depending on the considered optimisation variable; i.e. (T) time-based, (OP) operation-based, (C) cost-based, or (O) other to be specified.
- Identifying the modelling approach; i.e. (C) conceptual, (A) analytical, (H) heuristic, (S) simulation, and AI.
- Identifying the modelling software.
- Identifying the solution approach.
- Identifying the software solution.

From the analysis of the scheduling process, it should be noted that: (i) 51 of the 68 documents making up the reviewed literature considered this process; (ii) the most widely used product typology was MIML (18), followed by SIML (8), MISL (4) and SISL (1), which placed those problems with multilevel products ahead in research interest terms; (iii) the most researched workshop typology corresponded to job shop in its two variants, JS (10) and FJS (9), followed by the flow-shop typology, with its variants FS (7) and FFS (6) and, finally, by the CPA typology (1); (iv) research focused on a dynamic flow of task delivery (37), which denoted more interest in researching problems with stochastic demand, with only a few cases in which flow was static (4); (v) the most frequently objective function was time (22), followed by cost (13), operations (6) and, finally, by other (5), with which it can be deduced that in scheduling, and in the sample represented by the reviewed literature, the two most valued resources were time and money, and in that order; (vi) the commonest modelling approaches were heuristic (10) and simulation (9), followed by AI (7), analytical (7) and, at a longer distance, the conceptual approach (2); (vii) three quarters of the papers did not specify the software tools employed in modelling (39) and the solution (38). Of those that did, clarity was limited. There was a high diversity in the stated software tools and none stood out in number from the others. Fig. 14 represents the salient information about this second step of the literature review about the treatment of the scheduling process.

The analysis of the DT technology in the reviewed documents is set out in Appendix G and consists of the following:

- Detailing the role played by the DT.
- Specifying the physical and virtual entities in the DT.

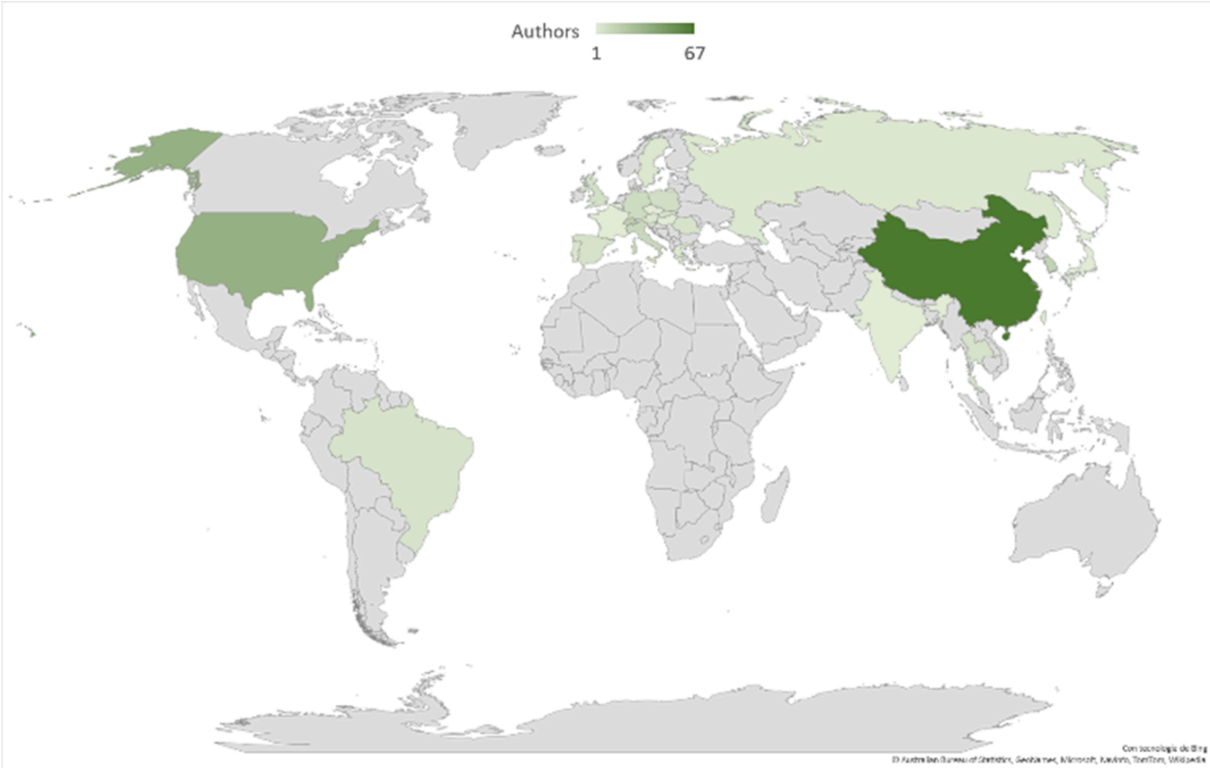

Fig. 7. Geographic distribution of affiliations.

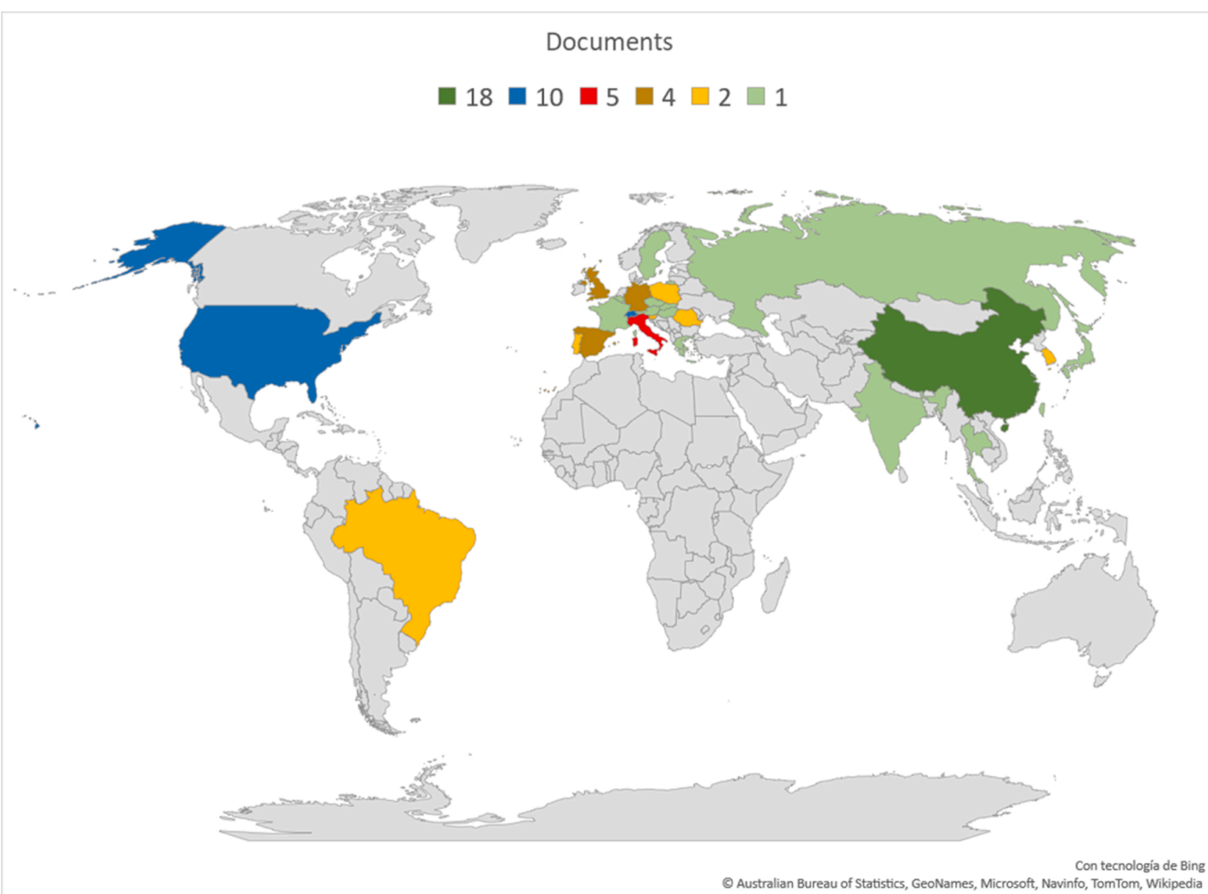

Fig. 8. Geographic distribution of published documents.

Table 3
The first authors with more publications in the literature review (P > 3).

Author	Author's institution	P
Foivos Psarommatis	École Polytechnique Fédérale de Lausanne (Switzerland)	7
Elisa Negri	Politecnico di Milano (Italy)	3
Theodor Borangiu	Centre of Research and Training in Robotics, Industrial Informatics and Material Engineering (CIMR), University Politehnica of Bucharest (Romania)	3
Julio C. Serrano-Ruiz	Research Centre on Production Management and Engineering (CIGIP), Universitat Politècnica de València (Spain)	3

- Identifying the basic purpose of the virtual process; i.e. (OP) optimisation, (S) simulation, (P) prediction, (A) analysis, (MPI) multiphysics integration, and (O) others.
- Determining the level of integration of twins into virtualisation; i.e. (DM) digital model: with no data exchange between physical and virtual entities; (DS) digital shadow, with an automated one-way data flow from the physical entity to the virtual one; the DT, with the data flow between the entities fully integrated in both directions.
- Identifying the main virtually replicated parameter sets; i.e. (S) state: usage, completeness, processes, etc., (L&F) location and shape: dimensions, size, tolerances, position, etc., (F) functionality: functional capability, machine parameters, control, energy, etc., (H) health: monitoring, analysis, management, etc., (T) time: timeliness, exposure, idle and working time, etc., (P&P) process and performance: scheduling parameters, models, defective, etc, (H) health: monitoring, analysis, management, etc., (T) time: timeliness, exposure, idle and working time, etc., (P&P) process and performance: scheduling parameters, models, defective parts or products, etc., (E) environment, (M) miscellany.
- Identifying the main enabling technologies that integrate DT design; i.e., (BD) big data, (DM) data mining, (S) sensing, (IoT) Internet of Things, (CC) cloud computing, (SM) simulation, ML, (AR) augmented reality, (AM) additive manufacturing, and (PHM) prognostic and health management.
- Identifying the implementation software.

From the analysis of DT technology, it is worth noting that: (i) 61 of the 68 papers in the literature reviewed address DT technology; (ii) the basic purpose of the virtual process was mainly multiple and with a tendency to group most designated basic purposes, where the most repeated combination was that integrating optimisation, simulation, prediction and analysis, which was present, on its own or combined with multiphysics integration or other purposes, in 26 out of the 61 papers that addressed DT technology; (iii) the most frequently addressed basic purpose was S (52), followed by A (46) and OP (45); the least frequent was P (33), with MPI (13) and O (13) being rare; (iv) regarding the data flow integration level, the general interest in the literature lay in the DT

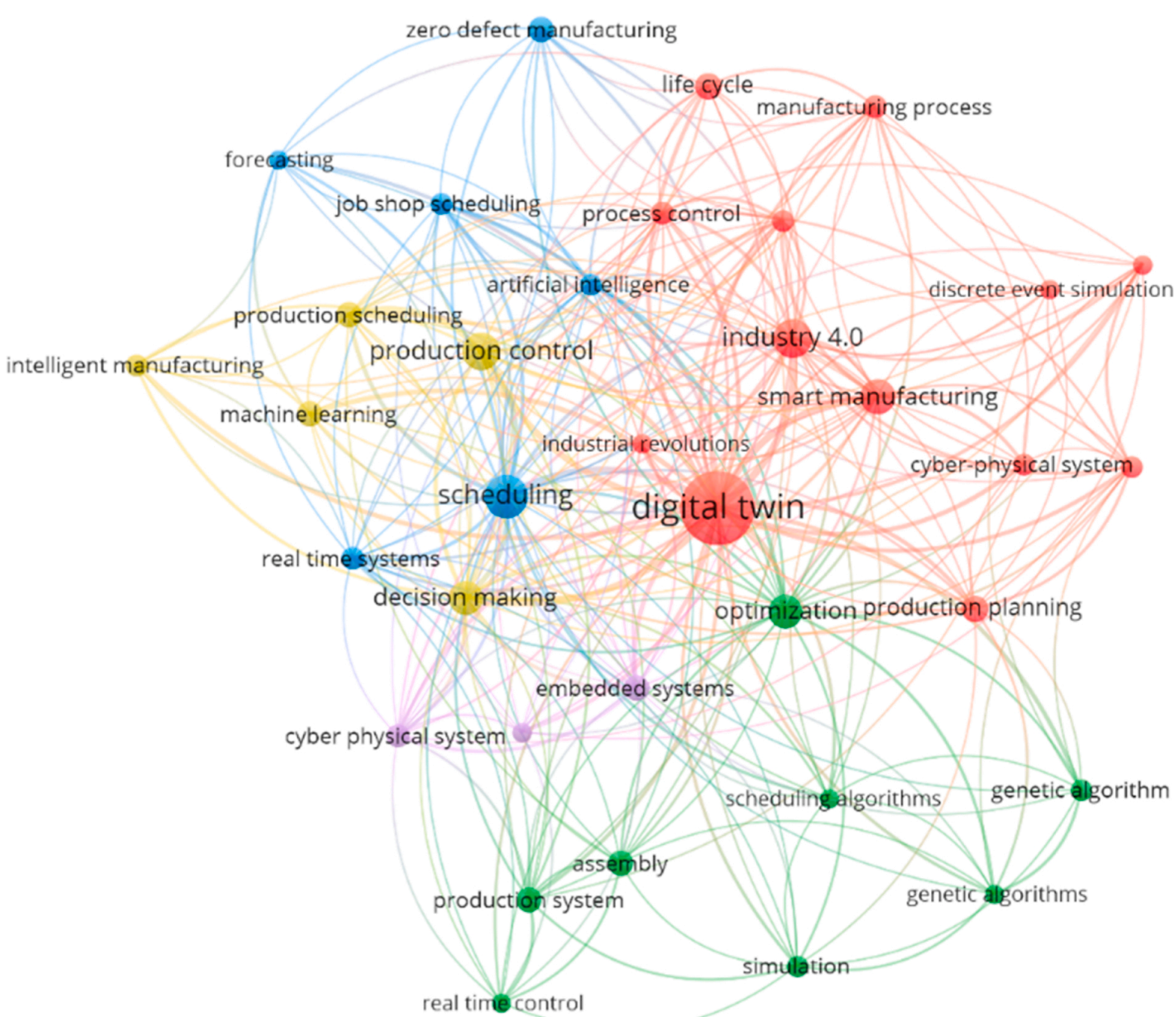

Fig. 9. Co-occurrence analysis map.

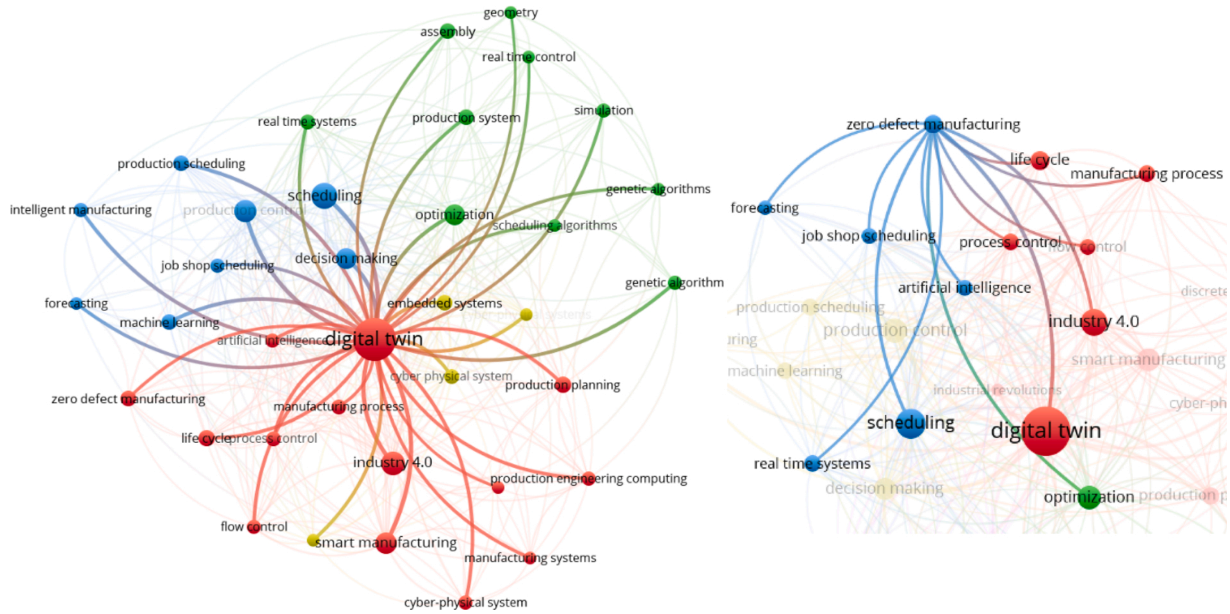

Fig. 10. Co-occurrence relations of the DT and the ZDM concepts in the literature review.

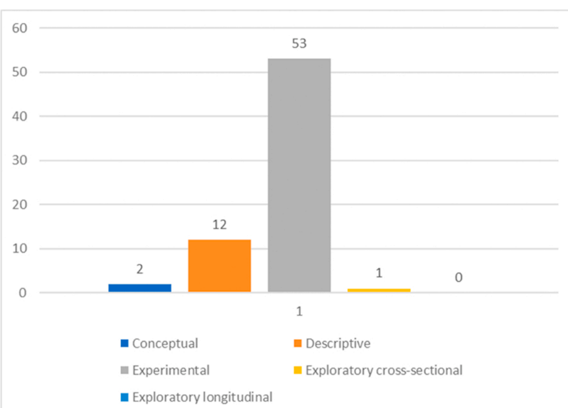

Fig. 11. Research methodologies.

(46), i.e. the technology enabling data flow between the physical entity and its virtual counterpart in both directions; DS (7), which involved data flow only from the physical entity to the virtual counterpart; and DM (2), with no data exchange, which were scarcely studied; (v) as the scheduling process was mostly addressed, the most frequent parameters replicated in the DT were those of the P&P (40), T (36) and S (34) groups; (vi) of the explored enabling technologies, the most frequently present were SM (51), S (31), IoT (24), BD (21), ML (20) and CC (18). Finally, with significantly fewer occurrences we found other more specific technologies like DM (12), PHM (12), AR (9) and, finally, AM (2); (vii) almost half the documents (32) did not specify the software tools employed to implement the DT. Of those that did, diversity is very high with none standing out. For more detailed aspects of the analysis, readers are referred to Appendix G. Fig. 15 represents salient information about this third step of the literature review analysis of treating DT technology.

Finally, the analysis of the treatment of the ZDM management model in the documents making up the literature reviewed is set out in Appendix H, and consists of the following [21]:

- Detailing the role of the ZDM management model.
- Specifying in relation to the treatment given to the defects, which ZDM strategies were considered: (D) detect, (R) repair, (PD) predict, and (PV) prevent.
- Determining the automation level of ZDM strategies: (M) manual, (S) semiautomatic and (A) automatic.
- Evaluating the way to integrate ZDM into manufacturing systems: (IL) in-line, (OL) off-line, (LAB) in a laboratory.
- Determining the stage of implementing ZDM strategies into the manufacturing cycle: (B) beginning of the manufacturing life, (M) middle of the manufacturing life or (E) end of the manufacturing life.

About the ZDM model in the reviewed literature, it is worth mentioning that: (i) 21 papers of the 68 selected address this issue, (ii) there was a tendency to combine the use of ZDM strategies in relation to the treatment given to defects because, of the 21 papers, seven combined

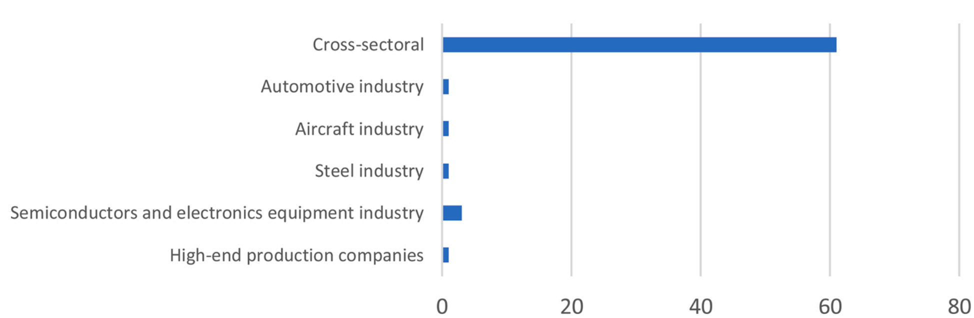

Fig. 12. Industrial sectors.

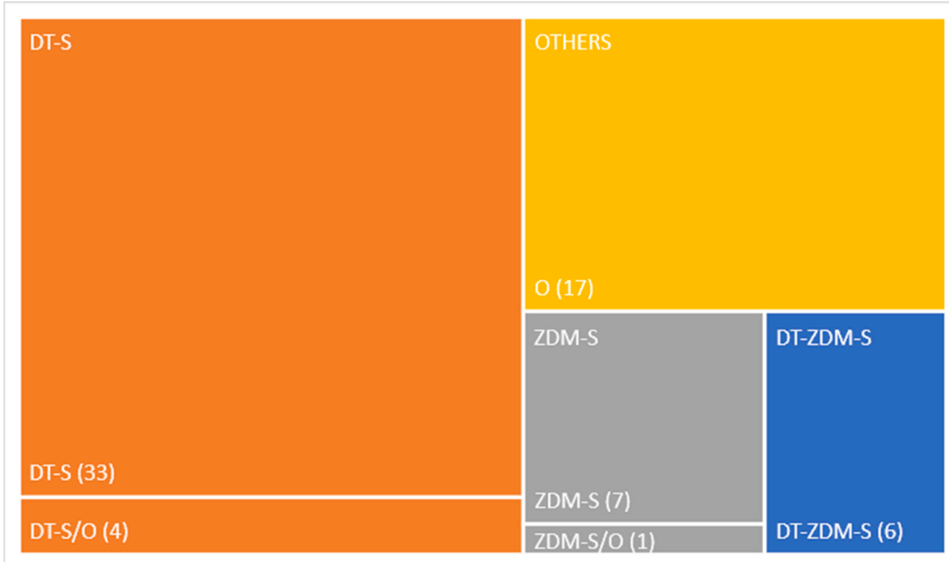

Fig. 13. Conceptual schemes.

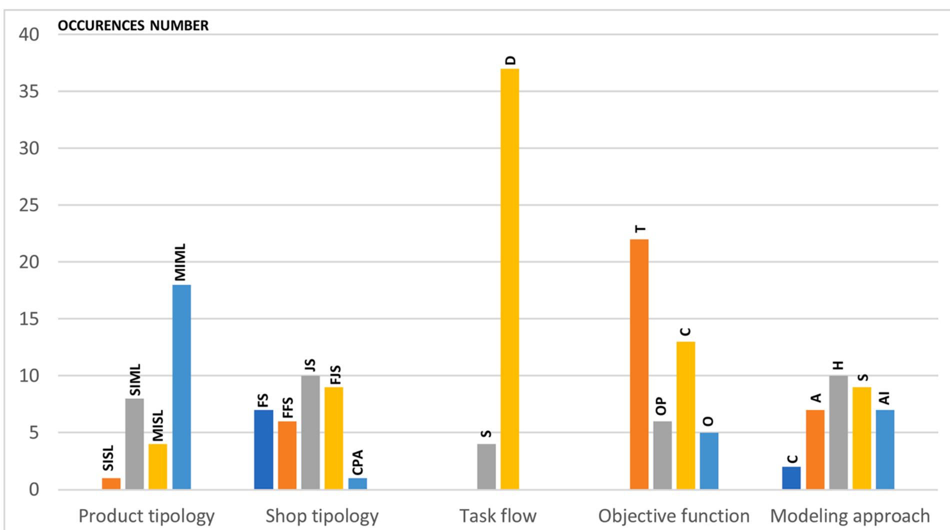

Fig. 14. Scheduling process.

all four strategies, and six others combined three which, together, accounted for 62 % of the total; (iii) strategies D (15) and PV (15) were the two most frequent ones, followed by PR (9) and R (8); (iv) the reviewed documents contained semi-automation approaches (8) or automation (7) to ZDM strategies; only one case identified a level of implementation comparable to M (1); (v) the integration of ZDM into manufacturing systems was IL (18) in practically all cases, but also with OL (1) and LAB (1); (vi) almost all the documents proposed implementing ZDM strategies from the beginning of the manufacturing cycle for B (17), M (1) and E (0). For more detailed aspects of the analysis, readers can refer to Appendix H. Fig. 16 depicts the salient information about this fourth step of the literature review analysis on the treatment of DT technology.

3.3. Taxonomic analysis

Indeed there are three main technological trends revealed by the analysis of the literature review based on the approach adopted to align with SMS: (i) approaches whose alignment with SMS lies in applying DT technology and/or the ZDM management model; (ii) approaches whose alignment with SMS is highlighted by the application of one of the main enabling digital technologies; (iii) approaches whose alignment stems from providing scheduling systems with capabilities inherent to SMS. Additionally, these three methodological trends were divided into 13 alignment axes with SMS, which show that the main implementations of the reviewed literature for scheduling assisted by DT technology and the ZDM management model are characterised by automatic and autonomous management, and synchronised in real time with the physical workshop processes.

3.3.1. Trend 1: applying the DT technology and/or the ZDM management model

The taxonomic analysis of the reviewed literature that aligns with SMS through the application of the DT and/or ZDM shows three different alignment axes with SMS: (i) fully coincident with the DT-ZDM-S scheme; (ii) with the support of scheduling systems based on DT technology; (iii) with the support of scheduling systems on the ZDM management model.

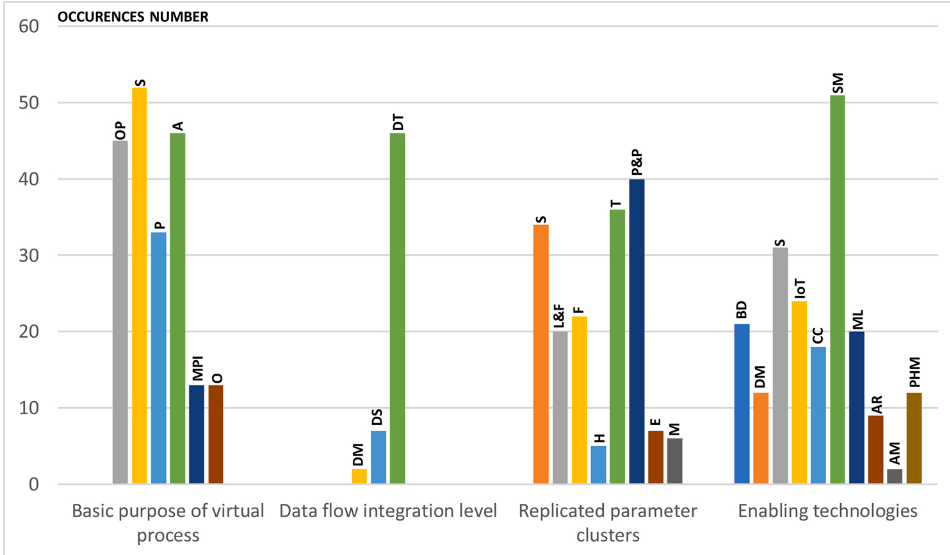

Fig. 15. DT technology.

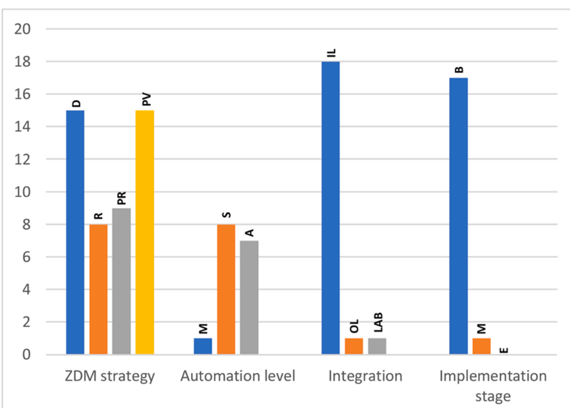

Fig. 16. ZDM management model.

3.3.1.1. SMS alignment axis 1.1: application of the DT and ZDM (DT-ZDM-S). Here we find the overview presented by Serrano et al. [5], which moves in the same direction as SMS and lays the foundations for the combined use of DT technology and the ZDM management model for better scheduling process performance. Other studies, like that by Lindström et al. [17], Borangiu et al. [35], Psarommatis [72] (the only paper with a single author of the 68 reviewed ones), Serrano et al. [16] and Serrano et al. [78], take a perspective aligned with the same approach. Lindström et al. [17] focus on proposing a formal model for ZDM and admit the possibility of improvement based on the support of DT technology. The model is empirically validated with a qualitative study in five Swedish companies, in which the scheduling process is limited to the role of being one of the model's seven strategy areas. The approach of Borangiu et al. [35] differs from the previous one. The importance of the roles played by DT technology and the ZDM management model are reversed here insofar as the zero-defect objective is also considered, but is merely taken as another element of the proposed model's overall cost function. On the contrary, this model is structured around a complex and detailed virtualisation system based on a multi-role DT that, on the one hand, enables easy scheduling and rescheduling in a flow-shop type workshop and, on the other hand, examines the management of the health of manufacturing resources and their predictive maintenance. In virtualisation, the physical production assets (resources, products, orders) and the physical system (control, monitoring, maintenance) are transformed into information about the past, present and future states, and on the behaviour of the workshop's resources, processes and results, i.e. not only the scheduling process is virtually replicated, but also a considerable part of the workshop's assets and organisational system. On the other hand, for Psarommatis [72] the weight of all three concepts making up the DT-ZDM-S scheme is more balanced, which approaches all three with similar depth and from a symbiotic perspective that configures a robust model that, in this case, completely focuses on the scheduling process. The studied shop typology is flow shop, and the fundamental research motivation is to optimise the rescheduling solutions in real time triggered by events like the arrival of urgent orders or the presence of defective products in the production flow. The model starts with an objective function that includes up to 17 different production variables to optimise time, operations and costs. As a novelty, the objective function also includes the optimisation of ZDM spectrum strategies in relation to the treatment of defects that are, thus, incorporated into the mathematical model. The role of the DT does not support the scheduling process itself, but the management of the applied ZDM. The DT is configured to predict the so-called utility value of the used set of ZDM control parameters. The process is carried out by combining simulation and heuristic tools with a custom-designed dynamic method. The research work performed by Serrano et al. [16] is limited to a descriptive and preliminary study of a framework for the semi-automatic or automatic management of the scheduling process in a job shop governed by the ZDM management model, and based on an AI approach. In this framework, the DT plays a prescriptive role for semi-automatic management, or a decision-maker role for automatic management. Serrano et al. [78] present another study, which is also descriptive, and addresses a scheme that also considers the assistance of the DT technology and the ZDM management model for the planning tasks of the OM area in the whole supply chain space.

3.3.1.2. SMS alignment axis 1.2: DT application. In the research by Dobler et al. [38], the DT mission is to assist decision making on the job-shop scheduling problem for its solution it in real time with local intelligence based on AI, in order to compare in a business demonstrator, as evaluator and validator, the solution obtained by this methodology to that obtained by other commoner procedures, all without a DT, and based on simulation and heuristics. The research of Fang et al. [40] presents a job-shop scheduling method based on the DT and validated with a typical instance of five machines and five jobs, which satisfies the shop floor's production needs in real time, robustness, accuracy, etc.

Another similar approach, in which the subject of replication is not only scheduling, but also the production line and the resources integrated on it, is that of Lin and Low [54], in which the DT allows visibility of the scheduling process, easier monitoring, higher accuracy and decision support. Vijayan et al. [83] place a physical entity to replicate the scheduling process, in this case a flexible flow shop, to obtain real-time visual feedback of processes to perceive variations in the different factors that affect process performance. The dynamic DT job-shop scheduling model by Xu and Xie [87] also responds to this basic approach by basing the DT on edge computing, as does the study by Zupan et al. [95] based on the simulation of "what-if" scenarios. Debevec and Herakovic's [37] perspective on the DT's role differs from previous approaches: in the presented model, which is called "unique type of production", the DT is a tool that trains production specialists and indicates which is the production system response to changes in its parameter settings. The DT is a learning tool that moves away from viewing the DT as a mere scheduling assistant. With a different approach, the work of Hu et al. [49] takes the DT as a bridge between the real world and the information world that allows product quality tracing in all product life cycle phases, from the product design and process planning phases to assembly and distribution, including health management and, of course, scheduling.

3.3.1.3. SMS alignment axis 1.3: ZDM application. Psarommatis et al. [19] adopt this approach in a particular way in their dynamic job-shop scheduling by means of a preventive approach, which mitigates disturbances to the scheduling process, based on an *ad hoc* designed ZDM algorithm. Psarommatis and Kiritsis [67] present a hybrid decision support system to automate the decision-making and planning processes in the event of detecting defects by analysing defect characteristics, suggesting feasible repair processes, creating several alternative scenarios to mitigate defects and evaluate optimal alternatives. In Psarommatis et al. [69], a similar strategy based on a dynamic scheduling tool is adopted, which acts by triggering rescheduling in real time whenever urgent orders are received or defective products are detected on the shop floor. Psarommatis et al. [71] identify the critical reaction time for unexpected events, which can disrupt the normal operation of manufacturing systems, in order to keep productivity and costs within acceptable ranges. In line with these, the research by Dreyfus and Kyritsis [39] also adopts the same vision of predictive, reactive and autonomous scheduling. Schmidt et al. [76] propose a different system that focuses efforts to achieve a zero-defect objective on an advanced quality control system that monitors and controls the machining of product parts online so that, if a defect is detected, it can generate a new schedule that also integrates repair operations. Although not strictly speaking with a ZDM strategy, it is worth mentioning the particular case of Barni et al. [33], who combine lean production as a management model with a production line DT to mitigate performance losses in scheduling due to the wide variability of cycle times in the job shop with a compensation method.

3.3.2. Trend 2: applying enabling digital technologies

It is worth mentioning here the relevant literature papers in which alignment with SMS arises from assistance provided by the most frequently used digital enabling technologies: (i) simulation; (ii) sensing; (iii) IoT; (iv) big data; (v) ML; (vi) cloud computing.

3.3.2.1. SMS alignment axis 2.1: using simulation technology. Dobler et al. [38] use a DT-based framework consisting of the Anylogic simulation software tool to generate a simulation model called "intelligent simulation" by providing it with intelligent capabilities through "as-is" simulations or ML-based simulations to allocate jobs in real time. The DT-based model by Ma et al. [56], called the DT-driven production management system and developed with the Dassault Delmia software tool, aims to manage the production life cycle and allows production processes to be simulated and optimised by achieving real-time synchronisation and high-fidelity virtualisation. In Negri et al. [60], a production system scheduling framework within a DT simulator stands out. It is based on genetic algorithms and field-synchronised simulation to provide scheduling alternatives with an innovative nuance from employing a equipment health index. The development framework centres on the Simulink tool in the MATLAB environment. Finally, the research of Shao and Kibira [79] is noteworthy as modelling and simulation are carried out with a "digital surrogate", which is advocated as an alternative to the DT, but is roughly similar to it. The digital surrogate is proposed here to represent, connect part or all of the manufacturing systems or processes, such as production planning, basis on Standard ISO 15531, which compiles standards on industrial automation systems and integration.

3.3.2.2. SMS alignment axis 2.2: using sensorisation technology. The research by Xia et al. [13] combines job scheduling with path planning in a flow-shop manufacturing cell composed of several robots where it is necessary to include proximity sensors that, in this case, are simulated. Something similar occurs with the research by Gaikwad et al. [43], but not due to the presence of robots, but because it is a hybrid production scheme with additive manufacturing that foresees multiple *in situ* sensors for data collection to predict different types of flaws, such as cracking and deformation. Other examples of similar uses are those by Vachálek et al. [82] or Zhou et al. [94]. On the contrary, for Negri et al. [61] the main mission of sensors is to optimise scheduling process by replacing "traditional" statistical distributions to describe stochastic behaviour with statistical models based on data obtained from both historic and real-time sensor data. A different approach is that by Preuveneers et al. [66], who assume that a DT is an imperfect system that can trigger cascading failures in the manufacturing flow, which must be avoided by including safeguards to ensure a fault-free manufacturing workflow. This model pursues DT-assisted predictive quality control with a very unique zero DT failures strategy to be considered, in which sensorisation plays a significant role.

3.3.2.3. SMS alignment axis 2.3: using IoT technology. Borangiu et al. [34] base their research on a model studied as a holonic perspective of a factory of the future based on the IIoT and cyber-physical production systems in a cloud computing framework to facilitate intelligent decision making in real time. The study by Guo et al. [47] presents a gradient intelligent manufacturing system that operates with job, setup, operation and logistics tickets to organise and control production operations with the help of IIoT and DT technologies, with the mission to achieve real-time information exchange, visibility and traceability for global coordination between multilevel segments throughout the manufacturing process. An integrated system assisted by the IIoT and simulation to support decision making in the industrial sector is the proposal by Santos et al. [75] to connect the physical and virtual shop floor by automatically inserting real-time data into simulation models with an IoT platform, and in such a way that it avoids using human resources in that task. Another unique approach is provided by Wang et al. [86], which addresses the research of workshops composed of isolated conventional machines, where the IoT is null or limited. It is a DT framework for real-time machine monitoring that overcomes lack of the IoT limitation and pushes relatively old manufacturing environments towards smart manufacturing. It is based on a solution supported by the J-Mobile, Modbus Simulation and SQL4 Automation tools.

3.3.2.4. SMS alignment axis 2.4: using big data technology. The study by De Modesti et al. [36] introduces the ProKnow-C methodology to identify and enable a deeper understanding of the gaps not covered by the state of the art and the production scheduling opportunities that are opening up using data science techniques, such as big data. Research like that of Borangiu et al. [34] is also noteworthy, which introduces the study of big data processing and analysis into the production environment to acquire knowledge from plant processes and to make intelligent decisions through ML, or that of Yu et al. [89] which uses a platform based on DT technology combined with prediction and the diagnosis of multisource dynamic interferences by big data analysis technology, key for error prediction and diagnosis.

3.3.2.5. SMS alignment axis 2.5: using ML technology. Xia et al. [13] base their robot manufacturing cell model on an intelligent scheduler with DRL to train the robots in the cell to adaptively and collaboratively perform stacking tasks. Dobler et al. [38] introduce a hybrid simulation method based on the DT and ML into their demonstrator to compare it to other traditional methods and improve the variability of the results in relation to other conventional methods. Hu et al. [48] propose a deep Q network algorithm with a Petri-net convolution network with which, compared to heuristic methods, to improve solutions of dynamic scheduling problems in terms of manufacturing throughput, computational efficiency and adaptivity. Reichardt et al. [73] propose a standardised procedural model for the practical application of ML-supported assistance systems for order sequencing and machine allocation in a flexible flow shop, which is assisted by a DT to generate a simulation and training environment in which scheduling programmes can be identified, tested and evaluated. Serrano et al. [16] propose a preliminary conceptual framework for scheduling semi-automatic production orders in a job shop with a ZDM strategy by implementing an intelligent DT with a prescriber role based on DRL. Hybrid methods combining simulation and heuristics with ML also appear, such as that by Xu et al. [87] which, in a DT context, addresses the flexible job-shop scheduling problem by a multischeduling knowledge model algorithm based on a combination of a decision tree algorithm, a random forest algorithm and a neural network with a radial basis function and a multi-objective evaluation.

3.3.2.6. SMS alignment axis 2.6: using cloud computing technology. Some examples are the research works by Borangiu et al. [34], Guo et al. [47], Park et al. [64], Serrano et al. [16] or Yu et al. [89]. Ma et al. [56] with their DT-driven production management system for production life cycle management and Zhang et al. [93] with their bilevel distributed dynamic scheduling architecture also consider including cloud computing as a future research line.

3.3.3. Trend 3: providing scheduling with SMS capabilities

Finally, the contributions of orient scheduling systems towards achieving certain capabilities inherent to SMS are particularly relevant, such as capacitating for: (i) real-time action; (ii) automation; (iii) autonomy; and (iv) mitigation and/or avoidance of disturbances and disruptions.

3.3.3.1. SMS alignment axis 3.1: using real-time scheduling. The approach reported by Feldt et al. [41] aims to solve the problem of the centralised rescheduling of orders and changes in production capacities to enable real-time reactions. The DT data-drive model presented by Gramegna et al. [46] examines the real-time reaction from process monitoring with advanced data mining and a cognitive approach to predict quality and efficiency. The DT-driven production management system for production life cycle management proposed by Ma et al. [56] is synchronised in real time with production processes. The dynamic production scheduling framework proposed by Negri et al. [61] synchronises with the field in real time. The second above-mentioned approach, which is applied in the presented demonstrator by Dobler et al. [38], focuses real-time action capability on raising situational awareness of the process by monitoring it with a DT system. For Guo et al. [47], it is the information exchange that has to be achieved in real time in their graduation intelligent manufacturing system. In the architecture for a manufacturing cyber-physical DT system proposed by Lin and Low [54], it is not the exchange, but the collection of, process and physical machine data that are achieved in real time. Santos et al. [75] deal with something similar, the insertion of real-time data into the system's simulation models. Finally, as with the case of Vijayan et al. [83], the DT-based simulation of the multiproduct hybrid layout production system provides decision-making data in real time.

3.3.3.2. SMS alignment axis 3.2: using automatic scheduling. The meaning given by Dreyfus and Kyritsis [39] to the automation concept is peculiar as the carried out research proposes the automation of the scheduling process so that mechanically, and based on an *ad hoc* designed algorithm, the system decides when to maintain, when to adjust the machine and when to produce an order to manage production in uncertain environments with a higher probability of success. Psarommatis and Kiritsis [67] study the automation of the decision-making process related to online defect detection and repair to integrate it into planning processes. Psarommatis et al. [71] situate their dynamic scheduling tool on a semi-automated assembly line. The real-time requirements of this environment make them consider the automation of rescheduling. In the research by Santos et al. [75], only data insertion into the simulation models of their decision support system is automated. For Schmidt et al. [76], adopting quality control tasks with a proactive approach into their zero-defect robotic deburring method confers the proposed architecture a flexible automation intelligent manufacturing approach.

3.3.3.3. SMS alignment axis 3.3: using autonomous scheduling. The line between automation and autonomy in the production knowledge field is a fine one. An automatic system reacts mechanically according to fixed rules to changes in its environment, but a change in the environment which is not programmed can render it ineffective. Conversely, a system's ability to act autonomously orients it towards adaptive behaviour and decentralised decision-making management to, thus, restrict the size of problems and to facilitate their convenient solution to essentially eliminate the need for other systems to intervene, or even the human operator. One example of this is the work of Gorodetsky et al. [44], in which the goal is for the cyber-physical multi-agent system presented for adaptive resource management purposes can also autonomously operate. The DT-driven production management system for production's life cycle management proposed by the research of Ma et al. [56] is able to make self-adjustments during the production process from product design to manufacturing, which denotes its capability as an autonomous entity. The framework for the DT technology presented in the study by Moyne et al. [59] addresses requirement aspects, such as reusability, interoperability, interchangeability, maintainability, extensibility and, also, autonomy. The research by Villalonga et al. [84] proposes aggregating several DTs by representing different physical assets that are configured with autonomous decision making, together with a global DT with which the optimisation of production scheduling is performed whenever necessary. Feldt et al. [41] understand the scheduling process itself as a function to be optimised by transforming it into an autonomous reactive one. Serrano et al. [16] also adopt this approach by taking the perceptual and cognitive capabilities arising from the DRL agent proposed in their preliminary framework as a basis.

3.3.3.4. SMS alignment axis 3.4: using disturbance- and disruption-resistant scheduling. The approach by Paprocka et al. [63] to this issue is to generate a predictive scheduling that can absorb disturbances and disruptions without affecting manufacturing as much as possible. On a predictive basis, Yu et al. [89] propose an intelligent scheduling platform in which incoming dynamic disturbances are predicted and diagnosed in time to develop corresponding compensatory strategies, which distinguishes this method from the previous one. A different work from former ones is that of Pinon et al. [65], whose research goal is to analyse and assess the impact of disruptions on the production system, and to identify strategies that best recovery from these disruptions. In

Psarommatis et al. [69], disruptions come from real-time events like rush orders and faulty products. The research objective of Psarommatis et al. [71] is to identify the critical reaction time for unexpected events that may disrupt the normal operation of manufacturing systems to keep productivity and costs within acceptable ranges. Vijayan et al. [83] propose a decision framework for a multiproduct hybrid design production system subject to random interruptions in real time using simulation models to generate schedules for parts, which also arrive randomly from certain predetermined schedules.

These SMS methodological trends and alignment axes make up a classification map whose core is formed by research that takes a completely coincident approach with the DT-ZDM-S scheme. From it, each trend and axis presents several complementary approaches that can shed some light during the digital transformation process of scheduling systems based on the SMS concept. Fig. 17 summarises the revised literature about the SMS concept and its application.

4. Discussion

The digitisation of production planning processes, as a strategy to successfully address inherent supply chain complexity, is a young and evolving topic, but a crucially important one for the OM area. Planning processes drive and guide procurement, manufacturing, and logistics systems towards their objectives. Yet in the event of any unforeseen event, acting with little or no foresight on the one hand, and being slow on the other, leads involved systems to react with inertia which, in economic terms, translates into unwanted costs. A good level of flexibility in supply chain structures can place it in a more favourable position to assimilate variations when planning objectives are altered by potentially disruptive disturbances, and the areas on which the design and management of these structures depend shoulder responsibility to make them more flexible. The direct responsibility for optimally adjusting both momentum and direction to procurement, manufacturing and logistics systems lies in the OM area. Anticipating changes and the speed with which they are introduced are important factors because they steer systems in such a way that inertial reactions and their potential negative impact are minimised. During the scheduling process, and given its short-term nature, the anticipation and speed of reaction are more important than ever. The digital transformation of scheduling must be oriented towards positions of improvement in both factors (anticipation and speed of reaction), and SMS stands out as a path with a very high potential to move towards these positions by being an approach that focuses on automating the scheduling process to provide it with the capacity to act in real time when faced with possible disruptions and to, thus, facilitate its autonomy. This potential is revealed by the growing interest shown by the scientific community in the last decade, that has been exponential since 2016 and accumulates more than half all the literature reviewed in 2020. The reasons behind this could be the maturity that DT technology is acquiring academically, its diverse application potential, and the renewed interest of both academia and industry in the ZDM management model.

The reviewed literature provides a wide spectrum of possibilities of approaching SMS. Obviously, it is not only important to consider its benefits, but it is also relevant to be aware of the limitations that it poses. The main findings and research gaps of each SMS methodological trend and alignment axis in this regard are discussed below.

4.1. Trend 1: applying the DT technology and/or the ZDM management model

The discussion of the first SMS methodological trend, by applying DT technology and/or the ZDM management model, is firsly addressed. Thus about the first SMS alignment axis of this first trend, which includes the core of scientific articles formed by the research that has a completely coincident approach with the DT-ZDM-S scheme, we find the overview presented by Serrano et al. [5] that warns about the importance of real-time action capability and flexibility in smart manufacturing contexts, and the convenience of eliminating scheduling failures to avoid disrupting procurement, manufacturing, and logistics operations. Real-time action capability, flexibility and disruption avoidance are three pivots around which SMS rotates. Hence this approach is relevant as it lays the foundations for the combined use of DT technology and the ZDM management model for better scheduling process performance in the same direction as SMS. The limitation of this

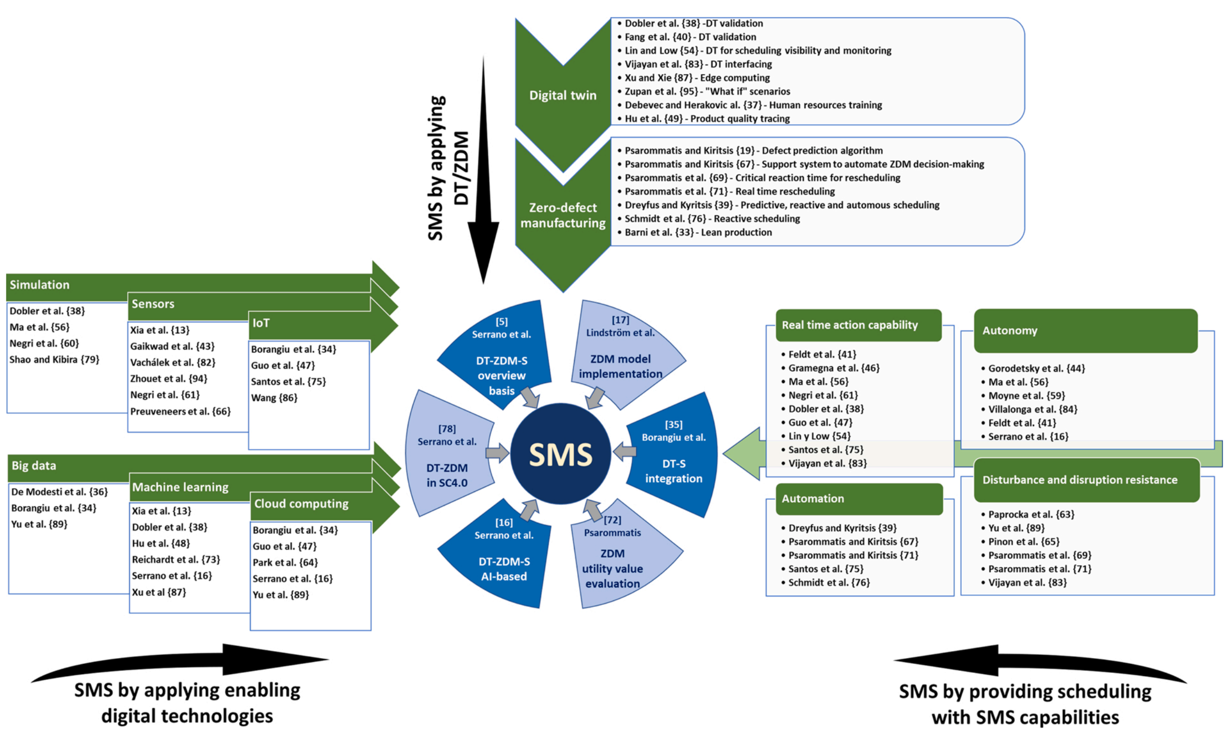

Fig. 17. SMS classification map.

overview arises from the restricted sample of scientific articles that it takes into account, which shows a partial scope in the literature that deals with the subject. One important aspect about rescheduling capability, which is critical for SMS, and its relation to flexibility, is contemplated in the initial ZDM model provided by Lindström et al. [17]. It considers that the ability to trigger scheduling optimally depends, to a large extent, on the redundancy of resources, but also on the flexibility of a system among other possibilities, and this ability is improved with the support of DT technology, a statement that aligna with SMS. The fact that the authors relate the DT to flexibility, but do not go into detail with its implementation, implies a limitation; they merely mention the support that technologies like ML, big data, IoT or cloud computing can confer the model. Another integral approach, that of Borangiu et al. [35], presents a model capable of generating scheduling and triggering rescheduling whenever necessary. Besides it focuses on operations control in a smart manufacturing environment that is not restricted to scheduling systems. This circumstance provides useful information to be considered in those projects that need to integrate a system with a DT-ZDM-S scheme into a larger set; for example, a system that integrates the processes of tactical and strategical decision levels, e. g. aggregated production planning, the master production plan or material resource planning. It is also a valuable example for the projects into which the DT-ZDM-S scheme is integrated with other supply chain management areas like quality control, maintenance, etc. One more sample of the variety of possible approaches is provided by Psarommatis [72] with a scheduling model that works with an objective function and includes up to 17 different production variables to optimise time, operations and costs. As a novelty, the objective function also includes the optimisation of ZDM spectrum strategies in relation to the treatment of defects that are, thus, incorporated into the mathematical model. Here the role of the DT does not assist the scheduling process itself, but the management of the applied ZDM. The DT is configured to predict the so-called utility value of the used set of ZDM control parameters without having to run the scheduling tool so that a specific ZDM strategy can be evaluated in a given manufacturing stage without interacting with the physical scheduling process without, therefore, altering the production rate, which makes it a relevant proposal for SMS. It might appear to be a substitute approach for that provided by Lindström et al. [17] to apply the ZDM management model, but a deeper analysis shows its complementarity: (i) on the one hand, for Psarommatis [72], the management scope of the ZDM model is basically limited to product defects (from which the need for quality control derives) and production processes (from which the need for productive maintenance stems). The the approach of Lindström et al. [17], which is broader in this sense, extends the management scope to five other areas, i.e. process parameter monitoring, collaborative production, data management, production reconfiguration and reorganisation, and production rescheduling; (ii) on the other hand, the level of depth at which the definition of the DT and the dynamic scheduling tool is addressed in the research of Psarommatis [72] exceeds that offered by Lindström et al. [17]. Therefore, both approaches present benefits and limitations that complement one another. The research by Serrano et al. [16] pursues alignment with SMS in another way: the scheduling framework proposed by the authors places this responsibility on the smart attribute, which is based on a modelling approach based on AI, specifically on a DRL algorithm which, in addition to a particular perceptual and cognitive perspective, confers the DT the capacity to act in real time. Additionally, the characteristics of the environment are configured from the particular smart DT perspective, arranged as a series of interrelated layers at which each layer delimits a defined physical or virtual subenvironment so that the smart DT merges all these subsets by making them converge in the human agent's interface as a single cohesioned environment. This structure layered in two physical and virtual environments represents a possible DT configuration for the SMS scheme. Finally, in the group of scientific articles that focus on coinciding with the DT-ZDM-S scheme, Serrano et al. [78] pose a planning framework that is not restricted to the scheduling process and the shop floor space, but addresses all the planning processes in the OM area in the whole supply chain space, which results in a very large problem that is difficult to address. It is really a matter of configuring a common superior framework to accommodate individual problems of a more limited dimension, like that addressed by Serrano et al. [16] for the job shop scheduling problem, but always characterised by their orientation towards DT-ZDM schemes so that they form an integrated whole when the models of the other planning processes defining OM, and of all the actors involved in the supply chain, are incorporated into successive contributions in this common framework,. The approach is challenging, and its success will depend on whether or not individual models are incorporated into the common framework in the future, which is currently a limitation. In the described framework, the supply chain is subject to a digital transformation process based on the DT-ZDM scheme, which favours the attribution of the qualities "fast in response" and "flexible", which are relevant attributes for SMS. On the second SMS alignment axis of the first trend, which collects the approaches to assist scheduling systems by applying DT, it is worth mentioning that, in its most basic and simple approach, DT technology can support the scheduling process by optimisation, simulation, prediction and analysis. These techniques benefit the SMS goal. Indeed the research by Dobler et al. [38], which employsexperiments carried out in the demonstrator, verifies that although the numerical results obtained by the DT-based solution approach are comparable in makespan terms, this method improves the variability of the results. Therefore, by considering the additional advantages of implementing DTs in terms of optimisation, simulation, prediction and analysing, and all this without interacting with physical processes, the DT-based approach is presented as a relevant option. The same conclusion is reached by Fang et al. [40]. Vijayan et al. [83] place the scheduling process as a physical entity to replicate, in this case, a flexible flow-shop scheduling to obtain real-time visual feedback of processes and to perceive variations in the different factors affecting process performance, which is aligned with SMS. The Debevec and Herakovic's [37] perspective might seem, *a priori*, not very useful in a workshop with an SMS approach, where the aim of semi-automation or automation is autonomy and, with it, human activity is relegated to merely supervisory action. However, in-depth knowledge of the behaviour of the system being supervised is important and can, therefore, be useful on a case-by-case basis and as a supplementary functionality in certain projects. The approach of Hu et al. [49] is product-centred and data-intensive and can be justified in certain cases when the complexity of the technological content embedded in the product is high, for example in the semiconductors and electronics equipment industry. Regarding the third and last SMS alignment axis of the first trend on approaches to assist scheduling systems by applying the ZDM management model, a strategy that is useful to minimise, mitigate or eliminate faults and defects during the production process by detecting and minimising them online [17], and from the SMS perspective, a failure or defect is understood as a disturbance that may impact the scheduling process and, in this context, the mission of the ZDM management model is to act on the scheduling process environment and its variability, on the number of disturbances of the process under control, and on the size of these disturbances and their disruptive potential, to facilitate automatic process control. With this context set, Psarommatis et al. [19] state in their study that not only online product defects can disrupt the scheduling process, but events like new orders received, prediction errors, machine defects, etc. can also disrupt it. Their research places the responsibility of predicting when faults or defects may occur on an *ad hoc* designed algorithm, which makes it possible in first place to act before they occur and, thus, minimise the effect of disturbances on the process and, secondly, to reschedule production whenever necessary. This preventive approach, which mitigates disturbances to the scheduling process, is considered valuable given its alignment with the SMS scheme, but it should be noted as limitation that the annotated document does not detail the algorithm's characteristics. In Psarommatis et al. [69], a similar preventive strategy is adopted, which acts by triggering rescheduling in real time whenever urgent orders are received or defective products are detected, albeit the dynamic scheduling tool to which they refer is not detailed. Equally, Psaromattis et al. [71] consider a preventive strategy by modelling the manufacturer's response time to unexpected events. Dreyfus and Kyritsis [39] also adopts the same vision of predictive, reactive and autonomous scheduling to absorb disturbances and disruptions which, consequently, orients it similarly towards the SMS scheme. The problem of automating decision making when defective parts or products appear online, a concern usually present in advanced ZDM environments, has led Psarommatis and Kiritsis [67] to propose a support system, which allows moving towards scheduling process automation, clearly aligned with the SMS, and by increasing its efficiency and reducing waste production. However, this system requires production facilities to be sufficiently flexible and does not consider the possible consequences of a significant increase in rescheduling, all of which translate into limitations that need to be duly contemplated. The system proposed by Schmidt et al. [76] is different since it focuses efforts to achieve a zero-defect objective on an advanced quality control system that monitors and controls production and generate a new schedule that also integrates repair operations when defects are detected. As an approach, it seems to differ from that specified for SMS as it does not prevent a fault or defect from appearing, but it must be considered, inasmuch as it is aware of how utopian it is in any workshop to achieve the zero-defect goal. So it should be taken as a supplementary possibility to SMS depending on the case that may arise and its characteristics. Finally, and in a very personal and different way, Barni et al. [33] aim to act against the variability of the environment caused by perturbation and disruption and, thus, align themselves with the SMs scheme, but from a lean perspective.

4.2. Trend 2: applying enabling digital technologies

The advance of the discussion towards the second SMS methodological trend, that of assistance to scheduling systems by applying enabling digital technologies, finds simulation as its first SMS alignment axis. Simulation is a concept that is very much present in the reviewed literature. Simulation is the most frequent enabling technology for DT and the second modelling approach in scheduling, according to the analysed papers. In Dobler et al. [38], the "intelligent simulation" model provides the DT with intelligent capabilities through "as-is" simulations and ML-based simulations to allocate jobs in real time, a valuable capability in the SMS scheme. It is worth mentioning that this demonstrator framework is limited by the absence of a heuristic approach specifically developed to fit small- and medium-sized enterprises' (SMEs) particular needs, and the limited integration and interconnection of the DT with shop floor elements. The DT-based model by Ma et al. [56] allows to simulate and optimise production processes by achieving real-time synchronisation and high-fidelity virtualisation, which exceeds the field of interest of SMS, only focused on planning. However, it may be useful for the possible need to integrate several areas into a single DT. Against this integration possibility lies the fact that the model does not operate through a cloud platform, which is an important restriction, and in addition data security mechanisms are lacking. The innovative nuance in Negri et al. [60], resultant from employing an equipment health index, is of interest for manufacturing environments governed by the ZDM management model, but this model is limited by not incorporating stochastic data sources such as risk factors or operator behaviour. Additionally, its validation in a real industrial environment, outside the laboratory, is pending. Finally, with regard to the research of Shao and Kibira [79] is significant that this is the only article in the reviewed literature that refers to a standard for implementing a DT. This research work provides an illustrative example, but no experimental evidence. Furthermore, it also leaves research areas unexplored, such as modelling methodologies or implementation guidelines for digital surrogates in specific manufacturing domains. The second SMS alignment axis of this second SMS methodological trend is sensorisation technology. It is also the second technology whose use is most frequently reported in the reviewed literature. The sensorisation of the shop floor allows increased situational awareness about its resources and environment through monitoring, which provides visibility, favours the reduction of defects, and increases the robustness of decision-making processes, all valuable in SMS. In the reviewed literature the sensors presence is usually related to the planning needs; however, when the shop floor integrates production cells that include some type of robot, sensors are also used for other purposes, such as path planning. This is the case of the research by Xia et al. [13]. Something similar occurs with the research by Gaikwad et al. [43]. As we can see, both are approaches in which the basis of the presence of sensors is more related to the physics of processes than to favouring the scheduling function, although they indirectly achieve this. Other examples of similar uses are those by Vachálek et al. [82] or Zhou et al. [94]. On the contrary, for Negri et al. [61] the main mission of sensors is to optimise scheduling process. In the DT approach of Preuveneers et al. [66] to ensure a fault-free manufacturing workflow, the sensorisation plays a significant role. However, the performed experiments only provide information on its feasibility. From a quantitative point of view, more statistical evidence and longitudinal studies are needed, and the presented model only detects errors and prevents their further propagation, but does not provide mechanisms to solve them, which represents a remarkable limitation. The use of IoT and its industrial version IIoT as the third SMS alignment axis of the second trend is widely reported in the relevant literature and, although authors' development approaches sensibly differ, they have a common general purpose: enabling of environments in which interconnection and connectivity are enhanced. The holonic perspective of a factory of the future based on the IIoT and cyber-physical production systems of Borangiu et al. [34] tends to facilitate intelligent decision making in real time, but the model is limited to a descriptive approach that leaves further research on the topic pending. On the other hand, the ticket system supported by IoT of Guo et al. [47] is simple and resilient; for production management, it takes customer demand and real-time production constraints as stochastic inputs, which falls in line with the SMS scheme, but depends on the rest of the production system for real-time action capability, which is an important restriction. The integrated system proposed by Santos et al. [75] to connect the physical and virtual shop floor can help to reduce human intervention in the task of inserting real-time data into simulation models by means of an IoT platform, noteworthy aspect. Finally, the solution of Wang et al. [86] to overcome the lack of the IoT in manufacturing environments composed of isolated conventional machines is limited by the fact that it proposes a framework for individual machines, and not for processes or systems. Big data technology, which is the fourth SMS alignment axis of the second trend, is gradually making inroads in industry, albeit at an uneven pace, and depending on the awareness of the users (managers and technicians) and the availability of sufficient data to exceed its profitability and efficiency threshold. Additionally, knowledge on data exploitation technologies in semantic interoperability conditions when real-time data are involved is critical for big data and other data-driven technologies, such as DTs, to ensure efficient and accurate data transfer communication among the various software applications and devices [97], an issue in which the use of ontologies has been proven as an effective tool for enriching existing information systems in the digital data modelling domain [98] and for facilitating data ETL (extract, transform and load) processes. The advances in big data and their impact on manufacturing are recognised in the study by De Modesti et al. [36]. Research works like those of Borangiu et al. [34] or Yu et al. [89] are also noteworthy for the role that they confer this technology. In fact the latter study highlights the use given to the big data technique in the model, which is key for error prediction and diagnosis, and helps the effective prediction and diagnosis of the dynamic disturbances that act on the production process to develop the corresponding compensatory strategies in advance. In contrast, their research does not address the construction and optimisation of the data analysis or the big data-driven prediction model and algorithm. ML is the fifth SMS alignment axis of the second trend. All the research works in the reviewed literature that take ML into account in their frameworks were published in 2020 and 2021. It is, therefore, a very recent trend, but one that is increasingly present, and is also significantly aligned with SMS as the purpose of ML methods is often to obtain the intelligent attribute and real-time action capability. With ML, scheduling can be adapted more quickly in the event of changes, and errors in planning can also be minimised [38]. The manufacturing cell model of Xia et al. [13] is based on an intelligent scheduler with DRL and point to SMS. However, validating the applicability of this methodology requires more diverse manufacturing tasks and material flows, including collaborative assembly jobs, visual inspection, optimised rework or continuous motion tasks. The hybrid simulation method of Dobler et al. [38] is based on the DT and ML and, thus, improves the variability of the results in relation to other conventional methods. The deep Q network algorithm with a Petri-net convolution network proposed by Hu et al. [48] improves solutions of dynamic scheduling problems.Nevertheless, the model does not consider stochastic machine failures and stochastic processing time. Reichardt et al. [73] also propose a model for ML-supported assistance systems for order sequencing and machine allocation in a flexible flow shop, although this procedure is pending empirical validation, and is acknowledged that without further developing AI applications, the process model cannot yet replace detailed planning. In any case, the developed method offers a high potential in the production planning and control field, and deserves further research. The conceptual framework based on DRL of Serrano et al. [16] aims, just like SMS, to reduce the risk caused by disturbances that can alter the production course to, thus, save costs and increase the efficiency of the production system, but does so at a descriptive level and is, therefore, limited. The last of the contributions of this SMS alignment axis, the hybrid method combining simulation and heuristics with ML of Xu et al. [87], is highlighted for being a solid alignment with SMS. It is worth noting that, while the results of the model come close to the optimums achieved by other techniques, they do not exceed them in maximum production system capacity and total machine load terms, but approach the optimal scheduling scheme for multi-objective screening and outshine common heuristic scheduling rules. The research results provide a reference for the DT application in the job-shop scheduling field. In any case, all the research points to ML as a methodology in effervescent development with a significant potential within the framework of the present literature review which, to a large extent, depends on future research advances, the development of new and better software tools, and increased computational power. The sixth and last SMS alignment axis of the second trend, which often goes hand in hand with IoT or IIoT technologies, is cloud computing. The aim of this technology is to move towards greater modularity, interconnection, connectivity, decentralisation in decision making and energy efficiency. Therefore, several papers in the reviewed literature address it to a greater or lesser extent and all take a similar focus based on significantly simplifying the data transfer between remote systems or elements. Some examples are the research works by Borangiu et al. [34], Guo et al. [47], Park et al. [64], Serrano et al. [16] or Yu et al. [89]. Ma et al. [56] with their DT-driven production management system for production life cycle management, and Zhang et al. [93] with their bilevel distributed dynamic scheduling architecture, who also consider including cloud computing as a future research line.

4.3. Trend 3: providing scheduling with SMS capabilities

Advancing towards the four SMS alignment axes making up the third and last SMS methodological trend detected in the reviewed literature, that of providing the scheduling process with SMS capabilities, we find the system's capacity of action in real time as the first axis, which enables an interaction with its environment in temporal synchrony without introducing delays, other than the natural delays of the environment itself, or making late interventions. In turn, within a process automation and autonomisation framework, the capacity of action in real time enables decisions to be made in synchrony with the environment's time scale, which avoids periods existing during which the environment awaits a decision to be made to continue a process or to modify its course of action. This is, therefore, a crucial quality of a planning system oriented towards SMS. The reviewed papers that address this capability do so from several perspectives, but there are two main ones: sometimes it is a capability that is expressly acquired by one part of the system, but is transmitted to the system as a whole; at other times capability is not transmitted and remains as a partial capability of that part of the system. In the first group we find the approaches of Feldt et al. [41], Gramegna et al. [46], Ma et al. [56] and Negri et al. [61]. In the approach reported by Feldt et al. [41] to solve the problem of the centralised rescheduling to enable real-time reactions, the fact that this capability is restricted to SMEs, as they are less complex, must be considered. The DT data-driven model posed by Gramegna et al. [46] is also restricted to SMEs. The DT-driven production management system proposed by Ma et al. [56] is synchronised in real time with production processes. The dynamic production scheduling framework proposed by Negri et al. [61] also synchronises with shop floor in real time, but is limited by communication protocols that provide limited sampling frequencies. This last aspect, that of sampling frequencies in communication with the CPS, is a limiting factor that must be considered in the design phases of production systems. As for the papers belonging to the second group, that of approaching the partial real-time capability of systems, we find the research of Dobler et al. [38], Guo et al. [47], Lin and Low [54], Santos et al. [75] and Vijayan et al. [83]. The second approach of Dobler et al. [38] focuses on real-time action capability through the process monitoring by means of a digital avatar system specially designed for this, but it does so without endowing the scheduling system with this capability. For Guo et al. [47], the real-time capacity is limited to the information exchange. And in the architecture for a manufacturing cyber-physical DT system proposed by Lin and Low [54], it is not the data exchange, but the collection of process and physical machine data that are achieved in real time. In the research by Santos et al. [75] the real-time capability is also limited to a part of the system, in this case to the function of data insertion into the system's simulation models. Finally, Vijayan et al. [83] limit this capacity to the function of providing real-time data for decision making. As second SMS alignment axis of this third trend is automation, that has as main exponents the research by Dreyfus and Kyritsis [39], Psarommatis and Kiritsys [67], Psarommatis et al. [71], Santos et al. [75], and Schmidt et al. [76]. Dreyfus and Kyritsis [39] centre the automation of the scheduling process in an algorithm to decide when to maintain, when to adjust the machine and when to produce an order. By automating not the scheduling process itself, but the decision-making process related to online defect detection and repair, the decision support system proposed by Psarommatis and Kiritsis [67] indirectly advocates the goal of shopfloor scheduling automation, and constitutes an approach that deserves to be paid special attention for being a relevant path towards SMS. In Psarommatis et al. [71], the assembly line is the one that is semi-automated and implies the automation of rescheduling, but limit it to the reception of urgent orders and the detection of defective products. In the research by Santos et al. [75], only data insertion into the simulation models of their decision support system is automated. And for Schmidt et al. [76], the proposed architecture is the one that acquires a flexible automation intelligent manufacturing approach. The third SMS alignment axis of the third trend is autonomy. The reviewed literature offers several examples of providing systems with autonomy, one example of this is the cyber-physical multi-agent system presented by Gorodetsky et al. [44] that can autonomously operate, although, however, the authors admit that a cyber-physical system's full autonomy to manage resources as well as, or better than human resources still requires researchers taking a long time and making many efforts. Another example is provided by capability of self-adjusting of the DT-driven production management system of Ma et al. [56], which denotes it as an autonomous entity. Moyne et al. [59] addresses aspects such as autonomy in the presented framework for the DT technology. The research by Villalonga et al. [84] is relevant because their complex DT model, built at two levels, is configured with autonomous decision making, although only the first level DTs are provided with autonomy, and the model does not provide scheduling systems with autonomy. One of the approaches that is more aligned with SMS is that of Feldt et al. [41], which understands the scheduling process itself as a function whose optimisation implies gaining autonomy. The work by Serrano et al. [16] also adopts this approach by means of a DRL agent that provides the system with a prescriptive role or, in a more advanced stage, a decision-maker role. Lastly with the fourth SMS alignment axis of the third trend, which provides scheduling with disturbance and disruption resistance it is worth mentioning the approach of Paprocka et al. [63] to generate predictive scheduling that can absorb disturbances and disruptions without affecting manufacturing. Such an approach is aligned with SMS. At the core of this resilient behaviour lies a policy whose aim is zero machine failures, zero defective products and zero accidents at work, which is consistent with the formulated scope of purpose, but requires involving several areas of production, including maintenance, quality control and human resources. The intelligent scheduling platform of Yu et al. [89] predicts and diagnoses incoming dynamic disturbances. The problem here is that there is no real-time synchronisation between the shop floor and the DT, which can cause disruption *per se*. Conversely, Pinon et al. [65], analyse and assess the impact of disruptions and identify strategies that achieve the best recovery from these disruptions. Therefore, this research starts by accepting the inevitability of these disruptions and proposes how to recover from them. This approach is relevant and may be an appropriate strategy when the resources to invest to achieve a zero-disruption objective are simply prohibitive. Accordingly, Psarommatis et al. [69] and Psarommatis et al. [71] start by accepting the possibility of disruptions in the production environment by adopting a method to efficiently incorporate rush orders into an existing schedule, and a predefined reaction strategy to trigger rescheduling before a calculated time limit, respectively. Vijayan et al. [83] propose a scheduling generator based on simulating stochastic interruption scenarios based on the DT to generate schedules for parts, which also arrives randomly from certain predetermined schedules that can be useful in schemes based on simulation.

Here the main discussed findings are summarised as follows: (i) the ability to trigger scheduling optimally is improved with the support of DT technology; (ii) an SMS approach of the ZDM model application requires extending its scope beyond product defects and production processes towards process parameter monitoring, collaborative production, data management, production reconfiguration and reorganisation, and production rescheduling; (iii) modelling the scheduling problem with a preventive approach by predicting faults or defects helps to mitigate disturbances and make it resilient; (iv) in any case, accepting the possibility of disruptions in the production environment is necessary, which must lead to the design of optimal recovery strategies; (v) a DT-ZDM combined scheme favours SMS; (vi) big data, simulation techniques and AI guide scheduling to real-time action; (vii) the automation of scheduling systems implies considering preventive maintenance processes in problem modelling; (viii) autonomy and optimisation are closely related concepts from the SMS perspective.

The main research gaps identified in this literature review include: (i) SMS implementation has implications for the remaining OM area planning processes that need to be considered, which makes it a challenge to address, and on that is usually neglected in the literature; (ii) the same applies to a full SMS approach, which also needs to involve other production areas, such as maintenance, quality control and human resources; (iii) the literature often tends to disregard SMEs' specific needs and focuses on more complex contexts; (iii) some articles merely address SMS from a descriptive perspective and, with experimental approaches, many model validations are made under laboratory conditions, and not in real industrial environments by means of case studies or longitudinal research works; (iv) in general, the full autonomy of CPS to manage resources and/or better human resources will continue to demand long times and many efforts of researchers; (v) in particular, replacing detailed planning through AI applications is still a challenging issue; (vi) the approach to the real-time action capability in the literature is often based on considerations that ignore the importance of the physical limitations of the devices making up systems, e.g., sampling frequencies in CPS-to-CPS communications systems.

5. Conclusion

This research has provided a review of the scheduling problem literature from the symbiotic approach perspective offered by DT technology and the zero-defect model to provide scheduling systems with self-management capability, understood as a composition of real-time action capability, automation and autonomy, referred to herein as SMS, which is a barely explored and discussed topic made up of conceptual elements like DT technology and the ZDM management model whose study has individually been the subject of much interest by researchers in the last decade, especially in recent years. SMS can make a significant contribution to develop advanced production schedules that respond to the digital transformation patterns implied by current production paradigms, such as Industry 4.0 or supply chain 4.0, shop floors for which improving scheduling process performance and its effect on production are key aspects in time, resources, performance, or energy efficiency terms. Here this research has presented a systematic literature review of the scientific publications in which a partial or complete relation is established among Industry 4.0, scheduling, the DT and ZDM concepts, regardless of their focus, but by placing an emphasis on those oriented towards an automatic and autonomous shop floor scheduling model synchronised in real time with physical processes. This main objective has been addressed by exploring the literature review, and by means of a content, thematic and taxonomic analysis of the selected literature, composed of 68 research articles.

The main findings have revealed that the interest shown by the academic community in this framework increased significantly halfway through the pandemic in 2020, when the number of publications tripled those of 2019. Knowledge on the topic centralised mainly in People's Republic of China, the USA and the Swiss Confederation, which account for 52 % of the authors and 47 % of scientific output in the form of publications. Table 3 shows the first authors to address this topic and highlights the works by Foivos Psarommatis from École Polytechnique Fédérale de Lausanne. Research that combines both DT technology and the ZDM management model to favour the scheduling process in an integrated approach is not yet plentiful, but exists, while the most frequent partial scheme is that of the DT-assisted scheduling process, which accounts for more than half the publications in the reviewed literature. The most widely used objective function approach for modelling the scheduling problem is that which prioritises time minimisation, followed at a distance by cost minimisation. The most frequent modelling approach is the heuristic approach, followed closely by analytical and simulation. However in the last 2 years, the AI modelling approach has reached a comparable level to the three aforementioned approaches. The purpose that academics give DT technology within the SMS framework is very diverse with no marked trends, yet simulation, optimisation and analytics approaches are more numerous. As for the commonest ZDM strategies in the reviewed literature, defect detection and prevention stand out in relation to the lesser considered repair or prediction strategies. The most frequent way of implementing ZDM is through semi-automation or automation, integrated with online processes, and preferably at the beginning of the manufacturing cycle. Three main trends of alignment with the SMS scheme come over in the documents making up the literature review: (i) research approaches whose alignment with SMS mainly lies in applying DT technology and/or the ZDM management model; (ii) approaches whose alignment with

SMS is highlighted by applying one of the main enabling digital technologies; (iii) approaches whose alignment stems from providing scheduling systems with SMS capabilities. These three trends are, in turn, broken down into three, six and four alignment axes, respectively, which have been extensively addressed. The papers responding to the DT-ZDM-S scheme have presented the highest degree of affinity with the SMS approach, and constitute the core of knowledge on the topic by providing information on its basic foundations, the implementation of the ZDM model, integration with broader schemes into the supply chain organisation, the assessment of the ZDM model's utility value, the assistance of AI, and the fit and role of DT technology and the ZDM model in 4.0 supply chain organisation. From this core, other documents identified in the other alignment trends and axes offer valuable contributions to the SMS scheme. They are recorded by highlighting the information they provide in terms of validating DT tools; interfacing, edge computing solutions; simulations of "what-if" scenarios; training supervisory personnel in the scheduling process; product quality tracing; defect prediction algorithms; predictive, reactive and autonomous scheduling; intelligent simulation models; equipment health indices; zero DT failures; connection between physical and virtual workshops; error prediction; AI schedulers; cloud computing solutions; real-time scheduling frameworks; real-time data insertion, sharing and collection; ZDM strategy automation, rescheduling automation; scheduling process autonomy, among others. This core and vectors of knowledge constitute the current state of the art of SMS, and their individual benefits and limitations are also discussed in the research.

Managerial implications are oriented to both the information collected, analysed and discussed, and the structure with which it is provided sets the precedents for a deeper understanding of the subject matter that will form the basis for future research on autonomous scheduling management frameworks oriented towards the SMS scheme or a similar one. Almost 78 % of the reviewed research articles have taken an experimental research approach and have, thus, undergone some type of empirical validation. Therefore, the step from the academic to the business sphere is a challenge, and some of the presented conceptual frameworks and models are likely to be transferred, with the corresponding modifications or adaptations, to real workshops that face digital transformation processes, or plan to carry them out in a relatively near future.

Finally, it should be noted that this research has some limitations. The consulted databases, i.e. Scopus, Web of Science, ScienceDirect, Pro Quest, IEEE XPlore and Google Scholar, are constantly being updated and the provided data correspond to those obtained at the time when the research was conducted. Furthermore, despite having followed a systematic search process, some valuable papers may have been overlooked for this review. In any case, some limitations that were revealed while conducting the study are an opportunity for further research that is worth noting. On the one hand, it was found that the DT-ZDM-S scheme forces the OM area to interact with other supply chain management areas, e.g. quality control or maintenance. A deeper understanding of its organisational implications would provide valuable academic and managerial information during the digital transformation processes of workshops governed by this scheme. Hence the multi-agent architecture presented by Zheng et al. [99], simultaneously based on the MPFQ-model (material, production process, production function/future, product quality) and DT technology, could be adopted as the basis of new research. On the other hand, scheduling is only one of the planning problems in the OM area. A rational strategy in the area as a whole would imply following a certain uniformity of criteria for all the processes under its umbrella of responsibility. Therefore, further research that assesses the desirability of transferring DT-ZDM schemes jointly at the three decision-making levels, i.e. strategical, tactical and operational, and provide more knowledge on the methodology for doing so, would allow a more coherent approach to the digital transformation processes of the OM area on the whole. In addition, descriptive studies have addressed frameworks with AI-based DT-ZDM-S schemes, e.g. with the DRL method. Advancing this line of research with experimental studies that provide empirically validated models would help to accurately assess the contribution of AI schemes to the problem at hand. Finally, with the Industry 5.0 paradigm already in the making, a global SMS model in which the human factor play a special role would contribute new knowledge in the digital planning context [100,101].

Declaration of Competing Interest

No potential conflict of interest is reported by the authors.

Acknowledgments

This work was supported by the Spanish Ministry of Science, Innovation and Universities project entitled 'Optimisation of zero-defects production technologies enabling supply chains 4.0 (CADS4.0)' (RTI2018-101344-B-I00), the European Union H2020 research and innovation programme with grant agreement No. 825631 "Zero Defect Manufacturing Platform (ZDMP)" and the European Union H2020 research and innovation programme with agreement No. 958205 "Industrial Data Services for Quality Control in Smart Manufacturing (i4Q)".

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.jmsy.2021.09.011.

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