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Review

Intelligent manufacturing execution systems: A systematic review

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ABSTRACT

The fast-growing demand for effective Industry 4.0-ready systems from academics and practitioners has required an assessment of the state-of-the-art research and implementations in Manufacturing Execution Systems (MES). This paper primarily carries out a systematic literature review of the pertinent fields to identify the promising research topics with high potentials for further investigations. In this paper, we adopt a bibliometric and network analysis to create insights that have not been captured before in this domain. It identifies the key institutions, authors and countries that have the highest impact on today's MES solutions. The trending and pioneering technologies, having high potential to be used in the new generation of MESs, are highlighted for further examinations. We subsequently reviewed the recent surveys related to these technologies and outlined the research limitations, gaps and opportunities that are discussed in the reviewed literature. Inspired by Industry 4.0 maturity steps, five intelligence levels are defined to examine the Industry 4.0 compatibility of the MES models. Besides, this paper briefly reviews the well-known MES solutions and examines their functionalities and intelligence levels. The paper additionally discusses the gaps between the degree of progress in academic and industrial MES solutions and the challenges that impede the adoption of novel MESs by practitioners. Lastly, we propose a conceptual framework, called Intelligent MES (IMES), to illustrate what an industry 4.0-ready MES should contain.

1. Introduction

The concept of Manufacturing Execution System (MES) emerged in mid-1990s to address the Enterprise Resource Planning (ERP) layer's insufficiency in real-time management of operations on the shop floor [1]. ERP includes modules for production planning, inventory control, demand forecasting, cost accounting, and marketing for manufacturing enterprises [2]. Since ERP collects and integrates the information required for implementing these modules from the shop floor and other organizational functions on a daily, weekly, or monthly basis, it lacks the speed and level of detail that is vital to respond immediately to every single transaction occurring on the shop floor [3].

To solve this issue, the MES concept was developed to make a connection between the shop floor and ERP layer. From a top-down view of the management hierarchy, MES creates a detailed operational plan by combining preliminary production plans from the ERP with real-time information on processes, materials, and operations from the machines, controls, and individuals on the shop floor. This plan enables real-time management of production activities on the shop floor from order receipt to finished products. From a bottom-up view, MES provides ERP with abstract information on the shop floor execution. For instance, it updates ERP on the completion status of an order, which can affect the release of upcoming planned orders [4].

In the automation pyramid (Fig. 1), an MES system is the main production management tool that provides a bidirectional link between the enterprise planning layer and the shop floor control/automation layer [5]. From a bottom-top view, the MES receives data on the status of the shop floor through actuators and sensors residing in the supervisory control and data acquisition (SCADA) system such as distributed control systems (DCSs), programmable logical controllers (PLCs), and other

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smart devices. The information is then abstracted to the level required by the ERP system for decision-making [6]. The abstraction is required because the data generated by the SCADA system contains highly granular information with a limited scope (e.g., a specific resource), while the ERP system at the enterprise planning layer requires abstract information for decision making [4]. The ERP system uses abstracted information such as statuses of orders being processed to make a decision on the release of upcoming planned orders [7]. In a top-down view of the management hierarchy, the ERP system provides data on the planned orders including product mixes, sizes, and due dates for the MES. Thereafter, the MES translates the production goals (planned orders) into a detailed schedule for execution at the shop floor [7]. The MES operates on a daily to real-time basis in order to translate monthly to daily decisions made at the enterprise planning layer into real-time schedules needed to maintain shop floor control [4].

The main functionalities of the MES are data acquisition and abstraction, detailed scheduling of operations, resource allocation and control, dispatching production to machines and workers, controlling product quality, and managing the maintenance of equipment and tools [8]. The implementation of MES in manufacturing enterprises improves the critical key performance indicators (KPIs) of the company including reduced lead time and cost, improved quality, production transparency, and increased efficiency [1]. In addition, MES can provide online information on the raw material inventory, machine breakdowns, and delays at the shop floor of each manufacturer across the supply chain. Thus, it also helps the Supply Chain Management (SCM) layer, which interacts with the ERP layer, to better respond to disturbances and disruptive events [4]. Industry 4.0 is defined as bringing intelligence, flexibility, operational efficiency, and fully predictive production to manufacturing enterprises [9]. The first step toward achieving this goal, as shown in Fig. 2, is to collect and integrate data from the MES as well as other information systems, the internet, and manufacturing resources [10]. The collected data can then be analyzed and used to bring intelligence to the product design, planning, and production stages, as well as equipment maintenance. In particular, MES can be realized as one of the key enablers of the fourth industrial revolution in manufacturing enterprises due to two important reasons. First and foremost, the fundamental features of MES serve as the foundation for implementing Industry 4.0 concepts. Second, using Cyber-Physical Systems (CPS) and Cyber-Physical Production Systems (CPPS), MES can enable business processes in ERP and tiers across the supply chain to become smarter by supplying online data from smart products and machines on the shop floor [11,12]. In Industry 4.0 context, the main roles of MES are as follows [5]:

1. Lie in the center of smart supply chains and coordinate the horizontal integration of all facilities and trading partners;
2. Help to further integrate the vertical business processes within the ERP including logistics, engineering, sales, compliance, quality, maintenance, and operations;
3. Schedule tasks in the production line according to the real-time capacity of machines and current status of products;
4. Implement advanced optimization algorithms for rescheduling the production and maintenance plans in case of failure;
5. Collect and store big data from the manufacturing processes and provide them for quality control and predictive maintenance tools;
6. Measure the KPIs of the manufacturing processes.

Integrating Artificial Intelligence (AI) with MES is one of the main research frontiers with the goal of adopting current generation of MES to the Industry 4.0 context. Production lines consist of robots, conveyor belts, machines, and supporting activities such as maintenance, quality control, and material handling aiming to efficiently manufacture the desired product. The inherent inter-dependency and uncertainty in manufacturing operations lead to a non-linear and stochastic system [13]. Despite this complexity, such systems should operate in an optimal condition in order to keep the company competitive in the market and meet the productivity, quality, and cost objectives, while guaranteeing safety in the working environment. AI tools have the unique capability to classify and identify non-linear and multivariate patterns that remain undiscovered by the production engineers. Moreover, AI tools such as machine learning and deep learning algorithms can be trained by big data sets generated by machines, ambient sensors, controllers, and worker records to reveal patterns that can contain important clues to solve challenging problems in manufacturing processes [14,15]. AI tools are widely applied to MES for productivity estimation, quality faults detection, root cause diagnosis of quality defects, job dispatching and scheduling, resource allocation, human-robot collaboration, machine vision, robot manipulation, condition-based/predictive maintenance, and manufacturing process control [16].

Digital Twin (DT) and Augmented Reality (AR) are two other current research frontiers in MES. DT is a simulation model representing the same characteristics of a physical object in the digital world. In other words, DT creates a bilateral connection between the intelligence layer of MES and the physical world [17]. It obtains data from the production line by reading sensors embedded in the shop floor in real-time. The current state of the production line is then provides to the MES intelligence layer. The intelligence layer uses AI tools to automatically supervise and control the physical world based on the inputs provided by the DT. After decision making, the intelligence layer provides the DT with actions that should be taken on the physical equipment [18]. AR is a core technology in facilitating human integration with MES. Although the focus of industry 4.0 is to build MESs that are seamlessly intelligent, flexible, adaptable, and autonomous, humans still play a key role in industry 4.0-based MESs [19]. AR is an interface through which humans

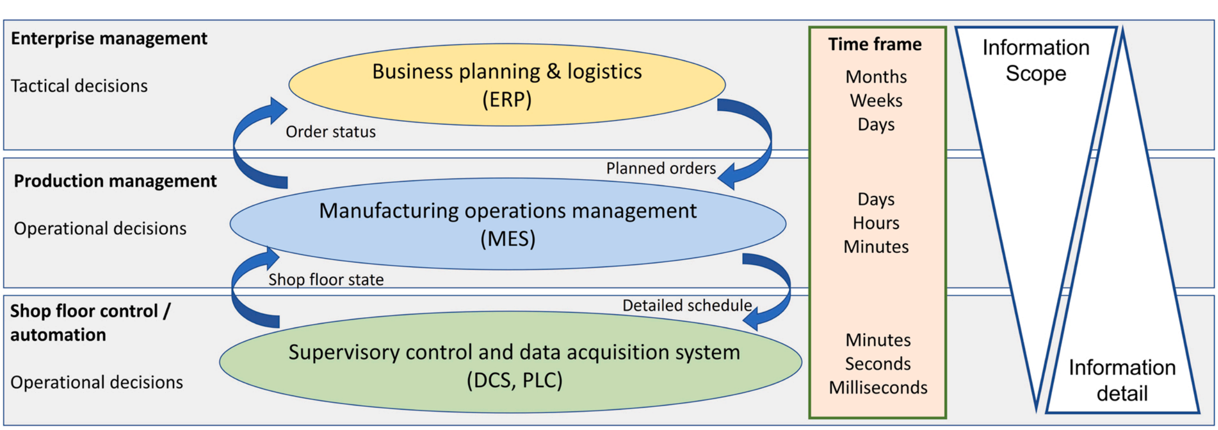

Fig. 1. Information and management systems for planning and control [4].

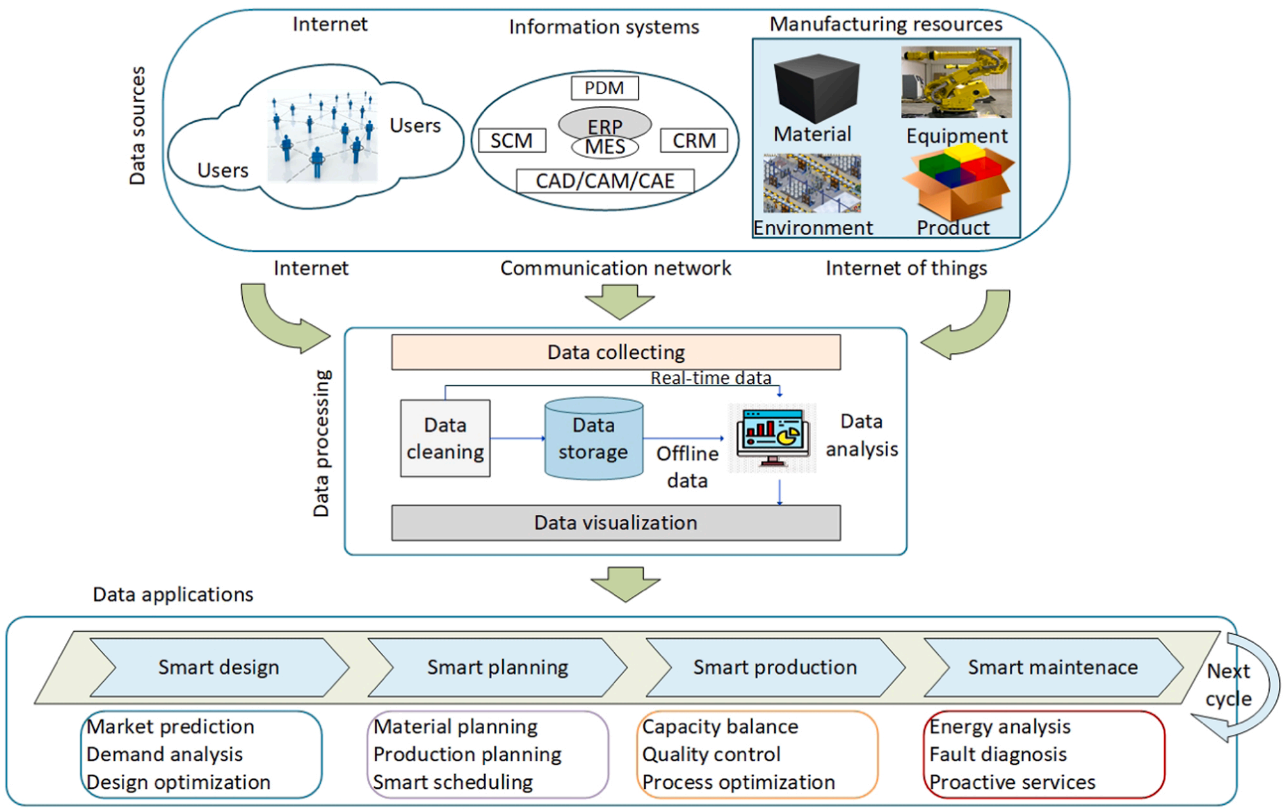

Fig. 2. The sources, processing and applications of data in manufacturing enterprises under industry 4.0 context [10].

can communicate with the digital world of the production line. Assembly, maintenance, quality inspection, and logistics activities are the main fields in manufacturing systems where AR can be applied to support human operators and provide them with visual data [20].

Characteristics of MES for Industry 4.0 - Industry 4.0 is about technologies that collect data to inform intelligent actions in the physical world. These technologies help manufacturers improve efficiency and minimize manual work. Connected machines collect vast amounts of data that can provide valuable insight into various aspects of their operation. This data can be analyzed to identify patterns and insights and can be used to improve efficiency. MES software is an integral part of the Industry 4.0 transformation to gain real-time visibility of operations [21]. It helps manufacturers reduce manual work and improve efficiency by implementing digital processes. It can also be used to transform operations by identifying areas of potential competitive advantage.

MESs will still have a significant role in the production area. Optimal production process and support in decision making are the main tasks that must be performed in real-time. This can be achieved by monitoring and ensuring that the right resources and processes are available. This is accomplished with a fully integrated central MES.

Industry 4.0 is a concept of future manufacturing that allows for reduced costs, improved quality, and higher throughput. It is a platform where smart products and equipment engage with one another autonomously to provide real-time dynamic optimization. Some of the technologies required for Industry 4.0 include the Internet of Things (IoT), mobile computing, cloud storage, big data, advanced analytics, machine learning, robotics, and Virtual Reality (VR) and AR. MES is the cornerstone of connection and coordination of these technologies. Companies must construct one crucial foundation component which is a new MES that is Industry 4.0-ready. MESs must be service-oriented and adaptable in order to be Industry 4.0-ready. That means they must be able to analyze IoT data, interact with AR, and run on both mobile and cloud platforms. Additionally, MESs should facilitate interactions between autonomous products and equipment on the shop floor [5].

Our contributions - There is an increasing interest in smart manufacturing and industry 4.0, yet, there is no systematic and extensive literature review that comprises the recent advancements and researches on MESs. In this paper, we first provide a systematic literature review that explores the status of the research in the related domains and highlights the fertile trending technologies that are employed in novel MESs and manufacturing systems. We then analyzed the related existing surveys to identify the technologies that have been reviewed in the field and extract the research challenges and gaps identified in the publications. Industry 4.0 requires an MES solution that broadly make the shop floor autonomous, adaptable and smart; To this end, main MES functionalities and five intelligence levels are presented, based on which we analyze the body of the literature and the proposed MES frameworks. On the other hand, we used these two metrics to evaluate novel industrial software systems. Based on our findings from the literature and the industrial cases, we propose a conceptual model that can carry out MES tasks with prediction capabilities and high adaptability, making it suitable for the Fourth Industrial Revolution.

The rest of the paper is arranged as follows. Section 2 explains the research methodology and the research questions. In Section 3, and Section 4, detailed graph and bibliometric analyzes are carried out, resulting in the identification of influential authors, clusters, and research trends. Having identified the current trends, we reviewed the most recent surveys related to MES in Section 5. Section 6 presents the main functionalities of MES and introduces five intelligent levels. Then it categorizes the proposed solutions in literature into these levels and functionalities to identify the research gaps. The current ready-to-use novel MES solutions and their features and shortcomings are discussed in Section 7. It also presents some obstacles that the practitioners face towards adopting new MESs. In order to provide a concept of a smart and integrated MES that can alleviate the obstacles in industry 4.0 realization, we introduce a model, IMES, in Section 8. We conclude this paper in Section 9 with a discussion on the research gaps, limitations, and the future of MESs.

2. Research methodology

In order to evaluate the body of literature and identify its potential research gaps and the boundaries of knowledge, a literature review is required. A systematic literature review provides a neutral data collection that not only facilitates the identification and evaluation of scientific works related to the research topic but also helps construct a better interpretation of the research advancements and trends [22]. The literature searching policy of this paper is structured based on Preferred Reporting Items for systematic review and meta-analysis (PRISMA), proposed by Moher et al. [23].

In this section, the research questions are outlined to define the scope and overall objective of this systematic review. This paper uses a search policy to include the relevant reviews and frameworks that are proposed in MES literature. The obtained data are then analyzed to extract some useful insights and answer the following research questions: .

- RQ1. What are the current research trends in MES?
- RQ2. How can we categorize the literature of MES with respect to their levels of intelligence?
- RQ3. What are the challenges and research gaps of designing an IMES?
- RQ4. What are the most influential institutions and countries on the current MESs?
- RQ5. What are the challenges and obstacles for the practitioners in the adoption of higher intelligence levels in MESs?
- RQ6. Can we propose a conceptual MES model that eases the implementation of Industry 4.0?

A query, a two-level keyword assembly to gather information related to smart manufacturing literature, is defined to address these research questions. Table 1 shows the related keywords identified. In terms of the research context, a paper can be considered related if it includes at least one of “Manufacturing Execution", “Production Line", “Smart Factory" or “Manufacturing System", either in its title, keywords or its abstract. On the other hand, in terms of the model, only papers that include AI models, VR, AR or DT in their titles, keywords or abstracts are collected. These keywords define the scope and the focus of the paper. To narrow the analysis to research trends of the past 10 years, only papers published between January 2012 and the end of 2021 are considered. The papers are also limited to only English publishing sources, excluding book chapters and conference papers to analyze the papers with greater impact, higher quality, and more originality. More than 790 papers are extracted from the Web of Science database using this query. The extracted dataset is cleaned by removing duplicate papers and papers without any available full-text, resulting in 1383 papers to analyze Table 2.

Table 1
The proposed two-level keyword assembly structure.

Context	Query	Searching field
Domain	"Manufacturing Execution" or “Production Line*" or “Smart Factory" or “Manufacturing System*" or “Smart Manufacturing" or “Intelligent Manufacturing"	Title & Keywords & Abstract
Model / Technology	"Computer Vision" or “Reinforcement Learning" or “Virtual Reality" or “Augmented Reality" or “Digital Twin" or “Deep Learning" or “Machine Learning" or “Machine Vision" or “Autoencoder*" or “Convolution* Net*" or “Long Short Term" or “Blockchain" or “5 G"	Title & Keywords & Abstract

Table 2
The share of papers in each Web of Science category.

Web of Science Categories	No. papers	Percentage
Engineering Manufacturing	389	31.170%
Engineering Electrical Electronic	278	22.276%
Engineering Industrial	213	17.067%
Computer Science Information Systems	193	15.465%
Computer Science Interdisciplinary Applications	181	14.503%
Operations Research Management Science	180	14.423%
Telecommunications	163	13.061%
Automation Control Systems	144	11.538%
Computer Science Artificial Intelligence	142	11.378%
Engineering Multidisciplinary	105	8.413%
Materials Science Multidisciplinary	96	7.692%
Instruments Instrumentation	90	7.212%
Physics Applied	77	6.170%
Engineering Mechanical	64	5.128%
Chemistry Analytical	47	3.766%

3. Bibliometric analysis

The authors, affiliations, and country statistics of the selected papers from Web of Science are presented in this section. This type of analysis is helpful in a variety of ways. Identifying the influential researchers and universities in the MES can be beneficial for scholars and students interested in conducting research about MESs. Raw extracted data from the Web of Science is parsed to gather authors' affiliations and countries of affiliations. Furthermore, determining the leading universities in the MES research area aids in highlighting relevant topics and new research. Also, Table 3 identifies the most active journals in intelligent manufacturing during the recent decade among the extracted papers from the Web of Science. The analysis in this study focuses on the following data fields: authors, title, abstract, keywords, journal, publication year, affiliations and their countries, number of citations, and references. The raw data is manipulated using Python libraries such as NLTK, Pandas and some other built-in native functions of Python3 to gain valuable insights. The NLTK library is used to tokenize and analyze the abstract section of the papers. After tokenizing, the Term Frequency and Inverse Document Frequency (TF-IDF) algorithm is used to determine trending topics in Section 3. Moreover, because the formatting of each column in the extracted data is not uniform, NLTK is used to parse complex columns. This paper uses the NetworkX Python library to generate graph-structured data. In terms of visualization, graph-structured data from the NetworkX library is passed to the Gephi tool to generate graphs.

3.1. Influential authors

. Table 4 outlines key contributing authors based on the number of published papers. The frequency of authors appearing in all 1383 papers is determined by extracting author names from the data. Only 643 out of 4636 contributing authors have collaborated on more than one paper, leaving 3993 authors who've contributed in only a single paper. In addition, the top authors based on total citation among the MES-related papers are outlined in Table 5. Those two tables demonstrate that Robert X. Gao has put a lot of effort into reaching smart manufacturing. His team focuses on deep learning (DL) and reinforcement learning (RL) to add more ability of perception to manufacturing processes to achieve better automation. An analysis to identify key paired authors who contributed together in more than one paper is also conducted. Interestingly, it shows that two authors who collaborate with each other most frequently also produce crucial and significant papers in the MES field. Li Xinyu and Gao Liang appear in both tables and have a considerable impact on the MES field. They use various techniques such as machine learning (ML), RL, and simulations to make MES more intelligent. This finding may point to the need for more active scholars to interact with authors from other institutions, countries, and disciplines to investigate

Table 3
The most active journals in intelligent MES since 2009.

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
IEEE Access	–	–	–	–	–	–	–	1	5	12	14	35	30	**97**
Journal of Manufacturing Systems	–	–	–	–	–	–	–	–	1	10	1	20	36	**68**
International Journal of Advanced Manufacturing Technology	–	1	1	–	–	1	1	1	2	5	4	18	18	**52**
Sensors	–	–	–	–	–	–	–	–	1	4	7	12	21	**45**
Applied Sciences-Basel	–	–	–	–	–	–	–	–	1	1	3	9	30	**44**
IEEE Transaction on Industrial Informatics	–	–	–	–	–	1	–	–	1	1	8	8	12	**31**
International Journal of Production Research	–	3	2	2	–	–	–	1	–	1	4	11	7	**31**
Robotics and Computer-Integrated Manufacturing	2	–	2	–	–	–	1	1	–	1	3	12	8	**30**
Journal of Intelligent Manufacturing	–	–	–	1	–	–	–	1	1	1	3	11	8	**26**
International Journal of Computer Integrated Manufacturing	–	–	–	–	1	–	2	–	–	–	5	4	13	**25**
Computers & Industrial Engineering	1	–	2	–	–	–	–	1	3	2	7	5	**21**	
Computers in Industry	–	–	–	–	–	–	–	–	–	1	5	6	6	**18**
Sustainability	–	–	–	–	–	–	–	–	–	–	2	8	8	**18**
CIRP Annals - Manufacturing Technology	–	–	–	–	–	–	–	–	1	1	3	4	5	**14**
Expert Systems With Applications	2	–	–	3	–	–	–	–	–	–	–	1	5	**11**

Table 4
Top influencing authors by number of papers.

Author Name	#Papers
Gao, Robert X.	17
Liu, Qiang	14
Tao, Fei	14
Leng, Jiewu	12
Li, Xinyu	11
Gao, Liang	11
Chang, Qing	8
Chen, Xin	8
Shiue, Yeou-Ren	8
Zhang, Ding	7
Park, Kyu Tae	7
Xu, Ke	7
Wang, Lihui	6
Zhong, Ray Y.	6
Nee, A. Y. C.	6
NeeZhang, Jianjing	6
Noh, Sang Do	6
Zheng, Pai	6
Wen, Long	6
Wu, Dazhong	6

Table 5
Top influencing authors by number of citations.

Author Name	#Citations
Gao, Robert X.	1945
Tao, Fei	1449
Yan, Ruqiang	1216
Gao, Liang	1143
Li, Xinyu	1118
Zhao, Rui	1117
Wen, Long	1100
Mao, Kezhi	1068
Wang, Peng	993
Wang, Jinjiang	891
Wu, Dazhong	800
Chen, Zhenghua	780
Liu, Qiang	671
Leng, Jiewu	648
Zhang, Yuyan	639

smart MES issues, challenges, and barriers from various perspectives.

To better examine highly influencing authors in the related area, co-authorship and topic-based relations of countries and universities are investigated in section 4. The investigation highlights that many of these authors have also co-authored highly influential research in this area, indicating a possible positive relationship between the quantity and quality of papers published by the key contributing authors.

3.2. Influential institutes

Investigating the affiliations reveals that 1418 universities and institutions contributed to the MES research area, among 1438 primary papers collected. As shown in Table 6, Huazhong University of Science and Technology has had the most impact on this field regarding the total number of conducted papers. In addition, Table 7 provides insight on the overall citations of each university and institute, removing bias to achieve a true judgment of the universities' contributions. Although the majority of the top universities and institutions contributing to the MESs are from Asia, particularly China, universities and institutions from the United States and Europe are also represented. For instance, the most influential university in this field is Case Western Reserve University regarding the total citations. These top universities have worked on different methods such as deep learning, ML, RL, DT and simulations to make manufacturing at the MES level more intelligent.

3.3. Countries leading the MESs

Another organizational level analysis is the recognition of influential countries in the literature. The results are depicted in a worldwide heatmap, Fig. 3, which demonstrates that China has a significant lead in

Table 6
Top influencing affiliations by number of researches.

Affiliation Name	#Papers
Huazhong Univ Sci & Technol	37
Beihang Univ	28
Guangdong Univ Technol	23
Xi An Jiao Tong Univ	21
Nanyang Technol Univ	21
Shanghai Jiao Tong Univ	17
Zhejiang Univ	16
Case Western Reserve Univ	16
Chinese Acad Sci	16
Natl Cheng Kung Univ	15
Tsinghua Univ	14
Univ Hong Kong	14
Northwestern Polytech Univ	14
Natl Tsing Hua Univ	14
Nanjing Univ Aeronaut & Astronaut	13
Northeastern Univ	12
Hong Kong Polytech Univ	12
Univ Michigan	12
Natl Univ Singapore	12
Donghua Univ	11
Sungkyunkwan Univ	11

Table 7
Top influencing affiliations by number of citations.

Affiliation Name	#Citations
Case Western Reserve Univ	1945
Beihang Univ	1699
Nanyang Technol Univ	1443
Huazhong Univ Sci & Technol	1384
Xi An Jiao Tong Univ	1320
China Univ Petr	892
Guangdong Univ Technol	865
Natl Univ Singapore	687
Univ Cent Florida	490
Natl Cheng Kung Univ	436
Grenoble Inst Technol Grenoble INP	417
Univ Fed Rio Grande do Sul	417
Univ A Coruna	402
Penn State Univ	395
Shanghai Jiao Tong Univ	391
Univ Bremen	373
Univ Auckland	355
West Virginia Univ	353
Hong Kong Polytech Univ	352

this area. After China, the next two important countries that contribute significantly to this research area and play a key role in pushing forward the boundaries of MES research are the United States and South Korea, respectively. In order to have a more sense about the contribution of each country, there is a contribution number in the heatmap as well. As it is shown, the identified top three countries- China, USA and South Korea- together share more than 40% of the literature.

3.4. Relation between GDP and smart manufacturing

Following the identification of leading countries in smart manufacturing, it is worthwhile to investigate the relationship between GDP and the amount of effort in making manufacturing more intelligent Fig. 4Fig. 5.

Fig. 3 demonstrates the most influential countries that have made MES more intelligent. Furthermore, Fig. 6, shows the correlation between the GDP of different countries in 2020 and their impact on the smart MESs. As it can be seen, there is a strong positive correlation between these two features. The Pearson correlation coefficient of 0.76 with a p-value of 0.003 shows that the computed correlation number is statistically significant. However, this correlation cannot show any causal effect and cannot be interpreted that the countries with higher GDP have contributed more significantly to the researches published in this domain. Yet, for two countries having relatively lower GDP, the number of collaborations and publications was meaningfully high.

Another normalized correlation of the previous one is the correlation between world GDP during years and the number of i-10 papers for each year. This statistic shows us a correlation of 0.66 with a 0.01 p-value. It means there is a strong and positive correlation between having influential papers in the smart MESs and world GDP but no implication of causality.

4. Network analysis and literature mapping

This section investigates some network analysis and connections between countries, topics, and authors for a better understanding of contributors in novel MESs. In addition, a brief overview of the trending technologies used in smart manufacturing is presented, along with several research examples utilizing those technologies.

4.1. International collaborations

Co-authorship among different countries is another factor that is investigated. The countries that contribute the most to this area are shown in Fig. 3. China is the most active country, followed by the United States, with a significant amount of work over other countries.

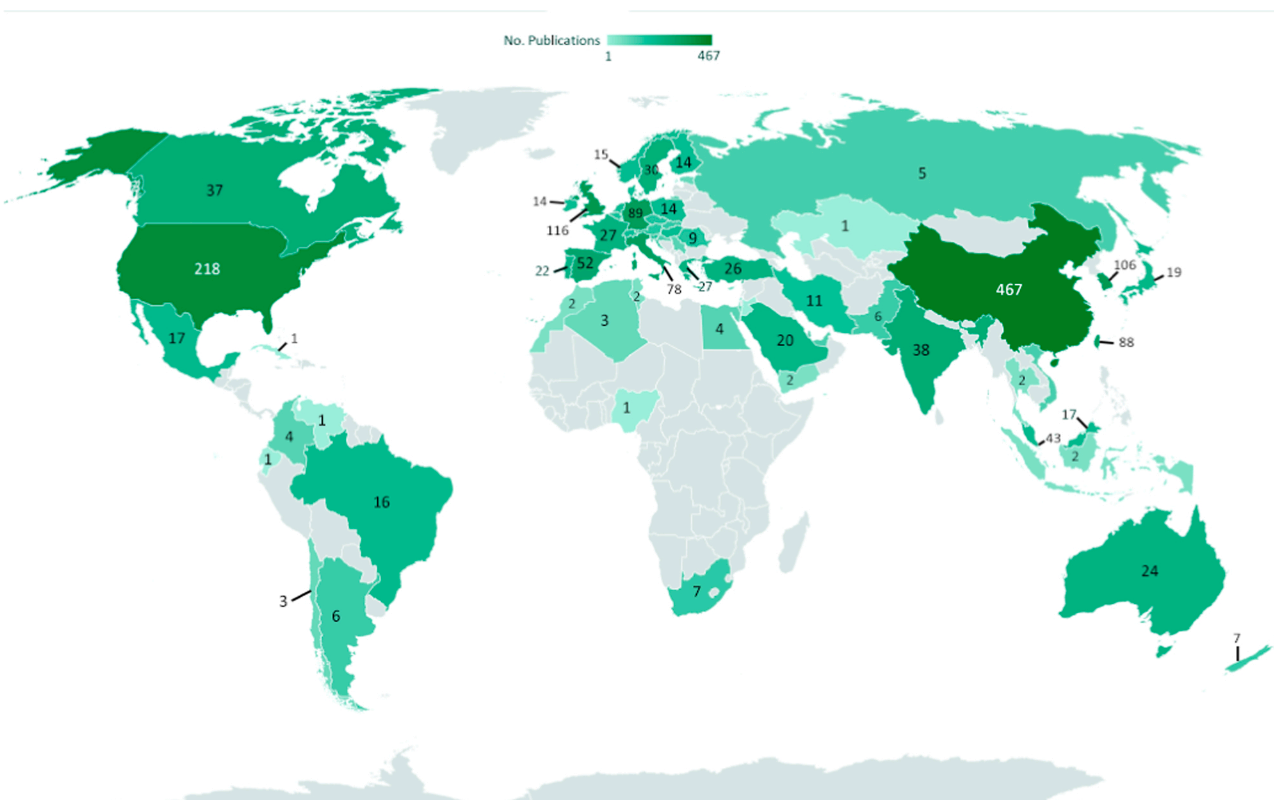

Fig. 3. Heatmap of country contributions to MES literature.

Fig. 4. Hub countries co-authorship weighted graph.

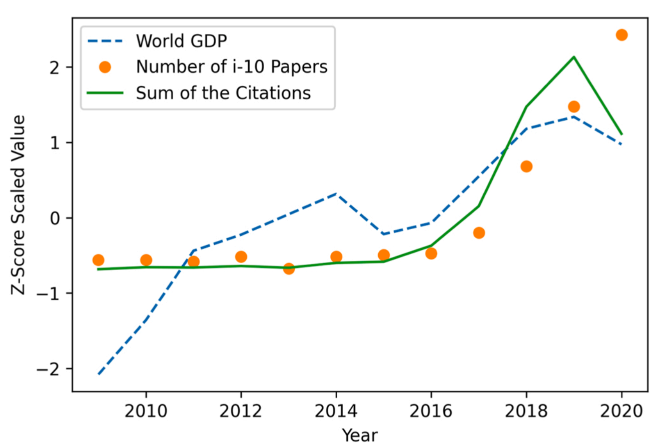

Fig. 5. GDP vs. i-10 papers of MES during time.

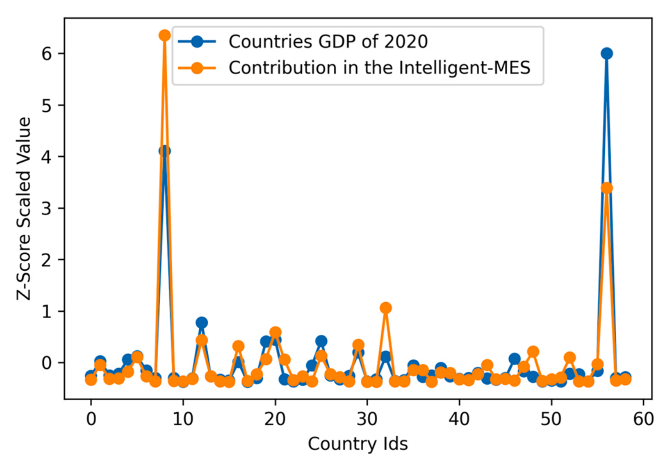

Fig. 6. Smart MES contribution and corresponding GDP in the 2020 among different countries.

Regarding the co-authorship between countries, countries' contributions are collected, and the result is shown in Table 8. It indicates that the most frequent collaborations come from USA and China, the two countries that are also the most active in this field, with 30 paper contributions. Surprisingly, China and Singapore are the second-highest contributor pair, while Singapore singularly ranks 9th among the countries' influence on the smart MESs. For better visualization, a contribution graph is presented in Fig. 4. In this graph, countries with a high number of co-authorship have a stronger red edge between them. Moreover, the names of countries appear larger with higher levels of contribution.

4.2. Trending topics during time

To determine the trending topics, this paper uses a new method adopted from a popular classic technique in natural language processing (NLP) called TF-IDF. The main idea behind TF-IDF is to determine the frequency of words as well as the commonness of each word [24]. This

Table 8
Top country pairs with a high co-authorship in the intelligent MES.

First Country	Second Country	#Papers Contributed
China	USA	110
China	England	46
China	Singapore	40
China	Canada	32
China	Australia	26
China	Taiwan	24
USA	England	22
China	Sweden	18
China	Saudi Arabia	16
USA	Germany	16
USA	South Korea	16
China	South Korea	14
China	France	12
USA	Sweden	12
USA	India	10
USA	Taiwan	10
Germany	Spain	10
Italy	England	10
Sweden	England	10

paper uses the same idea for calculating commonness in the domain of trending topics. Grouped based on each topic in a particular year, we calculate what portion of the papers in the last three years have been related to the same topic. A higher percentage means that the topic was commonly used in the previous three years; hence it is more common. On the other hand, if the percentage is low, the topic in this area, although not common, it is more niche. Specifically, $\frac{\rho}{\log_2 \frac{\delta}{N}}$, where ρ denotes the number of papers that use a certain topic in the year and δ denotes the number of papers that have used certain topic in previous three years and N is number of all papers in the MES in previous three years, is determining trendiness. Resulted trending topics that help MES to be more intelligent are investigated and are available per year in the Table 9.

In 2009, Li et al. investigated and solved a small dataset problem which most manufacturing systems face in the early stages due to lack of data. They propose a new method for sample generation - non-linear virtual sample generation (NVSG) - to overcome the aforementioned problem in manufacturing. They use a special non-linear classification technique to generate virtual samples. Their research is successful in inspiring more research that brings machine learning into MES to overcome problems and achieve an intelligent MES [25]. In 2010, Hallbeck et al. used the power of VR to fill the gap between available VR systems and the VR needs for small and medium-sized enterprises (SMEs). In their study, VR is used as a tool for designing early workstations by developing a simulation tool that provides critical information on layout for high efficiency, especially for SMEs [26]. Also, Zamfirescu et al. used AR technology to guide human operators and avoid human fault in the cyber-physical systems. Their work also addresses social aspects when this concept is adopted in factory automation. AR was the most trending technology used in novel MESs in 2016 [27].

Table 9
The top four trending topics and technologies used for making MES more intelligent regarding year, both being niche topic and high frequency of papers, are considered as described in Section 4.

Year	First Trending Topic	Second Trending Topic	Third Trending Topic	Fourth Trending Topic
2021	Digital Twin	Deep Learning	Reinforcement Learning	5G
2020	Digital Twin	Deep Learning	Blockchain	Reinforcement Learning
2019	Digital Twin	Blockchain	Deep Learning	Computer Vision
2018	Deep Learning	5G	Reinforcement Learning	Digital Twin
2017	Deep Learning	Digital Twin	Machine Learning	Blockchain
2016	Augmented Reality	Machine Learning	Virtual Reality	Computer Vision
2015	Augmented Reality	Virtual Reality	Computer Vision	Machine Learning
2014	Augmented Reality	Computer Vision	Virtual Reality	Meta-Heuristic Algorithms
2013	Deep Learning	Computer Vision	Machine Learning	Reinforcement Learning
2012	Reinforcement Learning	Machine Learning	Meta-Heuristic Algorithms	Virtual Reality
2011	Computer Vision	Machine Learning	Meta-Heuristic Algorithms	Virtual Reality
2010	Computer Vision	Reinforcement Learning	Virtual Reality	Meta-Heuristic Algorithms
2009	Meta-Heuristic Algorithms	Virtual Reality	Machine Learning	–
2008	Machine Learning	Virtual Reality	–	–

In 2011, Lee et al. used machine vision methods to perform quality assurance tasks in a glass production line. They place a CCD camera and laser diode to run a computer vision algorithm that measures the thickness of produced glass in real-time. Their study has inspired many intelligent automated quality control methods leading to machine vision-enabled manufacturing quality assurance [28].

In another paper, Liang et al. use machine learning techniques, especially regression, to make grinder systems in the production line more flexible and efficient. Because some factors of the grinding process are time-variant, there is a challenge to precisely control grinding removal for free-formed surfaces. They propose an off-line planning strategy for parameter tuning of the grinding robot based on an adaptive modeling method to construct a high-quality robot grinding system. This research is another study that uses machine learning techniques to make manufacturing more intelligent [29].

In 2013, Leiva-Valenzuela et al. used pattern recognition methods to first identify the orientation of blueberries, then separate stem and calyx ends, and assess damage to fungally decayed, shrivelled, and mechanically damaged blueberries. This research was crucial at that moment because the production of the South American blueberry had increased significantly during the years [30].

Umar et al. [31] use meta-heuristic algorithms to make manufacturing systems more intelligent. The paper uses a hybrid genetic algorithm to achieve a method for integrated scheduling, dispatching, and conflict-free routing of jobs and automated-guided vehicles in a flexible manufacturing systems environment. The proposed genetic algorithm applies a multi-objective fitness function that uses an adaptive weight approach to assign weights to each objective in every generation based on objective improvement performance. This study shows the importance of meta-heuristic algorithms in MESs. This type of algorithms can be used both for assigning parameters of the production line components and the optimization of these components, as well as the parameter tuning of the algorithms based on a neural network in the MESs.

In the previous papers, many researchers perform machine learning algorithms to achieve an intelligent MES. But now, considering the noise, varying length and irregular sampling behind sensory data, this kind of sequential data cannot be fed into classification and regression models directly. In 2017, Wang et al. performed deep learning algorithms and developed effective machine health monitoring systems. They address raw sensory data challenges by designing Convolutional Bi-directional Long Short-Term Memory networks (CBLSTM) instead of previous fusion-based methods [32].

In the last five years, DTs have become one of the most favorite technologies in manufacturing. This technique is used for a more realistic staging and simulation using available data. Kurfess et al. present outstanding research which is integral to realizing a complete digital model of the shop floor, known as the Shop Floor DT that can be used for production control and optimization. This research describes the development and implementation of a new MES, powered by mobile devices and cloud computing tools, that combines MTConnect data with production data collected from operators. Because of the low cost of implementation, the proposed MES is more fit for small manufacturing enterprises [33].

In modern manufacturing, most of the tasks are distributed on the cloud. One of the major challenges in cloud manufacturing systems is job scheduling for multi-projects. In other words, multi-projects face a multi-agent problem and scheduling should be addressed regarding multi-agent challenges. Chen et al. have significant research with the same research question. For tackling the problem, they perform a reinforcement learning algorithm for assigning policy (RLAP) of scheduling. Afterward, they design a dynamic state, representing an algorithm for agents, to determine their decision environment when using RLAP [34]. Their research yields excellent results, with significant improvements in both service load and schedule quality. Reinforcement learning is one of the most efficient and working methods, especially when a problem is multi-agent like scheduling, mobile robot collaboration, and task management.

Table 9 demonstrates that, beyond 2017, blockchain technology will continue to be one of the most popular MES and smart manufacturing technologies. There are a lot of applications of blockchain in manufacturing, such as edge computations and supply-chain. Shahbazi et al. have recently published a paper about designing a traceable food supply chain using the power of blockchain, machine learning, and fuzzy logic. They use the intrinsics of blockchain, which is fully traceable as well as being secure. They called their developed food supply-chain method Blockchain Machine Learning-based Food Traceability System (BMLFTS) that is based on the shelf life management system for manipulating perishable food [35]. There is no doubt that the popularity of blockchain and its features will lead it to be one of the most prominent technologies in MES and manufacturing in the coming years.

In recent years, one of the other trending technologies related to smart manufacturing is 5G. As it can be seen in Table 9, 5G has been attracting researchers' attention focusing on smart manufacturing since 2018. This technology is inevitable in the future of all intelligent production lines due to the volume of data generated in real-time systems. Cheng et al. at 2018 have claimed some of the most important reasons to start using 5G in cyber-physical manufacturing systems (CPMS) and outlined characteristics, key technologies and challenges of the 5G based Industrial IoT (IIoT). They have mentioned that in IIoT devices, real-time monitoring without delay is one of the crucial needs and systems with higher latency would be costly [36].

5. Insights from related surveys

So far, the initial bibliometric and network investigations are conducted and the promising topics and technologies are identified to be considered by researchers and practitioners who want to contribute to or study new MES frameworks. In order to address the RQ3, the paper reviews the literature to find opportunities, challenges and research gaps of designing an efficient MES and also analyzes existing survey papers in MES to know the relevant subject and technologies in MES that have been reviewed. In [37], Emrah Arica and DJ Powell develop and propose a taxonomy for characterizing MES to help in the efficient selection and successful implementation of MES. They expound on how MES can leverage the industry 4.0 technologies such as Internet-of-things, Industrial Big Data, Visual Computing, and Cyber-security to enhance their functionalities and fit for use in smart manufacturing systems.

Ugarte et al. [8] shows the state of MES as of 2009 in terms of MES architectures and models, connectivity and network, and data processing by referencing the technological trends and improvements to commercial MES solutions. This paper highlights the major challenges related to the use and implementation of MES technologies on the shop floor and examines the future opportunities for research and development, taking into consideration only commercial MES solutions as of 2009. Flexible manufacturing, better quality and improved productivity are the expectations of the next generation industry- Industry 4.0. This highlights the limitation of the centralized organization system to handle complexities and establishes that focus should be on multi-agent technologies in manufacturing systems [38]. [8] laid emphasis on the quality and the need for high-velocity information processing as a result of the advent of Industry 4.0.

Another survey paper by Jaskó et al. [5] presents three main points with the assumption that, if analyzed properly, they would facilitate the development of Industry 4.0-ready MES and serve as a guide for engineers and researchers in the field of MES. It explicitly states three questions that need to be addressed in order to design an Industry 4.0-ready MES and proposes solutions to these questions. The questions are: "What are the requirements of MESs in Industry 4.0?", "What kind of standards do exist which need to be considered?", and "What kind of modern, effective methods do exist in this area?". The paper confirms a conclusion made in [37], which suggests how MES can benefit from Industry 4.0 technologies. The MESs should interconnect all components of cyber-physical systems in a seamless, secure, and trustworthy manner to enable high-level automated smart solutions. Also, they recommend that a new generation of linkable data sources should be based on semantically enriched information [5]. In summary, this paper analyzes the Industry 4.0 requirements of MESs in terms of functionalities (i.e., what is required of MESs, what capabilities and functionalities should they have to satisfy these requirements and be Industry 4.0 ready), gives an overview of MES development methods and standards, and discusses the ontology-based and semantic models that can support such development.Generally, there is a lack of adequate research addressing the role of ERP and MES systems in Industry 4.0. The industry-led technology standardization (i.e., RAMI4.0[3] and IIRA[4]), and the main bulk of academic research on Industry 4.0 are completely disconnected [39].

The research limitations and remarks regarding the trending technologies are pointed out as follows:

1. Many ML-based models are applied to improve the quality of products, reduce machinery downtime, and increase machinery operational speed. These models have focused on single-server stations; however, new ML-based models should be defined for multi-server cases. On the other hand, applications of DL-based models in production lines are not explored in detail yet, while they can further improve the performance of currently applied ML models [40].
2. ML is widely applied for designing Predictive Maintenance applications, but it is still a new approach. [41] evaluates the proposed ML-based solutions in this field and concludes that there is a lack of improvement on equipment sensing approaches to improve data quantity and quality.
3. Although RL is commonly used for process scheduling, present RL-based models have some generalization difficulties. Moreover, due to the complexity and dimension of the job shop scheduling problem, these models still encounter some flaws [42].
4. Since DTs in production planning has become a hot topic in recent years, Kritzinger et al. conducted a review of the papers published in this field [17]. They found that these models mostly employ mid-level time-frequency simulations, however, the DT can also be used in domains with higher time-frequency. The authors highlight that in this area, a real DT is relatively scarce, while the majority of the proposed models are, in fact, either digital models or digital shadows.
5. Most of the DT-related literature only focuses on the conceptual models without concrete case studies. The majority of proposed DT applications in manufacturing do not mention the connection of the

[3] Reference Architectural Model Industrie 4.0

[4] Industrial Internet Reference Architecture

DT environment to the control system of the physical equipment [43].

6. Only a limited set of services and operations are offered in one single DT application, therefore a more comprehensive model should be developed to contain other operations. Further, the proposed DT models in the literature are usually not integrated with existing control systems [43].
7. Many AR systems are developed for maintenance, assembly, quality, logistics, and machine set-up applications in the literature. Nonetheless, enhancing the processing speed and ergonomics of AR tools still remains as the main challenges of this technology [20].
8. Chandra et al. review the VR applications in manufacturing [44]. They conclude that although VR provides high-quality visualization, interaction, and immersion, it still has some difficulties in becoming a high-fidelity, industrial-grade tool in digital factories. Besides, VR tools cannot stand alone and must be properly integrated with other simulation tools and machine control drivers. It also requires an intuitive interface.
9. Another survey [45] investigates the literature of blockchain applications to overcome the existing security-related Industry 4.0 problems. The authors outline that there is a lack of an industrial blockchain standard for manufacturing applications. Hence, implementing blockchain encounters some policy challenges when the manufacturer wants to transform from a conventional system to a decentralized network. These challenges are chiefly related to regulatory recognition and interoperability and standardization in i) manufacturing event data models for blockchain; ii) industrial consensus protocols; iii) interplay protocols; iv) signature algorithms; and v) Web-based access protocols which are essential for enabling blockchain systems to be interoperable in the manufacturing system.

6. MES functionalities and intelligence levels

In this section, the paper presents two taxonomies to categorize the proposed MES-related models in the literature. Based on these taxonomies, we assess whether a model meets the requirements of an Industry 4.0-ready MES. In fact, We use these two criteria to determine if the model comprises the tasks that an MES should execute, as well as how competent the model is in terms of performing the tasks autonomously and intelligently. Accordingly, we introduce the tasks that should be done at the MES level and then provide some levels for the intelligence aspect of the system.

Over the past three decades, the Manufacturing Enterprise Solutions Association (MESA) has identified eleven MES functions [49]. These functions include (1) **Resource allocation and status**; where the system manages the resource information and records a detailed history of the resources enabling the manufacturer to optimize production planning. (2) **Operations scheduling**; where the system should deal with the operation sequences and parallel or overlapping operations. (3) **Dispatching product units**; these tasks are associated with managing and monitoring the flow of production units, material and final products in the system. (4) **Document control**; where the system controls the forms, records, and documents related to the production line. (5) **Data collection and acquisition**; the MESs collect the data from the shop floor and maintain it in a database. (6) **Labour management**; the MESs should optimize the labor resources and allocate them in an efficient manner. (7) **Quality management**; where the system should recognize the unhealthy, broken, and low-quality product and maintain quality assurance. (8) **Process management**; this task is associated with production monitoring, decision systems, and production procedures. (9) **Maintenance management**; an MES solution should consider the maintenance activities on the machinery and the manufacturing physical assets. (10) **Product tracking**; the system needs to provide information about activities done on each product and the status of the product. (11) **Performance analysis**; the system has to provide some insights about the overall performance of the production line, the assets and the software system.

Nonetheless, a review of the literature on MES research solutions reveals that many of these tasks are neglected. In fact, there is no model that provides an integrated intelligent solution for all of these tasks. Moreover, many of the proposed solutions are not fully intelligent, automated and adaptable enough to substitute human labor. Therefore, to extract a better insight about the degree of smartness, this paper identifies five intelligence levels towards the realization of Industry 4.0 based on the Industry 4.0 Maturity Index [50]. These levels range from the lowest smartness, where simple computer solutions assist the system to perform more efficiently and optimize tasks, to the highest, where the system is intelligent enough to adapt itself to various scenarios in real-time. Table 10 summarizes 14 recent papers that have surveyed the new technologies in manufacturing systems.

6.1. Digitalization; Computerization of MES

The digitalization level of intelligence comprises the first two maturity levels of the Industry 4.0 Maturity Index [50], computerization and connectivity. These levels, considered together, are required for entry into the Industry 4.0 segment of the transformation path outlined in the index. The basis for digitalization is computerization, which involves the targeted use of information technologies (IT) to improve manufacturing practices [51] (for instance, a programmable machine that can perform repetitive tasks or a simple inventory system). However, each computerized system at this level is independent of the others and lacks the ability to communicate with one another.

The connectivity level brings communication by replacing the independent IT applications with network-connected equivalents. In this stage, the data from each information source is collected automatically in real-time and sent to the MES [5]. However, there is still a gap between the IT systems and the operative technologies as complete integration is not yet achieved at this intelligence level [50,51].

6.2. Visibility; Sensor-based MES

MES operations are highly reliant on sensor readings for realizing the current production status. The visibility level of MES collects and organizes data from sensors spread out across the factory floor. Base sensors, such as proximity sensors, are used in the low-level controllers to manage and operate the machines and devices of each manufacturing process. However, apart from the basic control, MESs can also draw insights from the data produced by these sensors. Other process-dependent sensors, such as temperature and pressure sensors, are also used in monitoring and ensuring each resource is operating as expected. These sensors can send data to the MES for monitoring production, assessing efficiency, and detecting error sources.

Along with the control level sensors, the visibility level of an MES also deals with the transfer of data between processes. This is important in MESs for keeping track of workpieces and specific details of an order. Auto-ID technologies such as RFID tags or barcodes are commonly used to label and track a workpiece throughout the production line [52–54]. With read and write capabilities at each stage, specific details can easily be identified and updated regardless of the production flow. These technologies are an important source of data, enabling real-time data-based transparency [55]. Collecting the vast amounts of data generated by sensors and auto-ID technologies allows for a complete recording of the production process from start to finish [51].

6.3. Transparency; adding perception to MES

Beyond basic sensor data, MESs can gain a more perceptive understanding of the production floor with the use of smart sensors and intelligent software. The transparency level of an MES brings synthetic intuition to software by enabling a more comprehensive record of the

Table 10
Summary of the selected surveys.

Paper	Focus	SLR *	Taxonomy	Proposed model	Industry	Case study	Year
[16]	AI solutions in the manufacturing for tackling different kind of challenges	Yes	NA	NA	General	NA	2020
[45]	Blockchain applications to overcome existing industry 4.0 problems	No	(1) Cybersecurity Issues in Smart Manufacturing; (2) Metrics that shows Blockchain is a good solution for an Issue in Manufacturing;	NA	General	NA	2020
[46]	Machine learning applications for sustainable manufacturing	Yes	Main challenges to sustainable manufacturing, Machine learning algorithms with their application area in manufacturing	An ML-based sustainable manufacturing (SM) framework. In the framework, three main components are considered, i.e. different phases of SM, opportunities of ML techniques and benefits from ML in all three dimensions of sustainability.	General	NA	2021
[5]	Impact of Industry 4.0 on MESs	No	(1) Maturity levels: Visibility, Transparency, Modularity, Predictive capability, Adaptability, Interoperability; (2) Integration direction: Horizontal, Vertical	NA	General	NA	2020
[17]	DT in Manufacturing	No	(1) Level of integration: Digital Model, Digital Shadow, DT; (2) Focused area: Layout planning, Product life cycle, Process design, Maintenance	NA	General	NA	2018
[44]	VR in Manufacturing	Yes	VR usage in digital factory: Manufacturing, Layout planning, Robot path planning, Virtual prototyping, Training	NA	General	NA	2021
[39]	Assessing the readiness of the agile manufacturing models for Industry 4.0	No	Industry 4.0 reference architectures: RAMI 4.0, IIRA	An OPC-UA-based architecture	General	Virtual assembly line	2019
[47]	ML in mining industry	Yes	(1) Application fields: Exploration, Exploitation, Reclamation; (2) Dataset type: Laboratory data, Data field, Open-source	NA	Mining	NA	2021
[41]	ML in Predictive Maintenance	Yes	(1) ML techniques; (2) Dataset type: Real, Synthetic	NA	General	NA	2019
[43]	DT in Manufacturing	No	NA	An OPC-UA-based DT that simulates a multi-station with the purpose of energy consumption monitoring	General	A prototypical mobile phone assembly line	2019
[42]	RL in Process Scheduling	No	NA	A Deep RL architecture for job shop scheduling	General	NA	2018
[20]	AR applications in intelligent manufacturing	Yes	Field of application, technology to visualize AR content, methodology to test AR applications, metric to evaluate the capability of the AR prototype;	NA	General	NA	2020
[40]	Machine learning applications in production lines	Yes	The studies were categorized according to the industry domain, targeted process, production line problem, machine learning model;	NA	General	NA	2020
[48]	Applications of machine learing in manufacturing	No	Field of application: decision support, plant and operations health management, data managment, lifecycle management	NA	General	NA	2018

* Systematic Literature Review

manufacturing environment. This involves compiling all data into a manageable format for analysis and advanced processing. With the organized data, AI applications can be utilized to gain knowledge from the historical events [56]. Fahle et al. review current AI trends in manufacturing and identify the areas in which machine learning has been implemented to improve manufacturing processes [56].

Improving the MES's real-time perception of the factory can lead to better safety precautions, maintenance scheduling, and overall operability. For instance, visual and audio sensors can provide MES with data to aid in human-machine collaboration, improving operator's control of equipment as well as safety responses of machines. One example demonstrated by Duckworth et al. shows the ability to extract low-dimensional representations of human movement from visual data perceived by mobile robots [57]. Their model identifies consistent patterns that represent detailed human body positioning and pose estimation, which could be applied in the MES perception level to gain knowledge of workers within the factory.

6.4. Prediction; Utilizing prediction methods in MES

In MES, the prediction level can be defined as the response to two questions of "What will be the state of the system in the future?" and "How this state transition will happen?". An effective response to these questions will improve the system's dependability and assist the MES in better preparing itself for future decisions. To this end, researchers have proposed solutions that simulate future realistic and probable scenarios while also providing system optimization capabilities. One of the issues that should be addressed within the MES prediction level is the ability to anticipate the requirement for maintenance of machinery, equipment, and robotics at a specific future time. Maintenance is a crucial factor in a company's competitiveness because it has a direct impact on the manufacturer's essential factors (i.e. the downtime, cost, deadlines and quality of the products or services) [58]. Advances in IoT devices and computational power have offered an unprecedented opportunity to gain insights from condition monitoring data and use them for intelligent predictive maintenance [59]. In recent years, many artificial intelligence techniques have been proposed to reduce maintenance costs, increase operational performance, enhance safety systems, and achieve a maintenance decision-support system that allows the manufacturer to take timely actions and prepare for maintenance operations [60]. Nonetheless, one of the gaps in the scope of Industry 4.0 is the lack of sufficient attention to include the predictive maintenance in the proposed MES models [61].

As discussed earlier, digital models can be categorized into the digital replica, digital shadow, and DT [62]. A digital replica highlights the automatic projection of system constructions. The digital shadow emphasizes mathematical modeling to simulate and mimic the physical or chemical characteristics of a system. To support the interaction between the digital shadow and the physical assets and provide real-time feedback to the system, the paradigm of DT is proposed. A DT integrates the multi-physics and multi-scale simulation of a system that can model the mechanical, electrical, software, and other discipline-specific properties across its lifecycle. A DT is therefore employed to optimize the physical product or system based on the updated real-time data synchronized from sensors [63].

Based on this definition, a DT is a high-level simulation system and integration paradigm which can fall in the MES prediction level. Through the study and investigation of information models, the DT can map physical information into cyberspace and manipulate physical objects [10]. Uhlemann et al. propose a concept for the realization of DT in small and medium-sized enterprises, where the digital counterpart acquires the data within the production system to predict the service demand using simulation software [64]. In [63], the authors design a DT concept for human-cyber-physical manufacturing systems, whose architecture enables the flow of information between the production line and the simulation environment to make an AR-based visualization. In spite of the promising features that these models bring to the MES, they are not adaptive enough to cope with event-driven production planning systems.

6.5. Adaptability; Self-optimization of MES

This maturity level aims to use real-time data to make the best possible decisions in different scenarios that the system faces and enable the system to optimize itself. Most often, these decisions need to be taken immediately; therefore, an effective adaptive MES has to be agile enough to perform on a real-time basis. The adaptation can range from simple dilemmas to highly complicated decisions; hence, a smart MES solution should support multi-objective real-time decision-making.

There are some self-optimizing and self-organizing intelligent systems proposed in the literature. In [65], the authors propose a self-organizing system for a networked manufacturing environment where scheduling of the shop floors is synchronized to control the assembly line. They use some numerical experiments to evaluate their proposed conceptual model. Similarly, [66] develop a self-organizing assembly system that spontaneously organizes itself in the shop floor layout in response to the arrival of product orders and manages the agents during the assembly processes. In order to achieve a collaborative routing of products, [67] propose a multi-agent manufacturing system that dynamically handles the potential rescheduling of orders already in the system. The proposed model employs the available resources, and their state, in a time-efficient way. To schedule the production line and manage the processes, Zhang et al.[68] design a multi-agent system that organizes itself in a ubiquitous shop floor environment. To collect and process the real-time shop floor data, they deploy some wireless devices such as RFIDs.

Nevertheless, these models and frameworks are only able to perform individual logical adaptations or limited MES functionalities autonomously. There is still a lack of a comprehensive solution to support an entire adaptation process from start to finish. This process is often largely human-driven, primarily based on the experience of system integrators. While there are methods and tools for solving specific problems, these methods and tools are not integrated into a general framework that can be used in a wide range of scenarios in different industries.

As the robots are not yet fully autonomous, sufficiently versatile and affordable by all industries, today's industry still relies on the agility, intelligence and perception of human operators alongside speed, power, accuracy, repeatability and insusceptibility to fatigue of the robots[69]. The limited autonomy of robots has brought up the term Human-Machine Collaboration. Mukherjee et al. reviewed the levels of autonomy of robots in industrial settings and identified the challenges in achieving fully-automated robots, especially due to the lack of sufficient and proper datasets. They also concluded that adaptive robots require low processing times to be able to operate in a real-time manner, while in many cases, it is challenging due to the technical difficulties or lack of computational resources [70].

. Table 11 briefly summarizes over fifty related papers that have been published since 2010; It can be concluded that most of the so-called intelligent solutions fall in the first two intelligence levels, digitalization and visibility. The table also specifies the above-mentioned MES functions that each paper includes in its intelligent framework. As it is highlighted, each paper has only addressed a few of these functions. In the highest intelligence levels, adaptability, only a limited number of papers propose MES-related functionalities: for resource allocation [71], operations scheduling[72], process management [73] and quality management [74,75]. Therefore, as mentioned before, to achieve an efficient industry 4.0 platform where the system is fully autonomous and digitized, an MES with complete functionality is required. As it is shown in the table, the proposed frameworks by [78] and [79] have comprised more MES functionalities, however, their solutions have still not achieved the adaptability level.

Fig. 7 shows the percentage of papers covering each intelligence level in the reviewed literature. All the selected papers have achieved at least the first intelligence level, digitalization. Mathematical models, linear programming and meta-heuristic algorithms for job shop optimization have filled the literature. However, as we go to higher intelligence levels, there are fewer papers proposing MES-related solutions. There are just above 600 and 300 papers that reach the second and third levels, respectively. Papers that reach the visibility level are associated with the use of sensors and auto-ID technologies such as RFIDs and process-dependent sensors to collect the data and keep track of workpieces in the shop floor. In the third level, on the other hand, the papers mostly propose AI algorithms to gain knowledge from historical events and provide deeper insight about the current state of the system. In our search, only 15% of the MES literature have used data-driven solutions to predict the future state of the shop floor. ML, DL and agent-based simulations are the most prevalent techniques at this level. As expected, we found out that adaptable solutions are relatively rare in the literature, with less than 5% of the papers achieving this level. It spotlights the gap in this level since there are still many MES tasks that have not reached adaptability.

7. Current industrial solutions

In the previous sections, we study the academic papers and outline the limitations and research gaps of solutions proposed in the literature. In this section, conversely, we go one step further and take a look at the industrial solutions that are provided in real business. We then discuss what kind of challenges and obstacles are out there that hinder the adoption of novel MES frameworks by the practitioners.

Table 11
Solutions regarding MES functions proposed in the literature.

Paper	MES Functions	Intelligence Level	Solution Features	Industry	Year
[71]	1–5	Adaptability	3D simulation - Order Batch to Robot Task Conversion algorithm	General	2021
[72]	2–5	Adaptability	Metaheuristics (genetic algorithm) - Mathematical model	General	2017
[73]	8	Adaptability	Double adaptive fuzzy sliding mode control - Numerical simulation	General	2015
[74]	5–7	Adaptability	Robotized vision based quality control	Home appliance industry	2014
[75]	5–7	Adaptability	Spatial repositioning of the vision system - optimizing Camera and Robot positions and settings	General	2016
[76]	1–2–5	Prediction	Hybrid control solution based on ANN and LSTM	Power Plants	2020
[77]	1–2–5–8	Prediction	Real-time multi-agent modelling	General	2014
[78]	1–2–3–5–8–10–11	Prediction	Agent-supported Simulation Environment	General	2014
[79]	1–2–3–5–8–10	Prediction	DT (quad-play CMCO architecture)	Glass manufacturing	2021
[80]	5–7	Prediction	IoT - Simulation - Machine Learning	Casting industry	2018
[81]	5–7	Transparency	Model for heat resistance, image transmission, and data alignment could	General	2018
[82]	5–8–10	Transparency	Conceptual solution	Motor Manufacturing	2020
[83]	1–5–10–11	Transparency	RFID and UAV-based inventory control - Blockchain - Distributed ledger	General	2019
[84]	1–5	Visibility	Fuzzy logic	General	2014
[85]	2–11	Visibility	Heuristic mathematical model	General	2018
[86]	2–5–11	Visibility	Metaheuristics (artificial bee colony algorithm)	General	2020
[87]	2–11	Visibility	Discrete-event simulation model - Metaheuristics	Semiconductors	2014
[88]	1–2–5–11	Visibility	Metaheuristics (hybrid genetic algorithm)	General	2016
[89]	2–5	Visibility	Metaheuristics (differential evolution-fused particle swarm) - Numerical simulation	General	2018
[90]	2–3–5	Visibility	Discrete-event simulation model	General	2017
[91]	2–11	Visibility	Discrete-event simulation model	General	2017
[92]	2–5–11	Visibility	Advanced production planning and scheduling	General	2014
[93]	2–5–11	Visibility	Artificial immune systems - Priority dispatching rules	General	2013
[94]	7	Visibility	Thresholding	Sandwish panel manufacturing	2019
[95]	5–7	Visibility	SVM	General	2019
[96]	5–7	Visibility	Fuzzy segmentation - multi-instance learning	General	2019
[97]	1 -	Digitalization	Multi-agent modelling	General	2005
[98]	2–5–6	Digitalization	Two-level optimization model	General	2021
[99]	2–5–6	Digitalization	Mathematical model	Automative industry	2017
[100]	2–8–11	Digitalization	Numerical simulation	General	2016
[101]	2–8	Digitalization	Metaheuristics (Simulated Annealing algorithms)	General	2019
[102]	2–11	Digitalization	Swarm intelligence - disjunctive graph-based model	General	2014
[103]	2–11	Digitalization	Metaheuristics (artificial bee colony algorithm) - Fuzzy logic	General	2016
[104]	2–11	Digitalization	Multi-objective integer linear programming	General	2014
[105]	1–2–5–11	Digitalization	Metaheuristics (variable neighborhood search algorithm)	Automative industry	2020
[106]	2–5–11	Digitalization	Mathematical model	Automative industry	2013
[107]	3–5	Digitalization	Numerical simulation	Semiconductors	2011
[108]	3–5	Digitalization	Numerical simulation	Semiconductors	2016
[109]	2–3	Digitalization	Mathematical model	Semiconductors	2018
[110]	2–3	Digitalization	Tabu Search - Monte Carlo simulation	General	2013
[111]	6–11	Digitalization	Numerical simulation	General	2007
[112]	2–6–11	Digitalization	Mathematical model	Automative industry	2020
[113]	2–6–11	Digitalization	Mathematical model - Branch and bound algorithm	Ceramic tile industry	2009
[114]	2–6–11	Digitalization	Metaheuristics (Genetic Algorithm) - Numerical simulation		2020
[115]	2–7–9–11	Digitalization	Mathematical model	General	2011
[116]	9–11	Digitalization	Discrete-time Markov chain	General	2013
[117]	1–9–11	Digitalization	Mathematical model	Cell industry	2012
[118]	1–9–11	Digitalization	Mathematical model	General	2012
[119]	7–9–11	Digitalization	Mathematical model	General	2016

7.1. A review of novel industrial solutions

In the domain of MES, there are some different solutions available in the market. These solutions may vary from standalone solutions to service-based solutions and from specific functionality to general purpose. In this work, some of the popular MES software, which include POMSNet Aquila [120], ABB MES [121], Siemens Opcenter [122], Proficy MES by GE Digital [123], 3DS's DELMIAworks [124], and finally PLEX's MES/MOM [125] have been studied in order to create a reference point for this research. More information about the MES features that each system provides and their intelligence characteristics are presented in Table 12.

POMSNet Aquila is designed with specific consideration for the life sciences industry [120]. It offers advanced biometric-based security features and features designed for Pharma 4.0. POMS markets its software as a flexible solution that does not require customization across different use cases, a one size fits all of MES software.

ABB's MES offers solutions designed for different industries [121]. Their marketing targets the following industries: discrete manufacturing; food and beverage; chemicals; pharmaceutical and life sciences; oil, gas and petrochemicals; cement manufacturing; metals; mining and minerals processing; and pulp and paper. ABB also provides other industry software for a truly customizable solution.

Siemens Opcenter is a suite of industrial automation software covering a wide range of functionality [122]. Opcenter contains four separate MESs: Opcenter Execution Pharma, Opcenter Execution Discrete, Opcenter Execution Process, and Opcenter Electronics. Each of these MES solutions is targeted at a specific industry and can be combined with other Opcenter software for more diverse applications.

GE Digital's MES software, Proficy, is also a suite of solutions that can be combined to fit the specific needs of various manufacturers [123]. GE Digital markets its suite as a data-driven solution with intelligent manufacturing and business insights. One key feature that is commonly mentioned on GE Digital's website is the application of lean principles throughout their software to reduce waste and improve production times.

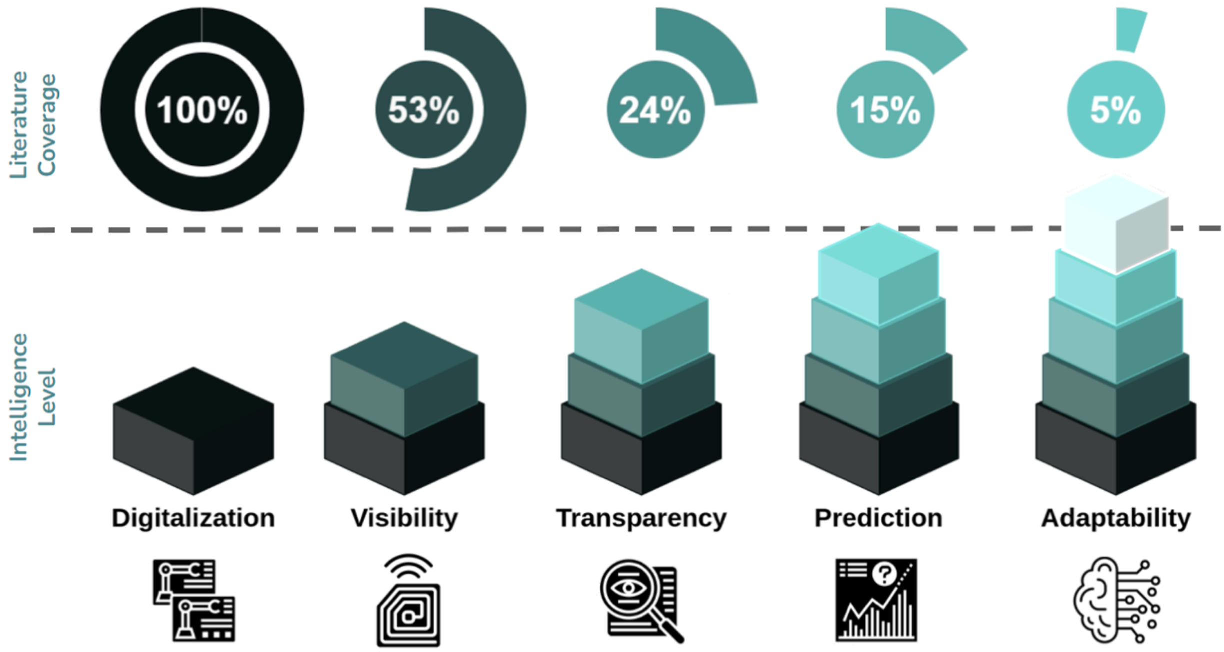

Fig. 7. The percentage of literature that covers each intelligence level.

3DS offers a complete MES and ERP solution with DELIMIAworks [124]. DELIMIAworks is designed as an all-in-one solution that strives to “offer it all". Their software solutions are customizable with the option to use a built-in ERP solution or integrate with other standalone ERPs.

The final MES solution considered in this survey is by PLEX systems, a Rockwell Automation company [125]. PLEX’s MES/MOM is a solution aimed at providing full visibility across the shop floor and business management. PLEX offers a paperless solution that automates tasks in order to prevent human error, with the goal of creating an error-proof shop floor. The unified user interface is designed as a single access point for production information and management.

Of the considered MES software, all allow for the visibility intelligence level to be reached. Each enables real-time sensor data to be recorded across the entire manufacturing facility, permitting the current production state to be monitored. This record-keeping functionality also allows states and events to be tracked for a more comprehensive understanding of a facility’s history. This provides a basic digital shadow that can show what is happening at any given time. The digital shadow is one of the key components of the visibility intelligence level and helps to make real-time management decisions based on real data [50].

Past the visibility level, some of the reviewed MESs also have functionality enabling basic data analysis. With these basic features, Opcenter, Proficy and DELMIAworks are reaching the transparency intelligence level in some aspects of their software but still require more actionable insights to support complex and rapid decision making in order to fully encompass the transparency level.

Further intelligence levels have yet to be reached with currently available MES solutions. The prediction intelligence level requires better anticipation of future events based on historical data accumulated by the MES. Proficy provides some basic predictive analytics to estimate material needs and forecasts future performance. However, more comprehensive predictive capacity and integration with digital models are needed to provide the necessary insights for planning future actions.

7.2. The challenges and impediments in adoption of novel MESs

As outlined in the previous sections, an effective MES can serve as a backbone in bringing the advanced Industry 4.0 solutions to the factory floor. However, there stand a few obstacles that prevent the successful adoption of this powerful technology. Although the most challenges are common across the industry, the literature review indicated that there are also few region-specific barriers that hinder the widespread adoption.

The primary and one of the most important barriers is the extensive amount of capital investment required to develop and maintain the MES solutions [126–128]. As a result, the benefit of these technologies is confined to a few multinationals and large firms with good financial standing [128]. On the other side, SMEs make the majority part of the economy. For example, 90% of the registered companies in Europe are SMEs [128]. While in Poland, SMEs account for 50% of the total revenue of the polish economy [127].

The second factor is the lack of a technically skilled workforce [129,128,127]. A proficient workforce is essential from two aspects. The first is to develop the MES solutions that are tailor-made to specific tasks or organizations. Such expertise again is associated with high expense in wages [127]. Secondly, the successful use of such technology also demands a certain skill set at the ground level. This may not be a concern in developed counties. However, in regions with a still growing economy, such as south Asia, most of the workforce working at this level have minimal to no qualifications [129].

The resistance to change is another common reason affecting the adoption of Industry 4.0 [129,127,130]. This resistance is further aided by the misconception of losing jobs to robots and machines [129,131]. The employee should be convinced about the benefits and advances of a novel MES for the adoption at large. The abundance of solutions is also one of the reasons behind the slower adoption rate of these advanced solutions [128]. The overwhelming rate of technological development has resulted in a wide range of solutions in the market. Therefore, it has become challenging to match the requirements of the SME to the right solutions.

Furthermore, there are a few challenges that are specific to the geographical location of the region. For Poland, the challenge is associated with the old equipment in the majority of SMEs and language barriers in the skilled workforce [127]. The lack of public-private partnership for such a development is identified as one of the weaknesses in Russia [131]. In India, lack of internet access, privacy, and security concerns pose additional predicament [130].

Apart from the aforementioned concerns with the adoption of novel

Table 12
Industrial MES solutions in the market.

MES Solution	Key Features	MES Functions	Intelligence Level	Additional Information
POMSnet Aquila [120]	order management, equipment management, materials management, weigh & dispense, specification management, quality management, personnel management, recipe execution, electronic batch records, review-by-exception & release-by-exception, worksheets and logbooks, device history	1, 2, 3, 4, 5, 7, 8, 10, 11	Visibility	ISA-95 based, web-based application, HTML5 UI/UX, Microsoft's.NET technology, mobile/touch enabled, onsite or cloud hosted, standardized integration, OPC connectivity, interfaces based on S88 batch standard, data protection, FDA21 CFR compliance, enhanced security with Nymi Band authentication
ABB MES[121]	production management, quality management, downtime management, materials management, warehouse management, labor management, equipment & maintenance management, overall equipment efficiency reporting, electronic work instructions, operations and plant performance reporting	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	Visibility	ISA-95 based, web-based application, B2MML support, Microsoft's.NET technology, Microsoft SQL Server, virtual environment support, NLS support, standardized integration, OPC and TCP/IP, process intelligence, production intelligence, production optimization
Siemens Opcenter[122]	data collection & acquisition, dispatching production, document control, labor management, maintenance management, materials management, operations & detailed scheduling, performance analysis, process management, production tracking, quality management, resource allocation	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	Transparency	ISA-95 based, comprehensive integration capabilities, cloud ready, touch friendly mobile interface, connected and aggregated data provides actionable insights
GE Digital Proficy[123]	resource, energy & efficiency management, quality management, production management & tracking, batch analysis, production process traceability, dynamic scheduling, supply chain coordination, data management and collection	1, 2, 3, 4, 5, 7, 8, 9, 10, 11	Transparency	web-based application, roll-specific dashboards, industry standards, OPC UA, MQTT, ISA 18.2, ISA 101, hybrid cloud and onsite data management, standardized integration, machine learning, predictive analytics
3DS DELMIAworks [124]	process monitoring, production monitoring, data collection, efficiency monitoring, inventory tracking, production traceability, material resource planning, production reporting, quality management, scheduling, warehouse management, product lifecycle management, tooling & project management, customer & supplier portals, document control, supply chain management	1, 2, 4, 5, 7, 8, 10, 11	Transparency	standalone ERP integration or built-in ERP, mobile app store, EDI/XML eCommerce, MS office interfaces, preventative maintenance, forecasting, manufacturing intelligence, business intelligence
PLEX[125]	production management, inventory management, quality management, production scheduling, production traceability, data analysis, task automation	1, 2, 3, 5, 7, 8, 10, 11	Visibility	cloud based, unified user interface, standalone ERP integration,

MESs, the development and implementation of such solutions constitute a wide range of additional challenges. Following are a few of such challenges as described in [132]:

1. **Lack of information:** Often time collection of useful information and data is necessary to develop a solution.
2. **Lack of clarity of goal:** One of the most challenging parts of developing a successful ML solution is to identify the right problem and define the performance metric to access the outcome. Projects with obscured scope have a very high chance of missing the mark.
3. **Convergence of cultures:** Bringing operational expertise together with information technology is a very important aspect to build working solutions in Industry 4.0. The absence of such convergence would either result in poor digital infrastructure or unsuccessful deployment of the solution.

8. The proposed conceptual model

In order to answer RQ6 and fill the gaps based on the literature review, we propose a conceptual framework for IMES, illustrated in Fig. 8. The components of this schematic model are described in the following.

8.1. IMES interface and controlling systems

Machine to machine communications - Communication between devices, software, and databases is a key component for enabling Industry 4.0 smart factories, especially at the MES level. To make real-time control decisions, MES software requires receiving status updates from all connected devices across the shop floor at near instantaneous speeds. It also needs to send updates and instructions to these devices in order to manage and control the production processes. For this to happen, a fast and secure communication protocol is essential. Communication should also enable machines to communicate with each other to share information on available resources and operation states. The current, most widely adopted industry standard is the Open Platform Communication Unified Architecture (OPC UA) [133]. OPC UA is a standardized communication protocol initially developed for machine-to-machine communication in industrial automation [134,135]. This communication platform enables standardized definitions of machine attributes such as data structures and interfaces and offers configurable security credentials [134].

Edge devices - Edge devices play an important role in IMES, enabling AI applications to process data where it is produced. Edge devices are IoT devices that perform relevant computations at the edge of a network rather than transmitting the data to be processed on the cloud [136]. Edge devices do not eliminate the need of the cloud, but rather they reduce the load on the network and can reduce the latency for AI-powered applications. This can speed up services and response times compared to a central or cloud-based processing method [136]. Cloud computing is still vital to MES operations and cannot be fully replaced by edge devices, but rather a hybrid edge-cloud solution is most beneficial [137]. Edge-enabled cloud architectures can relay important information to the centralized MES without having to send every single sensor reading and value. This can also increase security by eliminating the sharing of certain data over a network.

IMES interface - Because of the many distinct elements that comprise IMESs, a single integrated management interface is required to keep things organized and easy to use. A centralized interface for managing MES software should not only allow for user-based management but also incorporate standardized APIs and protocols for integrating with other software that may be used across manufacturing enterprises [138]. The purpose of an MES is to assist human decision making for the management of manufacturing operations, and as such, the presented information and user, options should be intuitive and

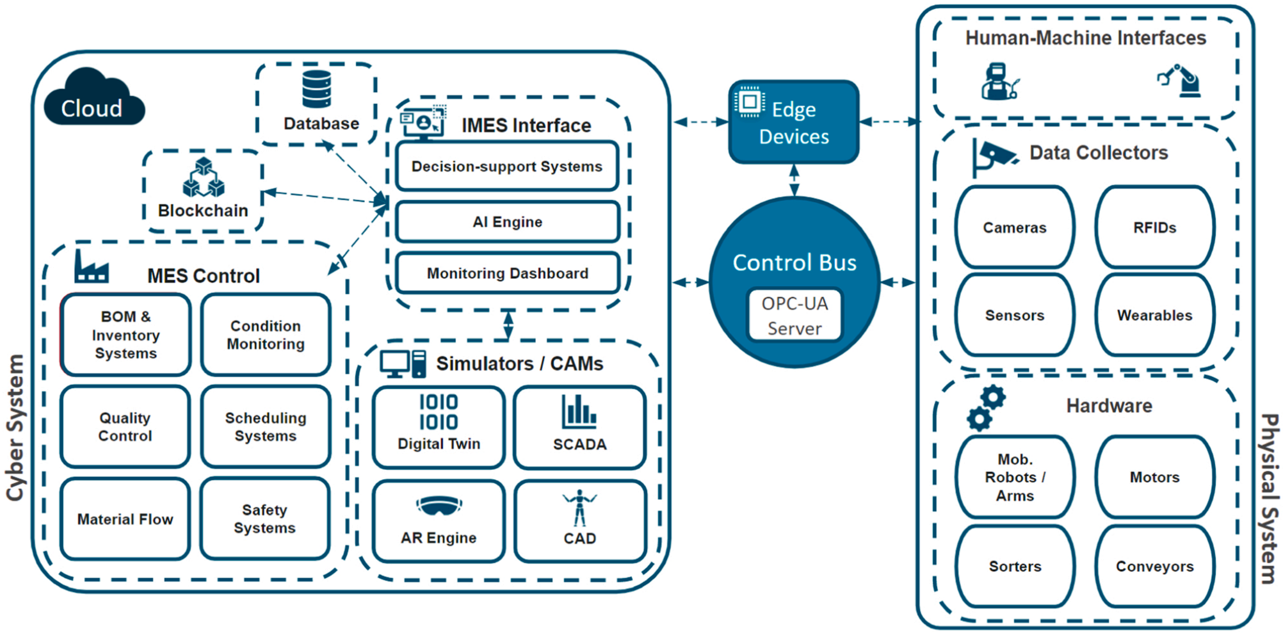

Fig. 8. The components of the proposed conceptual IMES model.

functional. AI can also be incorporated in the MES interface to create a more user-friendly experience. For instance, Mantravadi et al. propose the use of AI chatbots in MESs as a technical assistance system for users [139]. Their findings show that MES users can benefit from an interactive chatbot by creating a more dynamic experience with enhanced responsiveness and better data retrieval. This is just one way that AI can help improve efficiency in MES interfaces.

8.2. IMES software systems and ML modules

One of the crucial elements of the new MES generation is its controlling ability over the shop floor operations. The controlling section consists of inventory systems, condition monitoring, quality control, system scheduling, material flow and safety systems. All of these subsystems are connected with databases, blockchain systems and the OPC-UA server. In every state of the software part, AI should be present for automation and increasing the efficiency of the production line [140].

In the proposed IMES framework, manufacturers should store system logs and product logs consisting of their status and features in a proper database system [141]. We recommend keeping a redundant version of the data in a blockchain system as well [142,143]. Mentioned redundancy is beneficial in different ways. Blockchain systems have high availability and are easy to access across edge devices. In some cases, these blockchain features enable us to remove SPoF (single point of failure) related to data. Because of systems' pseudonymity and security, we can rely on storing data in the same way that database management systems (DBMSs) do [45,143].

We suggest selecting DBMSs and designing a blockchain system regarding the production line use cases and needs of each inventory system [144]. Some scenarios illustrate the importance of selecting a proper DBMS; As an example, some MESs use the power of deep learning to categorize goods within the production line stages into different classes, e.g., their ability to recycle. When an MES needs to store the aforementioned product features, such as recyclable or hazardous, into specific classes, a relational database or a column family database, such as Cassandra, is preferable. In contrast, if the MES uses an unsupervised method, relational databases are not a good fit because of the unpredictable output classes of these algorithms. Using document-based databases such as MongoDB may be a better choice because it has a null-free structure in the design [145,146].

The proposed IMES design should have a fully automated **document control** toolbox. This toolbox should facilitate the review, modification, issuance and accessibility of documents. For this to happen, the MES model should have some [5]NLP modules after recognizing the document images; secondly, a cloud-based decentralized software should be developed to make the documents more accessible[147]. To this end, designing a private blockchain system with distributed computation ability or employing well-known blockchain systems ([148–150]) with the ability to run scripts can be helpful. Thus, these systems should have computer vision models that are trained and ready for recognizing the documents. The automated document control part should understand the meaning of the recognized documents in the next stage and give a reasonable and logical response to them [151,152].

Another essential software part of the proposed new generation of MES is the **supply chain**. Companies need a trackable, transparent, secure and reliable supply chain for both their customers' reliability and their own profits. To achieve this goal, records of the production stages should save in a consortium or hybrid blockchain [144,153]. Due to the blockchain's transparency, decentralization, and pseudonymity [154], this technology is a good fit for the new MES generation and some companies already apply this solution to their supply chain [45,155].

Quality control is another aspect that next-generation MESs should deploy with added intelligence. This part is more connected to the OPC-UA server and database logging because it requires more data from cameras, sensors, and auto-ID technologies. In addition to having computer vision parts for fault recognition and recognizing anomalies [156–158] in the production line, other technologies should be acquired to avoid faults. For instance, the new generation of MESs should contain a digital twin in their production line and should develop simulation software before launching new features in the production line. VR and AR are also beneficial for eliminating human error and teaching new workers how to perform routine tasks [159].

Safety systems are another essential toolbox that should be considered in the IMES. For ensuring safety, many sensors are used in the MESs, namely temperature, humidity, fire detector [160,161]. In addition to the sensors, live video analysis and computer vision modules should be developed to detect the hazardous conditions for the

[5] Natural Language Processing

employees in the production line [162]. Moreover, due to the recent COVID-19 pandemic, there is a high demand for automatic control of emergency response protocols in the production line [163].

8.3. IMES connection to the physical assets

Field devices - Depending on the industry and the manufacturing field, there can be a range of machines, devices and hardware available for shop floor operations. Conveyors, sorters, actuators, robots, CNCs, motors, and rotating machinery are some examples of such devices. The IMES framework has to communicate with and control these field devices. Therefore, an IMES has to consider the IoT connectivity and the employment of controllers, which are two of the most important components based on Reference Architecture Model for Industry 4.0 (RAMI4.0) [164].

Data collectors - Since data collection is one of the key functions for MESs; the new MES generation needs to automatically and effectively collect the data from the shop floor (e.g., equipment, workers, material and products) using sensors, RFIDs, different camera types and wearable devices. RFID middleware is an essential part of the IMES, however, there should be some security measures to avoid any data loss [165]. To cope with the speed, variability, and size of the data being gathered from the physical assets, the proposed IMES should use a cloud-based data architecture solution such as cloud-enabled distributed architecture [166], blockchain-based distributed network [167] or others [168,169].

9. Concluding remarks

MES is one of the key layers of the automation pyramid. It connects the high-level management layer (ERP) to the control layer and shop floor operations. Nevertheless, there is a lack of adequate attention to the MES models' compatibility with Industry 4.0 standardization [39]. This work presents how recent technologies and trends in Industry 4.0 solutions can have an impact on the development of MES frameworks and also identifies the gaps and pitfalls that can obstruct the adoption of a practical MES.

This paper carries out a systematic literature review to extract the trending technologies that resulted in the selection of over 1300 papers. After initial statistical and graph analyses, among them, we selected 65 papers, including 14 survey papers, for further examinations. After reviewing these papers, we extracted insights about the research gaps and the limitations related to the trending technologies and MES models.

Further, the selected papers are classified into five intelligence levels, in accordance with the Industry 4.0 maturity and readiness, to see whether current models can meet Industry 4.0 requirements. We highlight that despite the plethora of automation and optimization solutions for Industry 4.0, there is still a considerable gap between the current solutions and an intelligent MES (IMES) that is basically a fully autonomous and intelligent system. Further, we have presented the main MES functionalities and mapped the literature accordingly to identify the functions that have not been addressed adequately. Our findings suggest that: i) none of the proposed MES models have addressed these MES functions altogether; ii) we did not identify any MES-related papers that take "document control" into account; iii) most MES related papers published over the last decade focus primarily on the first two steps of industry 4.0, i.e., the Digitalization and the Visibility levels, and iv) our analysis shows that there are still significant steps remaining to reach higher intelligence levels in dispatching product unit control, maintenance management, product tracking and labor management.

We emphasize that in the future, an IMES should focus more on flexibility, predictability, adaptability, and thoroughness that comprise all the MES functionalities; Such a model can help the practitioners to replace their traditional procedures and let machines and robots perform a majority of tasks in different manufacturing systems. We expect that some trending technologies contribute further to the realization of an efficient IMES. Examples include digital twins (DTs) with higher complexities and deeper perceptions, AR and VR solutions for human-machine interactions, more powerful generative algorithms to synthesize realistic datasets and solutions, and the blockchain technology to make the supply chain system more transparent and track the units more efficiently.

In the systematic review part of this paper, we highlight the most trending technologies used to make manufacturing more intelligent during the last decade. According to Table 9, it can be concluded that from 2009 to 2012, machine learning, computer vision and VR were the top two technologies employed for re-innovating manufacturing. Computer vision techniques are used for adding more automation to production lines as well as fault detection purposes. Also, researchers designed some quality assurance modules in manufacturing using VR technology during that period. After that, pattern recognition and reinforcement learning technologies became popular and frequently used. In 2015, AR was also widely used and created a new idea into IMES, especially for employee on-boarding and quality assurance.

The DT and use of deep learning algorithms are also revolutionizing the manufacturing sector and are increasingly applied in new frameworks. New trending technologies such as 5G and blockchain can be of great importance in edge communications. Blockchain is beneficial and a good solution for many production lines and companies regarding the supply chain due to the privacy, transparency and decentralization that blockchain can provide. According to the hot topic trends and traces, we think a hot area in 2021 and 2022 will be 5G, blockchain and Generative Adversarial Networks -GANs-. GANs are also a new approach and method that can be used in manufacturing to helpfully achieve the goal of IMES.

There are some obstacles that wedge a gap between industrial implementations and state-of-the-art reported in literature. We outlined the gaps in the well-known industrial MES frameworks and highlighted the roots of the problem with industry not being able to adopt fully smart manufacturing technologies and strategies. The first barrier is the lack of sufficient investment in renewing the hardware and provision of novel technology platforms. In addition, the lack of technical skill sets required and the absence of cultural convergence have resulted in poor collaboration between experts that could address the identified knowledge gaps in a timely fashion. SMEs, comprising the majority of the industry, struggle the most to adopt intelligent solutions. Nevertheless, due to the adoption of middle-wares [170], and cloud-based solutions [171,172] that have made this transition more affordable and highly scalable, more and more SMEs will adopt smart MESs [165,173].

In conclusion, the authors suggest closer collaboration between industry R&D divisions and academic research laboratories to alleviate and remove the impediments we presented in this paper. Hence, a comprehensive MES model that integrates all the MES functionalities with more intelligence levels is required. To this end, we proposed a conceptual framework, called IMES, that shows briefly what an industry 4.0-ready MES should contain. This framework aims at improving each MES task to its highest level of intelligence and ensuring that the MES model can be practically implemented by practitioners.

CRediT authorship contribution statement

Ardeshir Shojaeinasab: Conceptualization, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Todd Charter:** Data curation, Visualization, Writing – original draft, Writing – review & editing. **Masoud Jalayer:** Conceptualization, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Maziyar Khadivi:** Investigation, Writing – original draft. **Oluwaseyi Ogunfowora:** Investigation, Writing – original draft. **Nirav Raiyani:** Investigation, Writing – original draft. **Marjan Yaghoubi:** Writing – original draft. **Homayoun Najjaran:** Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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