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Maintenance transformation through Industry 4.0 technologies: A systematic literature review

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ABSTRACT

Industry 4.0 is revolutionizing manufacturing, increasing flexibility, mass customization, quality and productivity. In today's competitive manufacturing scenario, maintenance is one of the most critical issues and companies are approaching its digital transformation from technological and management perspectives.

This article carries out a systematic literature review aimed to investigate how maintenance tasks and maintenance management strategies are changing in Industry 4.0 context, analyzing the state-of-the-art of Industry 4.0 technologies currently employed in maintenance and the resulting potential innovations in maintenance policies and manufacturing management. In addition, the most relevant trends in current maintenance policies have been investigated, such as "remote maintenance" and the attractive possibility of a "self-maintenance". Also, the importance of human factor has been considered. The results are summarized in a comprehensive database, to provide, through concepts and empirical evidence present in literature, examples and strategies for the implementation of maintenance in Industry 4.0.

1. Introduction

The term "Industry 4.0" refers to the fourth industrial revolution and was introduced for the first time at the Hannover Fair of Industrial Technologies, in 2011 (Industry 4.0: Agility in production, 2012). Industry 4.0 consists in the introduction of Cyber Physical Systems (CPS) and the Internet of Things and Services into core manufacturing processes (Jazdi, 2014; Kagermann et al., 2013), taking a considerable step forward from the computerization or automation of processes that characterized the third revolution (Alqahtani et al., 2019). In a more detailed description, Industry 4.0 is enabled by nine technologies or "pillars" and a substantial change in manufacturing and human resource management (Vaidya et al., 2018; Pierdicca et al., 2017; Jones et al., 2019; Cristians and Methven, 2017). This digitalized era sees the contamination of manufacturing processes with information and communications technology (ICT) (Kamble et al., 2018), with the aim of developing efficient "smart factories" able to meet management goal and current industry scenarios in a flexible way (Wittenberg, 2016). Furthermore, Industry 4.0 helps to improve and identify new business models (Gökalp et al., 2017; Manogaran et al., 2017) and to satisfy the emerging demand of customization of products through an intelligent process control and management (Mourtzis and Vlachou, 2018).

One priority area in Industry 4.0 is the interdisciplinary cooperation between production and maintenance planning, to achieve a quick and efficient maintenance service, allowing companies to implement a cost-effective production system (Rødseth et al., 2017). McKinsey (2015) includes maintenance within two of the eight main value drivers for Industry 4.0, that are "Asset utilization" and "Services and aftersales".

Definitely, according to Mosyurchak et al. (2017), most companies consider maintenance management one of the initial steps to be applied in Industry 4.0 context, implementing an important transition from breakdown and periodic maintenance to predictive and proactive maintenance policies, with the aim to obtain economical and technical advantages.

According to Jazdi (2014), Alqahtani et al. (2019), Jones et al. (2019) and Cristians and Methven (2017), the transition to Indus-

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try 4.0 always results in the implementation of new technologies and in a substantial change in manufacturing and human resource management.

The present paper reviews literature on state-of-the-art Industry 4.0 technologies currently employed in maintenance tasks and how they can offer new opportunities for management strategies. This analysis also provides broader insight and knowledge of the perceived trends and existing difficulties, underlining critical aspects occurring in the implementation of maintenance in a smart factory.

While a comparable study have been performed to address the role of maintenance for aspects related to the sustainability in the Industry 4.0 context (Franciosi et al., 2018), to the authors' best knowledge, no articles exist to define the state-of-the-art of Industry 4.0 technologies currently applied in maintenance tasks. The data collection has been performed through a systematic literature review of published peer-reviewed journal articles.

The paper is organized as follows: Section 2 illustrates the background, providing an overview of the main aspects of maintenance management and the main technologies available in Industry 4.0; Section 3 illustrates the adopted methodology and materials for the literature review; Section 4 contains content analysis, a thematic synthesis of maintenance in Industry 4.0 and a discussion of results. Finally, in Section 5 the conclusions of the study are provided.

2. Background

The aim of this section is to provide a brief overview of the principal concepts and activities of maintenance management and of the technologies developed in the Industry 4.0 field.

2.1. Maintenance management

According to the European Standard EN 13306:2017 (1330) "Maintenance is the combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function". Furthermore, the Standard also describes maintenance management as the set of activities "that determine the maintenance objectives, strategies and responsibilities, and implementation of them by such means as maintenance planning, maintenance control, and the improvement of maintenance activities and economics".

Maintenance planning regards all the activities related to the development of a regularly scheduled work program to guarantee satisfactory equipment operation and prevent major issues. These activities includes the choice of the optimal maintenance policy and job planning and scheduling (Dhillon, 2002). On the other hand, maintenance control and supervision is related to the various aspects that should be monitored to ensure the correct implementation of maintenance management in an industrial plant: collection of on-field data to monitor the performance reliability of assets, work control and reporting, inventory management and cost accounting and control (Process, 2010).

Moreover, maintenance has a key role in ensuring the success of a manufacturing company (Misztal et al., 2014), due to its impact on both productivity and quality. Since maintenance management in an industrial plant connects various organizational business functions and activities, its implementation is complex and requires the upmost attention.

Every management system comprises an organizational structure supported by three main aspects: procedures, people and technology to control and optimize the use of resources and guarantee the achievement of the company's objectives (Morvay and Gvozdenac, 2008).

In regard to the procedures, maintenance policies have evolved with the course of time: historically the first type of maintenance applied was the corrective or reactive one, which was led by the "run-to fail" logic. In time, the approach to failure prevention instead of correction was implemented, leading to the implementation of Preventive Maintenance. In this category are included, both schedule and condition-based maintenance. The subcategory of condition-based maintenance comprehends also the predictive maintenance, which is considered its evolution since it is focused on the prediction and prevention of failure or degradation. Lately, more proactive concepts of maintenance are being introduced, using management tools and strategies based on ICTs (Information and Communications Technologies) they consider the possibility of adapting the activities to the dynamic changes of the environment and aligning them to the business strategies and external requirements along the entire life cycle of the system (Guillén López et al., 2018). As job planning and maintenance scheduling regard the optimization of the resources' use factors like the personnel availability, inventory and stock management, as well as compatibility with production planning, have to be analyzed (Santolamazza et al., 2018).

In order to do so, the maintenance planning and execution processes are supported by the information system to ensure the management of work lists and inventory, procedure and technical specifications, scheduling and resource management, transmission of requests of interventions, spare parts monitoring and management, cost reporting and controlling, reliability evaluation tools (Process, 2010). However, the role of technology is not only represented by the need of an information system closely connected with every relevant asset of the company, but also by the tools used by the operators to always ensure more reliable interventions.

Finally, the role of the operators is essential since they are responsible for carrying out the maintenance actions and preserve the knowledge base needed to guarantee the machines' health. Thus, to foster the continuous improvement of the skills and performance of maintenance technicians, their training is also critical (Dhillon, 2002).

In order to map all the relevant processes in which Maintenance can be broken down, the European Standard EN 17007:2017 (1700)EN 7:, 2017EN 17007:2017 (1700) can be used as reference. It identifies processes, classifying them into three main families: the Management process (it entails the definition of objectives, policy and ensures the coherence of the realization and support processes); the Realization processes (they encompass all activities related to the realization of the expected results); the Support processes (they are in charge of providing the other processes with the necessary resources).

In this section, we focused on the following aspects:

- the maintenance definition according to European Standard EN 13306:2017;
- the key role of maintenance;
- the categorization of maintenance management aspects and the use of European Standard EN 17007:2017 to map the Maintenance process.

2.2. Industry 4.0: the technological pillars

Several studies (Vaidya et al., 2018; Pierdicca et al., 2017; Jones et al., 2019; Cristians and Methven, 2017) are in accordance in summarizing technological advancements in nine pillars able to drive improvement in the designated areas, whether used alone or in combination.

These technologies include Industrial Internet of Things (IIoT), Big Data and Analytics, Horizontal and vertical system integration, Simulation, Cloud computing, Augmented Reality (AR), Autonomous Robots, Additive manufacturing and Cyber Security. The nine pillars of Industry 4.0 transform the factory in an “intelligent” or “smart” factory, full integrated, automated and with an optimized production process (Zolotová et al., 2018).

Furthermore, a greater efficiency and innovative relationship can be established between suppliers, producers, and customers, as well as between human and manufacturing systems (Vaidya et al., 2018). The *Industrial Internet of Things (IIoT)* extends the concept of Internet of Things (Atzori et al., 2010; Gubbi et al., 2013) to an industrial field. It refers to a machine-to-machine interaction without human intervention (Xu et al., 2014). The IIoT enables the interconnections of physical objects through sensors using standard internet protocols. The realized network involves systems that are part of the entire supply chain. According to Nunes et al. (2015), Internet of Things is the basic technology of cyber-physical systems (CPSs) (Lee et al., 2015; Monostori et al., 2016), that are systems provided by computation, communication and control systems (cyber space). Saldivar et al. (2015) consider CPSs able to realize a merger of virtual and physical world, eliminating boundaries between them. CPSs have been descripted as “the systems in which natural and human made systems (physical space) are tightly integrated with computation, communication and control systems (cyber space)” (Monostori et al., 2016). In a smart factory, complex and heterogeneous systems are integrated each other to carry out high performance and reliable operations (Morgan and O’Donnell, 2015). The data collection originated from CPSs, as well as the customer-management system, is the base of the *Big Data* analysis (Vaidya et al., 2018). It supports, alongside powerful computation capacity and high bandwidth for data transmission, the real-time decision making.

According to the definition provided by Witkowski (2017), Big Data is made up of four parts: Volume of data, Variety of Data, Velocity of generation of new data and analysis, Value of Data. Big Data, Cloud and CPSs create an industrial network and their coordination brings to the creation of the smart factory (Erboz, 2017). Moreover, new data supplied by the diffusion of sensors and IoT allow the development of Big Data Analytics and Machine Learning tools applicable in various fields such as trend analysis, process monitoring, quality prediction and control, fault diagnosis, fault classification, online soft sensing and process control (Ge et al., 2017).

Horizontal and vertical system integration refers to an integration across the entire supply chain, reaching a total connection between all the actors in a highly dynamic system (Peres et al., 2018; Stock and Seliger, 2016).

Simulation is a digital tool that can support the design of production systems, enabling effective maintenance. Simulation is involved in value networks and real time optimization of data from intelligent systems (Chong et al., 2018).

Cloud computing (Zolotová et al., 2018; Hassan, 2011) is a technology that provides sharing of processing resources and other devices on demand. Thanks to cloud technology, it is also possible to share information between systems from a production line to the entire plant (Marilungo et al., 2017), as well as execute offsite analysis (Tao et al., 2018). As result, it is possible to enhance the scalability and flexibility of intelligent manufacturing systems (Chen et al., 2018).

Augmented Reality is a human-machine interaction technology that superimposes digital data onto reality, mixing them coherently (Figueiredo et al., 2014). It can provide operators with real time information for maintenance, logistics, and other common operating procedures (Chong et al., 2018; Nee et al., 2012; Ong et al., 2008). Information can be supplied by smart devices as wearable AR or head mounted devices.

Autonomous Robots provide several services and are ever more autonomous, cooperative and involve multiple applications. Autonomous Robots can interact with each other or directly help operators (cobots) to perform their tasks (Djuric et al., 2016; Sadik and Urban, 2017). *Additive manufacturing* concerns the possibility to convert a digital design (i.e. 3D CAD) to a physical object by a 3D printing (Chong et al., 2018). This technology is suitable for producing small batches of customized products (Chua et al., 2010). Finally, *Cyber Security* is the technology able to protect shared information and CPSs from cyber-attacks (Wells et al., 2013).

In this section we presented the nine technological pillars, that are:

- Industrial Internet of Things (IIoT);
- Big Data and Analytics;
- Horizontal and vertical system integration;
- Simulation;
- Cloud computing;
- Augmented Reality (AR);
- Autonomous Robots;
- Additive manufacturing;
- Cyber Security.

3. Research methodology

3.1. Research objectives

Considering the complexity of maintenance management and the many opportunities arising from Industry 4.0, the present study aims to analyze, in a systematic way, the current relation between maintenance and Industry 4.0, evaluating different points of view and players involved. In particular, it addresses the following research question:

- How is maintenance changing through Industry 4.0 technologies?

Therefore, our research motivation is to determine the state-of-the-art of maintenance in an Industry 4.0 context and to understand how maintenance is changing to meet its requirements, in order to define the concept of “Maintenance 4.0”, with particular regard to critical aspects and future trends.

3.2. Research materials and methods

A systematic literature review (SLR) is a methodical rigorous way to identify and evaluate the existing state of knowledge about a given question. In reason of its high transparency, scientific and replicable character (Tranfield et al., 2003), it differs from the traditional review, in particular for avoiding the risk of bias introduction and lack of a critical analysis (Tranfield et al., 2003; Briner and Denyer, 2012; Kitchenham, 2004). A methodological design is demanded to figure out the state of knowing for the given question, but also what is not known (Briner et al., 2009).

Emerging from medicine and biology areas, systematic literature reviews are gaining importance in several fields, as social sciences, engineering, business and economics (Stuck et al., 1999; Aquilani et al., 2017; Colicchia and Strozzi, 2012; Bastas and Liyanage, 2018). According to the approach proposed by Briner and Denyer (2012), the main phases to implement a SLR consists in the following steps: 1) formulation of the research question; 2) examination and deep analysis of relevant literature, through specific and ad hoc chosen keywords; 3) inclusion of only those papers that meet research criteria and research purposes; 4) design of a database where papers and findings are assessed and sorted and 5) synthesis phase in which results are extracted from database and discussed.

Table 1
Summary of the systematic literature review process.

Step 1	Research Question
Formulation of the research question	How is maintenance changing through Industry 4.0 technologies?
Step 2 and **Step 3**	Electronic databases
	Scopus (scopus.com), IEEE (ieeexplore.ieee.org), Google Scholar (scholar.google.com), Web of Sciences (WoS), References
	Search Period
Locating, selecting and evaluating articles	2015−2019
	Inclusion Criteria
	Papers that developed or investigated maintenance tasks in Industry 4.0 context
	Exclusion Criteria
	Conference papers and articles in languages that differ from "English"
	Search Strings
	"industry 4.0" AND "maintenance"
	"maintenance" AND ". . .*each of 9 industry 4.0 technologies*"
	"Smart manufacturing", "smart maintenance", "intelligent maintenance", "digital maintenance", "e-maintenance" and "maintenance 4.0"
Step 4	Analysis phase
Assessment of findings	Iterative compilation of the database
Step 5	Synthesis phase
Reporting of findings	Emerged aspects and results are extraction from database and discussion

An overview of the SLR process followed in the present study is shown in Table 1. Our research investigated on main electronic databases, including Scopus (scopus.com), IEEE (ieeexplore.ieee.org), Google Scholar (scholar.google.com) and Web of Sciences (WoS). Studies that matched with the scope of the review have been selected, considering only major journals, in reason of their establishment and availability for the readers. Although the Industry 4.0 definition dates back to 2011, the first relevant article, which falls within the scope of this study, is dated 2015 and the last one was published in 2019.

As first step, we considered results of the following search strings:

- "industry 4.0" AND "maintenance"
- "maintenance" AND ". . .*each of 9 industry 4.0 technologies*"

Other keywords and their potential combination are emerged from the first cluster of selected papers and they were used to enhance the exploration of literature. In fact, some researchers from different geographic regions use "smart manufacturing" as synonym of "industry 4.0". Furthermore, several definitions for maintenance in Industry 4.0 were found, such as "smart maintenance", "intelligent maintenance", "digital maintenance", "e-maintenance" and "maintenance 4.0". Finally, all references found in articles that match with the scope of the review were included. Table 1 summarizes the phases of the systematic literature review, including all the search strings. Conference papers and articles in languages that differ from English were not considered.

In a first phase, the abstract of each paper was read independently by three of the authors. Each author has expressed a judgment on the relevance to the objectives of the SLR. Each author could judge the relevance adequate, inadequate, or partially adequate. Papers deemed inadequate by at least two authors were excluded from the subsequent phases of analysis. Articles that passed the first selection phase, focusing on SLR question, were deeply analyzed. In particular, the papers considered unanimously relevant were read by a single author, who highlighted the salient points. In case of discordant judgments, the full text of the paper was read by three authors and the final judgment on the paper was expressed collectively at the end of a discussion. This analysis of papers was fundamental to identify the classification criteria. Several studies are focused on a particular innovative technology that is designed for maintenance tasks. Some studies show how Industry 4.0 technologies can offer new and more effective opportunities for maintenance strategies. Several articles focus on the role of the "maintenance operator" (or "maintenance technician") in Industry 4.0 and also these aspects were taken into account during the content analysis. Finally, each information considered relevant to the research was extracted and included in a database. Others key concepts that emerged were the inspiration for further investigations on each of the articles in the database, through an iterative process. The result was summarized in a table that shows the issues addressed for each article. Finally, a synthesis process allowed to identify three major fundamental aspects to be taken into account to understand how maintenance goals and strategies fit into Industry 4.0 environment. The selection procedure is showed in Table 1 and Table 2.

The selection process of papers has been conducted according to the SLR protocol, that consists in 4 main steps:

a) papers that comes from different literature databases have been removed;
b) a preliminary screen has been performed on titles and abstract to assess relevance;
c) papers that met the predefined inclusion criteria have been selected;
d) full text of selected papers has been reviewed to determine the definitive inclusion in the final analysis.

4. Results and findings

4.1. Descriptive analysis

The final database contains 65 papers available online from 2015 to 2019. The 2015 year corresponds to the beginning of the academic discussion on the impact of Industry 4.0 in maintenance management. Since 2015–2018 the number of publications has generally increased from year to year (Fig. 1), with the exception of 2019. Most of the literature consists of case studies (38.5 %) and conceptual (354%) applications. The remaining 26 % of the papers concerns theoretical simulations (9.2 %), experimentation (7.7 %), prototype (6.2 %) and survey (3.1 %). Case studies generally contain a validation of theoretical concepts through empirical applications, these studies have been developed in universities or inside innovative activities undertaken by companies in developing new products or services.

In a similar way, experimentation approaches and prototype provide the means to examine design problems and evaluate solutions. On the other hand, conceptual papers explain how innovative

Table 2
Summary of the systematic literature review search process (Moher et al., 2009).

	Identified articles	Articles post removing duplicates	Articles post abstract review	Articles post full text review
Total	*1101*	*329*	*109*	***65***

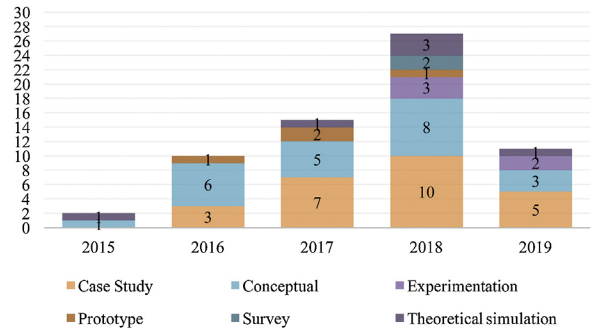

Fig. 1. Temporal distribution of articles for each research typology. Source: Authors' elaboration based on database.

ideas and new Industry 4.0 challenges may have effect in manufacturing and maintenance.

Papers that involve a theoretical simulation generally consider a virtual model in which data reflect the physical world, with the purpose to describe several scenarios that include machines, products and operators. Finally, survey papers are particularly useful for providing blended learning models to integrate Industry 4.0 into engineering teaching, through important feedbacks from experts and customers. The distribution of articles for each research typology is shown in Figs. 1 and 2.

As for the bibliographic distribution, the articles in the database were published on 46 different sources (Fig. 3). The journals with the highest number of publications are MM Science Journal and Computers & industrial Engineering, with 5 and 4 publications respectively.

With reference to the first author of each research, the 65 articles included in the database are written by 63 different first authors. The large number of authors testifies to the interest of the scientific community on these topics.

Table 3 shows all the papers included in this SLR; authors are listed by date. The database contains the technology employed in each study, as well as the "Research approach" and "Maintenance policy". In particular, "*technology*" can represent the technology employed, described or discussed in the single paper. Last five columns contain the main issues that are debated in each article. Indeed, the analysis of papers showed five recurrent most debated aspects related to maintenance, that are: sustainability, safety, costs, time and social (or human factors). In Table 3, the ticked cells indicate studies that examine such aspects. Each article can deal with either single or multiple aspects, with different accuracy. In this sense, an article can be entirely focused on *costs* or *time* aspects, or, for example, it may consider costs and time only as variable involved in an algorithm or simulation, or even provide general information in relation to maintenance. We identified 30 articles that involve costs, 27 the time and 18 both costs and time. Moreover, *sustainability* identifies articles (9 articles were identified) that relate the technological development of Industry 4.0 with sustainable development goals. At the same time, continuous changes in maintenance technology have to be in accordance with *safety* requirements and policies, and we found 21 articles related to these aspects. Finally, we identified 17 papers that relate the

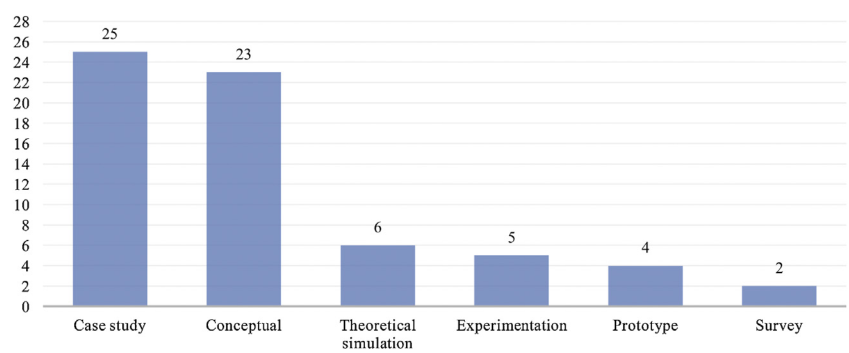

Fig. 2. Distribution based on type of research.

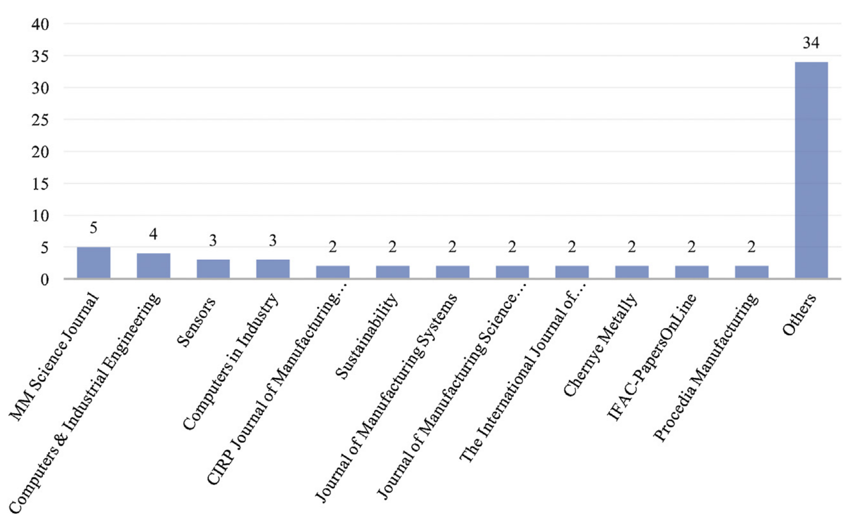

Fig. 3. Distribution based on bibliographic sources.

Table 3
Articles included in the literature review.

Year	Author	Technology	Research approach	Maintenance policy	Sustain-ability	Safety	Costs	Time	Social/human aspects
2019	Ooijevaar et al. (2019)	Industrial Internet of Things	Case study	Condition monitoring	√		√	√	
2019	Sahal et al. (2020)	Big data	Conceptual	Predictive maintenance		√	√	√	
2019	Qiao and Weiss (2019)	Industrial Internet of Things, Simulations	Experimentation	Condition monitoring			√		
2019	Xia et al. (2019)	Industrial Internet of Things	Theoretical simulation	Opportunistic maintenance				√	
2019	Xia and Xi (2019)	Industrial Internet of Things, cloud computing	Case study	Opportunistic maintenance			√	√	
2019	Gattullo et al. (2019)	Augmented Reality	Case study	remote maintenance		√	√		
2019	Alqahtani et al. (2019)	Industrial Internet of Things	Experimentation and case study	both warranty and preventive maintenance	√		√	√	√
2019	Goodall et al. (2019)	Simulation	Case study of operations	–		√			
2019	Olaf and Hanser (2019)	Industrial Internet of Things	Conceptual	Predictive Maintenance		√	√		
2019	Karkalos et al. (2019)	Industrial Internet of Things, cloud computing and Big Data analytics	Conceptual	–					
2019	Hesser and Markert (2019)	Big Data analysis, cloud server	Experimentation	Predictive maintenance					
2018	Kumar et al. (2018a)	Big Data	Theoretical simulation	–	√		√		
2018	Subramaniyan et al. (2018)	Simulation, Big Data	Case study	reactive and proactive maintenance				√	
2018	Frieß et al. (2018)	Big Data, simulation	Experimentation	Condition monitoring and selective maintenance				√	
2018	Chong et al. (2018)	–	Survey	–	√	√	√	√	√
2018	Peres et al. (2018)	Big data, cloud	Conceptual	predictive maintenance					
2018	Silva et al. (2018)	Industrial Internet of Things	Survey	–		√			
2018	Dinardo et al. (2018)	Industrial Internet of Things	case study	predictive maintenance					
2018	Guo et al. (2018)	Big Data	Conceptual	–		√	√		
2018	Tsai and Lai (2018)	Industrial Internet of Things	Case study	preventive maintenance	√		√		
2018	Kiangala and Wang (2018)	Big Data, Industrial Internet of Things	Experimentation	predictive maintenance					
2018	Ansari et al. (2018)	Big Data and analytics	Conceptual	perspective of maintenance			√	√	√
2018	Alonso et al. (2018)	Industrial Internet of Things	Case study	predictive maintenance					
2018	Scurati et al. (2018)	Augmented Reality	Case study	collaborative maintenance.		√			
2018	Fernández-Caramés et al. (2018)	Augmented Reality, cloud	Case study	predictive maintenance					
2018	Susto et al. (2018)	Simulation, Industrial Internet of Things	Case study	predictive maintenance		√	√		
2018	Mourtzis and Vlachou (2018)	Cloud	Case study	Condition based maintenance			√		
2018	Fusko et al. (2018)	Industrial Internet of Things, cloud	Conceptual	proactive maintenance					
2018	Simon et al. (2018)	Internet of Things	Theoretical simulation	Predictive - Reliability based - Condition oriented - Reactive		√	√	√	
2018	Pelantova and Cecak (2018)	–	Conceptual	preventive maintenance			√		√
2018	Ringhofer et al. (2018)	Internet of Things, Big Data and analytics	Conceptual	preventive and predictive maintenance	√		√		
2018	Purohit et al. (2018)	Simulation	Case study	Preventive maintenance			√	√	

Table 3 (*Continued*)

Year	Author	Technology	Research approach	Maintenance policy	Sustain-ability	Safety	Costs	Time	Social/human aspects
2018	Seneviratne et al. (2018)	big data, robots	Conceptual	–		√	√		√
2018	Fantini et al. (2018)	–	Theoretical simulation	Predictive maintenance		√			√
2018	Sénéchal (2018)	Industrial Internet of Things	Conceptual	condition based	√	√	√	√	√
2018	Uva et al. (2018)	Augmented Reality	Prototype	–				√	√
2018	Zolotová et al. (2018)	Internet of Things, Cloud	Case study	predictive maintenance		√			√
2018	Kumar et al. (2018b)	Industrial Internet of Things, Cloud	Experimentation	prescriptive maintenance				√	
2017	Li et al. (2017)	–	Case study	predictive maintenance					
2017	Rødseth et al. (2017)	Big Data, Industrial Internet of Things	Case study				√	√	√
2017	Mosyurchak et al. (2017)	–	simulation	preventive and proactive maintenance					
2017	Holub and Hammer (2017)	Industrial Internet of Things	Conceptual	Predictive and proactive maintenance			√	√	
2017	Yan et al. (2017)	Big Data	Case study	predictive maintenance				√	
2017	Chiu et al. (2017)	Industrial Internet of Things, Big Data, Cloud	Conceptual	Predictive maintenance					
2017	Mueller et al. (2017)	Robot, Industrial Internet of Things, cloud	Conceptual	–				√	
2017	Vesely (2017)	Cloud	Case study	–			√		
2017	Wan et al. (2017)	Big data, cloud, robots	prototype	Preventive maintenance		√		√	
2017	Upasani et al. (2017)	Cloud	Conceptual	Preventive maintenance		√	√	√	
2017	Venables (2017)	Augmented Reality	Case study	Preventive maintenance			√	√	
2017	Masoni et al. (2017)	Augmented Reality	Prototype	Remote maintenance				√	
2017	Koch et al. (2017)	Robots	Case study	–		√			√
2017	Lalanda et al. (2017)	Industrial Internet of Things	Case study	Predictive maintenance			√		√
2017	Bärenfänger-Wojciechowski et al. (2017)	–	Conceptual	–			√	√	√
2016	Janak et al. (2016)	–	Case study	–		√			
2016	Xu et al. (2016)	–	Conceptual	Predictive maintenance		√			
2016	Huber (2016)	Industrial Internet of Things	Conceptual	–	√				
2016	Jerzembeck (2016)	–	Case study	Predictive maintenance	√		√		
2016	Castellano et al. (2016)	–	Conceptual	Remote maintenance					
2016	Wittenberg (2016)	Industrial Internet of Things, cloud	Conceptual/ Survey	–					√
2016	Rakyta et al. (2016)		Conceptual	Proactive maintenance			√		√
2016	Kans et al. (2016)	Industrial Internet of Things	Case study	Predictive maintenance - self-maintenance		√			
2016	Aschenbrenner et al. (2016)	Augmented reality	Prototype	Remote maintenance					√
2016	Roy et al. (2016)	Augmented reality, Big Data and analytics, Industrial Internet of Things	Conceptual	Autonomous maintenance	√		√	√	√
2015	Janak and Hadas (2015)	Industrial Internet of Things	Conceptual	Condition based maintenance		√	√		
2015	O'Donovan et al. (2015)	Big Data	Theoretical simulation	Predictive Maintenance			√	√	

social impact of Industry 4.0 technologies, and how maintenance operator has to adapt to changes.

Through this descriptive analysis, we identified:

- 65 papers grouped in: Case study, Conceptual, Theoretical simulation, Experimentation, Prototype, Survey;
- 5 main subject matters: Sustainability, Safety, Costs, time, Social/human aspects;
- 10 main maintenance policies: Predictive Maintenance, Condition based maintenance, Remote maintenance, Self-maintenance, Proactive maintenance, Preventive maintenance, Condition based, Reactive maintenance, Reliability based, Opportunistic maintenance.

4.2. Content analysis and thematic synthesis of Industry 4.0 and maintenance

This SLR investigated the main topics concerning Industry 4.0 and its implications in maintenance activities through several perspectives. As mentioned in introduction section, the transition to Industry 4.0 always results in the implementation of new technologies and in a substantial change in manufacturing and human resource management. In fact, such new technologies, that include multi-sensory data analytics or autonomous features, are able to develop new basis for the implementation of innovative strategies for maintenance and to optimize common practices. For example, data analytics and maintenance simulations can optimize schedule planning, predicting typical lifecycle stages, as well as Augmented Reality offers a guidance for diagnostics and inspection.

One important challenge appears to be the combination of basic maintenance concepts with technological development and advancement. All these aspects also implicate a change in maintenance policies to meet requirements of a digitalized production, as well as the role of the maintenance operator appears to be remodeled.

4.2.1. Maintenance technology in Industry 4.0

The introduction of Industry 4.0 technologies has led the factory to be “intelligent” and smart (Zolotová et al., 2018). As previously stated, the list of technologies has been categorized in nine pillars by a large number of authors and some of them play a key role in maintenance activities. In particular, Industrial Internet of Things and Cloud Computing are almost present in each study, confirming how these concepts and technologies are at the basis of Industry 4.0 (Zolotová et al., 2018).

Industrial Internet of Things is the technology enabling the interconnections of physical objects via internet for exchanging global or local data (Alqahtani et al., 2019; Olaf and Hanser, 2019; Karkalos et al., 2019). Such Cyber Physical Systems (CPS) are the technological drivers for an efficient collaboration within organizations. With the purpose of reaching common goals, CPSs enable an efficient communication among all the actors through multiple sensory input/output devices (Dinardo et al., 2018; Roy et al., 2016). CPSs have an important impact on industrial services in manufacturing. In particular, these communication technologies are critical for maintenance, improving its efficiency and quality. A direct reason lies in the CPSs possibility in predicting and triggering services activities and remote diagnostic. In addition, CPSs also allow to collect a significant amount of real time information about current state of machines and this is the base for the Big Data analysis (Peres et al., 2018), that is a powerful support for maintenance planning. For example, Ooijevaar et al. (2019) present a study in which the monitoring of conditions of bearings and gears is performed through a wireless data transmission and diagnostic algorithms by using portable vibration sensors. Qiao and Weiss (2019) analyze a prognostics and health management (PHM) methodology based on an advanced sensor system for monitor the health of industrial robots, with the aim of optimizing future maintenance strategies. Xia et al. (2019) develops a sensor-driven maintenance policy to prepare maintenance activities in advance, minimizing costs. According to Xia and Xi (2019), CPSs, through current advances in sensing and information technologies, allow to reach an efficient support to PHM decision-making, predicting machine deteriorations. In this regard, Yan et al. (2017) affirm that industrial Big Data analytics will bring several advantages, such as achieving near zero downtime, ensuring predictive maintenance and more. Kumar et al. (2018a) use Big Data to design an efficient and sustainable robust layout for industry, evaluating maintenance as the key aspect for its planning. In managing, maintenance decision-making acquires a very relevant dimension (Ansari et al., 2018; Sénéchal, 2018), allowing to achieve optimal strategies (Simon et al., 2018; Kumar et al., 2018b). The main goal of Big Data analysis is to allow real-time decision-making and this is generally pursued through analytical data-driven algorithms (Subramaniyan et al., 2018). Mourtzis and Vlachou (2018) list some paradigms for an inexpensive and reliable monitoring system, when data from different sources are considered. In particular, they deal with an adaptive scheduling multi-criteria algorithm that takes into consideration, in real-time, various data from elements of the production lines (i.e. machines or human operators) and finally they provide maintenance guidelines. Frieb et al. propose a fuzzy interpretation of machine states for deriving dynamic characteristic values for the “machine health”. Sahal et al. (2020) analyze technological gaps between the demands of Industry 4.0 applications and the available Big Data technologies currently used for the predictive maintenance. They provide a data processing framework for overcoming some weaknesses that emerged from their study.

On the other hand, computer Simulation techniques are considered a vital component to develop smart manufacturing systems. They can be used for predicting the behavior of real manufacturing systems, support scheduling and maintenance decisions (Goodall et al., 2019; Purohit et al., 2018), but also for validating the engineers' design choices (Rødseth et al., 2017). In particular, Goodal et al. affirm that a simulation that easily adapts to changes in the data and information level can reduce time and cost of maintenance. This scenario is typical for remanufacturing operations. Susto et al. (2018) use simulations to predict a risk function, comparing “health factors” of systems to specific maintenance thresholds derived, for example, from historical data.

The Cloud technology can be considered complementary to IoT, Big Data and Simulation. In reason of the double concept connected to Cloud technology that refers to both storage solution and cloud computing. In fact, a cloud system is not only essential for the storage of gathered information from CPSs (Mourtzis and Vlachou, 2018; Fernández-Caramés et al., 2018; Wan et al., 2017), but also for on-demand computing. Indeed, in addition to data, Cloud computing allows the sharing of processing resources and other devices on demand; in this way, users and enterprises can process their data accessing to a shared pool of configurable computing resources, as networks, servers, storage, applications and services (Zolotová et al., 2018).

Masoni et al. (2017) consider the Augmented Reality (AR) as one of the leading technology of Industry 4.0 and this evidence is confirmed by eight papers dealing with this technology (Table 3). AR represents for maintenance task a valid support, offering a step-by-step guidance for diagnostics, inspection and training operations (Roy et al., 2016). In fact, according to Gattullo et al. (2019), in maintenance tasks and operations “the supportive information given is not delivered properly” and, moreover, when used to create technical documentation, it is also demonstrated that AR can reduce the cognitive load for the operators. They proposed a methodology to convert display mode documentation (i.e. texts or pdf files) to an

AR based technical documentation with the result of a documentation made of more graphics (symbols and icons) and less text. The conversion of text in graphical symbols has also been studied in Scurati et al. (2018), where a guideline for AR communication and instructions is presented.

Several forms of AR are suitable for maintenance and the projector-based AR appears to be more appropriate than others. Uva et al. (2018) demonstrate the benefit to use this form, showing technical advantages if compared to other forms. AR Tablets have a frequent use in maintenance (Gattullo et al., 2019; Aschenbrenner et al., 2016; Roy et al., 2016), with obvious limitations in reason of battery power requirement and not being a hand-free technology and then reducing the practicality and safety. On the other hand, wearable AR or head mounted devices (HMD) are the most popular AR devices used in the applications. Their physical limitations are the weight and the possibility of working with a potential lack of a complete wireless connection. In addition, the prolonged use of these technologies by maintenance technicians can impact on their health and this represents one of the major challenges (Roy et al., 2016). AR technology can be also employed to explore hidden structures within the real-world environment (Cristians and Methven, 2017), this helps some difficult maintenance procedures, as the detection of faults for parts installed behind surfaces. Data glasses are an "eyes free – hands free" device that allows to display information in the normal visual field of the user. Furthermore, interactions between the device and the operator are enabled through a specific touchpad (Wittenberg, 2016). Aschenbrenner et al. (2016) present an AR architecture that consists in a tablet device equipped with a high precision localization system. This system has been thought for remote maintenance, using advantages from AR technology together with the basic telephone support. Moreover, experts, that are located in external workstations, can detect failure or perform other maintenance activities without traveling to the production site. This scenario is an example of how industry 4.0 technologies are substituting the conventional ones.

Robotic applications are widely used to acquire data on inspections or to perform maintenance tasks. Seneviratne et al. (2018) discuss the possibility to incorporate inspection data with maintenance data by means of Big Data technologies and Autonomous Robots. In particular, they consider Unmanned Aerial Vehicles (UAVs) particular useful for linear assets, that are defined as engineering structures or infrastructures that occupy a long distance and composed by subsystems able to perform the same functions but with different loads and conditions. In this scenario, UAVs are particularly indicated for explorations and inspection purposes, but the same authors state that a complete maintenance cannot be performed by robots because they are still not sufficiently technological advanced. Human-robot interaction has been proposed in Koch et al. (2017), where the possibility to perform a maintenance process through a continuous interaction between a human operator and a robot has been discussed. Robots for collaborative interaction are generally named "cobot" and they are designed for being able to communicate and learn how to interact directly from the human operator, through an easy communication.

Enhanced 3D drawing skills and the possibility to realize 3D-printed prototypes has been considered a valid way to study and learn production procedures more rapidly, including maintenance (Chong et al., 2018).

Mueller et al. (2017) state that maintenance in an Industry 4.0 context has two critical aspects. One aspect is the link, in real-time, between physical production and digital factory. The second one is the difficulty to merge relevant data from very different systems. Roy et al. (2016) also affirm that maintenance based on Big Data needs a very complex decision support system and this is due to the diversity of data. As obvious consequence, an optimized decision-making model is not always easy to realize and, for overcoming this issue, advanced mathematical tools are often employed for algorithms, such as the Fuzzy logic (Frieß et al., 2018; Simon et al., 2018) and the Analytic Hierarchy Process (AHP) (Simon et al., 2018).

Information and communication technologies and CPSs are generally very sophisticated and many companies and are still not ready for the transformation of conventional maintenance into intelligent maintenance (Fusko et al., 2018). In this sense, it is interesting to consider the possibility to retrofit conventional machinery to meet Industry 4.0 technology. This study was carried out by Hesser and Markert in (Hesser and Markert, 2019), where they prove the possibility to transform conventional systems in CPSs, through low-budget and all in one sensing technologies.

Cyber Security, protecting shared information, ensures stable long-term operation of systems, as well as data accuracy and a more reliable manufacturing in Industry 4.0 (Olaf and Hanser, 2019). Alonso et al. (2018) note how security aspects should always be addressed in industrial environments and taken into account in deploying of Internet of Things solutions. Moreover, according to Alqahtani et al. (2019), the Internet of Things capabilities also "results into data explosion, causing challenges to data security, data privacy, networking of data centers, and storage management". Also Roy et al. (2016) state that security is a critical issue and it must be guaranteed for IoT-based future systems. The same authors also affirmed that maintenance of complex engineering systems demand security features both at the hardware and software level.

In this section:

- we investigated articles that deal with each of nine technological pillars in relation to maintenance;
- findings are listed and discussed.

4.2.2. Maintenance policies

The rise of smart digital technologies entailed new opportunities for management strategies. The level of collected digital data in a smart factory, combined with advanced analytics skills, has upset common industrial maintenance strategies and allowed to develop more effective ones (Kumar et al., 2018a).

The *predictive maintenance* have been the subject of interest over the last thirty years for both academia and industry (Dinardo et al., 2018), and it is becoming ever more accuracy and efficiency. Recent studies propose architectures for predictive maintenance as a service based on the IIoT, Cloud Computing and Big Data Analytics (Erboz, 2017). These technologies are able to generate new and relevant knowledge that provides additional insight for factory management. Alonso et al. (2018) verified that Industrial IIoT is mainly applied to the predictive maintenance for improving both performance and quality, in addition they implemented a predictive algorithm in a real Industry 4.0 scenario. Another prediction approach is proposed in Susto et al. (2018) where authors consider, through an in-house algorithm, a cost-minimization perspective.

It is important to note that predictive maintenance is able to reduce the total machine downtime from 30 % to 50 % and extends the operation life from 20 % to 40 % (McKinsey, 2015). In this sense, the possibility to generate new knowledge from data processing represent the key aspect for an intelligent or smart maintenance.

The *proactive maintenance* approach appears to be the first step for the implementation of Maintenance 4.0, in reason of its focus on monitoring the causes of failures and not only symptoms (Fusko et al., 2018). In fact, this maintenance strategy is characterized in an "anticipation action", based on monitoring, diagnosis, prognosis and the use of decision-making algorithms for data processing (Mosyurchak et al., 2017; Fusko et al., 2018). In Rakyta et al. (2016), we found interesting recommendations and basic steps to implement proactive maintenance in a company. Several authors proposed indexes to monitor the health status of factory devices (Chiu et al., 2017), Susto et al. (2018), Kumar et al. (2018b) and Janak and Hadas (2015) focus on the so-called “Health Factors” or “Component Health”. These quantitative indexes are an important approach in prognostic, in reason of the possibility to define the current status of the system under examination and to assess its future status.

Only one study Kumar et al. (2018a) indicates smart maintenance as a “*prescriptive maintenance*”, considering it as the goal achieved by technology implementation and advanced analytics of Industry 4.0. Wan et al. (2017) explore data processing in an Industry 4.0 perspective, comparing traditional maintenance mode and Cloud based computing system architecture for the collection of real-time Big Data. In particular, they implement algorithms for a centralized and unified management mode through a system architecture that includes a real-time data acquisition from CPSs (alarms, logs and equipment status), a wireless data transmission, a real-time centralized Big Data processing and finally a visual surveillance.

As explained above, *Remote Maintenance*, or “*telemaintenance*” (Aschenbrenner et al., 2016), is fully supported by technologies of industry 4.0, firstly by Augmented Reality (Masoni et al., 2017; Aschenbrenner et al., 2016; Roy et al., 2016; Janak and Hadas, 2015). Predictive maintenance coupled with remote maintenance can typically reduce the maintenance cost from 10 % to 40 % (McKinsey, 2015).

Finally, some studies address to the possibility of *“self-maintenance”*, thanks to a continuous and non-intrusive monitoring process (Rødseth et al., 2017; Dinardo et al., 2018). In Peres et al. (2018), self-predictiveness and self-awareness are defined as the key aspects in Industry 4.0; furthermore they can also maximize capacity and utilization of devices minimizing shutdowns (Kans et al., 2016). Seneviratne et al. (2018) affirm that self-maintenance activities are mainly associated with robots technology and that an ever more large number of industries are using this technology when they deal with high risk activities. Finally, according to Roy et al. (2016), the implementation of autonomous maintenance can reduce the through-life cost of the equipment, increasing customer satisfaction.

In this section:

- we investigated articles that deal with maintenance policies;
- findings are listed and discussed.

4.2.3. The maintenance operator in Industry 4.0: technical and social implications

Industry 4.0 context has increased complexity and dynamics of processes and products. The technological and industrial development is also influenced by how humans will manage and use new technologies (Fusko et al., 2018). In 2011, a McKinsey report (Manyika et al., 2011) highlighted that Big Data Analysis is an authentic driver for the economical innovation, but, at same time, a lack of operators with the skills needed for deriving insight from Big Data may decelerate this innovation. In this scenario, operator has been transformed in an Operator 4.0 which is characterized by increased physical, sensing, and cognitive skills (Zolotová et al., 2018), achieving new capabilities in support of all relevant aspects of maintenance processes. In particular, Operator 4.0 elevates the real-world perception through Augmented Reality and virtual assistants, analyzing acquired data and working in collaboration with robots, thus improving both maintenance control and execution. Wittenberg (2016) affirms that its predominant role is to supervise, through a monitoring system, the automated production, acknowledging that the increased amount and complexity of information made classical user interface unsuitable. This problem can be solved by a new user interface concept with site-directed information access. On the other hand, Cyber Physical Systems are principally designed to interact and collaborate with human operators, with the aim to achieve common goals, such as the decrease of the failure rate (Ansari et al., 2018). Ansari et al. (2018) describe the criteria to identify optimal collaboration between human and CPSs in a Maintenance 4.0 context, while Fantini et al. (2018) propose a methodology to design different work situations where humans interact with CPSs.

Furthermore, Virtual Reality can train and help the operator in decision-making during production (Zolotová et al., 2018), e.g. during new procedure of maintenance, promoting a fast improvement of the personnel’s technical skills. In a survey performed in 2016 (Wittenberg, 2016), most of maintenance technicians stated that mobile devices would reduce the uncertainty in the actions to be taken. In Fantini et al. (2018), the importance of customizing workplaces and human-computer-interfaces is discussed. The aim is to adapt them to different conditions of workers (e.g. stress or fatigue) and to overcome potential inexperience-related limitations for a proper human-automation symbiosis. Finally, Koch et al. (2017) deal with the interaction between humans and robots during maintenance tasks, describing proper interface and skills that are demanded.

In this context, where Industry 4.0 has increased complexity and dynamics of manufacturing systems, several advantages can be identified for the Operator 4.0, such as the possibility of a hand-free technology, real-time feedbacks for manufacturing processes, and a more effective training. Moreover the Operator 4.0 has the responsibility, through the application of Big Data analytics, to discover useful information and predict all relevant events (Russom et al., 2011; Chen et al., 2012), as well as to interact with CPSs, computers, databases and collaborate with robots. Finally, Industry 4.0 has also established a continuous change for manufacturing systems (Perez et al., 2017; Gilchrist, 2016) and Operator 4.0 should have the ability to adapt rapidly to digital innovations.

The substantial changes in the role of the maintenance operator in the Industry 4.0 context also have important consequences from a social point of view. On the one hand, it is necessary to rethink operator training for future generations, providing training courses aimed at providing necessary knowledge.

From this perspective, the social role of the operator 4.0 rises and is recognized as a highly professional profile with very specific skills. This phenomenon will inevitably lead to the outsourcing of maintenance services in small productive contexts, without the necessary technical and economic resources (Vacík and Spacek, 2018).

On the other hand, it is essential to guide the transition towards the use of new technologies for operators already included in traditional manufacturing contexts. In particular, the changes towards maintenance 4.0 must be gradual and allow the operator to get used to new and often unknown tools. Otherwise, there is a risk that the implementation of new technologies could be harmful and not profitable.

This need to safeguard operators accustomed to operating in a traditional way becomes even more important in reference to the workforce

aging we are witnessing in recent times, since older workers are usually more reluctant to change and to use new technologies (Eurostat, 2019; Katiraee et al., 2019).

In this section, we investigated:

- how maintenance is changing the role of the operator in an Industry 4.0 context;
- responsibilities of the Operator 4.0.
- technical and social implications.

	Industrial Internet of Things	Big Data and Analytics	Simulation	Cloud computing	System Integration	Augmented Reality	Autonomous Robots	Additive manufacturing	Cyber Security
MAN: Manage maintenance (strategy and improvement, human resources, continuous improvement, compliance, etc.)	✓	✓	✓	✓	✓				✓
PRV: Prevent undesirable events by avoiding failures and faults	✓	✓	✓		✓				
COR: Restore the items in required state	✓				✓	✓	✓		
ACT: Implement preventive and/or corrective actions on the item	✓	✓	✓		✓	✓	✓		
IMP: Improve the items			✓					✓	
HSE: Ensure personal health and safety to individuals and preserve environment in maintenance	✓				✓	✓	✓		✓
BUD: Budget maintenance of items	✓	✓		✓					
DOC: Deliver the operational documentation				✓	✓				✓
DTA: Manage data	✓	✓		✓					✓
IST: Provide the needed infrastructures				✓	✓				✓
MRQ: Deliver maintenance requirements during items design and modification	✓		✓		✓				
OPT: Improve the results	✓	✓	✓		✓				
RES: Provide internal human resources	✓	✓	✓		✓	✓	✓		
SER: Provide external maintenance services	✓			✓	✓				
SPP: Deliver spare parts	✓			✓				✓	
TOL: Deliver the tools, support equipment and information system	✓			✓				✓	

Fig. 4. Summary of the possible application of the Industry 4.0 pillars to the Maintenance Process. Rows present different processes that are part of the Maintenance process as described by the European Standard EN 17007:2017. Source: Authors' elaboration.

4.3. Discussion: current and future research developments

The performed analysis has pointed out key aspects for understanding how maintenance is changing to fit into the Industry 4.0 context. These aspects mainly concern technology, policies and human factor.

The following two paragraphs focus on the description of the current research and the possible future developments in reference to the challenges identified.

4.3.1. Current research

An intelligent or smart factory has a digitalized production with a large amount of real time data to process and ever more detailed databases as reference. The possibilities that Industry 4.0 can offer to maintenance are notable and the necessity of a proper design of maintenance in a modern factory is quite clear. It is noticeable that authors of papers collected in our database (Table 3) refer to maintenance in various ways, such as "smart maintenance", "intelligent maintenance", "digital maintenance", "e-maintenance" and "maintenance 4.0". The change of processes and manufacturing systems led maintenance to be subjected to a general reorganization of its policies and to count on innovative modalities. Remote maintenance has become more effective, thanks to Augmented Reality and autonomous robots combined with Big Data analysis. This is a very attractive solution and particularly useful for industries that deal with high risk activities.

The role of operators appears to be remodeled and it mainly consists in supervising the automated production through ever more advanced monitoring systems and user interfaces. Big data analysis, Simulations and decision-making algorithms represent the "intelligence" of a smart factory and, through their implementation, it is possible to "prescribe" corrective actions, transforming the conventional maintenance policy in a "prescriptive maintenance". The main skill that is demanded to the maintenance technician is to handle smart devices, as wearable, tablets data glasses or head mounted devices, and to have the attitude to interact with a smart world inside the factory. Through the use of smart devices connected to cloud, the operator can be instructed by videos or text information. Furthermore, the operator findings and experience represent the essential feedback for the database itself. Operator 4.0 should also be able to interact efficiently with autonomous robots, additive manufacturing, and Augmented Reality. Additionally, thanks to Augmented Reality, the training process is accelerated for both new staff and technical experts when they are training for learning new tasks.

From the point of view of technology, each of the nine pillars described in Section 4.2.1 can have a role in maintenance. The new digitalized environment, promoted by the introduction of Industry 4.0 innovations, can provide great advantages to maintenance management in all its relevant activities. The real-time connection of assets and availability of mobile devices can improve both maintenance control and execution, improving the constant awareness of the assets' real state of health. Supporting technical interventions, these technologies can also ensure a more reliable performance by the operators. Furthermore, planning and scheduling can be improved by such digital environment that enables the constant acquisition of feedbacks from the environment, in order to guarantee the optimization of maintenance objectives in terms of availability of machines the use of resources.

Table 4
Summary of the relevant criticalities in the application of the Industry 4.0 technologies in the maintenance process.

Industry 4.0 pillar	Criticalities
Industrial Internet of Things (IIoT)	The need to make heterogeneous devices talk to each other entails investment to retrofit the present hardware if possible or to acquire new instruments. Communication protocols' compatibility is also an issue.
Big Data and Analytics	The reliability of AI models is linked to many factors such as the quality and representativity of data used, as well as the skills of the Data Scientist. Indeed, the knowledge required for this process is often not yet present in the organizations.
Horizontal and vertical system integration	The compatibility of different platforms is not always guaranteed. This pillar is also strictly linked to the issue of Cyber Security.
Simulation	As in the case of Big Data Analytics, the quality of data used is essential to the success of the simulation. Moreover, it requires a deep knowledge of the phenomenon simulated as well as a proper software and hardware infrastructure. Finally, simulations can be very time consuming, thus they are not always feasible to help the decision-making process in a continuously changing environment.
Cloud computing	The use of cloud platforms requires high-speed internet connection in the whole industrial site. Moreover, the risk of cloud outages is to be evaluated in order to avoid serious consequences. This pillar is also strictly linked to the issue of Cyber Security.
Augmented Reality (AR)	Mobile systems adopted for AR are often heavy, thus causing strain to the maintenance operators. Moreover, their use for long periods is not recommended since they can provoke eye strain. In reference to AR glasses, they should be adaptable in order to allow their use also by operators that already wear prescription glasses.
Autonomous Robots	The use of autonomous robots is not possible for sensitive tasks that usually require human supervision. Their cooperation with human workforce is still limited and should be highly regulated. A huge ethical problem in their introduction is the risk of unemployment and de-skilling of the workforce.
Additive manufacturing	This technology is still growing in terms of use of different materials, therefore its application in the maintenance field could still be limited. Its use requires the presence of skilled personnel in the organization.
Cyber Security	The use of external platforms (also in reference to a real-time connection with suppliers and customers) and, more generally, the presence of an enterprise internal network implies always the risk of attacks from malicious parts. This area of knowledge is becoming increasingly complex and its administration requires personnel highly skilled.

Furthermore, as discussed in previous sections, Industry 4.0 technology naturally meets the requirement of a predictive, proactive or prescriptive maintenance policy. Indeed, innovative and effective solutions, as remote or self-maintenance, are enhanced by Industry 4.0 technology, offering to industrial practitioners, senior managers and decision makers attractive solutions, guiding the transition towards more advanced maintenance policies.

In order to summarize the different applications of the Industry 4.0 pillars in the Maintenance Process, a schematic representation is also provided in Fig. 4. In the rows the different processes, part of the Maintenance process as described by the European Standard EN 17007:2017, are presented:

- the management process: MAN - Manage maintenance (strategy and improvement, human resources, continuous improvement, compliance, etc.);
- the realization processes:
  - o PRV - Prevent undesirable events by avoiding failures and faults;
  - o COR - Restore the items in required state;
  - o ACT - Implement preventive and/or corrective actions on the item.
  - o IMP - Improve the items;
- the support processes:
  - o HSE - Ensure personal health and safety to individuals and preserve environment in maintenance;
  - o BUD - Budget maintenance of items;
  - o DOC - Deliver the operational documentation;
  - o DTA - Manage data;
  - o IST - Provide the needed infrastructures;
  - o MRQ - Deliver maintenance requirements during items design and modification;
  - o OPT - Improve the results;
  - o RES - Provide internal human resources;
  - o SER - Provide external maintenance services;
  - o SPP - Deliver spare parts;
  - o TOL - Deliver the tools, support equipment and information system.

The columns, instead, report the nine technological pillars of Industry 4.0, therefore every marked cell represents the possibility to apply the single pillar to the specific process examined.

It is clear that the introduction of IIoT, System Integration and, to a lesser extent, Cloud computing are considered fundamental in order to carry out more efficiently the majority of the maintenance processes. Big Data Analytics and Simulation are predominately used to improve existing practices or to allow the evolution towards more complex maintenance strategies, whereas pillars such as Augmented reality and Autonomous robots are prevalently used in the support processes.

Finally, the study shows that the scientific discussion on this topic is ongoing and great benefits have been related to the introduction of Industry 4.0's maintenance management. The study brings to the light also some critical aspects of maintenance transformation. Indeed, complexity of the technology and the need of advanced decision-making algorithms are important aspects to take into consideration during the design of maintenance strategy. Another important issue is the reliability of artificial intelligence, health indexes and the accuracy of simulations which need specific know-how and complex high-quality data for being implemented efficiently. Furthermore, some smart devices have physical limitations, such as weight and the necessity of a continuous wireless connection.

Critical aspects are also identified for the Operator 4.0. Some smart devices are not a hand-free technology, and this can represent a limitation for the operator activity and safety. The purpose to achieve a good human-automation symbiosis can be achieved with proper workplaces and user-friendly human-computer interfaces.

Since all these innovations are still being studied and evaluated, in order to support the Industry 4.0 revolution, it is also important to shed light on the possible drawbacks of these technologies to support their improvement. In Table 4, relevant issues linked to the applications discussed are reported.

4.3.2. Future research development

The path towards a comprehensive and widespread implementation of this new paradigm of maintenance in industry is still long and not clearly defined.

Indeed, from the point of view of academia, some of the technologies examined are still undergoing a rapid transformation. For instance, AR, Addictive manufacturing and Autonomous robots are still expanding their applications and functionalities to overcome the existing limitations in terms of applicability, safety and efficiency. Big Data Analytics and Cyber Security, on the other hand, are fields in continuous change and the skills required to manage them are highly technical and uncommon. Undeniably, in order to provide the industrial sector with more reliable tools to foster the evolution of their maintenance policies it is also critical the ongoing research on diagnostic and prognostic algorithms and their application to different assets.

From the point of view of industry, there is a lack of a clear view of the steps that an organization has to take to begin a conscious transformation of their maintenance management. Thus, scientific researchers should work to address this issue providing a comprehensive guidance to integrate this paradigm in a real factory. Since a common practical drawback of this transformation is the requirement of investments, a structured action plan to guide an organization in this direction should also help in addressing this issue.

Moreover, it is also very important to address more properly the implications of this transformation on the personnel since a sustainable technological progress should never imply the increase of unemployment.

All these aspects are limiting a widespread implementation of this new paradigm of maintenance management. Therefore, the scientific research should provide a clearer view of steps that an organization has to take for beginning a conscious transformation of maintenance management, as well as a deeper and comprehensive description of how Maintenance 4.0 could be integrated in a real factory. Moreover, it is also important to address the implications of this transformation for the personnel and to examine in depth the research on diagnostic and prognostic algorithms, as well as their application to different assets. In this way, more reliable tools will be available for companies interested to promote innovative maintenance policies in an Industry 4.0 environment.

5. Conclusions

The primary aim of this systematic literature review was to determine the state-of-the-art of Industry 4.0 technologies that are currently employed in maintenance and how maintenance is changing through these technologies. We examined 65 articles, published between 2015 and 2019. During the analysis, information from each paper were collected in a database and part of it is shown in Table 3, where researches are listed by date and several details and features are provided for an easy and rapid consultation.

The SLR investigated the implication of Industry 4.0 technologies for maintenance, analyzing several perspectives:

- the impact of each technology in maintenance tasks has been identified;
- current trends in maintenance policies have been investigated;
- Remote Maintenance had an impressive increase, due to the implementation of Augmented Reality combined with smart devices;
- the strategy of "self-maintenance" is ever more an attractive possibility for smart factories;
- the importance of human element has been considered;
- the role of the "Operator 4.0" appears to be remodeled consisting mainly in supervising the automated production through advanced monitoring systems and user interfaces;
- the operator can be instructed by videos or text information through smart devices and can share in real-time its findings and experience, contributing to a continuous improvement and development of an efficient and safe maintenance.

Finally, our SLR did not find relevant articles that discussed maintenance from a perspective of "horizontal and vertical system integration" pillar. The complexity of such aspect suggests a further review focused on how maintenance has been integrated across the entire supply chain.

CRediT authorship contribution statement

Luca Silvestri: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration. **Antonio Forcina:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **Vito Introna:** Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Supervision, Project administration. **Annalisa Santolamazza:** Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **Vittorio Cesarotti:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors report no declarations of interest.

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