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Predictive maintenance in the Industry 4.0: A systematic literature review

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A R T I C L E I N F O

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A B S T R A C T

Industry 4.0 is collaborating directly for the technological revolution. Both machines and managers are daily confronted with decision making involving a massive input of data and customization in the manufacturing process. The ability to predict the need for maintenance of assets at a specific future moment is one of the main challenges in this scope. The possibility of performing predictive maintenance contributes to enhancing machine downtime, costs, control, and quality of production. We observed that surveys and tutorials about Industry 4.0 focus mainly on addressing data analytics and machine learning methods to change production procedures, so not comprising predictive maintenance methods and their organization. In this context, this article presents a systematic literature review of initiatives of predictive maintenance in Industry 4.0, identifying and cataloging methods, standards, and applications. As the main contributions, this survey discusses the current challenges and limitations in predictive maintenance, in addition to proposing a novel taxonomy to classify this research area considering the needs of the Industry 4.0. We concluded that computer science, including artificial intelligence and distributed computing fields, is more and more present in an area where engineering was the dominant expertise, so detaching the importance of a multidisciplinary approach to address Industry 4.0 effectively.

1. Introduction

The need to adapt and use new technologies made the industry evolve into a new era. Connectivity, amount of data, new devices, inventory reduction, customization, and controlled production gave rise to the so-called Industry 4.0. Term created to meet the demands of innovation and changes announced in Germany "as the fourth industrial revolution" (Lee et al., 2014). The differences between the current industries and the 4.0 model are divide into three main lines: components (self-aware, self-predictive); machines (self-aware, self-predictive, self-compare); productive system (self-configure, self-maintain, self-organize). Customization and availability of data, allowing actions by people or machines, are some of the essential characteristics of Industry 4 (Jin et al., 2017; Lee et al., 2014).

Data is the key to this generation of information that can anticipate or collaborate in making predictive decisions. The idea that "Manufacturing industry needs to turn into predictive manufacturing" published by Lee et al. (2013, 2006) has motivated our study. Predictive Maintenance (PdM) is historic data-based, models, and domain knowledge. It can predict trends, behavior patterns, and correlations by statistical or machine learning models for anticipating pending failures in advance to improve the decision-making process for the maintenance activity avoiding mainly the downtime (Lee et al., 2006; Sezer et al., 2018). The implementation of PdM and methodologies aimed at improving manufacturing capabilities generate other definitions such as intelligent industry or intelligent manufacturing (Kiangala & Wang, 2018).

The maintenance has attained critical importance for industries, due to the growth in complexity of the interactions between different production activities in increasingly extended manufacturing ecosystems (Sezer et al., 2018). In this way, another concept that also adds value to the PdM process is the Internet of Things (IoT). With a specialization denominate Industrial Internet of Things (IIoT), it uses the IoT technologies in an industrial environment, incorporating Machine Learning (ML) and Big Data (BD). Methods that reinforce

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the philosophy that "smart machines" show higher efficiency in comparison to humans in terms of accuracy and consistency for data management (Sezer et al., 2018).

Another system that has been making use of the IoT is the Cyber–Physical System (CPS), which is an area that refers to the next generation engineered systems (Gunes et al., 2014; Lee, 2016). The term coined at the National Science Foundation (NSF) in the United States around 2006 (Gunes et al., 2014). A key aspect of modeling and studying CPS is by having enough information about the machine and physical process to create an abstract representation for the intended purpose (Saez et al., 2018). Its architecture consists of several layers, such as digital connection, data-to-information conversion, high-performance computing infrastructure, cognition, and configuration layers (Wu et al., 2017c).

The integration of the concepts, as mentioned earlier, set the base for the development of the PdM area. In our search for related literature, we found surveys targeted at Industry 4.0, data analytics, and machine learning (ML), in which PdM is often one of the challenges (Lee et al., 2014, 2013; Muhuri et al., 2019; O'Donovan et al., 2015). However, we verified the need for a systematic literature review with a more specific discussion of PdM and its directions. As the main contribution, we proposed a taxonomy, emphasizing the use of PdM in the context of Industry 4.0, divided into three essential topics as maintenance types, principles, and domains in applications. Besides, we organized the main concepts related to the area, presenting the main predictive and monitoring models, identifying the challenges and future directions, aiming to create a reference for predictive maintenance.

The following text has six sections. Section 2 summarizes the essential PdM concepts. Section 3 detaches the related work and why the necessity and motivation of our study. Section 4 discusses the used research strategies and selection methods. Section 5 presents the taxonomy proposed, and it accomplishes a discussion responding to the scientific challenges and the research questions. Section 6 elaborates challenges and future directions, ending with our conclusion in the last Section.

2. Predictive maintenance (PdM)

Predictive maintenance (PdM) has been gaining prominence in multidisciplinary research groups, proposing the creation and integration of lines of research related to data acquisition, infrastructure, storage, distribution, security, and intelligence. This section presents the essential content for understanding PdM and directs the results of this study.

The impact of maintenance represents a total of 15 to 60% of the total costs of operating of all manufacturing (Haarman et al., 2017; Mobley, 2002). However, the companies do not measure correctly the amount spent related. Thereby, we can justify the need for studies on how to use new technologies that can change this scenario. In this review, the research focuses precisely on PdM growth and shows that it will be a differential in the implementation of Industry 4.0.

Data collected from the multiple sensors in Industry 4.0 environments provide new opportunities for solutions of remaining life prediction of an asset (Yan et al., 2017). The idea that PdM can generate scheduling action based on equipment performance or conditions through time becomes exciting and even primordial for the future of the Industry (Wu et al., 2016). One of the main requirements for effective PdM achievement is enough amount of data from all parts of the manufacturing process (Kiangala & Wang, 2018). As a result, it can diminish maintenance costs and downtime, and improve productivity and quality as well.

The challenge of predicting the Remaining Useful Life (RUL) of an asset is common in engineering, mechanics, and automation applications. This concept is a part of Prognostics and Systems Health Management (PHM), a complete industry management cycle. In PHM, there are three main axes: observation, analysis, and action (Kwon et al., 2016; Terrissa et al., 2016; Zerhouni et al., 2017). In this context, research related to the PdM is directly linked to the observation axis of PHM and using intelligent methods to predict the failure (Carvalho et al., 2019). Some authors consider that PdM is part of PHM components together with Equipment Health Monitoring (EHM) and Mean-Time-To-Repair (MTTR) as in Iskandar et al. (2015).

In maintenance, we have four categories of occurrence: corrective, preventive, predictive, and prescriptive. In the corrective case, the maintenance occurs when the fault is detected, or there are signs. The preventive maintenance use schedules at specific times. On the other hand, PdM uses time-based information and knowledge to report a possible failure avoiding downtime. In prescriptive maintenance is possible to answer: "How can we make it happen?" or, in other words, "How can we control the occurrence of a specific event?" useful advice for making decisions improving and optimizing upcoming maintenance processes (Matyas et al., 2017; Nemeth et al., 2018). In the PHM, are also four types of maintenance technics: corrective, fixed-interval preventative, failure-finding, and Condition-Based Maintenance (CBM) (Kwon et al., 2016; Zerhouni et al., 2017) on what, asset monitoring uses sensors, algorithms, and math for evaluation of RUL (Kwon et al., 2016).

Another essential content related PdM regards the three classifications of the approach used for prediction (Deutsch & He, 2018; Wang et al., 2018; Wu et al., 2017c):

Physical model-based: has as its main feature mathematical modeling with reflexes in the condition of a component, needing the precision of the condition and measurement of failure, and statistical methods to limit these indices (Wu et al., 2017c);

Knowledge-based: approaches that reduce the complexity of a physical model, for this reason, is often used as a hybrid strategy, for example, expert systems or fuzzy logic (Ayad et al., 2018; Wu et al., 2016);

Data-driven: models most found in the current evolution of PdM solutions are statistics-based, pattern recognition, or artificial intelligence (AI) and models based on machine learning algorithms.

In addition to the classifications cited, we found other hybrid definitions, for example: Cloud-based (Jin et al., 2017; Kiangala & Wang, 2018; Schmidt et al., 2017; Silva et al., 2016; Wu et al., 2016, 2017c, 2017d), Deep Learning-Based (Deutsch & He, 2018; He & He, 2017; Lee, 2017; Lee et al., 2017; Liu et al., 2018; Yan et al., 2018), IoT-Based (Kwon et al., 2016; Lamonaca et al., 2018; Wu et al., 2017c), Fleet-based (Jin et al., 2017), Time-Based (Jantunen et al., 2016; Kaur et al., 2018; Wu et al., 2017b). Time-Based has advantages in anticipation of the onset of equipment failure, and it was the main search of this review, applications of PdM that presented the time characteristic.

All the highlighted contents were essential in the formulation of our research questions, and we will bring more details when we discuss our answers.

3. Related work

We start with the example of a systematic mapping study relative to Big Data in manufacturing. The survey of O'Donovan et al. (2015) evaluates and makes a rating of the articles, indicating researches growth linked to Big Data and Industry 4.0. The result of two research questions in this mapping attracted our attention - "What type of analytics are being used in the area of big data in manufacturing?" and "What type of research is being undertaken in the area of big data in manufacturing?". Furthermore, the provocation in future works, citing the need for researches related to maintenance and diagnosis, collaborated with the continuity of our study.

Regarding maintenance, a methodology and a framework presented by Lee et al. (2017, 2013) detailed a CPS template with Big Data for PdM and shows that, with the use of technology, it is possible to make the degradation of an asset visible to human users. The same happens in the survey published by Gunes et al. (2014) that brought concepts, applications, and challenges in CPS domain types. In Lee et al. (2014) reports the "recent advances in industrial informatics concerning Big Data environment, CPS and Industry 4.0". In the same context, Rodríguez-Mazahua et al. (2016) presents the Big Data impact as a knowledge domain, as a result, classified the works into twelve areas of application and six Big Data challenges.

The survey of Lu (2017) contributes with a discussion about challenges and trends of future researches in Industry 4.0, and it detaches three contents - "Smart factory and manufacturing, Smart product and Smart City". Another more recent article presents a relevant and detailed bibliometric analysis in Industry 4.0 - "research growth, most productive and highly cited authors, top source journal, top 40 highly influential papers, top keywords and top 10 subject areas, countries and institutions publishing on Industry 4.0" (Muhuri et al., 2019).

In articles after 2015, we perceive the growth of related content to acquisition data and maintenance, bringing subjects such as IoT, cloud computing, machine learning, anomaly detection, and services. As in the case of the survey that presents the current issues, and it ranks seven basic contents linked to cloud manufacturing (Henzel & Herzwurm, 2018). In Mohammadi et al. (2018) survey, we found significant contributions about IoT data and its challenges for Deep Learning (DL) methods application. The research also catalogs applications of IoT with DL in various sectors, identifying "five foundational services along with eleven application domains".

Although many articles that focus on the area of Industry 4.0, describe CPS, Big Data, and challenges associated with the significative data volume, mention the need for predictive maintenance, but they did not detail on this subject (Ayad et al., 2018; Jin et al., 2017; Kwon et al., 2016; Lee et al., 2014; Yan et al., 2018). We had found a few technical reports that better describe PdM solutions and services (Haarman et al., 2017). However, none of those specifically focus on PdM application, except two recent systematic reviews, which specifically cover ML and applications of data-driven methods in PdM (Carvalho et al., 2019; Zhang et al., 2019). Even though, the discussion is not as broader as we propose in this article. We researched and described several essential contents for PdM researchers.

The works that approach PdM, commonly describe data acquisition, pre-processing, wear identification, and pointing out the possibility of failure (Kwon et al., 2016; Terrissa et al., 2016). This description is very similar in works that address PHM and its cycle involving analysis, observation, and action. According to Zerhouni et al. (2017), in literature, PHM has been studied by researchers from different engineering areas to increase reliability, availability, safety, and cost reduction of engineering assets. Authors as Lee et al. (2013) consider the subject as an essential point in researches using advanced forecasting tools. The reason we highlight PHM content in this review.

4. Material and methods

To carry out this study, we based on the principles of systematic reviews to achieve reproducibility and high-quality results (O'Donovan et al., 2015; Petersen et al., 2008; Zaveri et al., 2016).

The main scientific challenges to be addressed in this review are:

1- propose a taxonomy for predictive maintenance in the context of industry 4.0;
2- organize the main concepts related to the area;
3- present the main predictive models and monitoring applied to industry 4.0;
4- identify the main challenges and future issues related to industry 4.0.

With the scientific challenges, we defined that the PICOC O'Donovan et al. (2015) and Petersen et al. (2008) is the ideal because our goal is the search, comparison, contextualization, discussion, and presentation of PdM challenges in Industry 4.0.

4.1. Research questions

With scientific challenges and contributions identified, we create the main question (MQ) and sub-questions (SQ) of Table 1 to guide this review.

We formulate the MQ to report how is the application of PdM in Industry. The SQ's collaborate and detail the scientific contributions of this review. The SQ1 question lists the main means of disseminating research the PdM and Industry 4.0. SQ2 identifies and relates the methods and models used. The SQ3 surveys the most found terms, for the creation of standardization and presentation of the taxonomy proposal. SQ4 discusses the applications, taking into account the cases and data collected for the proposed predictive solution, the SQ5 question brings the challenges and future directions.

4.2. Search strategy

As the next step, we defined the string and databases. We chose Google Scholar as our starting database because it performs a free search in publications title and texts. Our idea is to obtain a higher volume of results, even that the return of some publications are not focused on predictive maintenance. It would be an opportunity to evaluate the results of the created string and to identify possible challenges related to PdM during cataloging. After, it was necessary to adapt the string and apply it to the bases of the Association for Computing Machinery (ACM), IEEE, ScienceDirect, Scopus, and Web of Science, in this order.

We focus the search string on the PdM applied to Industry 4.0 because of future challenges and directions in this research line (Haarman et al., 2017; Lee et al., 2013). The string takes into account some identified characteristics, for example, that the majority of the data of approaches of PdM involves mechanical and electrical variables. Fig. 1 presents our research string resulting.

4.3. Article selection

The string presented in Fig. 1 applied on 10/27/2018 at Google Scholar, with filter considering ten years 2008–2018 removing patents and quotations. Then, we exported the articles to Mendeley software resulted in 1143. The intention of our screening was precisely to receive a higher volume of results to the catalog and the same time to evaluate the context of the string and the MQ and SQ's questions. For the cataloging, we use the following exclusion criteria are listed in Table 2.

After the cataloging performed in Google Scholar, we modified the string to the bases of ACM, IEEE, ScienceDirect, Scopus, and Web of Science. In that order, we repeat the process and include the removal of duplicate articles. The result of our search strategy is in Fig. 2.

Highlighting the selection format is essential. As we have done the cataloging by a group of researchers, we have made the first selection through equal distribution of articles, and periodic meetings to discuss the results. With the realization of the analysis of about 100 articles, we realized that some terms brought content they did not attend the criteria 5. Smart grids, logistics, supply chain, and cybersecurity, approach information and strategies within Industry 4.0 but does not apply predictive maintenance.

At the end of the first selection seen in Fig. 2, 118 articles were selected using the method based on analysis on the abstract, keywords, section contents checking, and conclusion. In these, we performed the complete reading, and the primary criterion applied was the 5, we validate if the article contributed to the application of the PdM taking into account time-based monitoring and not just an alert.

Concluded criteria application, we searched for articles with relevant content for use in the context of this article and related survey works, reviews, mapping, and articles that brought tendency and challenges related to predictive maintenance or application examples into Industry 4.0.

The selected articles are listed in Table 3 with types of publications, publishers, and conference or journal names of our corpus.

Table 1
Research questions.

Identifier	Issue
MQ	What are the models, methods, or architecture related to predictive or monitoring being used in the Industry 4.0
SQ1	What are the main means of disseminating research aligned with PdM in Industry 4.0?
SQ2	What are the most commonly predictive models found in the Industry 4.0?
SQ3	Is it possible to create a taxonomy using the terms found for predictive application or monitoring?
SQ4	How are the results of the surveys that present models, methods or architecture?
SQ5	What are the challenges and open questions identified?

Table 2
Quality assessment criteria.

Section	Description
Criteria 1	Filter looking for period of 10 years, 2008 to 2018;
Criteria 2	Remove books, technical reports, dissertations and theses;
Criteria 3	Remove documents less than 4 pages long and are not in English;
Criteria 4	Remove all publications that do not use the search terms industry 4.0, intelligent factory, smart factory, smart manufacturing or internet of things in the title, abstract or keywords.
Criteria 5	Remove all publications that do not address prediction or monitoring applied to Industry 4.0, smart factory, or IoT as a model, method, or architecture.

(("industry 4.0" or "intelligent factory" or "smart factory" or "smart manufacturing") and ("internet of things" or "iot") and (monitor* or predict*) and ("model" or "method" or "architecture") and (mechanic* or electric*))

Fig. 1. Search string.

5. Results and discussion

In this section, we present the results and discussions based on the questions previously elaborated with the objective of responding to the MQ.

SQ1 — What are the main means of disseminating research aligned with PdM in Industry 4.0?

To answer this question, we present the analysis of: 1. Table 3, which lists the conferences and Journals of each article and; 2. Fig. 3, which shows the articles distribution by publisher and publication type.

The bar graph we can highlight IEEE and Elsevier as publishers with the most significant number of publications. The distribution of articles analysis using means of publication reinforces the observation that PdM applications present a multidisciplinary characteristic involving several areas of knowledge. In ACM case, the Computation does not give a volume of publications linked to PdM precisely because computing is one of the tools used and requires knowledge aligned with automation, mechanical, and electrical generating more content in other means of dissemination.

The journals and conferences that presented more than one occurrence were: two articles in the IEEE Conference on Automation Science and Engineering (CASE), Journal of Manufacturing Science and Engineering, and CIRP Annals – Manufacturing Technology – three in the Journal of Manufacturing Systems, and IEEE Access. Fig. 3 shows the distribution of the articles selected by the publisher (bar graph) and by type (pie chart).

In Fig. 4, we show the annual growth of publications, with emphasis starting from 2016. The factor for that we highlight the growth of IoT dissemination in Industry 4.0.

As we see in the graphs, we have IEEE and Elsevier as being the highlights of means of disseminating PdM in Industry 4.0. The division between conferences and the journal is very close. The publications show a significant increase in 2018, which points to a pattern in the following years. Another point that we can highlight is that many PdM solutions come from journals with an impact factor in Engineering, which is not repeated for Computing.

SQ2 — What are the most commonly found predictive models in the Industry 4.0?

We answer this question in different contexts used to evaluate the articles: first, we bring information related to the three methods of prediction classification: Physical model-based, knowledge-based, and data-driven. Second, a discussion regarding the approaches applying Artificial Neural Networks (ANNs), Machine Learning, and algorithms. Third, we discuss the articles maturity which addresses engineering contents as PHM, CBM, and RUL.

We started the discussion by the context of three methods of prediction classification; we listed articles related in Table 4, and we have done a brief description of the articles that address the methods listed.

Solutions using Physical Model-Base method typically bring hybrid approaches. In Liu et al. (2018) is presented a dynamic deep learning model based on incremental compensation for bearing equipment fault diagnosis. A solution named continuous maintenance has performed a study on Self-healing using IoT and cloud computing (Roy et al., 2016). In Kwon et al. (2016), the author featured the IoT-based PHM and created a predictive warranty service and highlighted better results using a hybrid approach.

The Knowledge-based approaches are common in monitoring alerts and also hybrid solutions. We highlight two articles one subdivide two

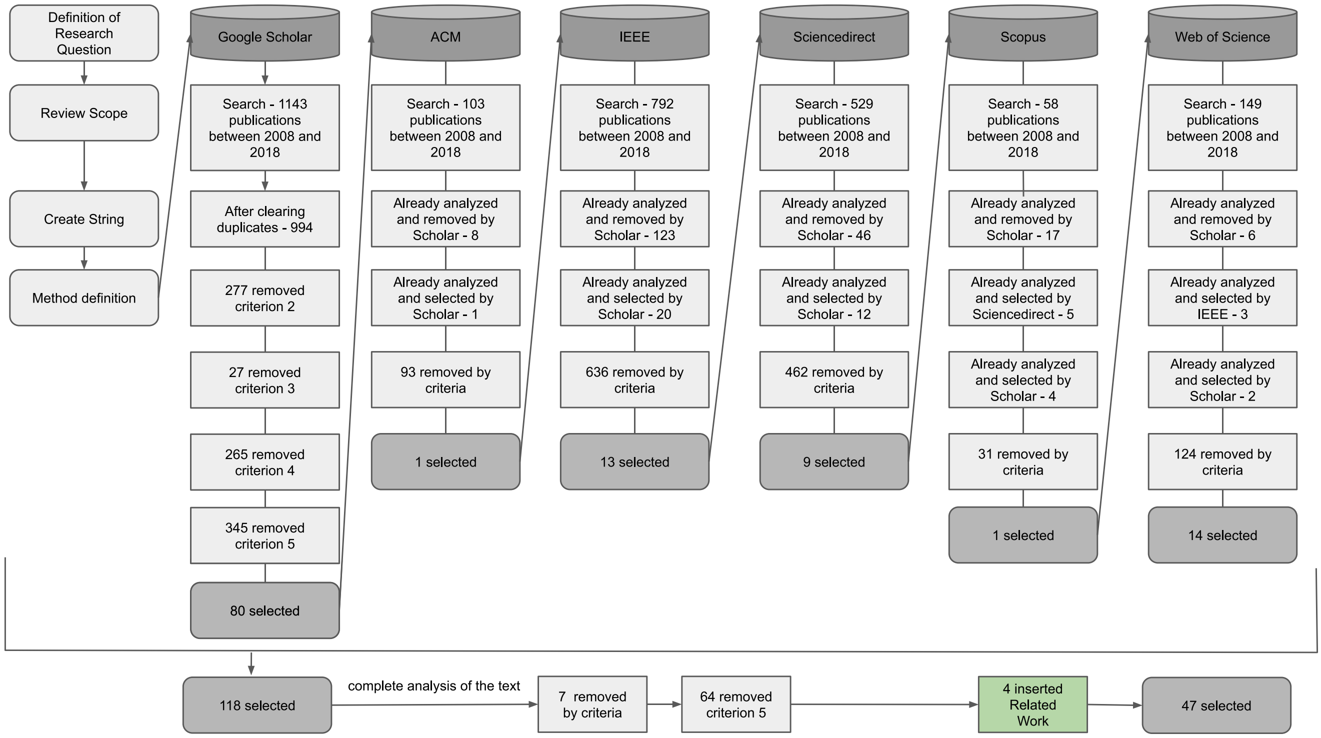


Fig. 2. Screening of research.

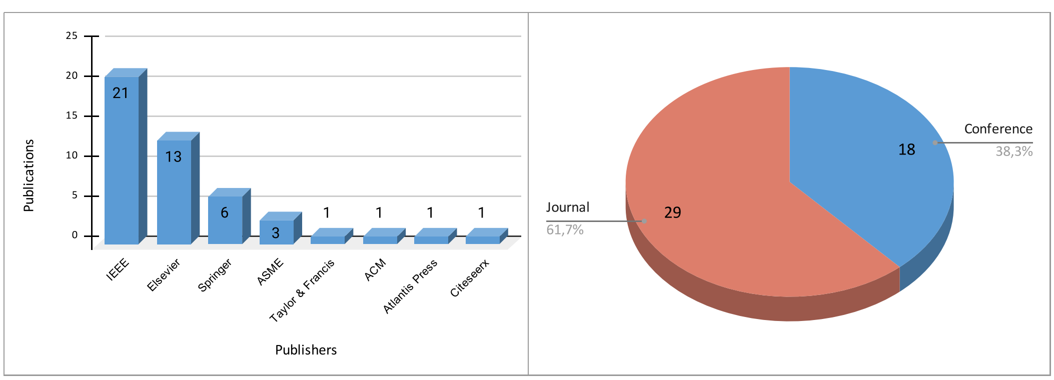


Fig. 3. Distribution of publications by Publisher and Type.

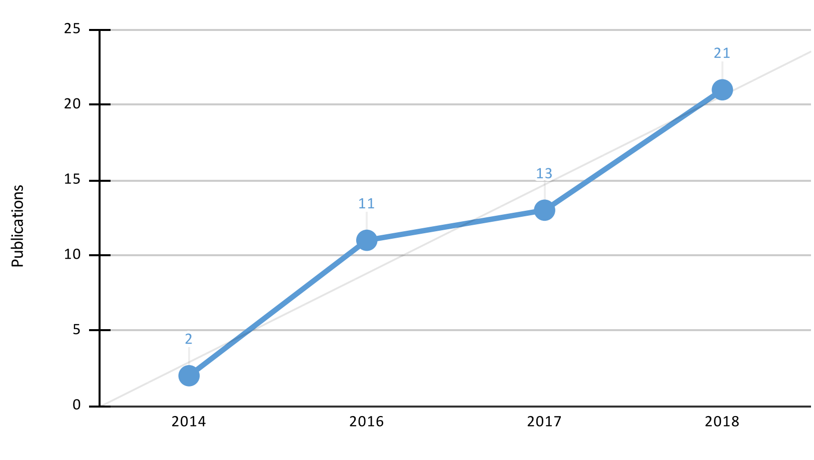


Fig. 4. Distribution and tendency of publications by year.

Table 3
Selected articles sorted by year.

Article	Type	Publisher	Name
Lee et al. (2014)	Conference	IEEE	International Conference on Industrial Informatics (INDIN)
Gunes et al. (2014)	Journal	Citeseerx	KSII Transactions on Internet and Information Systems
Silva et al. (2016)	Journal	Elsevier	IFAC-PapersOnLine
Terrissa et al. (2016)	Conference	IEEE	International Colloquium on Information Science and Technology (CiSt)
Lee (2016)	Journal	Elsevier	Procedia CIRP
Jantunen et al. (2016)	Conference	IEEE	International Workshop on Emerging Ideas and Trends in Engineering of Cyber–Physical Systems, EITEC
Roy et al. (2016)	Journal	Elsevier	CIRP Annals — Manufacturing Technology
Rodríguez-Mazahua et al. (2016)	Journal	Springer	Journal of Supercomputing
Yang and Zhang (2016)	Conference	IEEE	International Joint Conference on Neural Networks (IJCNN)
Kwon et al. (2016)	Journal	IEEE	Access
Wu et al. (2016)	Conference	IEEE	International Conference on Big Data (Big Data)
Li (2016)	Journal	Elsevier	Computers and Chemical Engineering
He and He (2017)	Journal	IEEE	Transactions on Industry Applications
Lee et al. (2017)	Journal	Springer	Production Engineering
Jin et al. (2017)	Conference	IEEE	Prognostics and System Health Management Conference, PHM-Harbin
Spendla et al. (2017)	Conference	IEEE	International Symposium on Applied Machine Intelligence and Informatics (SAMI)
Yan et al. (2017)	Journal	IEEE	Access
Wu et al. (2017b)	Conference	ASME	Manufacturing Equipment and Systems
Wu et al. (2017c)	Journal	ASME	Journal of Manufacturing Science and Engineering
Wu et al. (2017a)	Journal	ASME	Journal of Manufacturing Science and Engineering
Wu et al. (2017d)	Journal	Elsevier	Journal of Manufacturing Systems
Lee (2017)	Journal	Elsevier	Journal of Manufacturing Systems
Xia et al. (2017)	Journal	IEEE	IET Science, Measurement & Technology
Schmidt et al. (2017)	Conference	Elsevier	CIRP Conference on Intelligent Computation in Manufacturing Engineering
Matyas et al. (2017)	Journal	Elsevier	CIRP Annals — Manufacturing Technology
Qin et al. (2018)	Conference	IEEE	Conference on Automation Science and Engineering (CASE)
Deutsch and He (2018)	Journal	IEEE	Transactions on Systems, Man, and Cybernetics: Systems
Ku (2018)	Journal	Springer	Wireless Personal Communications
Ayad et al. (2018)	Conference	IEEE	International Conference on Advanced Systems and Electric Technologies, IC_ASET
Man and Zhou (2018)	Journal	Elsevier	Computers & Industrial Engineering
Wang et al. (2018)	Conference	IEEE	International Congress on Big Data (BigData Congress)
Mulrennan et al. (2018)	Journal	Elsevier	Polymer Testing
Saez et al. (2018)	Conference	IEEE	Conference on Automation Science and Engineering (CASE)
Kaur et al. (2018)	Conference	ACM	International Conference on the Internet of Things
Cho et al. (2018)	Conference	Springer	Advances in Production Management Systems. Smart Manufacturing for Industry 4.0
Rúbio et al. (2018)	Conference	Springer	HELIX — Innovation, Engineering and Entrepreneurship
Ren et al. (2018)	Journal	Elsevier	Journal of Manufacturing Systems
Sezer et al. (2018)	Conference	IEEE	International Conference on Engineering, Technology and Innovation (ICE/ITMC)
Nemeth et al. (2018)	Journal	Elsevier	Procedia CIRP
Yan et al. (2018)	Journal	IEEE	Access
Cipollini et al. (2018)	Journal	Elsevier	Reliability Engineering & System Safety
He et al. (2018)	Journal	IEEE	Signal Processing Magazine
Liu et al. (2018)	Journal	Atlantis-Press	International Journal of Computational Intelligence Systems
Amihai et al. (2018)	Journal	IEEE	20th Conference on Business Informatics (CBI)
Kiangala and Wang (2018)	Journal	Springer	International Journal of Advanced Manufacturing Technology
Lamonaca et al. (2018)	Conference	IEEE	Workshop on Metrology for Industry 4.0 and IoT
Ardolino et al. (2018)	Journal	Taylor & Francis	International Journal of Production Research

Table 4
Classification of the prediction.

Prediction classification	Identifiers
Physical model based	Kwon et al. (2016), Liu et al. (2018), Roy et al. (2016)
knowledge-based	Kiangala and Wang (2018), Nemeth et al. (2018)
Data-driven	Cho et al. (2018), Cipollini et al. (2018), Jantunen et al. (2016), Kaur et al. (2018), Kiangala and Wang (2018), Kwon et al. (2016), Lee et al. (2017), Man and Zhou (2018), Nemeth et al. (2018), Ren et al. (2018), Roy et al. (2016), Wang et al. (2018), Wu et al. (2017a, 2017b, 2016, 2017c, 2017d), Xia et al. (2017)
Hybrid	Ayad et al. (2018), Deutsch and He (2018), He et al. (2018), Kwon et al. (2016), Saez et al. (2018), Yang and Zhang (2016)

prediction classes, a statistical-based-model, and another monitoring of component conditions. The monitoring solution is based on knowledge-based and is related to the examination of the wear processes in mechanical components. The statistical model is responsible for the prediction, it uses data-driven for the evolution of solution linked to forecasting and monitoring, and names the solution as a cloud-based condition (Kiangala & Wang, 2018). The second article brings to prescriptive maintenance with review discussing evolutionary models using data-driven (Nemeth et al., 2018).

From the three methods, we highlight data-driven approaches, due to the increase in data acquisition and the utilization of AI-related theories, especially ANNs. We start data-driven description approaches with five works of a group that cites the growth of data-driven intelligence. The focus is on predictive solutions using Random Forest (RF) because they claim that only machine learning techniques are not computationally efficient for the PHM in data-driven methods (Wu et al., 2017a, 2017b, 2016, 2017c, 2017d). Another example is the anomaly detection solutions that require volumes of historical information. In Wang et al. (2018), presents anomaly information of a single sensor compared to several sensors.

Regarding the prediction of the RUL using data-driven, in Man and Zhou (2018), two categories of mechanical failures are presented: a soft failure that informs that the component will fail and the other hard failure that is the component stops. In Kaur et al. (2018), they discuss the union of CBM with the PdM, and they present a framework calling it Condition-based predictive maintenance (CBPdM). A framework for predicting RUL using deep autoencoder and Deep Neural

Table 5
ANNs, ML and algorithms.

ANNs, ML and algorithms	Identifiers
Random Forest	Amihai et al. (2018), Mulrennan et al. (2018), Wu et al. (2017a, 2017b, 2016, 2017c, 2017d), Yang and Zhang (2016)
Deep Learning	Amihai et al. (2018), Deutsch and He (2018), He and He (2017), Lee (2017), Lee et al. (2017), Liu et al. (2018), Ren et al. (2018), Xia et al. (2017), Yan et al. (2018)
Other strategies linked to the ANNs and ML	Ayad et al. (2018), Cipollini et al. (2018), Lamonaca et al. (2018), Man and Zhou (2018), Qin et al. (2018), Sezer et al. (2018), Wu et al. (2017c), Xia et al. (2017)

Networks (DNN) presents in Ren et al. (2018) and reinforces the growth of data-driven with promising use for bearing RUL prediction. With essential collaborations, Jantunen et al. (2016) brings principles of wear monitoring (time, load, and wear) and forms of measurement, signal analysis, diagnosis, and prognosis.

As already mentioned, the use of AI has considerable responsibility for data-driven choice, for example, a CPS framework using data-driven with DL and Restricted Boltzmann Machine (RBM) (Lee et al., 2017). One statistical Data-Driven Model (DDM) applied to naval propulsion systems using the ML methods supervised and unsupervised (Cipollini et al., 2018). A prediction and fault diagnosis based on Stacked Denoising Autoencoder (SDA) and DNN (Xia et al., 2017). A hybrid solution of ML, not and semi-supervised to PdM in smart factories (Cho et al., 2018).

We can highlight more articles with hybrid characteristics. The case that estimated the asset operational state based on dynamics functionality, and their interactions in what it was called "data-based classification model based on supervised learning" (Saez et al., 2018). The solution used Deep Learning-Based with RBM for PdM in rotating components and compared existing methods in PHM (Deutsch & He, 2018). A proposal of Hybrid Intelligent Model of classification and regression for the diagnosis of multiple failures and prediction of RUL denominated Network of Extreme Learning Machines (N-ELM) (Yang & Zhang, 2016). A hybrid model using model-based and data-driven to determine the current situation of the equipment and perform the RUL prediction Ayad et al. (2018). A discussion of recent challenges and advances, introducing a case called Pavatar, the real-world industrial IoT system that enables comprehensive surveillance and remote diagnostics for Ultrahigh-voltage Converter Station (UHVCS) (He et al., 2018). However, if analyzed, we will find the use of hybrid methods that have not been labeled with a prediction classification, for example, the case of the monitoring solutions that use data-driven but used knowledge-based features to perform alerts.

As a response to the classification approach context, we identify that PdM cases with time-based prediction, it is necessary to use data-driven because of the need for historical data, validation, and verification of heterogeneous data. However, some works contrast deficiencies in the use of traditional data-driven. The extracted resources are robust and require domain experts, historical events that labs do not simulate different situations. With this, the importance of having a minimum of physical knowledge of the components under evaluation (Cho et al., 2018; He et al., 2018; Kwon et al., 2016; Man & Zhou, 2018). Another problem is the difficulty of extracting labeled data for use in solutions using supervised ML techniques that require classified data (Xia et al., 2017).

The second context to respond to SQ2 is about solutions that use ANNs, ML, and algorithms. For this context, we divide the articles into three main blocks, methods connected to Random Forest (RF), linked to Deep Learning (DL), and other strategies using ANNs and ML. The selected articles are listed on Table 5.

Considering the use of RF approach, a cloud-based parallel machine learning algorithm employed MapReduce, resulting in MapReduce-Based Parallel Random Forests (PRFs) (Wu et al., 2016, 2017c). The structure uses a scalable cloud computing system, and test with condition monitoring data collected from milling experiments realized in Wu et al. (2017a, 2017b) that compare analyses of three ANNs, support vector regression (SVR), and RF for tool wear in milling.

Another approach uses polymers (Mulrennan et al., 2018). A soft sensor model to measure pressure and temperature for the inline prediction of Tensile Properties Another approach uses polymers (Mulrennan et al., 2018). A soft sensor model to measure pressure and temperature for the inline prediction of Tensile Properties of Polylactide (PLA) with four approaches: Bagging, RF, Principal Component Analysis (PCA) with Bagging and PCA with RF, and the tests used R for generation and data randomization. The idea is to create an online quality verification system that reduces the need for analysis offline, cost, and waste. of Polylactide (PLA) with four approaches: Bagging, RF, Principal Component Analysis (PCA) with Bagging and PCA with RF, and the tests used R for generation and data randomization. The idea is to create an online quality verification system that reduces the need for analysis offline, cost, and waste.

The proposal of Amihai et al. (2018) used the vibration data collected from 30 industrial pumps in a chemical plant for two and a half years and applied RF with persistence technique and Key Condition Indices (KCIs) for CBM monitoring.

As already mentioned, Wu et al. (2017d) presents a Fog Computing method for data acquisition of force, rotational speed, temperature, vibration, acoustic emission, and torque sensors. Edge devices made data acquisition and the "cleaning" work while the Cloud performs the "heavy" prediction and data analysis activities. The tests went with 50 sensors installed in 16 selected pumps and CNC machines to collect data in real-time related to vibrations and consumption power.

The second significant group was the solutions that used DL. An approach of RUL prediction uses Deep Belief Network (DBN) as a stacked version of a Restricted Boltzmann Machine (RBM) that also describes of DBN-Feedforward Neural Network (FNN) (Deutsch & He, 2018). Two tests performed, one using files available from NASA related the Spiral Bevel Gear Data — vibration Condition Indicators (CIs) and Oil Debris Mass (ODM) to detect pitting damage and the second in the laboratory using Hybrid Ceramic Bearing. An example of a dynamic algorithm based on incremental compensation with DL uses SVM to classify the weighted modes in a supervised manner, and the Backpropagation (BP) algorithm to fine-tune the model to complete the DL dynamic and compensatory adjustment was published by Liu et al. (2018).

Solutions using DL introduce an application characteristic and data a bit different from other methods, for example, generated Acoustics Emission (AE) and images are more common in DL. An example is a proposal for a "framework of cyber–physical ball screw prognostics systems" with data acquisition using accelerometers, thermometers, and Acoustic Emission (AE) sensors with a predictive diagnosis of different modes of failure of the component with RBM algorithm (Lee et al., 2017). Another example method with AE using DL realizes fault diagnosis in bearings, approaching pre-processes the sensor signals using the short-time Fourier transform (STFT) (He & He, 2017). A simple spectrum matrix obtained by STFT, and a DL structure optimized for large memory storage retrieval (LAMSTAR), was built to diagnose faults.

One research that drew attention by the analogy presented was a concept of Device Electrocardiogram (DECG). It uses an algorithm based on autoencoder and regression operation for the prediction of the RUL of industrial equipment with tests in CNC (Yan et al., 2018). With relevant documentation on fault prognosis and RUL based on DL, the article brings pseudocode of the Algorithm of Integrated Deep Denoising Autoencoder. It reports that "one of the most obvious advantages of DL is its ability to extract the features automatically such as a Convolutional Neural Network (CNN) and Recurrent Neural Network

(RNN)". Another point is that in addition to the PHM, the article discusses the factory information system (FIS) and makes a relationship between the two.

We also find different proposals, such as an interesting study of frameworks for use in CPS for multiple sites and multi-products (Lee, 2017). A framework using torque sensors measures the magnetic field and its degrees in a compression engine. Changes are sent to the Cloud using a beacon. The article makes a comparison with SVR, Radial Basis Function (RBF), and Deep Belief Learning-based Deep Learning (DBL-DL) to identify two types of faults: shorted circuit and insufficient soldering between the cable and a connector. Another case presents a new prediction structure based on DNN named "A novel eigenvector based on time–frequency–wavelet joint features is proposed to effectively represent bearing degradation process", (Ren et al., 2018).

In the last block of solutions found in the corpus, we divided into a collection of strategies that applied ANNs and methods linked to ML. We started with a low-cost CPS architecture for small businesses that measure the temperature and vibration variables of a CNC with Recursive Partitioning and Regression Tree (RPaRT) in R (Sezer et al., 2018). A solution of Neural Network (NN) and Neuro-Fuzzy Networks with a hybrid solution using model-based and data-driven to determine the current situation of the equipment and predict the RUL presented by Ayad et al. (2018). However, the study describes in detail the physical part of the proposal. Differently, Man and Zhou (2018) brought a full explanation of the mathematical techniques used as variations validated by stochastic degradation signals, Wiener process, parameter definition using the Maximum Likelihood Estimation (MLE) method and prediction of Mean Residual Life (MRL). The article compares BP Neural Network (BPNN) and NN using R, in tests on the start process of automotive engines with 13 lead–acid batteries.

Another case realizes data analysis methods to facilitate the understanding and prediction of the energy consumption of digital production processes under an IoT structure (Qin et al., 2018). The study is done in a selective Laser Sintering System (LSS) in Additive Manufacturing (AM), using three techniques of data analysis: the Linear Regression (LR), Decision Tree (DT) and Back-propagation Neural Network (BPNN). In the comparison results, the solutions using DT and BPNN gave better results than LR.

A differentiated case proposes CBM prediction for the main components decay state in a Naval Propulsion Sys (NPS) formulating the statistical Data-Driven Model (DDM) (Cipollini et al., 2018). Describes supervised strategies Kernel Methods (KMs), Ensemble Methods (EMs), Bayesian Methods (BMs), and Lazy Methods (LMs) and unsupervised cases with SVM and KNN.

To end this context of SQ2, an Structural Health Monitoring (SHM) for historic buildings, bridges, civil structures, and soils. After data collection with IoT, the predictions apply NN and Genetic Algorithms (GAs). The prediction problem is different from the others selected and brings a proposal that can be used in industrial plants (Lamonaca et al., 2018).

To respond to the context related to the use of ANNs, ML, and algorithms, we can say that the range of algorithms used is not very large, and there are specific patterns for each type of need. What is clear is that in the solutions that involve a larger mathematical volume, it is necessary physical knowledge to adjust features, filters, and parameterization of prediction functions. As already mentioned, the RF is frequently used in problems related to the anomaly, and also providing a problem structure visualization. We also highlight the growth of DL used in more recent studies. Anyway, the articles that bring a method, framework or architecture focus on the explanation of the physical structure and in data acquisition, the articles listed here are those that presented a minimum of information related to the logical process of prediction. We can point out examples with significant contributions (Deutsch & He, 2018; Man & Zhou, 2018; Mulrennan et al., 2018; Ren et al., 2018).

Table 6
Important terms for prognosis.

Terms for prognosis	Identifiers
Prognostics and Health Management (PHM)	Ayad et al. (2018), Deutsch and He (2018), Jin et al. (2017), Kaur et al. (2018), Kiangala and Wang (2018), Kwon et al. (2016), Lee (2016), Lee et al. (2014, 2017), Man and Zhou (2018), Ren et al. (2018), Roy et al. (2016), Terrissa et al. (2016), Wang et al. (2018), Wu et al. (2017a, 2017b, 2016, 2017c), Yan et al. (2018)
Condition-Based Maintenance (CBM)	Cipollini et al. (2018), Jantunen et al. (2016), Kaur et al. (2018), Kwon et al. (2016), Lee (2016), Man and Zhou (2018), Schmidt et al. (2017), Sezer et al. (2018), Silva et al. (2016), Wang et al. (2018)
Remaining Useful Life (RUL)	Amihai et al. (2018), Ayad et al. (2018), Deutsch and He (2018), Jin et al. (2017), Kwon et al. (2016), Lee et al. (2017), Man and Zhou (2018), Nemeth et al. (2018), Ren et al. (2018), Roy et al. (2016), Terrissa et al. (2016), Wang et al. (2018), Wu et al. (2017a, 2017b, 2017c, 2017d), Yan et al. (2018), Yang and Zhang (2016)
Predetermined Maintenance (PRM)	Cipollini et al. (2018)
State of Health (SoH)	Ayad et al. (2018), Lee et al. (2014), Wang et al. (2018)

As a response to the third and last context of SQ2, we have listed articles that use concepts of prognosis PHM, RUL, and CBM in its proposal, model, framework, or architecture. We consider it essential to highlight works that use these approaches in their solutions because presenting differentiated results. Besides these, we have found some derivations, for example, Predetermined Maintenance (PrM) in Cipollini et al. (2018) e Condition-Based Predictive Maintenance (CBPdM) in Kaur et al. (2018). The articles that addressed prognostic strategies for performing the PdM are listed in Table 6.

To summarize, the most commonly found prediction classification is data-driven, but the most significant results use the physical knowledge of the assets. We see that this trend is visible in two other points: the physical importance of calculating the RUL and the PHM cycle knowledge for applying ML approaches. In solutions with significant volumes of data, we highlight the anomalies and similarities identification. Still, in the most current articles, we notice the growth in the use of Neural Networks and Deep Learning. An example would be the use of LSTM due to its characteristic of keeping the memory of data already processed, something crucial when using time series in PdM (Bruneo & De Vita, 2019).

SQ3 — Is it possible to create a taxonomy using the terms found for predictive application or monitoring?

We answered this question by addressing one of the scientific challenges of this review. In Fig. 5, we demonstrate the sequence of the methodology used, with the accomplishment of the research and definition of the articles we started the identification, separation, and discussion of the results. For this, we use the VOSviewer tool to contribute to the visualization of the main terms found and creates a more comprehensive taxonomy than the initially planned.

In order to establish logical reasons for the process of taxonomic definition, we have adopted three criteria for creating the taxonomy for Industry 4.0 with a focus on PdM:

First criterion: Generating the mapping and clustering using VOSviewer, which implements Smart Local Moving (SLM) optimization algorithms and method created by the Center for Science and Technology Studies (CWTS) (Klavans & Boyack, 2017). The first process was the generation of a file with the vital information to create the maps: authors, terms, and citations. For this, we chose Scopus, and an individual search of the selected corpus done. The VOSviewer applies bibliometric data methods for filtering and relating by co-occurrences

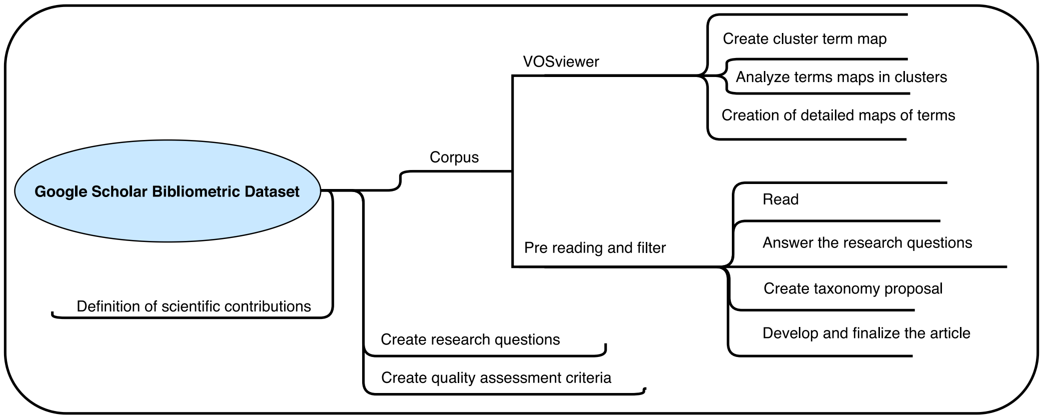


Fig. 5. Methodology created to generate the taxonomy.

Table 7
Co-occurrence terms configuration file.

Label	Replace by
Learning algorithms	Machine learning
Learning systems	Machine learning
Internet of things	Internet of thing
internet of thing (iot)	Internet of thing
internet of things (iot)	Internet of thing
Cyber–physical systems	Cyber–physical system
Cyber–physical systems	Cyber–physical system
cyber–physical system (cpss)	Cyber–physical system
cyber–physical systems (cpss)	Cyber–physical system
cyber–physical systems (cps)	Cyber–physical system

Table 8
Key terms to generate a root for Industry 4.0 with focus on PdM.

Key terms
Big Data
Cyber–physical systems (CPS)
Smart Manufacturing/Manufacture
Internet of Things (IoT)/Industrial Internet of Things (IIoT) - Fig. 8
Machine Learning/Artificial Intelligence
Predictive Maintenance/Maintenance/Fault prognosis Fig. 7

of keywords. This process analyzes the links between the words using a natural language algorithm (Nees Jan van Eck). To avoid redundancy, we have applied filters for similar terms, according to Table 7. This technique to prevent that synonymous words, different writing, or even meaning is plotted on the map separately.

Second criterion: To verify all terms that are related hierarchically with direct relation to Industry 4.0 and PdM, we use the relation map and heat of the VOSviewer. The maps of Fig. 6a refer to a relationship and 6b to the heat map. Therefore, we enable us to see that we contemplate the main terms used in the string proposed in this review.

This criterion we highlight the definition of the main terms found for Industry 4.0 with a focus on PdM in Table 8.

Third criterion: For each significant term identified in Table 8, we generate a representation of the next level of the taxonomy tree. Its direct relation was verified, selecting those terms that belong to the same cluster according to Figs. 7 and 8. We removed terms that did not maintain the direct connection and connected others if necessary.

Fig. 7 presents the main links with the following terms: maintenance, smart manufacturing, Big Data, decision support systems, data handling, and production system.

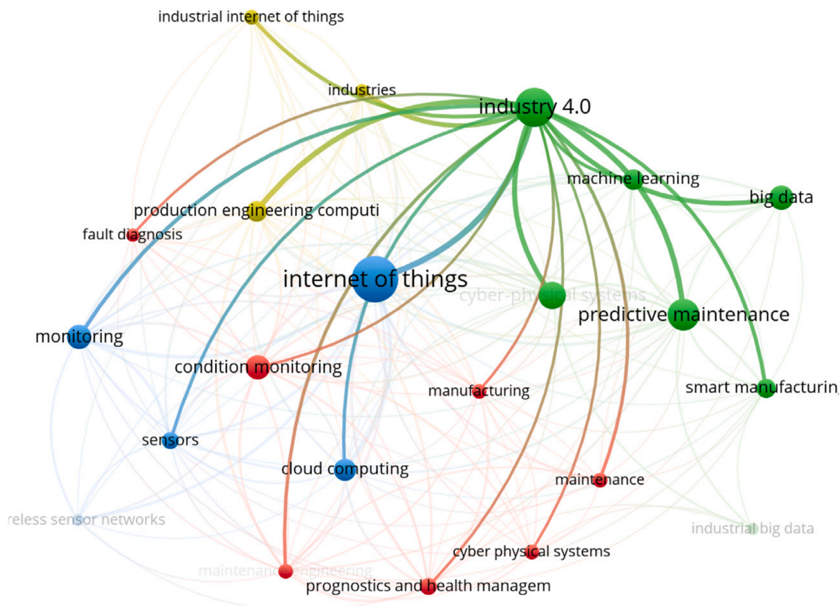
IoT cluster, in Fig. 8, mapped the same process and presented the following terms: monitoring, conditions monitoring, big data, cloud computing, machine learning, intelligent manufacturing, industrial research, industrial environment, fault detection, RUL, and deep learning.

We carry out the mapping with all key terms, and the results of each related cluster are demonstrated in Table 9.

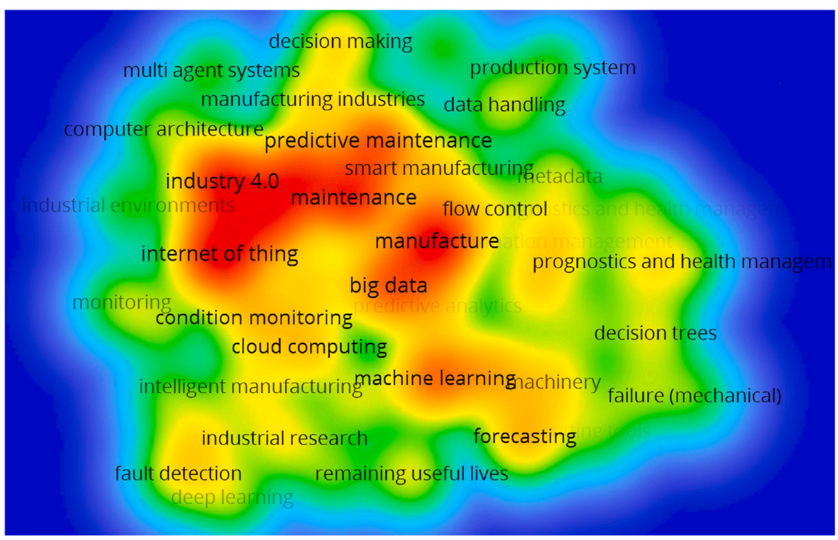
After fulfilling all three criteria, we created the taxonomy of Fig. 9. Based on the selected articles and discussions held in the SQs, the CPS environments can be considered as the precursors Smart Factoring, for being the first work to bring the massive data usage's provocation besides the possibility of an M2M application. The same occurs with the prognosis, in which PHM used an idea of intelligent monitoring and industry life cycle before the emergence of PdM. The usage of IoT is also something real, but we found several occurrences in legacy solutions or prototypes to data acquisition and studies of ML and PdM.

As the main contribution in this review, we present the taxonomy proposal shown in Fig. 9: started with the item **Monitoring in the Context of Industry 4.0**, the term identified as the best representation of the discussion scenario to create a reference for maintenance. In sequence, the item **Types maintenance** extends to the **Analyze Based in History** and **Analyze Based on snapshot**. Analyze Based in History refers to maintenance in predictions that can generate histories with temporal characteristics. From this, we present the four maintenance categories: corrective, preventive, predictive, and prescriptive (Nemeth et al., 2018). Analyze Based on snapshots are linked as immediate actions, for example, alert Monitoring. **Principles** list important collaborations about monitoring principles (Jantunen et al., 2016). **Domains in applications** bring the progress and applicability related to PdM, as well as, the terms PHM, RUL, and CBM (Lee et al., 2013, 2006; Zerhouni et al., 2017). In **Predictive Maintenance (PdM), in the context of industry 4.0**, we have the taxonomy proposal's core and, therefore, it involves more details. **Interactions** deal with manufacturing based in the cyber system and service innovation so that there is interaction with products and industrial services (Lee et al., 2014). Among all items, **Methods** deserves attention because it is possible to find the PdM classification approach used to contextualize with the SQ2 answers, for example, **Data-driven** with its importance and straight methods and models application linked to AI. **Models** emphasizes that the key to the PdM it is related to the PHM. The health management of an asset uses four strategies types. In **Monitoring focus**, according to the model for the prediction of RUL Man and Zhou (2018), we emphasize the importance of minimal physical knowledge of the monitored components. Ultimately, **Goals** represents possible results obtained according to this monitoring taxonomy representation in the context of Industry 4.0, reducing maintenance costs and downtime, besides improving maintenance and quality related to maintenance.

Methodology and criteria used for visualization and to create our taxonomy proposal are directly related to all the research carried out. Even the unselected articles demonstrated adherence to what we build. Through our taxonomy, it is possible to have an overview of the current situation that resulted from our string. Our main objective was to create



(a) Map of related concepts



(b) Heat map of related concepts

Fig. 6. Maps generated with terms and direct relation to industry 4.0 with focus on PdM.

a reference for future research, and the result can be considered the most important of our review.

SQ4 — How are the results of the surveys that present models, methods or architecture?

The discussions related to applications depart from Table 10, which presents a summary with the primary information about the models, methods, frameworks, and architectures. We highlight the name or description of the research, case of application, and data acquired to carry out the prediction. We do not list selected articles that have survey characteristics of reviews or mappings in Table 10, because they present different challenges and concepts.

We observe, in Table 10, that the solutions for evaluation of vibration, temperature, and wear in rotational components were the most common. Some cases with relevant documentation have brought applications using AE (He & He, 2017; Lee et al., 2017), images (Yan et al., 2017), and polymers (Mulrennan et al., 2018). We can highlight two examples solutions: one brings a concept of Device Electrocardiogram (DECG) (Yan et al., 2018) other a low-cost Industry 4.0 proposal for Small and Medium-sized Enterprises (SME) Sezer et al. (2018).

We also highlight some cases that used essential initiatives for the IoT, such as — Android Things (Google), Predix [General Electric (GE)], Azure IoT Suite (Microsoft), and MTConnect communication protocol. The standardization linked to data acquisition, enabling communication, security, and scalability is necessary for the growth and adoption of CPS and IoT (He et al., 2018; Jin et al., 2017; Lee, 2016; Lee et al., 2017; Saez et al., 2018; Wu et al., 2017d).

Each article has its particularity, either the use of sensor, acquisition, communication, return form, but most applications follow a line of concern with the old plants, one of the biggest challenges for those who want to adopt Industry 4.0 without many resources. In this section, we seek solutions with a structure that could present a standard deployment flow, but which had different practical applicability.

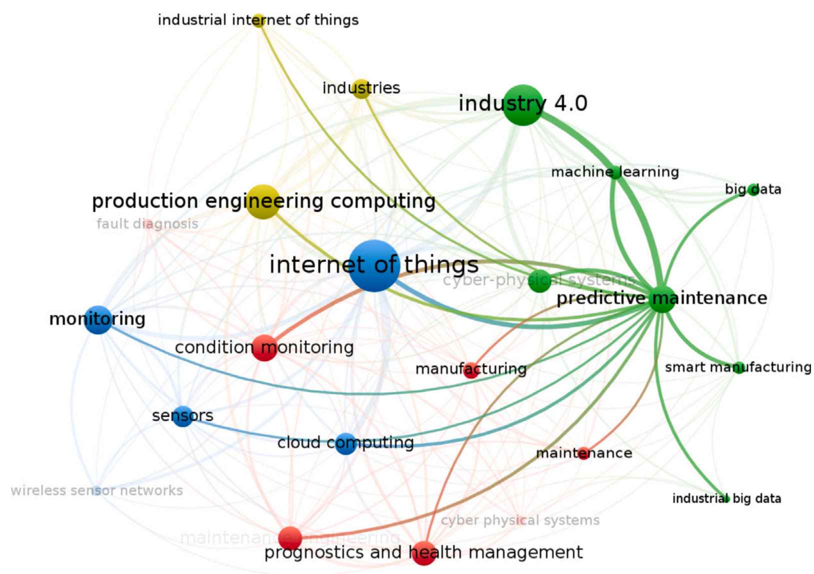


Fig. 7. Mapping in VOSviewer of the Predictive Maintenance (PdM) cluster.

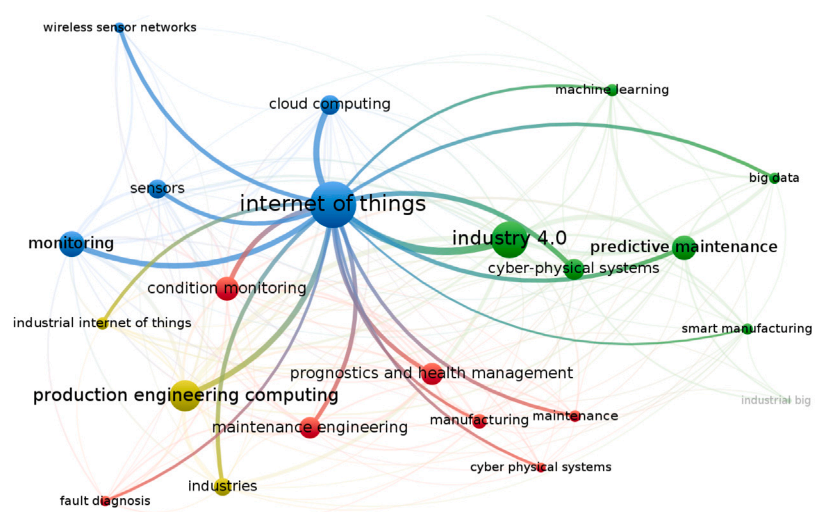


Fig. 8. Mapping in VOSviewer of the Internet of Things (IoT) cluster.

Table 9
Key terms and related clusters mapped.

Key terms	Clusters
Big Data	maintenance, PdM, data handling, decision support systems, production system
CPS	computer architecture, multi-agent systems, decision making, manufacturing industries, predictive maintenance, manufacture, IoT, RUL
Smart Manufacturing	industry 4.0, CPS, computer architecture, multi-agent systems, decision making, life-cycle, manufacture, embedded systems
IoT - Fig. 8	monitoring, conditions monitoring, big data, cloud computing, machine learning, intelligent manufacturing, industrial research, industrial environment, fault detection, RUL, deep learning
AI	metadata, PHM, systems engineering, decision trees, failure, forecasting
PdM Fig. 7	maintenance, smart manufacturing, Big Data, decision support systems, data handling and production system

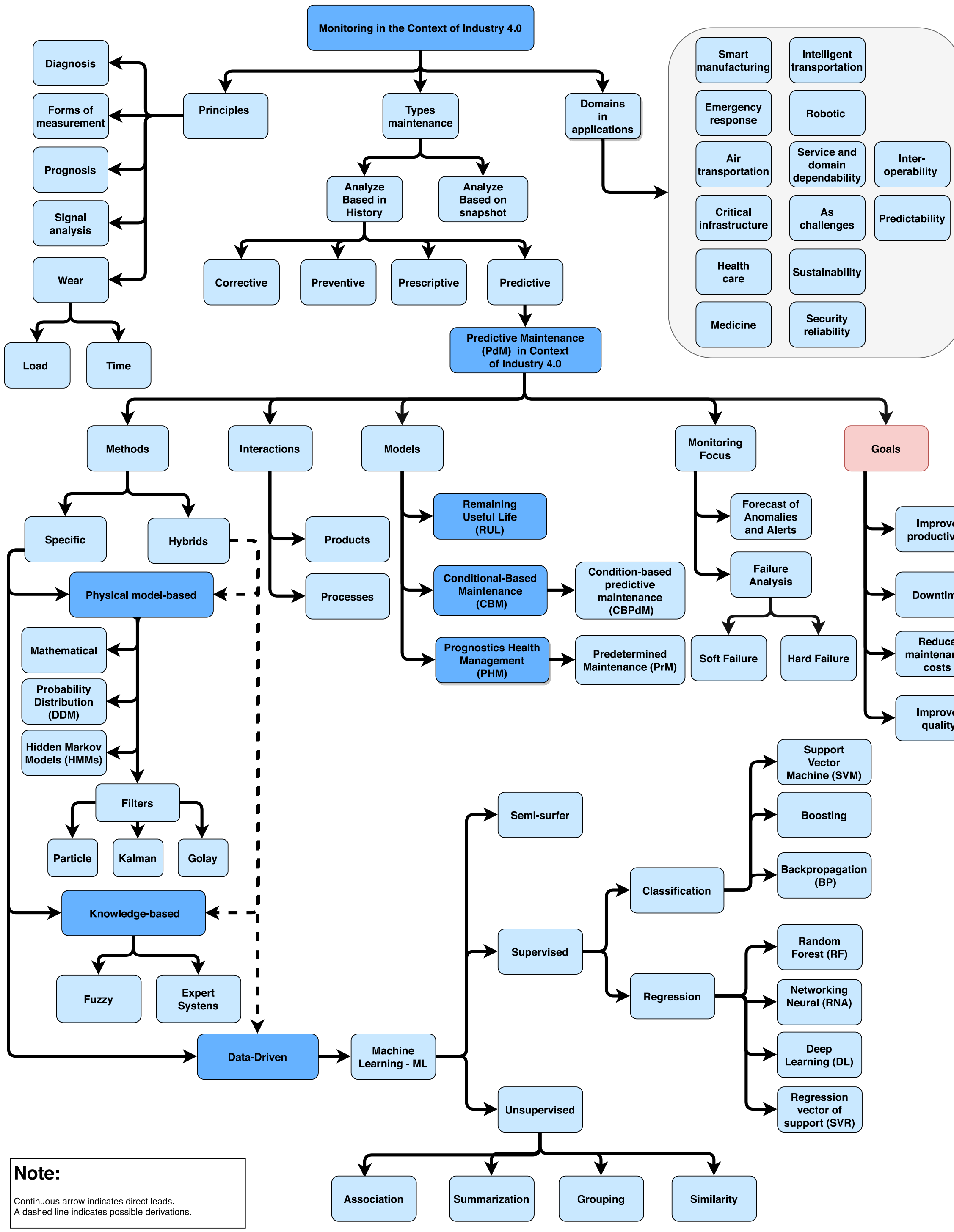


Fig. 9. Taxonomy — Monitoring in the context of Industry 4.0.

The research results have improved over the years, but we emphasize the importance of terms that have been part of solutions for some time. The most recent studies have pointed to the prediction with time series, improving the idea of only alert monitoring. The possibility of creating distributed models and applications allows this evolution and application in real-time of future challenges. We can expect a considerable growth of models and architectures in the coming years.

6. Challenges and future directions

In this section, we will present our perceptions regarding some challenges and opportunities and, provide the answer to the question **SQ5 — What are the challenges and open questions identified?**

Real time-based PdM application: The first challenge, and focus of this research is the application of time-based PdM (Jantunen et al., 2016; Kaur et al., 2018; Wu et al., 2017b). We found that many research treat prediction as simple alert monitoring. Few solutions leave it clear

Table 10
Models, methods or architecture presentation.

Identifiers	Name or description	Case	Variables
Lee et al. (2014)	Framework of the application of PHM algorithms in detecting invisible issues in industry using Watchdog Agent® tool	Industrial Robot, Virtual Battery	Torque, speed and voltage current, temperature, speed GPS, EV Weigh
Gunes et al. (2014)	A survey on concepts, applications, and challenges in CPS	–	–
Silva et al. (2016)	Cloud-based Architecture for device monitoring and control	Exhausting system	Vibration, temperature, humidity
Terrissa et al. (2016)	PHM as a Service in Cloud	Generic Method	Generic
He and He (2017)	Deep learning based method for bearing fault diagnosis	Bearing	AE
Lee (2016)	Framework of big data analytics platform for PdM	Band saw Machines	Vibration, temperature, AE
Jantunen et al. (2016)	Generic data processing architecture in Mantis	Electro Chemical Machining, Off-road and special purpose vehicles, Energy Production, Healthcare Imaging Systems	Generic
Roy et al. (2016)	Continuous maintenance and the future	–	–
Rodríguez-Mazahua et al. (2016)	A general perspective of Big Data	–	–
Yang and Zhang (2016)	RAE-ELM structure for a set of ELM slices	electric load, prime mover, gearbox, flywheel, asynchronous generator	Vibration
Kwon et al. (2016)	Physics-of-failure(PoF) PHM, Fusion PHM methodology, IoT-based PHM	–	–
Wu et al. (2016)	Cloud-Based Machine Learning for Predictive Analytics	3-axis high-speed vertical CNC	Cutting force, vibration, AE
Li (2016)	Strategic framework of the smart factory in the petrochemical industry	–	–
Lee et al. (2017)	5C Architecture of CPS, Framework of CPS ball screw prognostics systems	Ball screw	Acceleration, temperature, AE
Jin et al. (2017)	5C architecture for future CPS-enabled smart wind farm	Wind turbines	Turbine performance, speed, power
Lee (2017)	HID cable manufacturing and fault detection issues with cloud architecture	HID cable	Torque, proximity
Spendla et al. (2017)	Knowledge discovery model	Generic Model	Generic
Yan et al. (2017)	Novel framework for structuring multisource heterogeneous information	Vertical milling center	Vibration of cutter, images by a 3D laser scanner, acoustical signal, power
Wu et al. (2017b)	Data-Driven Methods for Tool Wear Prediction	3-axis high-speed vertical CNC	Cutting force, vibration, AE
Wu et al. (2017c)	Cloud-Based Parallel Machine Learning for Tool Wear Prediction, MapReduce Programming Framework	3-axis high-speed vertical CNC	Cutting force, vibration, AE
Wu et al. (2017a)	Comparative Study on Machine Learning Algorithms for Smart Manufacturing	3-axis high-speed vertical CNC	Cutting force, vibration, AE
Wu et al. (2017d)	Framework for Fog-Based Cyber-Manufacturing System	Pumps and CNC machines	Cutting force, vibration, AE
Xia et al. (2017)	Stacked denoising autoencoder SDA-based feature learning and fault diagnosis	Bearing	Vibration, AE
Schmidt et al. (2017)	Semantic framework for predictive maintenance in a cloud environment	Generic framework	Vibration
Matyas et al. (2017)	Procedural approach for prescriptive maintenance planning, Approach for wearout calculation of a machine component	Triaxial machining centers of an automotive manufacturer	Failure protocols
Qin et al. (2018)	IoT Framework of Energy Consumption Analysis	Energy consumption of digital manufacturing systems	Temperature, power

(*continued on next page*)

that the maintenance might be done, taking into consideration the specific time in a particular condition. Even the selected articles, which attended to this criteria, do not make it clear they will make the prediction indeed. A single case predicted a 7-day interval for failure using RF (Amihai et al., 2018). Other cases bring situations such as reactive form, schedule maintenance, scheduled preventive operations, and scheduling condition monitoring among other denominations for the time (Ardolino et al., 2018; Cho et al., 2018; Cipollini et al., 2018; Gunes et al., 2014; He et al., 2018; Kwon et al., 2016; Lee, 2016, 2017; Lee et al., 2014, 2017; Li, 2016; Roy et al., 2016; Saez et al., 2018; Sezer et al., 2018; Silva et al., 2016; Terrissa et al., 2016; Wu et al., 2017a, 2017b, 2016; Yan et al., 2017, 2018; Yang & Zhang, 2016). There are

Table 10 (*continued*).

Identifiers	Name or description	Case	Variables
Deutsch and He (2018)	Deep Learning-Based Approach	Rotating Components	Vibration condition indicators (CIs), oil debris mass (ODM)
Ku (2018)	RHadoop-based big data analysis platform	Generic Method based on PLC	Temperature, speed, distance etc
Ayad et al. (2018)	IoT Approach for a Smart Maintenance	Generic Method	Generic
Man and Zhou (2018)	Stochastic degradation signals using Wiener process and proportional hazards model	Automotive engine cranking	Battery resistances
Wang et al. (2018)	Framework for sensor data based anomaly prediction in manufacturing	Coal Mill	Coal feed sensor, electricity, bearing vibration
Mulrennan et al. (2018)	Soft Sensor for Prediction of Mechanical Properties of extruded PLA sheet	Stress of the extruded PLA sheet	Pressure transducer, thermocouple
Saez et al. (2018)	Anomaly Detection and Productivity Analysis for CPS	Start-stop conveyors, Automotive assembly plant	Velocity, current voltage, presence sensors, emergency stop button
Kaur et al. (2018)	OIIE Architecture for IIoT	Generic Architecture	Generic
Cho et al. (2018)	Architecture for the PdM pilot	Milling machines and CMM machines	Generic
Rúbio et al. (2018)	Architecture of a CPS	Electric motors	Vibration gravity
Ren et al. (2018)	Deep autoencoder RUL prediction model	Bearing	Vibration
Sezer et al. (2018)	Low Cost PdM Approach	CNC Turning Centre	Gyroscope, accelerometer, magnetometer, temperature, barometric pressure and humidity
Nemeth et al. (2018)	PriMa-X: A reference model for realizing prescriptive maintenance and assessing its maturity enhanced by machine learning	–	–
Yan et al. (2018)	Device electrocardiogram	CNC machining center	Uninformed
Cipollini et al. (2018)	Condition-based maintenance of naval propulsion systems	Diesel-electric and gas propulsion plant	Speed, torque, temperature, pressure
He et al. (2018)	Pavatar-Power Systemś Digital Twin	ultrahigh-voltage converter station (UHVCS)	Temperature, humidity, noise, air quality, liquid leakage
Liu et al. (2018)	Dynamic deep learning algorithm based on incremental compensation	Bearing	Ten conditions of vibration
Amihai et al. (2018)	Case study based on vibration monitoring	Rotating Equipment with High Imbalance	Vibration
Kiangala and Wang (2018)	Decentralized vibration speed monitoring through cloud-based reporting tool	Conveyor motor in a bottling plant	Vibration
Lamonaca et al. (2018)	IoT for Structural Health Monitoring(SHM)	Engineering structures	Vibration, AE
Ardolino et al. (2018)	Research framework-digital technologies and Data-Information-Knowledge-Wisdom(DIKW) hierarchy	–	–

also cases of prescriptive maintenance, which, by its characteristic, may become the standard for this challenge (Matyas et al., 2017; Nemeth et al., 2018).

Heterogeneous data, bench tests: most of the tests applied in PdM use simulation benches. The explanation for this scenario is the complexity of stopping a machine for evaluation or allowing failure. Even by having all data collected, it is possible to evaluate only one machine at a time — therefore, the challenge to analyze heterogeneous data. Some articles have already cited this complexity to evaluate the situation of a machine, and after that put into production (Amihai et al., 2018; Cho et al., 2018; Deutsch & He, 2018), this challenge shows the need of physical knowledge applied to prediction (He et al., 2018; Kwon et al., 2016; Man & Zhou, 2018).

Creating a new maintenance classification: the maintenance classifications commonly encountered are corrective, preventive, and predictive. We call attention to the prescriptive denomination (Matyas et al., 2017; Nemeth et al., 2018). It can be the solution for the factor of being predictive or not, creating a prescription pointing to a specific situation, as already mentioned in the description made by Nemeth et al. (2018) "How can we make it happen?" or "How can we control the occurrence of a specific event?". In this review, one of the challenges would be to include a new designation called maintenance based on monitoring or autonomous alert. We understand that, if the machine is presenting an alert, it would not be a prediction yet. We could consider this monitoring something prescriptive, but we keep the idea that prediction must involve time.

Image-based PdM: the use of images to make the prediction is a challenge. We found some articles that took into consideration images and thermography, but only Yan et al. (2017) is among the selected ones. Thereby, we highlight some image-based strategies as challenging to the PdM accomplishment, especially the thermographic models.

Linking the PdM to the production process: the integration between industrial processes and intelligent automation is one of the Industry 4.0 pillars, so a way of using time-based PdM would be the integration of the maintenance process with the production already suggested by some articles (Jantunen et al., 2016; Jin et al., 2017; Kiangala & Wang, 2018; Lee, 2017; Nemeth et al., 2018; Qin et al., 2018; Wu et al., 2016). The case of Lee et al. (2017) with the 5C Architecture of CPS, prediction production quality Spendla et al. (2017), integration energy flow and logistics (Li, 2016). The case of the article Kwon et al. (2016) presents arguments and challenges to manufacturing, heavy industry: mobile assets, energy generation, transportation and logistics, infrastructure assets, automobiles, medical consumer products, warranty services, and robotics. The article also presents a vision of challenges making IoT-based PHM work analytics: machine learning and data mining, security, energy harvesting, new business models for IoT-based PHM, licensing, and entitlement management. We draw attention to, production schedule based on the forecast of maintenance, logistics, and energy consumption in a sustainable way. We highlight the Factory Information System (FIS) related to PHM is a conceptual information model that may be the standard for such integration. The idea would be exactly a factory intelligence system (Yan et al., 2018).

The dissemination of important multidisciplinary contents for maintenance proposals: we talked with professionals in the areas of mechanics, electrical, and automation, where PHM, CBM, and RUL are more common, we did not find a significant group that talks about them. In the case of computing area, the return was almost zero.

If we take into consideration the application of computing in the industry, we can say that it has many challenges. Initially, the participation of computing in PdM is in the use of ML, but computing is embedded in security, scalability, cloud computing, IoT, and other technologies. We need to know where this is applied to have more effective collaboration. The dissemination of these terms can generate a greater standardization and increase the multidisciplinarity of solutions focused on prognosis.

A vision of the computing within Industrial applications: computing has significant challenges in this new scenario of Industry 4.0, and based on this research, we visualize the predictive demand, but computing works together with other areas because it usually performs requirements of the problem. However, there is not a deepening in the question as a whole, so there are many opportunities already available that can be used in research in the field generating increased research in computational periodic. The technologies, mainly in the area of IoT, allow this insertion, and this would be a challenge.

In this SQ, we highlight challenges related mainly to applied computing, for example, the growth in the use of intelligent methods based on data. For this, new approaches using IoT will appear due to the need for acquisition asset information. Another point is the need for multidisciplinarity to obtain better results. Laboratories and research groups will need to have specialists in the areas in which the solutions will apply.

7. Conclusion

The maintenance activity requires strategies and planning to meet the needs of quality, safety, and productivity. The growth of the concepts of Industry 4.0 brings new opportunities and challenges. Among them, we understand that the maintenance in a predictive way would be the focus of our study in which we seek to understand the approaches used and existing applications. Thereby, the literature review presented in this article aims to provide an overview of PdM in the context of Industry 4.0. We performed a systematic literature review methodology that resulted in a total of 47 articles on methods, architectures, and technologies aligned with the application of predictive maintenance. We critically analyze the studies considering the main challenges of the area, including the visualization of possible standardizations and difficulties in their implementation.

From this review, we present the scientific contributions guided by the main question and five sub-questions, described in Section 4 and discussed in depth in our analysis of the state-of-the-art in Sections 5 and 6. The main question of our study covers the identification of standards, the main means of publication, applications and the most common terms about PdM and Industry 4.0. As the main contribution, we created a taxonomy of PdM in the context of Industry 4.0, the taxonomy presented the types of application, principles, following application models, methods, focus, and delimitation of objectives. As a limitation, in our research, we find several articles on maintenance with monitoring models, but without the main idea of predicting the possibility of time-based failures. The contents linked to failure prognostic can also be considered as a limitation because they are dominant in engineering studies, and uncommon in computing.

Regarding our future directions, first, we visualize some appointments found in related work as Muhuri et al. (2019), O'Donovan et al. (2015) and Zerhouni et al. (2017) that there are opportunities for research in Industry 4.0, specifically in the intelligent maintenance process. With our focus, in the PdM, we presented seven future directions discussed in Section 6, challenges that can be used by companies and researchers. We brought concept concerns, suggesting the creation of an autonomous monitoring classification with alerts, leaving the prediction for a time-based characteristic. We called attention to multidisciplinarity involved in the new challenges of Industry 4.0 and the integration necessity. Regarding the volume of data and the realization of the tests, how could we allow an asset failure to verify the right maintenance point? How to simulate the different scenarios of an industry? It is already related to applications we have the use of images and their information, for example, thermographic data. To finalize the idea of integrating more processes within the Industry. We believe that this can be a line of research in expansion along with the ideas brought by the FIS concept, that application will bring about considerable modifications and improvements to the industrial environment.

CRediT authorship contribution statement

Tiago Zonta: Writing - original draft, Conceptualization, Methodology, Investigation. **Cristiano André da Costa:** Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing, Supervision. **Rodrigo da Rosa Righi:** Methodology, Writing - review & editing. **Miromar José de Lima:** Methodology, Investigation, Writing - original draft. **Eduardo Silveira da Trindade:** Methodology, Investigation, Writing - original draft. **Guann Pyng Li:** Writing - review & editing.

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