Computers & Industrial Engineering 137 (2019) 106024

Contents lists available at ScienceDirect

Computers & Industrial Engineering

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

A systematic literature review of machine learning methods applied to predictive maintenance

Thyago P. Carvalho[a], Fabrízzio A. A. M. N. Soares[a,d], Roberto Vita[c], Roberto da P. Francisco[b], João P. Basto[c], Symone G. S. Alcalá[b,*]

[a] Institute of Informatics, Federal University of Goiás, Goiânia, Goiás, Brazil
[b] Faculty of Science and Technology, Federal University of Goiás, Aparecida de Goiânia, Goiás, Brazil
[c] Institute of Systems and Computer Engineering, Technology and Science (INESC TEC), Porto, Portugal
[d] Department of Computer Science, Southern Oregon University, Ashland, Oregon, USA

ARTICLE INFO

Keywords:
Predictive maintenance
Machine learning
PdM
Systematic literature review
Artificial intelligence

ABSTRACT

The amount of data extracted from production processes has increased exponentially due to the proliferation of sensing technologies. When processed and analyzed, data can bring out valuable information and knowledge from manufacturing process, production system and equipment. In industries, equipment maintenance is an important key, and affects the operation time of equipment and its efficiency. Thus, equipment faults need to be identified and solved, avoiding shutdown in the production processes. Machine Learning (ML) methods have been emerged as a promising tool in Predictive Maintenance (PdM) applications to prevent failures in equipment that make up the production lines in the factory floor. However, the performance of PdM applications depends on the appropriate choice of the ML method. The aim of this paper is to present a systematic literature review of ML methods applied to PdM, showing which are being explored in this field and the performance of the current state-of-the-art ML techniques. This review focuses on two scientific databases and provides a useful foundation on the ML techniques, their main results, challenges and opportunities, as well as it supports new research works in the PdM field.

1. Introduction

Currently, the industry is going through what experts have called "The Fourth Industrial Revolution", also called Industry 4.0. This fact is strongly associated with the integration between physical and digital systems of production environments. The integration of these environments allows the collection of a large amount of data that is collected by different equipment, located in different sectors of the factories (Borgi et al., 2017). In addition, new technologies from Industry 4.0 integrate people, machines and products, enabling faster and more targeted exchange of information (Rauch et al., in press).

The big amount of data, collected by industrial systems, contains information about processes, events and alarms that occur along an industrial production line. Moreover, when processed and analyzed, these data can bring out valuable information and knowledge from manufacturing process and system dynamics. By applying analytic approaches based on data, it is possible to find interpretive results for strategic decision-making, providing advantages such as, maintenance cost reduction, machine fault reduction, repair stop reduction, spare parts inventory reduction, spare part life increasing, increased production, improvement in operator safety, repair verification, overall profit, among others (Peres et al., 2018; Sezer et al., 2018; Biswal and Sabareesh, 2015).

The mentioned advantages have strong relationship with maintenance procedures. In industries, equipment maintenance is an important key, and affects the operation time of equipment and its efficiency. Therefore, equipment faults need to be identified and solved, avoiding shutdown in the production processes (Wan et al., 2017). For example, Vafaei et al. (2019) propose a fuzzy alarm system to predict early equipment degradation in a car production line, with the aim of reducing costs with sudden shutdowns. Wei et al. (2019) propose a condition-based maintenance strategy to determine the optimal action (e.g., no action and corrective replacement) based on the system state in order to minimize the average cost rate. On the other hand, Dong et al. (2019) develop a prognostic and health management framework to detect sensor degradation in manufacturing systems in order to

* Corresponding author.
E-mail addresses: thyagocarvalho@inf.ufg.br (T.P. Carvalho), fabrizzio@inf.ufg.br (F.A.A.M.N. Soares), roberto.vita@inesctec.pt (R. Vita), roberto.piedade@ufg.br (R.d.P. Francisco), joao.p.basto@inesctec.pt (J.P. Basto), symone@ufg.br (S.G.S. Alcalá).

https://doi.org/10.1016/j.cie.2019.106024
Received 22 April 2019; Received in revised form 13 August 2019; Accepted 27 August 2019
Available online 05 September 2019
0360-8352/

optimize the maintenance scheduling, with the aim of reducing maintenance cost, avoiding unnecessary down-times and supporting decision-making.

In literature, different nomenclature and groups of maintenance management strategies can be found. This paper considers the categories proposed by the works (Susto et al., 2012; Susto et al., 2015). They classify the maintenance procedures as follows:

- *Run-to-Failure* (R2F) or *Corrective maintenance* happens only when an equipment stops working. This is the simplest maintenance strategy, since it is necessary both the stop on the production and the repair of the parts to be replaced, adding a direct cost to the process.
- *Preventive Maintenance* (PvM), *Time-based maintenance* or *Scheduled maintenance* is a maintenance technique performed periodically with a planned schedule in time or process iterations to anticipate process/equipment failures. It is generally an effective approach to avoid failures. However, unnecessary corrective actions are taken, leading to an increase in the operating costs.
- *Predictive Maintenance* (PdM) uses predictive tools to determine when maintenance actions are necessary. It is based on continuous monitoring of a machine or a process integrity, allowing maintenance to be performed only when it is needed. Moreover, it allows the early detection of failures thanks to predictive tools based on historical data (e.g. machine learning techniques), integrity factors (e.g. visual aspects, wear, coloration different from original, among others), statistical inference methods and engineering approaches.

Fig. 1 gives an overview of the maintenance types. Each of the maintenance classes has its role. But, by opting for R2F, industries delay maintenance actions and assume the risk of unavailability of their assets; on the other hand, PvM anticipates maintenance interventions, resulting in a spare part exchange with half-life. Thus, a good maintenance strategy should improve the equipment condition, reduce the equipment failure rates and minimize maintenance costs, while maximize the life of equipment. Due to this fact, the PdM strategy is the one that stands out most among the other strategies (Jezzini et al., 2013), and it is attracting attention in the era of Industry 4.0 due to its ability of optimizing the use and management of assets (Kumar et al., 2019). Its advantages include: maximizing time of use and operation of equipment, delaying/reducing maintenance activities, and reducing material and labor costs.

As described before, PdM deals with faults or failures prediction before they occur. According to Jardine et al. (2006), maintenance approaches able to monitor equipment conditions for diagnostic and prognostic purposes can be grouped into three main categories: *statistical approaches*, *artificial intelligence* approaches and *model-based approaches*. As *model-based approaches* need mechanistic knowledge and theory of the equipment to be monitored, and *statistical approaches* require mathematical background, *artificial intelligence* approaches have been increasingly applied in PdM applications. For example, Baptista et al. (2018) compare a number of *artificial intelligence approaches* to a *statistical approach* (called life usage model) to predict when an equipment will be at risk of failure in the future; and the results suggest that *artificial intelligence approaches* outperform *statistical approaches*.

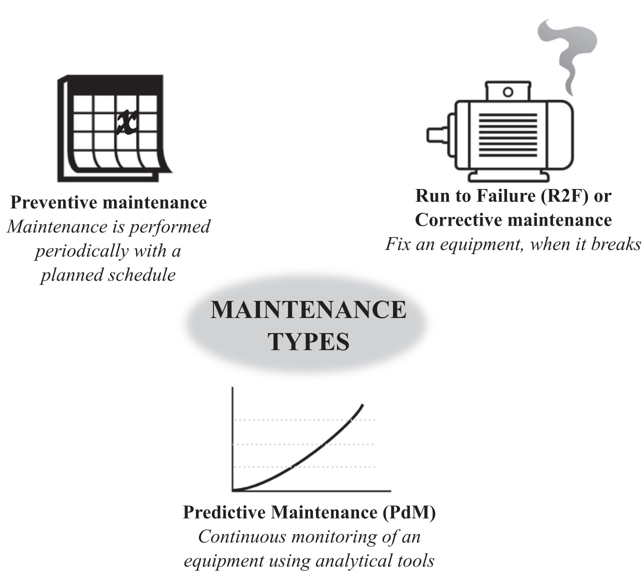

Fig. 1. Overview of the maintenance types.

Machine Learning (ML), within artificial intelligence, has emerged as a powerful tool for developing intelligent predictive algorithms in many applications. ML approaches have the ability to handle high dimensional and multivariate data, and to extract hidden relationships within data in complex and dynamic environments (such as, industrial environments) (Wuest et al., 2016). Therefore, ML provides powerful predictive approaches for PdM applications. However, the performance of these applications depends on the appropriate choice of the ML technique. Therefore, the aim of this paper is to present a Systematic Literature Review (SLR) covering the main published solutions of PdM techniques based on ML methods. This paper provides a useful foundation on the ML techniques, their main results, challenges and opportunities, as well as it supports new research works in the PdM field.

The rest of this article is structured as follows: Section 2 describes the planning and the execution of SLR. Section 3 presents an overview of the main steps on the development of a ML model. Section 4 presents a summary of the studied literature, highlighting the answers to some research questions and the main characteristics of PdM techniques based on ML. In Section 5, some public data sets are described and they can be used as a starting point for future researches using ML methods in PdM applications. Finally, in Section 6, the contributions obtained from this paper are highlighted, and concluding remarks are summarized. Table 1 lists the main nomenclature used in this paper.

2. Systematic literature review

Systematic Literature Review (SLR) is a well-known method that is

Table 1
Nomenclature.

ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ARIMA	Autoregressive Integrated Moving Average
BN	Bayesian Network
CART	Classification and Regression Trees
CNN	Convolutional Neural Network
DT	Decision Tree
FURIA	Fuzzy Unordered Rule Induction Algorithm
GLM	Generalized Linear Model
GPR	Gaussian Process Regression
k-NN	*k*-Nearest Neighbors
LDA	Linear Discriminant Analysis
LR	Linear Regression
LSTM	Long Short-Term Memory Network
MGGP	Multi-Gene Genetic Programming
NB	Naive Bayes
NB-B	Bernoulli Naive Bayes
NB-G	Gaussian Naive Bayes
PCA	Principal Component Analysis
PdM	Predictive Maintenance
PLC	Programmable Logic Controller
PvM	Preventive Maintenance
RD	Real Data
RF	Random Forests
R2F	Run-to-Failure
RNN	Recurrent Neural Network
SAFE	Supervised Aggregative Feature Extraction
SD	Synthetic Data
SVM	Support Vector Machine

widely used to identify, evaluate and interpret relevant parts of research for a specific issue, area or phenomena of interest (Kitchenham, 2004). SLR is a secondary study, which aims to carry out a survey of researches with the same scopes, evaluating them critically in their methodologies and bringing them together in a statistical analysis, meta-analysis, when this is possible. For the implementation of SLR, the proposed methodology in the work (Kitchenham, 2004) was used.

2.1. Literature review planning protocol

This paper considers the following planning protocol for the review:

- *Research questions*
  $Q1$. What are the ML methods that are being used to perform PdM?
  $Q2$. What equipment is being subjected to PdM techniques?
  $Q3$. What are the data used to apply PdM?
  $Q4$. Are the data real or synthetic?
  $Q5$. How the ML methods are employed in the PdM applications?
- *Databases for literature searching*
  This study was conducted on two well-known literature databases with scientific scope, which are IEEEXplore Digital Library[1] and ScienceDirect[2].
- *Exclusion criteria*
  E_1. Works not related to PdM and ML.
  E_2. Works that do not present any type of experimentation or comparison results, and make only propositions.
  E_3. Works dated before the year 2009.
- *Quality criterion*
  QC_1. Papers that compare the PdM results using different ML techniques.
- *Data extraction fields*
  D_1. Employed ML method, being able to consider any classical ML technique of the state-of-the-art or new ML techniques.
  D_2. Equipment that has been applied to the PdM strategy, being either equipment or only one component of the equipment.
  D_3. Data samples that have been used for ML purposes and the desired (output) predictions.
  D_4. Data origin that can be real data or synthetic data.

2.2. Execution

The choice of keywords for building the search strings was based on terms commonly found in the literature and terms related to this review (i.e. machine learning methods applied to predictive maintenance). For the SLR execution, specific keyword strings were formulated and used for each database (IEEE Xplore and ScienceDirect), as described bellow:

- IEEE Xplore: ("predictive maintenance" OR "PdM") AND ("machine learning" or "machine learning technique") with Meta-data in the command search.
- ScienceDirect: title-abstr-key(("predictive maintenance" OR "PdM") AND ("machine learning" or "machine learning technique")).

The survey was performed on October 18, 2018. Fig. 2 reveals the amount of searched documents in the databases using the selected keyword strings. The total of searched papers was 54, being that 36 papers were selected for this review and 18 articles were rejected using the exclusion criteria E_1 and E_2.

[1] http://ieeexplore.ieee.org
[2] http://www.sciencedirect.com

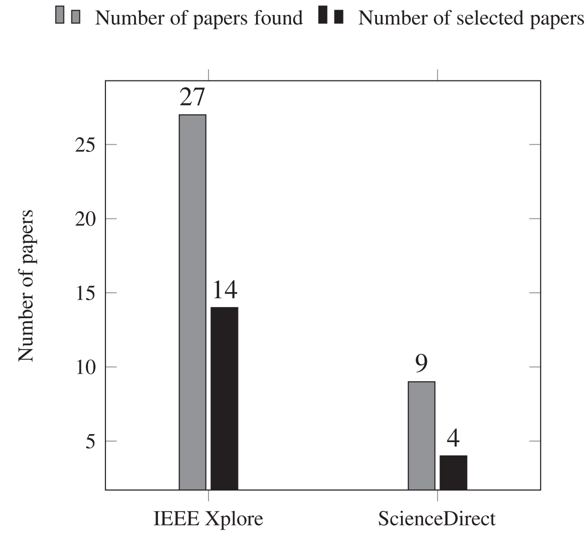

Fig. 2. Number of papers in the databases using the extraction criteria.

3. Background on machine learning

Before present the results of the review, it is important to introduce some concepts about the design of a ML model (e.g. a ML model for a PdM application). It involves some steps, which are: *historical data selection* step; *data preprocessing* step; *model selection, model training and model validation* step; and *model maintenance* step (Soares, 2015). Fig. 3 illustrates these steps.

The *historical data selection* step identifies how the data are collected and stored so that valuable data are selected for the ML model design. In PdM, this step is also called as *data acquisition* step, and it aims to obtain relevant data to system health (Jardine et al., 2006). The *data preprocessing* step processes and transforms data so that they can be efficiently processed by the ML model. This step includes *data transformation* (e.g. normalization), *data cleaning* (e.g. missing data treatment and outlier removal) and *data reduction* (e.g. dimensionality reduction and numerosity reduction). In PdM, the *data preprocessing* step handles and analyses the data collected for better understanding and interpretation of the data.

The *model selection, model training and model validation* step involves the selection of the adequate ML model, the model training (i.e. the model development) and the model validation (i.e. a procedure that evaluates whether the model can represent the underlying system). In PdM, this step can be called as *maintenance decision-making* step, and it aims to decide the best algorithm for the PdM application. The *model maintenance* step aims to maintain the model performance over time. This is because, industrial applications may change over time, leading to the degradation of the model performance. For further information about techniques that can be applied in each step, work (Soares, 2015) is recommend.

4. Results of the systematic literature review

4.1. Publication distribution along the years

Fig. 4 shows the number of articles published between 2009 and 2018 (using the extraction criteria of this paper) with a trend line (Glock et al., 2019). This search confirms that PdM is a new maintenance technique, since before 2013 only two papers were published. On the other hand, after 2013, it is possible to note a growing interest in this research area. Specifically, the average number of papers increased from 0.5 article per year in 2009–2012 to 11.3 articles per year in 2013–2018. This fact may be related to the increase in the amount of data generated by industrial equipment and the recent advances in ML algorithms.

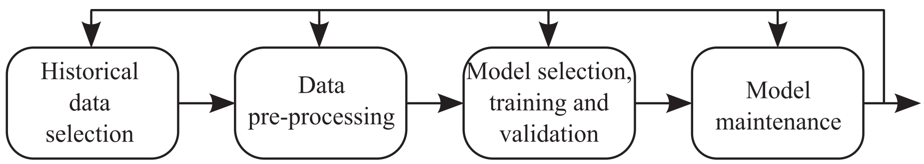

Fig. 3. The main steps for the design of a machine learning model.

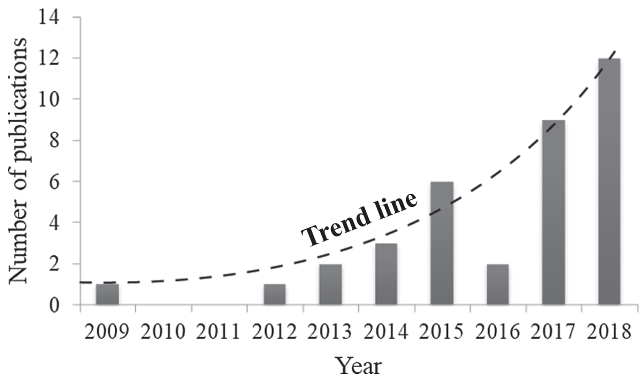

Fig. 4. Number of papers per year with a trend line.

Hashemian and Bean (2011) affirm that the small amount of works in the PdM area is due to the complexity of implementing efficient PdM strategies in production environments. On the other hand, the lack of use of ML algorithms in PdM applications is mainly related to two needs in a production environment: first, it is necessary to have professionals in the areas of ML and/or data science; and, secondly, to perform a PdM strategy, it is important to have previously R2F and/or PvM strategies to generate historical data of maintenance and equipment failures/faults.

4.2. Publication distribution among journals and conferences

The selected papers based on ML applied to PdM have been published in a wide range of journals and conferences with engineering orientations. From the 36 selected papers, 24 were published in conferences and 12 were published in journals.

The research papers belong to 11 journals. Among them, the *Transportation Research Part C: Emerging Technologies* journal is the top journal with 2 publications, while the other journals have 1 publications (Fig. 5). Most of the journals covered in the review belong to engineering and manufacturing domains, begin that only the *Engineering Applications of Artificial Intelligence* journal focuses in artificial intelligence applications (including ML applications).

On the other hand, the research papers belong to 22 conferences. Among them, the *International Conference on Emerging Technologies and Factory Automation* (ETFA) is the top conference with 3 publications, while the other conferences have 1 publications (Fig. 6). The conference papers belong to a wide range of domains, including embedded systems, control, intelligent systems, industrial applications, electronics, informatics, among others. It should be pointed that only the *International Conference on Prognostics and Health Management* focuses in the fields of diagnostics, prognostics, health management and facility maintenance; and the *International Conference on Machine Learning and Applications* (ICMLA) is an important conference in the ML field.

4.3. Citation analysis

The number of citations is an important key for an article, since it determines how many times an article has been cited by other articles. To perform a citation analysis, the Web of Science platform was selected to determine the number of citations of the selected papers in this review.

The citation analysis reveals that in the list of top 11 cited article, the work published by Susto et al. (2015), which relies on the development of multiple classifier ML algorithms for a semiconductor manufacturing PdM maintenance problem, received the maximum number of citations (citations = 58), as shown in Table 2. Moreover, an article published by Li et al. (2014) received much attention among the scientific community. It uses ML algorithms to improve the maintenance of a rail network. The citation analysis also revealed that the average number of citations of all the research papers is 4.39.

4.4. Research methods analysis

After an analysis of the papers between 2009 and 2018 using the extraction criteria, Table 3 was built. It contains an overview of the most recent papers for PdM, where each line is related to a paper. The first column, *Reference*, contains the paper reference; the second column, *Machine learning method(s)*, lists the used ML approach(es) in the paper; the third column, *Equipment*, shows the used equipment for maintenance prediction; the fourth column, *Description of the data applied for prediction*, describes the data employed for maintenance prediction purpose; and the fifth column, *Data type*, shows the data type used in the ML learning algorithm, which can be Real Data (RD) or Synthetic Data (SD).

With the review carried out, it can be verified that PdM is being used for the most diverse equipment of the most varied areas. However, one fact worth mentioning is that most papers use real data (89%) instead of synthetic data (11%). This may occur due to the specific characteristics of each PdM application; in most cases, synthetic data is not

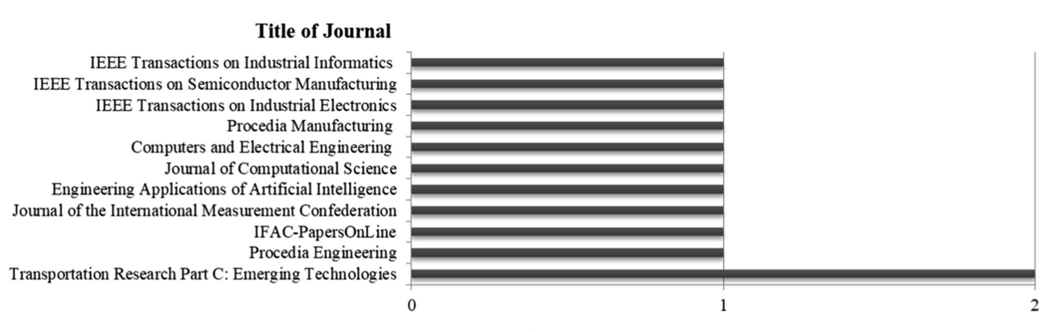

Fig. 5. Number of publications per journal.

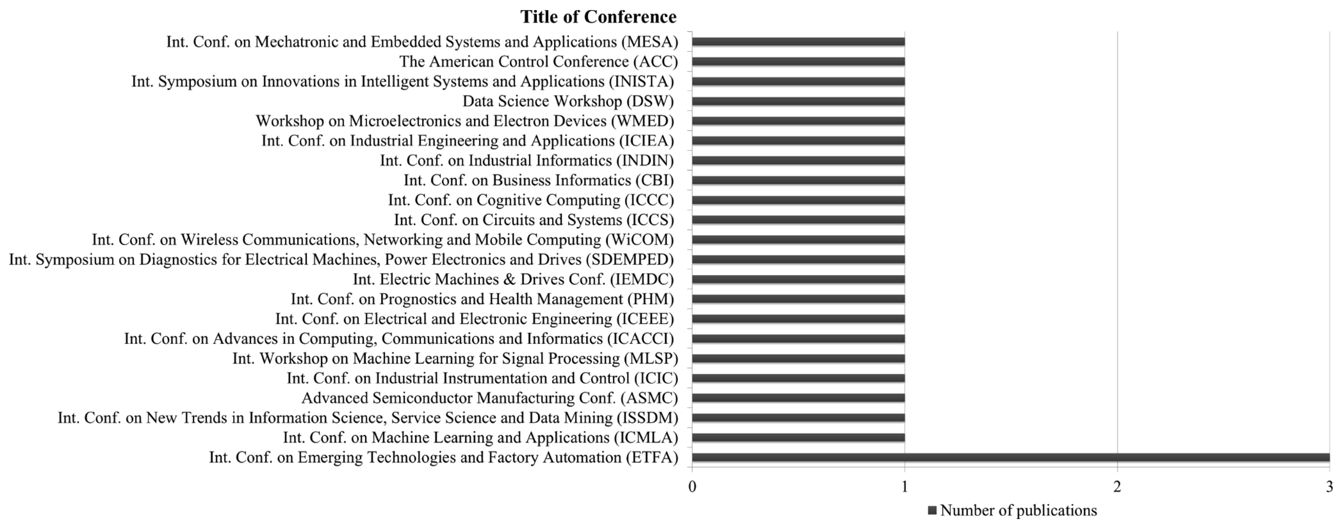

Fig. 6. Number of publications per conference.

able to represent a real application (for example, in (Prytz et al., 2015), the normal distribution of data does not represent the real environment); and generating synthetic data requires equipment knowledge.

Table 3 also reveals a preference for some ML learning methods. For example, the most employed ML algorithm is Random Forest (RF) - 33%, followed by neural network based methods (i.e. ANN - Artificial NN, CNN - Convolution NN, LSTM - Long short-term memory network, and deep learning) - 27%, Support Vector Machine (SVM) - 25%, and *k*-means - 13%. Table 3 shows that each PdM application use a specific equipment. The equipment includes turbines, motors, compressors, pumps, fan, among others. Other interesting aspect that emerges from Table 3 is a preference for vibration signal data to detect anomalies in equipment.

Through the mentioned characteristics of the most recent papers for PdM (Table 3), it was able to answer the research questions described in Section 2.1. That is, the most frequently used ML methods to perform PdM are RF, ANN, SVM and *k*-means; there is no a preference for an equipment to perform PdM strategies; vibration signals are the most common data used to design PdM models; there is a preference for real data to build PdM models; and finally, the next Subsections describe the main characteristics of the most used ML methods and how they are employed in the PdM applications.

4.4.1. Random forests

RFs were originally proposed by Leo (2001). As the name suggests, a RF creates a "forest" (ensemble) with multiple randomized decision trees and aggregates their predictions by simple average. According to Biau and Scornet (2016), RFs have shown good performance when the number of variables is larger than the number of samples (observations). RF is a supervised learning algorithm for both classification and regression tasks.

Although a RF is a collection of decision trees, there are differences that need to be emphasized: while decision trees generate rules and nodes from the calculation of information gain and index gini, RFs generate decision trees randomly. Additionally, while deep decision trees may suffer from overfitting, RFs avoid overfitting in most cases, because they work with random subsets of features and build smaller trees from such subsets (Leo, 2001; Prytz et al., 2015; Biau and Scornet, 2016).

In (Prytz et al., 2015), RF is used as a classification algorithm, along with two feature selection methods: wrapper feature selection approach based on the beam search algorithm, and a filter method based on the Kolmogorov-Smirnov test. The work develops a generic method for predicting repairs to various components of commercial vehicles. However, the method is evaluated using only air compressors. According to the authors, this choice was based on the difficulty of finding faults in this component, since, it is a component that has faults related to several other problems. Moreover, according to the authors, the two main contributions of the work are: demonstration of the use of a large database; and use of feature selection techniques in an inconsistent set of data with problematic class labels and data ambiguities.

In (Canizo et al., 2017), RF is employed to generate dynamically predictive models. This work proposes an improvement of the paper (Kusiak & Verma, 2011), where a monitoring of wind turbines is performed. To do this, status data (activated and disactivated alarms) and operational data (about the performance of the wind turbines) are employed to design the RF model. The main contributions of the paper (Canizo et al., 2017) are speed in data processing, scalability and automation. Its results demonstrate an improvement of 5.54%, in terms of predictive accuracy, when compared to the earlier work (i.e. Kusiak & Verma, 2011).

Table 2
Summary of top 11 cited articles (accessed on August 2, 2019).

Title	Publication year	Citations
Machine learning for predictive maintenance: a multiple classifier approach (Susto et al., 2015)	2015	58
Improving rail network velocity: a machine learning approach to predictive maintenance (Li et al., 2014)	2014	37
Predicting the need for vehicle compressor repairs using maintenance records and logged vehicle data (Prytz et al., 2015)	2015	13
Fault diagnosis of automobile gearbox based on machine learning techniques (Praveenkumar et al., 2014)	2014	12
A predictive maintenance system for epitaxy processes based on filtering and prediction technique (Susto et al., 2012)	2012	11
Principal components analysis and track quality index: a machine learning approach (Lasisi and Attoh-Okine, 2018)	2018	6
Real-time predictive maintenance for wind turbines using big data frameworks (Canizo et al., 2017)	2017	5
Model development based on evolutionary framework for condition monitoring of a lathe machine (Garg et al., 2015)	2015	4
A big data driven sustainable manufacturing framework for condition-based maintenance prediction (Kumar et al., 2018)	2018	4
Estimation of fuel cell life time using latent variables in regression context (Onanena et al., 2009)	2009	3
Cognitive acoustic analytics service for internet of thing (Pan et al., 2017)	2017	3

Table 3
A summary of the most recent papers for predictive maintenance.

Reference	ML method(s)	Equipment	Description of the data applied for predictive maintenance	Data type[a]
(Onanena et al., 2009)	LR	Fuel cell	Electrochemical impedance spectroscopy measurements	RD
(Hong and Zhou, 2012)	GPR	Bearing	Vibration data	RD
(Susto et al., 2012)	Linear regularization and Ridge regression	–	Ion Beam Etching process	RD
(Schopka et al., 2013)	LR, RF and BN	Filament	Process data, equipment data and logistic data of breakdown in an implanter ion source	RD
(Susto et al., 2013)	SVM	Tungsten filament	Historical maintenance cycles	RD
(Li et al., 2014)	SVM	Rail network	Historical detector data, failure data, maintenance action data, inspection schedule data, train type data and weather data	RD
(Praveenkumar et al., 2014)	SVM	Automobile gearbox	Vibration signals	RD
(Abu-Samah et al., 2015)	BN	–	Event driven maintenance	RD
(Garg et al., 2015)	MGGP	Metal lathe	Vibration and acoustic signals	RD
(Prytz et al., 2015)	RF	Air compressors in trucks and buses	Data collected on-board the vehicles and service records collected from equipment manufacturers	RD
(Biswal and Sabareesh, 2015)	ANN	Wind turbine	Accelerometer data	RD
(Machado and Mota, 2015)	ANN and SVM	Electrical power systems	Electrical signals	SD
(Susto et al., 2015)	SVM and *k*-NN	Tungsten filament	Benchmark of semiconductor manufacturing maintenance	RD
(Durbhaka and Selvaraj, 2016)	*k*-NN, SVM, *k*-means	Bearing	Vibration signal	RD
(Susto and Beghi, 2016)	SAFE	Semiconductor manufacturing	Maintenance cycle data	RD
(Aydin and Guldamlasioglu, 2017)	LSTM	Engine	Operational and sensor measurements data	RD
(Canizo et al., 2017)	RF	Wind turbine	Status data (alarms activations and deactivations) and operational data from the performance of wind turbines	RD
(Santos et al., 2017)	RF	Squirrel-cage induction motors	Current and voltage waveforms	SD
(Eke et al., 2017)	*k*-means	Oil immersed power transformer	Dissolved gases concentrations	RD
(Kanawaday and Sane, 2017)	ARIMA	Slitting machine	Sensor data from a slitting machine	RD
(Mathew et al., 2017)	SVM	–	Time-series sensor measurements	SD
(Mathew et al., 2017)	LR, DT, SVM, RF, *k*-NN, *k*-means, Gradient Boost, AdaBoost, Deep learning and ANOVA	Turbofan engine	Turbo fan engine data from a prognostics data repository of NASA	RD
(Pan et al., 2017)	CNN	–	Non-intuitive and unstructured acoustic sensor data	RD
(Kumar et al., 2018)	FURIA	Gas turbine	Big data set generated from a gas turbine propulsion plant simulator	SD
(Lasisi and Attoh-Okine, 2018)	LDA, SVM and RF	Sample mile track	Track geometry data	RD
(Su and Huang, 2018)	RF	Hard disk drive	Historical data (vibration, temperature, and other variables)	RD
(Uhlmann et al., 2018)	*k*-means	Laser melting	Machine tool sensor data	RD
(Amihai et al., 2018)	Deep learning	–	Vibration data	RD
(Amihai et al., 2018)	RF	Industrial pumps	Vibration data	RD
(Amruthnath and Gupta, 2018)	PCA, Hierarchical clustering, *k*-means, Fuzzy C-means and model-based clustering	Exhaust fan	Vibration data	RD
(Butte et al., 2018)	GLM, RF, gradient boosting and deep learning	Semiconductor	Process sensors, process recipe parameters and wafer count on a critical equipment component	RD
(Huuhtanen and Jung, 2018)	CNN	Photovoltaic panels	Daily electrical power signal	RD
(Kolokas et al., 2018)	DT, RF, NB-G, NB-B and ANN	Industrial equipment for anode production	Process sensor data from operation periods	RD
(Kulkarni et al., 2018)	RF	Supermarket refrigeration systems	Temperature sensor and defrost state	RD
(Paolanti et al., 2018)	RF	–	Data from sensors, PLCs and communication protocols	RD
(Luo et al., 2018)	Deep learning	Computer numerical control machine	Vibration signal	RD

[a] The data types are Real Data (RD) and Synthetic Data (SD).

The research developed by Su and Huang (2018) proposes a real-time predictive fault detection system, called “HDPass”, to perform hard disk drive faults. The proposed system consists of two stages: batch training, where RF models are generated/trained using historical data; and real-time predictions, which employs data collected from the end-user device to perform estimations. The result presented by this work is promising, since it achieves 85% of accuracy for real-time predictions.

Other PdM applications using RF are also listed in Table 3. For example, Santos et al. (2017) propose RF and Park’s Vector to detect stator winding short circuit faults in squirrel-cage induction motors. Kulkarni et al. (2018) apply a RF model to detect presence or absence of an issue in refrigeration and cold-storage systems. The proposed approach was able to obtain an accuracy of 89%. On the other hand, Paolanti et al. (2018) propose a RF model to predict different industrial machine states using data from various sensors, Programmable Logic Controller (PLCs) machines and communication protocols.

Beyond all the RF works mentioned before, many papers selected in this review compare their proposed approaches to the RF model. Therefore, RF is the most used and compared ML method in PdM applications. The main motivations are: decision trees provide a large number of observations to be part of the forecast, as discussed in (Mathew et al., 2017); and in some scenarios, RFs can reduce variation and increase generalization, as described in (Amihai et al., 2018). However, the RF method also has some drawbacks. For example, the RF method is complex, and takes more computational time when compared to other ML algorithms.

For further information about the RF theory and fundamentals, papers (Leo, 2001 and Strobl et al., 2009) are recommended. Moreover, a technical implementation using the Python programming language and the Scikit-learn library can be seen in (Li et al., 2018).

4.4.2. Artificial neural networks

ANNs are intelligent computational techniques inspired by the biological neurons (Biswal and Sabareesh, 2015). An ANN is composed of several processing units (nodes or neurons) that have relatively simple operation. These units are usually connected by communication channels that have an associated weight; and they only operate their local data that are indicated through their connections. The intelligent behavior of ANNs comes from the interactions between the processing units of the network.

ANNs are one of the most common and applied ML algorithms, and they have been proposed in many industrial applications, including soft sensing (Soares and Araújo, 2015) and predictive control (Shin et al., 2018). Their main advantages include: no expert knowledge to make decisions is needed, since they are based only on the historical data (as the *k*-means model); even if the data are inconsistent, they do not suffer degradation (i.e. ANNs are robust); and by building an accurate ANN for a particular application, it can be employed in real-time without having to change its architecture at every update. However, some disadvantages of ANNs are: networks can reach conclusions that deny the rules and theories established by the applications; training an ANN can be time-consuming; they are “black box” methods (that is, it is impossible to know why the ANN model has reached an output prediction); and a huge data set is needed for an ANN to learn correctly.

In this review, one of the selected papers that employ an ANN is (Biswal and Sabareesh, 2015). In this work, it was developed a bench test equipment designed to mimic the operational condition of a wind turbine to monitor its conditions. This procedure enables fault recognition in the critical components of the wind turbine. The authors collected vibration data in a healthy condition and in a deteriorated condition. In this last case, by replacing a healthy component with a defective component. Finally, ANN predictions were performed to classify characteristics of a healthy state and characteristics of a defective state. The results of the paper reveal classification accuracy of 92.6%.

Kolokas et al. (2018) compare ANN to other ML algorithms to detect faults in an industrial equipment for anode production in real-time, using process sensor data from operation periods. Kolokas et al. (2018) propose LSTM networks, a type of recurrent ANN, to predict current condition of an engine by using large-scale data processing engine Spark. In this case, data consist of 3 operational settings and 21 sensor measurements from temperature, engine pressure and fuel, coolant bleed.

Other techniques based on ANN are the so-called deep learning techniques (or purely multi-layered ANNs) (Mathew et al., 2017). In deep learning, data are learned at different levels of hierarchy. This learning capability at various levels of abstraction allows a system to learn complex functions that can map the input data directly to the output. Examples of works which use deep learning algorithms for PdM purposes include (Mathew et al., 2017; Amihai et al., 2018; Butte et al., 2018; Luo et al., 2018). In (Pan et al., 2017; Huuhtanen & Jung, 2018), Convolutional Neural Network (CNN), a class of deep learning algorithms, is proposed to predict faults in acoustic sensor and photovoltaic panel, respectively. Although deep learning models are very powerful predictive tools, they require expert knowledge in selecting the different levels of hierarchy for a particular application.

Details about ANNs and their algorithms can be found in (Zhang, 2000; and Schmidhuber, 2015) works. Additionally, Huang et al. (2011) and Kalra et al. (2016) discuss technical implementations and challenges on ANNs algorithms.

4.4.3. Support vector machines

SVM is another widely used and known ML method for performing classification and regression tasks, because of its high accuracy (Sexton et al., 2017; Chang and Lin, 2011). One of the main characteristics of SVM is the high precision in the separation of different classes of data, being able to determine the best point for separating classes of data (Susto et al., 2013).

SVM is a set of supervised learning methods that perform regression analysis and pattern recognition. Initially, SVMs were non-probabilistic binary classifiers. But, now they are also employed in multi-class problems[3]. In this case, SVM creates *n*-dimension hyperplanes that divide data ideally into *n* groups/classes.

Praveenkumar et al. (2014) propose a SVM model to identify failures in automotive transmission boxes. In this study, four gearboxes are tested at two different speeds and load conditions, and then the resources are extracted from the vibration signals acquired to train a SVM. The experimental results showed that the SVM model is able to classify gearbox failures with precision greater than 90%.

Another work that also proposes a SVM model for PdM purpose is (Susto et al., 2013). In this work, an ion filaments prediction module is built. The proposed model is based on the decision limit provided by the SVM model. The used data are synthetic and generated using Monte Carlo simulation. Although the work does not present a comparison between SVMs and other ML techniques, it compares the cost of using traditional PvM and the proposed PdM model. Thus, the authors state that the presented module has low-cost when compared to classical maintenance techniques (such as PvM).

In (Mathew et al., 2017), the authors employ a type of SVM for regression purposes called Support Regression Vector (SVR). In this work, a modified regression kernel is proposed to prognostic problems. Although the work does not perform any comparison between other ML methods, tests performed with a simulated set of time series show that the proposed SVR model outperforms a standard SVR model.

Other works that use SVM algorithms are (Li et al., 2014; Machado and Mota, 2015; Susto et al., 2015; Lasisi and Attoh-Okine, 2018). For example, Li et al. (2014) employ a SVM algorithm to predict alarm faults in a bearing of a rail network; Li et al. (2014) compare SVM and

[3] Multi-class problems are problems where the challenge is to separate elements into one of three or more groups/classes

Table 4
List of the public data sets for predictive maintenance.

Reference	Description of the data set
Lopes & Camarinha-Mato, 1999	Force and torque measurements to detect robot failures
Lopes & Camarinha-Mato, 2009	Failure data of a generic gearbox
Lindgren & Biteus, 2016	Operation data and failures of a pressure pressurizing system of a truck
Tarapore et al., 2017	Failure data in a simulated swarm of 20 e-puck robots (mobile robot with differential wheels)

ANN to classify faults in electrical power systems; Susto et al. (2015) propose multiple classifiers, that is SVM and *k*-Nearest Neighbors (*k*-NN), to identify failures that occur on machines due to the accumulative effects of usage and stress on equipment parts; and Lasisi and Attoh-Okine (2018) compare SVM, RF and Linear Discriminant Analysis (LDA) to detect geometry defects in railway tracks.

Despite the promising results obtained in the aforementioned SVM in PdM applications, some disadvantages of SVMs should be listed. For example, the difficulty in choosing a "good" kernel function for a SVM model; the training time of a SVM model grows as the number of samples increases; the final SVM model is not easy to understand and interpret; and the difficulty in incorporating business logic into the calibration of a model (Cawley and Talbot, 2010).

Additional materials about the SVM principles and methods are presented in (Noble, 2006 and Wang, 2008). Moreover, Abbas et al. (in press) detail the theory and some practical tasks about the SVM algorithms, such as the regularization factor, the kernel function and its parameters. On the other hand, Wang (2008) reviews different SVM algorithms and presents their advantages in different applications.

4.4.4. K-means

The *k*-means model is a popular clustering algorithm that uses an unsupervised strategy to determine a set of clusters (Dhalmahapatra et al., 2019). The main aim is to find the *k* partitions (or clusters) of the data set, so that "close" samples to each other are associated to the same cluster, and "far" samples from each other are associated to different clusters (Boutsidis et al., 2015). The *k*-means algorithm is easy to implement. In addition, it presents good performance and handles large data sets (as long as the number of clusters *k* is small), and it can change the centers of the clusters with retraining when new samples are available. Another important feature of the *k*-means algorithm is that it tends to minimize inter-class variance and increases the extra class distance (Hamerly and Drake, 2015).

Examples of papers that use *k*-means for PdM include (Durbhaka and Selvaraj, 2016; Eke et al., 2017; Mathew et al., 2017; Uhlmann et al., 2018; Amruthnath and Gupta, 2018). Especially, Durbhaka and Selvaraj (2016) employ *k*-means to analyze the behavior of wind turbines by using vibration signal analysis. In this work, *k*-NN and SVM algorithms are compared to the *k*-means algorithm to classify types of faults in the wind turbines. The authors also propose a Collaborative Recommendation Approach (CRA) method to analyze the similarity of all the ML algorithm results in predicting the replacement and correction of the deteriorating turbines to avoid sudden break downs. The *k*-means algorithm had 93% of predictive accuracy after the use of the CRA method.

In (Eke et al., 2017), *k*-means is applied to automatically extract groups (clusters) in a dissolved gases data in an insulating oil of a transformer. The aim was to identify the characterization of each cluster that induces to a fault or an alert for possible maintenance actions. The *k*-means clustering algorithm was developed using Euclidean distance, as a criterion of similarity. And the authors identified four clusters using the *k*-means algorithm: presence of an electric arcing with high energy; abnormal temperature rise of the oil; accelerated increase in the production of all gases; and post treatment periods of the oil.

Uhlmann et al. (2018) propose a *k*-means algorithm to identify clusters using data (i.e. sensors of the platform temperature, oxygen percentage in the process chamber and process chamber pressure) from a selective laser melting machine tool. The proposed algorithm was able to identify four clusters in the data: operation conditions, faulty conditions of the protection gas system, faulty conditions of the pressure system, and faulty conditions that keep the machine tool in a standby behavior. On the other hand, Amruthnath and Gupta (2018) compare a large number of clustering algorithms (hierarchical clustering, *k*-means, fuzzy c-means clustering and model-based clustering) for fault detection in a vibration data from an exhaust fan; and Mathew et al. (2017) also compare a number of ML algorithms (*k*-means, SVM, among others) to predict turbo fan engine failures before they happen.

Although, the *k*-means algorithm is easy to implement and understand, it has some challenges. They are: difficulty to determine the number of clusters (*k*); the use of random seeds in the algorithm may cause major impacts on the final results; the data entry order has impact on the final results; and the algorithm is scale sensitive (that is, data normalizing or standardizing will cause changes in the results).

For further information about the *k*-mean theory, paper (Blömer et al., 2016) is recommended. On the other hand, the full *k*-mean algorithm can be found in (Nazeer & Sebastian, 2009).

5. Public data sets for predictive maintenance

Table 4 lists some public data sets to test and evaluate PdM methodologies in different scenarios. However, it is important to highlight that a PdM methodology is unique and depends on the application. That is, it depends on the environment, produced data, equipment, among others. And if any of these entities changes, then, in most cases, the PdM methodology also needs to be changed. Although, these public data sets can support new researchers to develop, test and compare different ML techniques in PdM applications.

The first data set, proposed by Lopes and Camarinha-Mato (1999), aims to detect robot failures by using force and torque measurements. It consists of 463 samples and 30 attributes. The second data set, proposed by Lopes and Camarinha-Mato (2009), aims to detect faults and estimate magnitudes for a gearbox using accelerometer data and information about bearing geometry. The third data set, proposed by Lindgren and Biteus (2016), aims to detect component failures in an air pressure system of trucks. It consists of 76, 000 samples and 171 attributes. Finally, the fourth data set, proposed by Tarapore et al. (2017), aims to detect faults in robot swarms. For further information about the data set, see their references.

6. Conclusion

This paper explored a systematic literature review, covering the main papers of PdM using ML techniques, and answering the research questions described in the literature review planning protocol. As a result, it was possible to identify that each proposed approach addresses a specific equipment, so it becomes more difficult to compare it to other techniques. In addition, it is possible to remark that PdM itself emerges as a new tool of dealing with maintenance events. Since, after the Industry 4.0 advance, PdM becomes increasingly feasible and promising.

In addition, some of the works carried out by this review employ standard ML methods without parameter tuning. This may be due to the fact that PdM is a recent topic and is beginning to be explored for industrial experts. It is also important to point that for obtaining good results of a PdM strategy in a plant, it is necessary that it has already implemented the R2F and PvM strategies in its process to collect data for the PdM modeling. Based on this data, it becomes feasible to design and validate a PdM strategy.

During this review, it was noted that ML techniques are gradually being applied for designing PdM applications. In some applications, the integration of PdM and ML leads to positive results with cost reduction. However, it can be seen that the integration of PdM techniques with the latest sensor technologies avoids unnecessary replacement of equipment, saves costs and improves the safety, availability and efficiency of processes (Hashemian and Bean, 2011).

Additionally, it should be remarked that ML techniques, such as, SVM, RF, ANN, deep learning and *k*-means, have been successfully applied to design PdM applications. However, there are still some aspects in PdM and ML that need to be further investigated. Thus, recommendations for future research include:

- develop sensing techniques for equipment to improve the quantity and quality of data (since when more data is available, more feasible is to design and validate a PdM application) (Hashemian and Bean, 2011);
- develop works that compare the proposed PdM strategy to different ML algorithms (Amihai et al., 2018), besides use novel ML algorithms (such as, deep learning algorithm (Luo et al., 2018));
- develop works that propose multiple ML methods (ensemble learning) in a PdM application, leading to more robust and accurate predictions (Butte et al., 2018);
- create new data sets to be used and compared by the PdM works (Paolanti et al., 2018).

Acknowledgment

This work has been conducted under the framework of the "Flexible and Autonomous Manufacturing Systems for Custom-Designed Products (FASTEN)" project. This project has received funding from the European Union's Horizon 2020 research and innovation programme and from Brazilian Ministry of Science, Technology and Innovation (MCTIC) managed by Rede Nacional de Pesquisa (RNP) under the Grant Agreement 777096.

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