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An analysis of machine learning algorithms in rotating machines maintenance

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Abstract: The industrial maintenance activities represent an increase in production costs, mainly caused by unnecessary production stops. Recent technologies approaches are handling the continuous monitoring of industrial machines, storing sensors data, and also maintenance history. More data analysis is necessary specifically for rotating machines presenting methodologies to reduce the maintenance. In order to handle this problem, a comparative analysis of machine learning methods is presented. The strategy aims to predict failures and then indicates the maintenance necessity before a break occurs. Thus, it is applied and analyzed the specific machine learning algorithms, Gradient Boosting and Random Forest, using a dataset of rotation machines. The results show that both methods have an excellent performance (metrics accuracy, precision, and recall), with slightly better results in Gradient Boosting (hit rate of 99.93%) indicating the prominent application of these algorithms in this industrial scenario.

Keywords: Maintenance, Rotation machines, Machine learning, Intelligent inspection.

1. INTRODUCTION

The monitoring process is more complex with the technological advances highlighted by Industry 4.0 concepts. Rotating machines are among the most important parts of modern industrial applications. With the growing competition from the markets, companies are looking for new ways to maximize their profits, encouraging new research and stimulating the development of technologies that aim to improve production processes (Salunkhe and Fast-Berglund, 2020). These strategies have been gaining more space in the market, which brings the implementation of connectivity between machines to amplify the autonomy in decision making about many processes, as well as to shape the different requirements of products and demands (Aceto et al., 2019).

A new period in manufacturing is defined by the term Industry 4.0, which is characterized by digitization and the integration of products and production processes. Therefore, the entire industrial production sphere is transitioned through the fusion of technologies, such as the Internet of Things (IoT), Big Data and Machine Learning (Romanovs et al., 2019). Through the acquisition of historical data about operational variables of rotating machines, it is possible to perform predictive maintenance, which is a maintenance model to analyze machines during their operation. Thus, it seeks to anticipate the occurrence of faults, by monitoring variables such as temperature, tension, vibration, and pressure.

With this data, the objective is to predict the period in which the equipment may be out of operation. An algorithm analyzes irregularities that can point to non-standard behavior, which can predict the moment when such anomalies can lead to a fault. In this context, this data analysis based on algorithm and learning models represents the Machine Learning approach, a subfield of artificial intelligence, which allows the system to learn from its data, recognize patterns, and autonomously make decisions with a minimum of interference (Roscher et al., 2020). Machine Learning algorithms analyze a large amount of data through statistical methods, such as the classification method, which the present study is addressing, being possible to find patterns in the database and then make predictions.

The management of assets in industries derives in large part from the adequate use of equipment and machines, aiming at increasing their useful life and availability. In this context, rotating machines have significant importance for maintenance teams, considering that their operation requires high investments and their work is fundamental to the production process (Khadersab and Shivakumar, 2018). The malfunction of an element in a rotating machine represents an indication of reduced capacity to serve the specified minimum work requirements. If this malfunction is not resolved, it may return to a failure. The balance in this process is relevant because a lack or excess of maintenance results in high costs.

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Thus, the application of predictive maintenance is a fundamental tool to improve the efficiency of these machines, increasing the availability and useful life of these assets. Linked to predictive maintenance artificial intelligence methodologies, such as (Liu et al., 2018), have shown expressive results in this industrial perspective. In such a way, such methods are attractive for predictive maintenance, as they can learn from the previous data and predict the next event. In this way, this work contributes by presenting an analysis, application, and comparison between Machine Learning algorithms (here, Gradient boosting and Random Forest) for the diagnosis and predictive maintenance performed on rotating machines. The work evaluates the performance of these algorithms considering the main parameters obtained from datasets.

This paper is organized as follows: Section 2 presents a theoretical basis and related works; Section 3 describes the methodology and the algorithms applied; Section 4 presents the experiment setup and tests; Section 5 discusses the results; Finally, Section 6 presents conclusions and possibilities of future works.

2. INDUSTRIAL CONTEXT AND RELATED WORKS

Maintenance of machinery means a considerably significant fraction of the total cost of industry sectors. This task must be an iterative process, where the repair must always be identified to carry out the total productive maintenance, with the machines constantly evolving and the maintenance techniques must be improved and adapted.

Predictive Maintenance aims to reduce the probability of an asset failing. The predictive maintenance method is based on the state of the asset instead of predetermined conditions. The main indicators relevant to predictive maintenance are the health index, the probability of failure, and the remaining life span. The purpose is to predict the moment when an asset may fail and, as well, to act to prevent that failure (Zhang et al., 2019).

The use of fault detection in advance allows predictive maintenance to be scheduled for a machine stop. By using this activity, a longer downtime is avoided due to a failure of the rotating machine engine, increasing the availability of this asset. So, the implementation of Artificial Intelligence methods contributes to the reduction in the cost of maintenance of rotating machines.

Typically, fault behaviors can be: electrical, electromagnetic, thermal, environmental, mechanical, and dynamic. Most rotating machine failure situations are manifested in the form of high temperature or vibration. The failure is caused by the combination of several actions that act on the components of the machines (Loiselle et al., 2018). Rotating machines have faults that produce abnormalities in variables such as voltage level, increased vibration, decrease in torque average, reduction in efficiency, excessive heating, among others.

The life of a rotating machine is largely determined due to the remaining life of the winding insulation system, which is impacted by several factors, such as vibrations, humidity, corrosive environments, and others. Among these, the main one is the operating temperature of the insulating materials used. An increase of 8 to 10 degrees beyond the limit of the thermal class of the temperature of the insulation system is capable of reducing the life of the winding in half (Motors, 2020).

Among the elements of a predictive maintenance system for rotating machines, one key point is the sensing, which must be provided, maintained, and processed. The failure detection process must consider if there is any failure at an early stage, providing a diagnosis. This diagnosis can present a clear prescription when performing maintenance (Gritli et al., 2017).

These tasks can be supported by intelligent systems, with machine learning algorithms, based on classification and regression models, observing samples of data obtained from sensors. For example, classification models predict defined categorical variables (classes). The model's predictions and thus the capability of the prediction process can be visualized e.g. through confusion matrices. Regression models are based on specific numbers, where the inequality between the prediction and the analyzed value is measured. Mathematical methods such as the Mean Squared Error are used to analyze the inequality in all responses.

In (Liu et al., 2018) a review about AI algorithms in rotating machinery fault diagnosis, from both the views of theory background and industrial is presented. The advantages, limitations, practical implications of different AI algorithms, as well as some new research trends, are discussed. However, the work discusses only complex models not considering the scope of small machines where decision trees could solve the problem and be more explainable.

In (Caldas, 2015) the authors present a prototype of a Decision Support System that uses inputs to calculate metrics as the Health Index, the Failure probability, and the remaining lifetime of a Substation's assets and understandably present them. Using this application, an operator has access to a subset of the network of Substations and can check the condition of each Substation's assets. Different potential applications of Data Mining algorithms are also studied to detect patterns in the existing data and provide valuable inputs to maintenance planning. This work utilizes the Random Forest algorithm to perform predictive maintenance in a Substation's assets.

The work (Kanawaday and Sane, 2017) emphasizes the use of Internet of Things (IoT) technologies to obtain data from various sensors. The data are accompanied by a DateTime component which is crucial for the predictive modeling process. The work explores an approach named AutoRegressive Integrated Moving Average (ARIMA) forecasting on the time series data collected from various sensors from a Slitting Machine, intending to predict failures and defects. The use of Machine Learning is highlighted and together with IoT, it provides more quality management and quality control.

Similarly, the work reported in (Costa, 2018) presents a Continuous Maintenance System that continuously monitors machine performance, predicting when and where a failure will occur. A Gradient Boosting Classifier was used to predict incoming failures of assets in a manufacturing system. Thus the model was evaluated by comparing the system with the throughput optimization model and one reference system without it. The author highlights the high computational cost and that the implementation is not scalable for many machines.

The work (Li et al., 2019) emphasizes that the traditional intelligent diagnosis methods of rotating machinery generally require feature extraction of the raw signals in advance. In this direction, the work proposes a Deep learning method, as a novel machine learning approach, which simultaneously achieves feature extraction and pattern classification. The results presented show higher efficiency and accuracy than most fault diagnosis methods. But also it is important to consider the complexity of the model because deep neural networks contain multiple hidden layers, used to extract features and that are not designed by human engineers.

The focus on small industries and less complex machines also must be in concern, and in most cases, simple models as decision trees could solve the problem. The present work discusses this point and presents a brief comparison of two machine learning approaches that could help the engineer in decision-making about the moment of maintenance in industrial rotation machinery.

3. METHODOLOGY AND ALGORITHMS APPLIED

The related works and the presented theoretical basis support that the machine learning methods based on classification could be applied, in a clear way for maintenance prediction based on rotation machines datasets. Thus, the present work refers (Costa, 2018) as a study basis, which applies the method called Gradient Boosting to define the degradation rate in rotation machine monitoring, and also the study of (Caldas, 2015), which uses the Random Forest algorithm to perform predictive maintenance on assets of an electrical substation. The random forest works well with large-volume, multidimensional data, helping to identify more significant variables. Gradient boosting can optimize on different loss functions and provides several hyper-parameter tuning options, thus being more flexible. These characteristics justify the analysis of these algorithms in this study scenario, considering the prediction of failures, the amount and variety of data from rotating machines.

The Random Forest method is a supervised learning algorithm, which forms a forest at random. This forest creates an ensemble, that is, a combination of several decision trees.

This algorithm uses an estimator parameter that represents the number of threes to build, before taking the maximum voting or prediction average. A higher number of trees improve the results but reduces code performance. This parameter could be higher according to the processor capability because it results in more stable predictions. The processing is represented by a statistical model output of each tree, thus forming a prediction.

Gradient Boosting is another supervised learning technique, where the purpose of this method is to combine other classifiers, defined as “weak classifiers”. In this way, it is possible to create several classifiers, which are qualified to predict part of the group. It allows combinations of trees, where different models are trained, with a defined set of features. The basic idea of Gradient Boosting is to make each base learner pay more attention to the samples that were mislabeled from the previous weak classifier. Each tree learns with different factors and is represented by a numerical value. Therefore, the response will be an average of the decision value of each tree. In this research, it was applied a sequence of technical procedures presented in Fig. 1.

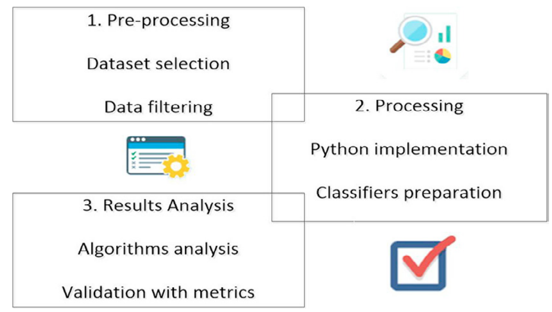

Fig. 1. Methodological procedures applied in the work.

In the first step, it was essential to select a good dataset to be analyzed, with valid and consistent historical data. Even if a dataset is relatively small, it is possible to analyze the applicability of these algorithms. However, the size of the dataset must be considered to continuously adapt the machine learning method.

Thus, for the present study, the dataset from Mary Wahl (Wahl, 2016) was used, which is composed of several measurements of sensors and also at least five distinct data types: 1. Telemetry data; 2. Failure history; 3. Maintenance history; 4. Errors registration; and 5. Machine information. It is important to highlight that the paper’s focus at this point is the algorithm analysis in the proposed scenario, thus, the dataset provides generic data events of maintenance without the specification of a specific component, part number, or a specific commercial machine. For future applications in another dataset, the same steps of this methodology must be applied according to the specific faults that need to be classified.

According to (Costa, 2018) and (Antão et al., 2018) the dataset was registered over a period of one year (in 2015), with an analysis of one hundred machines. Therefore, for 100 machines, the dataset contains 876,101 hourly records, totaling 87,610 records for each machine. The error and maintenance data consist of 7,211 records. In (Costa, 2018) the focus is the gradient boosting algorithm application and in Antão et al. (2018) the researchers have an experimental setup with a parallel production line using 3 of the 100 machines logs. A fundamental step at this point is the pre-processing and data filtering, which is responsible for preparing the original data, for the training and validation period of the classifiers.

The main concern is to present another view of this analysis, considering the comprehension of the model based on decision trees, and the applicability in small industries. Thus, this choice was appropriate for the present work. Table 1 shows some records of the dataset used.

The second step represents tools and the classifier’s preparation. For implementation, a set of libraries and tools specifically prepared for data analysis are used with Python programming. They are NumPy, Pandas, Scikit-Learn, and Jupyter Notebook.

Table 1. Dataset telemetry data example.

M ID	Date	Voltage	Rotation	Pressure	Vibration
1	2015-01-04 09:00:00	170.028	449.533	94.592	40.893
2	2015-01-04 10:00:00	164.192	403.949	105.687	34.255

The basic procedure for implementing the classifiers consists initially of a training phase, where each method is performed with input data already classified. Controlling the learning process with hyperparameter optimization. In this way, a model is generated as an output that will need to be tested with new data, verifying its predictions through performance metrics. The metrics used were Accuracy, Precision, and Recall. The training data needs to provide a set of experiences to the algorithm, qualifying it for new events.

Finally, in the third step, the algorithms are compared with the performance metrics, which are essential to evaluate the prediction model. The model is analyzed in separate data samples, which were not used to build the model (test set). The training set is used to create the model, and the test set is used to verify the prediction performance. Through cross-validation, it is possible to compare the performances of different predictive modeling procedures.

4. EXPERIMENTS AND ALGORITHM TESTS

According to the methodological procedures, an experimental setup to implement both algorithms was defined. The tests were performed in a computer Intel core i7-5500UU CPU 2.40GHz with 16 GB of RAM on Windows 10 64 bit. After the setup configuration, calibration tests were done before the effective tests avoiding any background software interference in the execution time.

In order the better understanding the dataset applied two different observations were done. First, the telemetry analysis plotting a data sample of one dataset attribute. This verification is important and allows a visual view of the data limits. As an example, Fig. 2 presents the voltage oscillation in machine 1 during the first six months.

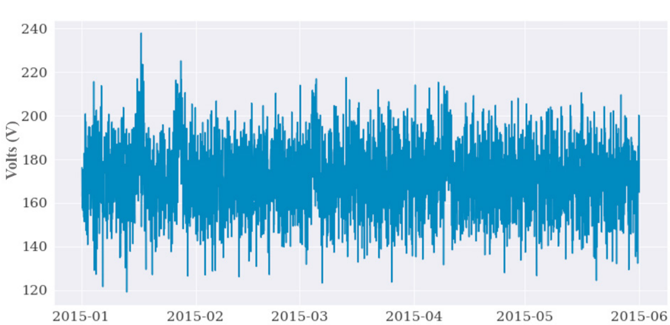

Fig. 2. Voltage variation in the Machine 1.

Second, another important analysis is the data distribution in the dataset, according to the machine model, quantity, and age. In this dataset, the oldest machine corresponding to 20 years of operation, and the newest represents less than six months of operation. Fig. 3 presents data distribution.

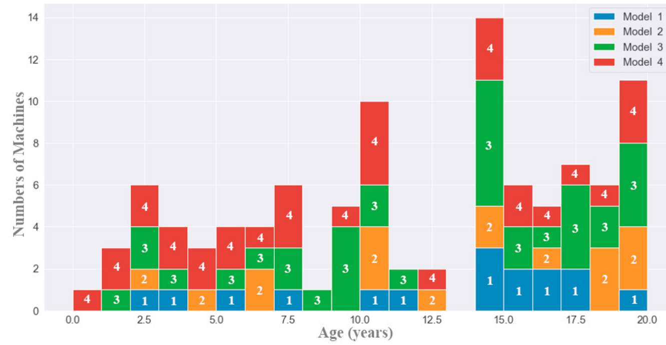

Fig. 3. Age distribution by model of rotating machines.

The first variable observed is the machine model, described by colors: blue represents model 1, yellow represents model 2, green represents model 3 and red represents model 4. The second variable analyzed is the number of machines, represented on the Y-axis. The third variable shown is the machine's operating age, in years, represented on the X-axis. Thus, it is possible to check the age distribution by the model type of each rotating machine.

The analysis presented in Fig. 2 and 3 supports feature engineering. This approach is a fundamental machine learning technique, that helps the resource extraction, contributing to the creation of new features. In this study, in a minimalist way, two feature extractions are applied, the observation of component degradation, and the creation of time windows - "lag features".

The maintenance records are checked, determining how long a component has been in use and has not been replaced. Thus, it is possible to correlate the degradation level of the component. The lag feature used includes a time series since the data in the dataset are timestamps. Two-time windows were created, one with the size of 3 hours, which represents changes in the machines in the short term, and the second with a size of 24 hours, representing changes in the long term. For each window, the mean and standard deviation were calculated.

The next step worked on in the experiment is the definition of the prediction model. For this, an important step is to carry out "cross-validation", and then to implement the defined machine learning methods. Cross-validation is a step that consists of dividing the database into several subsets of data to implement the training of the model several times, training the algorithm. This step is essential, as it validates the performance of the prediction in different spaces of the dataset, as it selects different samples from the entire dataset. The current implementation separated the dataset into 216,732 records for training and 73,809 records for testing, corresponding to 34.1% for the test set and 65.9% for the training set.

After the data was processed and separated, it was possible to implement these algorithms using the Python library specific. For the *Gradient Boosting* the *Random-state* = 42 and *n-jobs* = -1 (all computer cores) were used as parameters, guaranteeing the total processing for the training. For the *Random Forest* algorithm, fundamental parameters are also defined. The *criterion* parameter is a metric used in the construction of the decision tree, which can be "*gini*" or "*entropy*". The second option was chosen because it has more exploratory analyzes, however, it uses greater processing power. The *max-deph* parameter is used to indicate a maximum depth of 5, as tests with greater depths reproduced an *overfitting*.

Then, the *accuracy* metric is calculated, which generally defines how much the model is hitting the prediction. The *precision* metric also is calculated, which checks only the predictions, and what percentage of them were correct, and as the last metric, the *recall*, which represents how often the prediction is finding examples of a class. Fig. 4 illustrates the application of these analyzes.

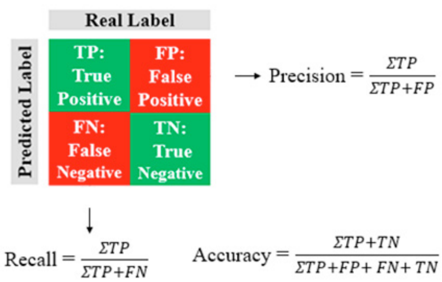

Fig. 4. Metrics application. Based on Ma et al. (2019).

Given the calculation of these metrics, it was possible to create graphs of the confusion matrices and tables with results of accuracy, precision, and recall, which are presented and discussed in the next section.

5. RESULTS ANALYSIS

After the algorithm's preparation and execution, it was possible to analyze the applicability of the failure prediction in rotating machines. In the test with the Random Forest Algorithm, the execution time was 1:31,82 (1 minute, 31 seconds, and 82 milliseconds). The test with the Gradient Boosting Algorithm takes 02:51,99 (2 minutes, 51 seconds, and 99 milliseconds). These observations consider the training and test sets and applying two feature extractions.

Presenting an analysis of algorithms application, the confusion matrix indicates the classifier performance. This matrix allows the results visualization of the prediction algorithms, facilitating the interpretation of the hits and errors produced by the technique. Considering a matrix A[i][j], all correct predictions are represented by the element position i = j, which are the elements located in the main diagonal. The remaining elements represent false positives. Fig. 5 and Fig. 6 show the confusion matrix for both Gradient Boosting and Random Forest algorithms.

The results on the X-axis indicate the correct responses, and on the Y-axis, the results are classified by the algorithm. For example, in Fig. 5, for component 1 (comp1), the algorithm hits 301 predictions and misses 9.

The Gradient Boosting method obtained the best performance for precision, corresponding to a 99.93% hit rate against 99.92% of the Random Forest method, however, we must restrict the use of the confusion matrix for a superficial analysis. According to the dataset used, most of the machines have no failures. This can result in an imbalance in the prediction process, impairing the performance

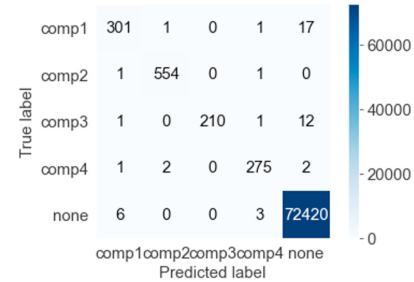

Fig. 5. Confusion Matrix for the Gradient Boosting.

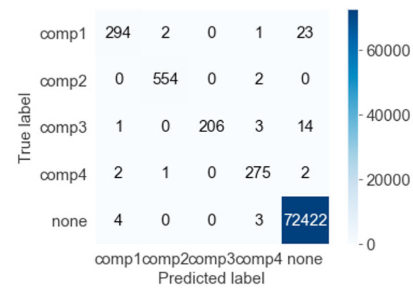

Fig. 6. Confusion Matrix for Random Forest.

analysis of the algorithm. Therefore, other performance metrics were calculated to compare the classifier under different conditions. On predictive maintenance, the metric "recall" is commonly used because it considers the correct number of failures predicted and the influence of incorrect predictions on the model. In addition, the metric accuracy and precision contribute to check the general prediction reliability. Fig. 7 shows all metrics values computed for both algorithms.

		none	Comp1	Comp2	Comp3	Comp4	Average
Random Forest	accuracy	99,92%	99,92%	99,92%	99,92%	99,92%	99,92%
	precision	99,95%	97,67%	99,46%	100,00%	96,83%	98,78%
	recall	99,99%	91,88%	99,64%	91,96%	98,21%	96,34%
Gradient Boosting	accuracy	99,93%	99,93%	99,93%	99,93%	99,93%	99,93%
	precision	99,96%	97,10%	99,46%	100,00%	97,86%	98,88%
	recall	99,99%	94,06%	99,64%	93,75%	98,21%	97,13%

Fig. 7. Metrics computed.

The algorithms resulted in a similar performance, the present work obtained superior results identifying predictions in the normal state of the machine and in component 1, whereas the study by Costa (2018) obtained better results in predictions in components 2, 3, 4, and in its average, represented by average, corresponding to an increase of 0.08% in the final average compared to the present study. Fig. 8 shows results comparison with Costa (2018) considering the metric "recall" and the Gradient Boosting algorithm.

In Costa (2018) it is implemented a Machine Learning algorithm using the Gradient Boosting classification method. However, it uses feature extractions from Genetic Algorithms to improve its prediction, resulting in a very high computational performance cost. In this work, the same dataset was applied with the purpose of verifying the

	none	Comp1	Comp2	Comp3	Comp4	Average
This Work	99,99%	94,06%	99,64%	93,75%	98,21%	97,13%
Costa (2018)	99,98%	93,44%	99,81%	94,64%	98,21%	97,21%

Fig. 8. Recall metric comparison.

performance of two machine learning methods, Gradient Boosting and Random Forest for the failure classification. The main features under concern were Machine ID, Tension, Rotation, Pressure and Vibration. Through these data, it was possible to analyze the operating time, the lifetime, the maintenance of each machine. A 3-hour time window was also created to analyze anomalies, using as mean, standard deviation, minimum, maximum, to represent the short-term history of telemetry.

The tests carried out in this study consider that this machine learning approach can be very useful in small and medium industries, with limited datasets and machine sensing. The results show that the values of the metrics above 90% and considering a supervised application, such algorithms generate benefits for the maintenance of rotating machines, even in a small time window.

Finally, it was possible to conclude that failure detection in rotating machines, through machine learning, is a valid and promising procedure to predict the eventuality or not of failures in a maintenance management system. However, the verification and way of obtaining the dataset need to be careful, because of the need to obtain sufficient historical data for the training and testing of the classifiers. Another critical point is the time in advance of the prediction, as the amount of data will influence the computational cost, arising from the constant need for refinement of the model. The application of the Random Forest and Gradient Boosting algorithms also contributes to a better understanding and explanation of what happens in the machine learning method, highlighting the simplicity of the decision tree-based models.

6. CONCLUSIONS AND FUTURE WORKS

This work presents an analysis of two machine learning algorithms that could improve predictive maintenance in rotation machines. This new analysis comparing with recent related researches emphasizes the aspects involving predictive maintenance on machines, as the dataset organization, the number of sensors, feature extraction, and the time window checked. Both algorithms achieved expressive results, representing accuracy, precision, and recall above 90% of correctness. Future work goes into the direction of applying and comparing these algorithms in other datasets and obtain data in runtime, making a better analysis of the relationship between the models, the computational cost, and hardware required for applications in the industry.

REFERENCES

Aceto, G., Persico, V., and Pescape, A. (2019). A survey on information and communication technologies for industry 4.0: state-of-the-art, taxonomies, perspectives, and challenges. *IEEE Communications Surveys & Tutorials*, 21(4), 3467–3501.

Antão, L., Reis, J., and Gonçalves, G. (2018). Continuous maintenance system for optimal scheduling based on real-time machine monitoring. In *2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA)*, volume 1, 410–417. IEEE.

Caldas, A.N. (2015). *Desenvolvimento de um Sistema de Apoio à Decisão para a manutenção preditiva dos ativos de uma subestação elétrica.* Master's thesis, Faculdade de Eng. da Universidade do Porto, FEUP, Portugal.

Costa, F.J.O. (2018). *Continuous Maintenance System for optimal scheduling based on real-time machine monitoring.* Master's thesis, Faculdade de Engenharia da Universidade do Porto, FEUP, Portugal.

Gritli, Y., Bellini, A., Rossi, C., Casadei, D., Filippetti, F., and Capolino, G. (2017). Condition monitoring of mechanical faults in induction machines from electrical signatures: Review of different techniques. In *11th int symp on diagnostics for electrical machines, power electronics and drives (SDEMPED)*, 77–84. IEEE.

Kanawaday, A. and Sane, A. (2017). Machine learning for predictive maintenance of industrial machines using iot sensor data. In *8th International Conf on Software Engineering and Service Science (ICSESS)*, 87–90. IEEE.

Khadersab, A. and Shivakumar, S. (2018). Vibration analysis techniques for rotating machinery and its effect on bearing faults. *Procedia Manufacturing*, 20, 247–252.

Li, Y., Zou, L., Jiang, L., and Zhou, X. (2019). Fault diagnosis of rotating machinery based on combination of deep belief network and one-dimensional convolutional neural network. *IEEE Access*, 7, 165710–165723.

Liu, R., Yang, B., Zio, E., and Chen, X. (2018). Artificial intelligence for fault diagnosis of rotating machinery. *Mechanical Systems and Signal Processing*, 108, 33–47.

Loiselle, R., Xu, Z., and Voloh, I. (2018). Essential motor health monitoring: making informed decisions about motor maintenance before a failure occurs. *IEEE Industry Applications Magazine*, 8–13.

Ma, J., Ding, Y., Cheng, J.C., Tan, Y., Gan, V.J., and Zhang, J. (2019). Analyzing the leading causes of traffic fatalities using xgboost and grid-based analysis: a city management perspective. *IEEE Access*, 7, 148059–148072.

Motors, W. (2020). Electric motors specification guide. Technical report, WEG Motor Specialist.

Romanovs, A., Pichkalov, I., Sabanovic, E., and Skirelis, J. (2019). Industry 4.0: methodologies, tools and applications. In *open conf of electrical, electronic and information sciences (eStream)*, 1–4. IEEE.

Roscher, R., Bohn, B., Duarte, M.F., and Garcke, J. (2020). Explainable machine learning for scientific insights and discoveries. *IEEE Access*, 8, 42200–42216.

Salunkhe, O. and Fast-Berglund, Å. (2020). Increasing operational flexibility using industry 4.0 enabling technologies in final assembly. In *Int. Conf. on Engineering, Technology and Innovation (ICE/ITMC)*, 1–5. IEEE.

Wahl, M. (2016). Predictive maintenance modelling guide - python notebook. In: <https://gallery.azure.ai/Experiment/Predictive-Maintenance-Modelling-Guide-Experiment-1/>.

Zhang, W., Yang, D., and Wang, H. (2019). Data-driven methods for predictive maintenance of industrial equipment: a survey. *IEEE Systems Journal*, 13(3), 2213–2227.