

Conference Paper

Modeling System Based on Machine Learning Approaches for Predictive Maintenance Applications

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Abstract

Industry 4.0 must respond to some challenges such as the flexibility and robustness of unexpected conditions, as well as the degree of system autonomy, something that is still lacking. The evolution of Industry 4.0 aims at converting purely mechanical machines into machines with self-learning capacity in order to improve overall performance and contribute to the optimization of maintenance. An important contribution of Industry 4.0 in the industrial sector is predictive maintenance and prescriptive maintenance. This article should be analysed as a methodology proposal to implement an automatic forecasting model in a test bench for the recognition of a machine's failure and contribute to the development of algorithms for preventive and descriptive maintenance.

Keywords: Industry 4.0, Artificial intelligence, Machine learning, Predictive maintenance, Prescriptive maintenance

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1. Introduction

The evolutions that increase the capacity of man in carrying out tasks that demand a large workforce and consequently low productivity or difficult access are always called "Industrial Revolution". They spot a new phase of industrial development and the natural evolution of society, markets and services. At the same time, reduces the labour force, increases the operation and automation of the machines, efficiency and productivity. However, it makes them more complex, automatic and sustainable.

In recent history, mankind went through three industrial revolutions. The first was marked by the mechanization of natural energy, is the largest example, the Steam Machine. The second was characterized by mass production and assembly lines with the use of electricity and oil. The third began in the second half of the XX century, is recognized by the application to the production of electronics, automation and IT.

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The industry revolutions increased industrial productivity, complexity, autonomy and sustainability in the process Productive [1].

The Industry 4.0 or Internet of Things (IoT), which is also called the Internet of Everything (IoE), is regarded as the new industrial revolution and defined as a new approach to the life cycle value chain of a particular product or service, and it is possible to adapt it more and more to the requirements imposed by the final consumer The evolution of the Industry 4.0 aims to convert purely mechanical machines, controlled by humans, into machines capable of self-learning in order to improve overall performance and contribute to the optimization of maintenance [2]. With the intend to reach those goals, it is necessary to construct an open and intelligent platform connected throughout a network information platform [3]. It is noteworthy that even in small and rapid researches, the importance and relevance of the theme industry 4.0. The subject is today presented as an emerging and developing theme in multiple areas, from health to the industry.

The main objective, in the days that run, is Industry 4.0 to respond to some challenges such as flexibility and robustness to unexpected conditions as well as a level of autonomy of systems, something's still missing [4]. Another issue in vogue that is directly linked to this new industrial revolution is the initial investment that, even if subsequently compensated by the increase in productivity and, consequently, by the increase in revenue generated, remains very high [5].

This industrial revolution, like the previous ones, is also supported by pillars that define the basis on which it should be developed and has the main objective of transforming isolated elements into an integrated, automated and optimized production flow. This transformation leads to greater efficiency – comparing to "traditional" processes – as well as changing the paradigm of the final producer/customer relationship, since there is access to a final product that goes more to its needs, without great need for adaptation. Thus, the main pillars are: Big Data; Simulation and Virtual Reality; System Integration; Cloud and Cyber Security; Additive production and process automation; Industrial Internet of Things (IIoT).

Industry 4.0 is the technology that has the need to treat large amounts of data, Big Data, often simultaneously. Data may be obtained from a variety of sources, such as production systems or machines, from management systems to energy or buildings of customer management systems. These skills help to transform IoT into a paradigm that contributes to decision-making in real-time [6-8].

The evolution of the graphic and dynamic levels allows integral copies of systems or structures in order to facilitate their analysis. The evolution to simulation and virtual reality allowed the development of 3D models and simulate reality in scenarios based

on virtual reality, even before implementing any machine in a factory or in construction. By coordinating the project the time of a machine implementation is reduced and the response against any requirement has an upgrade when it comes to quality and a reduced time of response.

The complete system integration joined with the automation of production processes, both in the horizontal and vertical aspects, also implies the automation of communication and cooperation, especially when it comes to standardized processes. The integration of numerous systems, to communicate with each other and with information inputs from other systems – even if they are not integrated with your – it is possible to optimize the product/service you want to present.

Clouds have become nowadays a very useful tool regarding connectivity and data exchange between machines, even if the distance between both is from a considerable magnitude. Connectivity is done through the network and is based on the connection of different devices in the same cloud in order to share data between each other and with some external machines. However, technological advances increased connectivity and the use of standard communications protocols are the subjects of discussions on the network and cloud security. Hence, companies are making efforts to make communications secure, as well as trying to develop sophisticated identity and access management.

Additive production allows the production of small batches of specific products, thus offering construction advantages, from the cost, since it avoids large-scale production that creates stock and consequently generates expenses, or the complexity of the product (at design and weight level). This technology is also supported by process automation, that allows a high accuracy level, greater flexibility and cooperation that increases with every day.

The IIoT is a global network of connected and uniform objects that communicate through standard protocols. IIoT promotes the connection of the physical elements (CPS) – such as sensors, actuators, motors, etc. – machine with production capacity and data processing to support decision-making. In this way it is possible to build a versatile, intelligent and globally connected value chain, integrating physical objects, human factors, sensors and production processes.

An important contribution of Industry 4.0 in the industrial sector is predictive and prescriptive maintenance. The field devices collect data that is subsequently treated in a way that simulates the intervention needed in the system, machine or machine part. Compared to the classic preventive maintenance programs, predictive maintenance increases machine performance by reinforcing the business model of companies. Due

to the inclusion of a set of sensing, condition monitoring, predictive analytics and distributing systems technologies, it is possible to perform and provide remote technical assistance based on continuous monitoring and maintenance support.

It is therefore essential that both software and data acquisition, do an additional effort in order to enable data analysis and intelligent planning operation and machines maintenance.

Predictive maintenance is a technique that is strongly promoted as the next phase of maintenance by incorporating IoT sensors and monitoring strategies. This technique is based on operating conditions and works in real-time while providing data updates of the machine and validates the next maintenance intervention when it is needed. Continuously or periodically, the devices monitor the actual conditions of the machine and the data is made available remotely, in the cloud. Each device provides an analysis of the time required for the next maintenance intervention in order to promote less downtime and improving productivity. There are positive examples in predictive maintenance projects connected with the avoidance or reduced costs, however, this will only be available in a few years from now.

Prescriptive maintenance is like predictive maintenance but a step ahead – has the goal to automate the maintenance process. It is not limited to monitoring and providing recommendations, the goal is machine learning and resorting to artificial intelligence (AI) techniques to enable the machine to make its own decision in relation to maintenance interventions. Machines and devices collect data as they are working and promote numerous recommendations to increase, e.g. the time interval of the next maintenance. In general, it is understood that both prescriptive and predictive maintenance can mean the same thing, but instead of just predicting the result – the greater value of prescriptive maintenance – predictive maintenance enables you to learn machine and logic to communicate what can be done and keep update, while the machine is still running. Thus, it requires real-time data, which compares with the different machines dispersed throughout the factory or building and executes the best in the whole factory to provide accurate results [9-11].

2. The Opportunity of the Active Machine

The continuous demand for reduction of industrial costs and in the face of current trends in the sectors has promoted the growth of investment in the Industry 4.0 concept in the application of Cyber-Physics (CPS) integrated into the global production system, some improvements related to the with [12]:

- Systems integration.
- Development and integration of cognitive models.
- Increased capacity of machine decision making, assisted by sensors and models.
- The interconnectivity of the machine with other machines and global production system. The CPS application at various levels in the machine also strengthens its capacity. Thus, generally regarded as passive, the machine is transformed into an active production environment, Integrated with the global production chain and with the decision-making capacity at [12]:
- Machine process optimization;
- Monitorization and evaluation of its state to define and perform maintenance actions before the failure happens;
- Parameters optimization of the operation and for energy optimization;
- Management of unexpected events;
- Connect with other machines, with production resources, with the production teams.

3. Opportunities and Challenges for the Industrial Sector

At present, only 1/5 companies in the industrial sector have digitized processes, although they want productivity to increase in the coming years. However, there is great hope that companies will implement Industry 4.0 solutions in all important business divisions. The digitization and interconnection of products and services (IoT/Services) will contribute strongly to ensure competitiveness and promises additional revenues of 2% to 3% per year on average [13].

For the machinery sector, the main challenges are focused on [12]:

- The sensorization and monitoring of the machine: Data acquired from sensors are used to take corrective actions, to increase knowledge about the use, reliability and efficiency of the machine/process;
- Predictive modelling based on data: Prediction models can predict machine and process behaviour so that both can be optimized;
- Cloud solution: It allows the manufacturer to manage the machine park for the customer. The collection and Registration of non-confidential data on the use of machines allows the manufacturer, through analytical techniques predictive,

anticipate the Remaining Useful Life (RUL) of vital components, establish predictive maintenance plans and promote digital services added value to customers;

- Interoperability: Standard base interface for communicating and sharing with other machines, CPS and cloud, to get useful services from them.

This article seeks to highlight the advantages of the implementation of predictive maintenance – provided by the benefit of Industry 4.0 – by focusing on remote monitoring and self-diagnosis of the condition of the machine's operating state. However, the main highlight of the article is the development of an integrated intelligent system for data acquisition and analysis processes for the future development of prediction algorithms for machine fault recognition.

4. Predictive Maintenance

The highest industrial sector is concentrated on customized and small-scale production of high-value-added machines and precision. For this level of service is required the application of proactive maintenance strategies, predicting potential failures and promoting the scheduling of maintenance interventions in the convenient periods in order to avoid unforeseen machine failures and interruptions not foreseen in production.

The integration of Smart Predictive technologies in machine contributed to avoiding unplanned stops. However, the industry is not yet familiar with these techniques and are not widely used in the production environment. The sensors and monitoring techniques required for the production environment are not the frequent standard and require substantial investments.

The key features for predictive success technologies are [12] the use of non-invasive monitoring techniques, investment availableness and effectiveness.

5. Designing a Smart System

For the development of an intelligent predictive and prescriptive maintenance system, it is necessary to make a framework of the technologies to be involved.

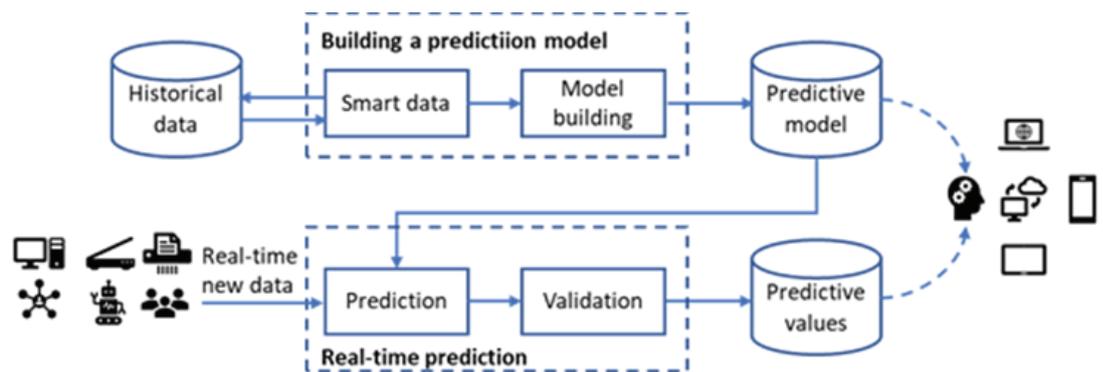
Fig.1 shows a functional procedure of predictive maintenance-based on techniques Machine Learning to predict future failures of the machine. The objective of this procedure is the following: (a) to develop a prediction model based on historical data and use algorithms Machine Learning and; (b) real-time submit new data to this model to identify possible failures. There are two architectural levels that analyze the edge

computing and the cloud proposing to approach the phase: (a) in the cloud which aims to (theoretically) analyze unlimited resources, while the phase: (b) which requires less computing resources, runs at the limit due to limited resources and increase responsiveness [14].

The smart data block obtains relevant static resources from the raw data. The block calculates a wide range of statistical indicators.

The model building block performs programming based on the historical data set. All data collected is related to a machine, machine part or device that can identify the failure.

In the validation block, the performance of the prediction block is evaluated by analyzing a stratified cross-validation. Forecasting performance is assessed using quality scores, such as accuracy and others that provide important information about forecasting performance. The display block provides a 3D visualization of machine/device, using the data collected in the field, along with the results of predictive maintenance algorithms. The proposed procedure based on Machine Learning predictive maintenance provides, effectively, and intuitively, presenting maintenance and operations data to local technicians or remote experts.



5.1. Prediction Models

In this section are analyzed different prediction methods. Prediction approaches can be sorted in 3 ways:

1. Stochastic model: It estimates the probability distributions of possible results, allowing random variations in one or more inputs over time. The random variation is usually based on fluctuations observed in historical data for a selected period [15]. Depending on the data selected and used to train the model, two groups of approaches can be identified [16-25]:

- (a) Univariate models: Models are calculated based only on time series history. You can find the following models NEST and Group: Auto-regressive moving average (ARMA) and Multiregression Combined (ARMR), Auto-Regressive Integrated Moving Average (ARIMA), Weighted moving average (WMA), Multiple Linear Regression (MLR), Multiple Quadratic Regression (MQR), Vector Autoregressive (VAR), etc.
 - (b) Multivariate models: The models integrate exogenous parameters to other inputs in addition to historical data (for example, climate-related data). Multi-Regression (MR), Multivariate Adaptive Regression Splines (MARS), Autoregressive Exogenous (ARX) and K-nearest meter knmVARX.
2. Machine learning algorithms: Artificial intelligence application gives systems the ability to automatically learn and improve from experience without being explicitly programmed. Among this category, you can find the following methods: Artificial Neural Network (ANN), Wavelet Neural Network (WNN), Non-Linear Autoregressive (NAR) ANN, Regression Trees (RT), Support Vector Regression (SVR), Ordinary Least Squares regression (OLS), Multilayer Perceptrons (MLP), Stacked Autoencoders (SA), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Time Delay Neural Network (TDNN), Gradient Boosting Tree (GBT), Power Long Short-Term Memory (LSTM), Deep Neural Network (DNN), etc. [16-30].
3. Hybrid models: They represent any combination of two or more of the methods described above [17, 25].

The forecasting process can be based on a single technique, among the various options available. However, in many situations, relying on the results of a single method may not be enough, because each method weighs the data differently. The group time series with similar characteristics don't bring considerable help in the prediction model, because only one model is suitable for all groups. Therefore, when using only one algorithm, information from other techniques ends up being discarded. Combination models can offer more information to provide a better prediction compared to an individual model. The prediction combination is a method that uses some mechanism to weigh different prediction results in order to obtain a combined final prediction. There are some main approaches to a combination that are defined in the literature: an objective and a subjective approach. The objective approach represents methods that use a mathematical function or a specific algorithm to assign weights to every single prediction. Then, the weighted predictions are combined to create a combined prediction. The subjective approach includes intuitive efforts to combine predictions,

through knowledge and opinion. It is often used with scarce data, during the release of a new product, for example. The principle is to use a combination of objective techniques with human judgment (subjective techniques). Based on historical data, the model is generated at the same time as human judgment is performed, adding contextual information to produce two predictions, one objective and one subjective. These predictions are combined and, based on contextual information, a single final prediction is generated. The subjective approach is influenced by the individual characteristics of the investigators, as well as by the aspects of the prediction context. It is still considered unexplored [25, 31].

In most studies found in the literature, the combination of predictions models leads to greater accuracy. In fact, regardless of how the combination is obtained, its result intends to cause an increase in the accuracy of the individual estimates. This is because individual forecasting techniques are based on different approaches that can capture distinctive characteristics of the temporal series and allow the combination to benefit from such characteristics [31-34]. The goal is to test different combination methods to assess whether they can overcome the performance of single models [25].

5.2. Metrics

Fault recognition accuracy predictions are essential to reduce uncertainties in the near future and thus anticipate the state of failure to make the best decisions. However, before such methods can be implemented, validation measures are required that can assess the accuracy and usefulness of volatility and noise failure predict entered by the data. Traditional metrics, as mean absolute percentage error (MAPE) or root mean square error (RMSE), can evaluate the quality of prediction performance under different perspectives. To complement these metrics, the integration of other metrics, such as the linear regression coefficient R^2 , normalized mean bias error or coefficient of variation, it can be useful [16-17,22-26]. Thus, considering several metrics, good performance evaluation can be made for prediction models. The idea is to have a variety of metrics to better understand the benefits of each prediction due to different aspects of prediction errors since different metrics allow a better understanding of the characteristics of each method.

5.3. Forecasting models features

To develop prediction models, a procedure is usually followed in seven steps [25]:

1. Collecting data; 2. Data pre-processing; 3. Identify the appropriate data; 4. Aggregate or group data; 5. Built the model with different parameters; 6. Model training and validation; 7. Model performance test.

5.4. Real-Time data

Data recorded at time intervals and sent at the end of the day for evaluation are not data in real-time. To adjust the predictions made by prediction models is recommended to use the data collected in real-time. The analysed data are intended to collect the characteristics and develop forecasting algorithms that contribute to the prevention of failures.

To get good results the selection of input data should be appropriate once they are important to the prediction models because they are dependent on data sets and significant changes can be observed in the accuracy of the results. Historical data has the greatest influence on predict, but an excess of historical inputs can lead to a drop in the quality of precision [25].

5.4.1. Approach to data analysis

To get the thumbprint of a machine you need to run a pre-defined test cycle in the absence of load condition in order to achieve better detection of failure and remove the noise that the normal loading process of the machine could introduce. In this way, the resulting method will be easily adapted to other similar machines and that could prevent adaptation problems if the properly developed modelling is from data that was collected on the machine during the training phase. It is the case of the training process of these machine learning algorithms, for which it is necessary to repeat the training/learning process in accordance with the particularities of each machine [12].

5.4.2. Monitoring and data acquisition

The use of different test benches for supplying information relevant to the project. For each of them, the objectives of the tests must be different, but they all have specific functions for the final task of evaluating the state of the machine. A list of Tests should be drawn up for the collection of the most relevant information [12].

5.4.3. Design and development of forecasting algorithms

For the development of an algorithm with good convergence, it is essential to have a group of samples whose majority have statistical relevance. Therefore, to determine the state of the machine, the first algorithm must be basic and focus on one fundamental machine part at a time. However, one must develop a procedure to improve and update the algorithm [12].

The evolution and improvement of the algorithm should be based on three steps [12]:

- **Fingerprint calibration Procedure:** Data collection must enable the machine's reference line to be established. The procedure should calculate the data uncertainty, e.g., the standard deviation. The procedure should also establish the periodic registration of the data subsequently produced for the evaluation and continuous comparison. The calibration procedure should reflect the normal operation of a machine in good condition.
- **Evaluation:** As new data is recorded and the comparison with the fingerprint has revealed the anomalies. The availability of data by machine operation and evaluation of machine condition can establish other operating limits. This information is significant importance for future trend analyses and RUL estimates. The advantage of this approach is the possibility of perfecting and adapting the algorithm as new data is collected.
- **Classifiers:** considering degradation levels, establish a procedure for machine learning classifiers that can be applied to improve the algorithm by learning.

Data collected from a machine part or a set must be available at every step and in real-time to allow for real-time tuning of failure predict. For time series of operation of each machine part, the machine learning algorithms, such as linear models, ANN and SVR should be used for predictions in real-time. First, different data are tested with an SVR and ANN model. After finding the appropriate data, other machine learning algorithms are implemented and compared: the algorithm that provides the best performance is preserved. Finally, the different predictions are tested with another set of data collected in real-time and based on the best performances, by analysing the metrics MAPE and RMSE, can bring a significant improvement in the predict. The prediction model that presents the best results and robust in the various tests should be selected for implementation.

6. Conclusions

The article presents a methodology of a prediction model of failure recognition of a machine to be applied in predictive maintenance by Industry 4.0 concept and technologies behind. The prediction method or combinations of prediction models must be analysed to evaluate performance across multiple aggregations, clusters, and characteristic groups created according to the time series characteristics. The predict resulting from the models should be adjusted while preserving the best of them. In the end, a study case should be carried out to assess the reliability of the prediction model. For this purpose, the metrics should be used to compare the performance of the prediction models. The metrics proposed in this article provide statistical information about the assessment of prediction models performance.

The combination of prediction models can provide a better prediction compared to an individual model, so several combining techniques should be compared. Additionally, one must evaluate if the fine adjustment of the model brings significant improvements.

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