Industrial environment: a strategy for preventive maintenance using Machine Learning to predict the useful life of equipment and Statistical Process Control for Continuous Monitoring of Variables

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Abstract. The industrial context, especially those involving technologies, can suffer significant impacts from the operation of equipment on the factory floor. In view of this, several strategies have been used involving the maintenance of equipment so that the amount of corrective maintenance is reduced compared to the execution of preventive maintenance. It is understood, however, that even preventive maintenance requires greater intelligence in the face of changes that arise in the programming of the production sector or even common variations in equipment and the environment. Thus, this article presents the results obtained by implementing a predictive maintenance strategy based on the equipment's remaining lifetime (RUL), combined with real-time monitoring of equipment operating variables with the support of statistical process control tools. In this scenario, three different algorithms (Random Forest, XGBoost, and LSTM) were implemented and tested on a data sample of 60,632 observations, which allowed the results obtained to be displayed in a panel and the user to have access to predictions within their needs.

Keywords: Industrial context, Predictive maintenance, Random Forest, XGBoost, LSTM

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1 Introduction

Predictive maintenance is one of the fundamental key technologies of Industry 4.0. According to [4], it enables manufacturers to continuously track machinery performance and to predict malfunctions prior to their occurrence. This is achieved using data analytic and machine learning algorithms that detect patterns and trends in the analyzed data.

Besides increasing machine readiness, predictive maintenance also enhances maintenance efficiency by reducing unscheduled downtime, slowdowns, and costs associated with these occurrences. According to [23], companies that deploy predictive maintenance can expect a substantial payback in a brief period, given the efficiency gains and repair and corrective maintenance savings.

Deploying predictive maintenance also benefits the environment. [11], advocates that by anticipating breakdowns before they take place, manufacturers may be able to reduce wasted resources and reduce their greenhouse gas emissions, as there is no requirement to undertake needless corrective maintenance or equipment replacements. Such a particular result expands the applicability potential of predictive maintenance solutions, crossing the boundary of operational or cost reduction, thus no longer raising doubts regarding its importance as an applied technology to Industry 4.0 and generator of economic, environmental, and operational benefits in the most varied industrial sectors [14, 13, 15].

A crucial element to any process of automation and intelligence regarding Industry 4.0 applications is the usage of sensors, a subject that has been the object of research by several scholars in the technological field. As per [9], integrating smart sensors enables real-time monitoring of industrial processes, leading to better efficiency and lower costs.

[25] emphasize that the usage of sensors, combined with artificial intelligence, enables autonomous systems and production optimization, leading to a more sustainable and effective industry. Clearly, it can be inferred from the placements presented in this paragraph the importance of combining the use of sensors with the construction of predictive maintenance applications for equipment.

These sensors are used to gather data and parameters used to create predictive models of the equipment's Remaining Useful Life (RUL), enabling them to create databases to maintain transactional and historical information on the functioning of the machines and assets components of the analyzed industrial environments.

According to [10], the equipment remaining useful life (RUL) concept is widely used in the field of equipment engineering and maintenance. RUL is defined as the remaining time that an equipment or component will remain useful to perform its functions with no requirement for maintenance or repair.

Establishing the RUL is essential for asset management, enabling the early identification of potential failures and the scheduling of preventive maintenance, saving time and service costs. Moreover, RUL is equally important when it comes to strategic decision-making, such as replacing outdated equipment with more efficient new equipment [22].

This study will use historical data on equipment operation in an industry manufacturer of memory modules (DRAM and SSD). Within the diverse equipment present in the industrial plant undergoing analysis, some of them have built-in sensor infrastructure, allowing real-time operating parameters capture, together with the temporal and quantitative detection of the respective equipment failures. Having the data, different machine learning algorithms will be used to assess their performance and accuracy in terms of estimating the remaining useful life of the equipment (RUL).

Finally, this study employs a method that relies on both regression models and multiple machine learning algorithms for RUL prediction and evaluation of their respective accuracy performances, aiming to speed up and provide a reliable choice of the optimal model to be integrated into the predictive maintenance strategy in an industrial environment as proposed in this study.

This paper is organized as follows: in Section 2, there is the related works presenting important foundations over the subject; in Section 3 there is a methodology applied in the study, explaining how predictive maintenance strategy was integrated as a solution, how data samples are organized, and other important aspects about the way to develop the experiment. The results and discussion are presented in Section 4, and the conclusion is in Section 5.

2 Related Works

Recent advancements in the field of machine learning have demonstrated the potential for the prediction of the Remaining Useful Lifetime (RUL) of industrial equipment. In 2021, researchers [5] utilized a data-driven method based on Deep Long Short-Term Memory Networks (DLSTM) for the RUL prediction of machinery. This study revealed that DLSTM could outperform traditional techniques, especially when dealing with time series data, suggesting a new approach in the predictive maintenance field.

Similarly, the work conducted by [7] employed the Random Survival Forest (RSF) algorithm to predict the RUL of industrial machinery. This study aimed to overcome the challenges posed by right-censored data, which is common in maintenance prediction. Results indicated that the RSF algorithm showed excellent performance in handling such data, proving superior to Cox Proportional Hazard models in certain scenarios.

Moreover, in another important research [24] adopted a two-stage hybrid model that integrated a Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) for RUL prediction of industrial equipment.

The CNN was used for feature extraction while the LSTM was used for prediction. The study demonstrated that this hybrid model was efficient and reliable in predicting the RUL of industrial equipment, particularly when dealing with high-dimensional data.

A different approach was undertaken by [16] who leveraged Reinforcement Learning (RL) to predict the RUL of industrial machinery. The study presented a framework that utilized RL to adaptively select the optimal features for the prediction. This approach proved to be robust against changes in the equipment operation environment and provided a promising perspective on RL application in predictive maintenance.

On another front, a comprehensive study by [20] evaluated a variety of machine learning techniques, including Support Vector Machines (SVM), Decision Trees, and Ensemble Learning methods to predict the RUL of industrial equipment. This study offered valuable insights into the suitability and efficacy of various machine learning techniques, giving practitioners a comprehensive guideline for choosing the most effective algorithm.

Finally, these recent studies indicate the evolving application of machine learning techniques in the prediction of RUL for industrial machinery, promoting proactive and predictive maintenance approaches. They underline the potential of techniques such as DLSTM, RSF, hybrid CNN-LSTM models, RL, and others for efficient, accurate RUL prediction, contributing to more effective, cost-efficient maintenance schedules, and better resource utilization.

3 Methodoloy

This section presents the methodology used in the elaboration of this study. First, the predictive maintenance strategy integrated solution used by the industry that is the object of this study is presented. Afterward, the data set employed is detailed by presenting the general characteristics of the sample, along with the variables and parameters used in the predictive model development.

In the sequence, the overall implementation flow of the forecast process through machine learning algorithms is presented. General information about the data preparation and pre-processing steps are also discussed, as are the technological tools and methods that are predominantly employed.

Finally, the most comprehensive concepts of all prediction algorithms applied in the study are presented, together with the tools provided by statistical process control and their use in the real-time monitoring of industrial equipment.

3.1 Integrated Predictive Maintenance Strategy Solution

It is of utmost importance to begin this section by stressing that this study is primarily focused on the presentation of the development procedures and results obtained by using RUL prediction models and statistical process control tools. It is also worth mentioning the limitation of the scope of this study due to the comprehensiveness of the Integrated Predictive Maintenance Strategy Solution.

The Integrated Predictive Maintenance Strategy Solution can be described as a broad system consisting of modules that deal with everything from data collection and processing to the phases of information presentation and visualization by the final users.

Figure 1, below, displays the complete diagram of the Integrated Predictive Maintenance Strategy Solution. In this image we highlight two modules of interest to this study, namely: 1) the RUL prediction module (1); 2) the Statistical Process Control Graphics module for real-time monitoring of equipment operation (2).

The present study only describes the actions undertaken to produce the modules of RUL prediction and Control Charts - SPC displayed in the Dashboard component of the main solution.

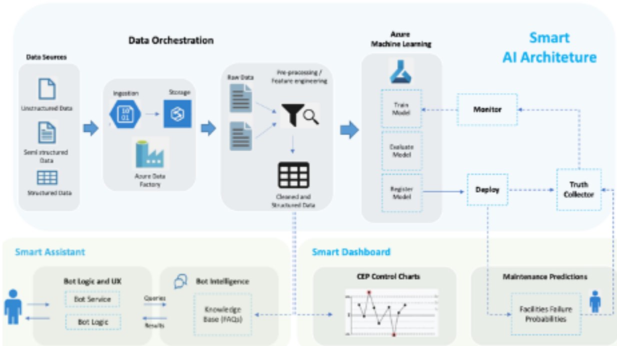

Figure 1: General diagram of the Integrated Predictive Maintenance Strategy Solution

It is worth mentioning that there are several functions of interaction between the modules of the Integrated Predictive Maintenance Strategy Solution and the final user with the plant environment monitored. A very relevant function in this study is the labeling performed by the user when there are breakdowns or failures in the industrial equipment monitored by the system. This labeling process provides for the subsequent structuring of the temporal-oriented data set, pinpointing the moments of occurrence of failures in the respective types of equipment, a crucial element for carrying out RUL predictions.

3.2 Data Sample

The data sample employed in the study was collected from the sensor infrastructure existing in the industrial environment analyzed. Several pieces of equipment used in the plant of the industry in which this study was conducted have sensors that can obtain data about the operation of these machines.

The present study examined the specific interest in three-phase energy metering equipment and their corresponding operating variables. Three-phase energy meters are electric energy measuring devices that quantify the energy consumed by an electrical installation, delivering precise information on the energy consumed, by analyzing electrical parameters of current, voltage, frequency, and power, thereby permitting more efficient energy consumption management and greater control of associated costs.

Figure 2, as follows, lists the parameters noted in the energy meters of the industry analyzed. Via the sensors placed in this equipment, time data on the operation of the energy meters are collected and logged in a database system for subsequent use in the modeling process and prediction of the equipment's useful life.

Medidores de Energia		
Variáveis	**Unidade**	**Temporalidade**
Tensão fase A	Volts (V)	Segundos
Tensão fase B	Volts (V)	Segundos
Tensão fase C	Volts (V)	Segundos
Corrente Fase A	Ampere (A)	Segundos
Corrente Fase B	Ampere (A)	Segundos
Corrente Fase C	Ampere (A)	Segundos
Corrente Neutro	Ampere (A)	Segundos
KWH acumulado (realizar cálculo)	kwh	Segundos
Demanda de energia	kwh	Segundos
Fator de potência	FP (KVAr)	Segundos
Frequência	Hertz (Hz)	Segundos

Figure 2: Parameters/variables of the Energy meters

The sample used in the study consists of 60,632 registers, collected along 8 months of operations in the industrial sector, organized according to the variables described in Figure 3. Equipment identification data, date and time of register collection, and time cycle characteristics stemming from the dates were additionally included.

Lastly, a key element of the sample structure used is the temporal indicative of equipment failure or shutdown. Besides automatically obtaining operating parameter data by means of sensors located in the energy metering equipment, the Integrated Predictive Maintenance Strategy Solution enables users to perform failure indicative labeling on the respective equipment, allowing subsequent use alongside RUL prediction models.

From the beginning of the operations of the energy measuring equipment, data are recorded and after an indefinite period, indications are made by the user regarding equipment failures or stoppages, through the data labeling function present in the Integrated Predictive Maintenance Strategy Solution. The quantification of periods between failures of energy meters makes it possible to define the number of time cycles between failures and later calculate the RUL values.

Finally, the initial volume of data (60,632) was divided into two subsets of data for training and testing the RUL prediction model, as follows: 70% of data for training, and 30% of data for testing and validation.

Índice	Campo de Dados	Tipo de Dado	Descrição
1	Id	Integer	Identificador do registro
2	Id Equipamento	Integer	Identificador do equipamento
3	Data (hh:mm:ss)	Date	Data_Hora do registro
4	Ciclo	Integer	Contador de ciclos
5	Parada	Boolean	Indicador de parada
6	TensaoFaseA	Float	Tensao Fase A do equipamento
7	TensaoFaseB	Float	Tensao Fase B do equipamento
8	TensaoFaseC	Float	Tensao Fase C do equipamento
9	CorrenteFaseA	Float	Corrente Fase A do equipamento
10	CorrenteFaseB	Float	Corrente Fase B do equipamento
11	CorrenteFaseC	Float	Corrente Fase C do equipamento
12	CorrenteNeutro	Float	Corrente Neutro do equipamento
13	Demanda de Energia	Float	Demanda de Energia do equipamento
14	FatordePotencia	Float	Fator de Potencia do equipamento
15	Frequencia	Float	Frequencia do equipamento
16	RUL	Float	Tempo de vida útil do equipamento

Figure 3: Structure of the Data Set Used.

3.3 General Process Flow of RUL Prediction Using Machine Learning Algorithms

RUL prediction models are extensively used in industry to estimate the lifetime of critical equipment. Such models are based on machine learning techniques, as they are able to learn patterns from historical data to anticipate upcoming equipment failure. Applying machine learning algorithms, such as artificial neural networks, decision trees, and linear regression, has proven quite effective to enhance the accuracy and reliability of such models [1].

Developing solutions capable of profiting from the results obtained using RUL prediction models requires the consideration of crucial steps as described in the diagram presented in Figure 4, below. In the referred image phases A and C are highlighted.

During phase A the present study chose to implement 3 different regressive algorithms to determine the final RUL prediction model, namely: Random Forest, Recurrent Neural Network - LSTM and XGBoost, all of which will be better described in the following sections of this work. Phase C refers to the process of continuous improvement of the final RUL prediction model, in which the user of the Integrated Predictive Maintenance Strategy Solution is able to indicate the accuracy of the model, which will then be taken into account in the new prediction interactions.

3.4 Data Preprocessing and Technological Tools

The initial data preprocessing and also the implementing of the machine learning algorithms for RUL prediction were performed using Python 3 under the Anaconda 2.3.2 environment.

More precisely, the input data is received in ".csv" format from the sensors that monitor the industrial

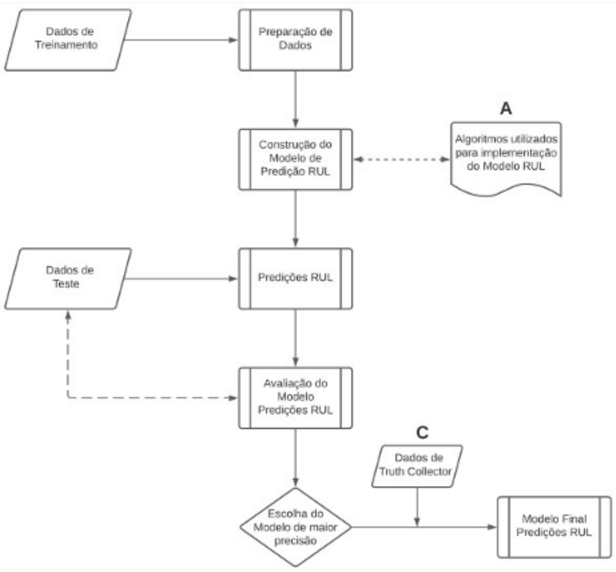

Figure 4: General Flow of the RUL Prediction Process

equipment, and then undergoes a cleaning and normalization process via the use of Python libraries such as Pandas, Numpy, and Matplotlib. Lastly, the Python libraries Sklearn and Xgboost were used to implement the Random Forest, Recurrent Neural Network - LSTM and XGBoost algorithms.

3.5 Fundamentals and Concepts of Algorithms Employed in the Study

Machine learning algorithms, i.e., artificial neural networks, decision trees, and linear regression, are routinely used for a variety of predictive applications. Particularly for predicting the remaining lifetime of equipment, time-based regression methods are frequently employed. Such a method is supported by regressing time information and equipment operating conditions to estimate the remaining useful life - RUL [5]. In this study, three regression algorithms extensively applied in prediction activities were selected for respective implementation and accuracy evaluation, namely:

- Random Forest: The Random Forest algorithm is a machine learning technique extensively applied to classification and regression problems. It is a combination of decision trees, in which each tree is trained on a random sample of data, and the resulting prediction is then obtained by averaging the predictions of the individual trees. The effectiveness of Random Forest is due to its ability to cope with problems of high dimensionality, missing data, and reducing data overfitting. Multiple applications using Random Forest have been reported, including cancer and heart disease predictions, customer satisfaction predictions, and weather forecasts [2]. When it comes to the use of the Random Forest algorithm for developing RUL prediction models, studies have shown that it outperforms other methods, for instance neural networks and decision trees, in terms of accuracy and execution time. Furthermore, various approaches for enhancing the effectiveness of Random Forest-based RUL prediction models have been proposed, such as using feature selection, clustering techniques, and resampling methods [11]. Hence, the Random Forest algorithm stands as a powerful tool for developing accurate and efficient RUL prediction models.

- Recurrent Neural Network - LSTM: The LSTM (Long Short-Term Memory) algorithm is a recurrent neural network model that has gained prominence in time series forecasting owing to its capability of capturing long-term dependencies. In contrast to other models, LSTM is capable of retaining information from past events for extended periods, making it effective in issues that demand sequential data forecasting. LSTM applications in areas as diverse as finance, demand forecasting, energy, traffic, and others are described in the literature. A number of authors highlight that the model can be further enhanced upon the addition of other techniques such as regularization, model ensemble, among others: [8]; [3]; [18]. The work conducted by [21] features an approach to using LSTM for RUL prediction, blending feature engineering techniques and usage of convolutional neural networks. This sort of approach has proven promising and fundamentally important to both enhance predictive maintenance and reduce costs in a variety of industrial areas.

- XGBoost: The XGBoost algorithm has demonstrated to be one of the most potent tools for creating predictive models in diverse areas, such as finance, healthcare, and marketing. The Gradient Boosting technique used by XGBoost provides robust and accurate models, besides enabling greater readability to the results obtained. Some recent studies have demonstrated the effectiveness of XGBoost in time series prediction, anomaly detection and data classification. When it comes to its application to the prediction process of the remaining machine lifetime - RUL, the XGboost algorithm has been largely applied for its modeling efficiency and speed. Some studies have related substantial improvements in RUL prediction accuracy by using the XGboost algorithm versus other machine learning algorithms. This algorithm application has been demonstrated to be a prominent option for RUL prediction in different areas, such as industry, transportation, and renewable energy [1].

3.6 Monitoring by Statistical Process Control

Statistical Process Control - SPC is a methodology applied to monitor and control industrial process quality. It relies on statistical techniques that permit the analysis of data collected over time to detect process deviations and act preventively to avoid them. CEP is an essential tool to guarantee product quality and cut production costs.

As per [12], CEP is a systematic approach that employs statistical methods to evaluate a process's variability. It is worth highlighting that variation is inherent to any process and hence cannot be entirely eliminated. The purpose of SPC is to bring the process variation down to an acceptable level, in a way that the products comply with the customer's requirements. The author also notes the significance of gathering data in a systematic way and analyzing them periodically, making use of control charts to detect process deviations. CEP control charts are tools used in industry to track the quality of products and processes. Such charts provide the ability to identify variations that may affect the process quality and performance, leading to decision making and preventive actions.

Apart from the RUL predictions, obtained by the prediction models based on machine learning algorithms used to compose the Integrated Predictive Maintenance Strategy Solution, the SPC control charts have been shown to be important as a real-time monitoring tool of the industrial equipment's operation. By using SPC charts it is possible to follow-up the current status of equipments and occasional variations and instabilities in their respective areas.

At last, the RUL prediction models combined with SPC charts constitute the Integrated Predictive Maintenance Strategy Solution, enabling the attainment of benefits characteristic of both initiatives: - at a first stage, the future insights of equipment maintenance stemming from the RUL prediction; - subsequently, the real-time monitoring of the operation of industrial equipment present in the workplace.

4 Results

The training and testing of the implemented RUL prediction models was carried out on the basis of the training and testing datasets presented in section 2.B of this study. The data set for training contains approximately 42,400 records, whereas the data set for testing the RUL prediction models contains approximately 18,200 records. The three algorithms employed in the study were both trained and tested on the previously mentioned respective datasets, and their results are presented in the following graphs.

Figure 5 depicts the variance behavior between the current values of RUL and the corresponding values predicted by the prediction models used. The graphs in items (a) and (b) correspond to the Random Forest and XGBoost models, respectively, and exhibit similar patterns, in which the lines of both current and predicted RUL values almost overlap, with very close trends and patterns.

This result indicates that these models have great performance and the predicted values are very similar to the observed values. Conversely, the graph coming from the predictions made by the Neural Network model - LSTM, introduced in item (c), demonstrates clear differences between observed and predicted values. Such graphical perspective indicates a model with inferior performance.

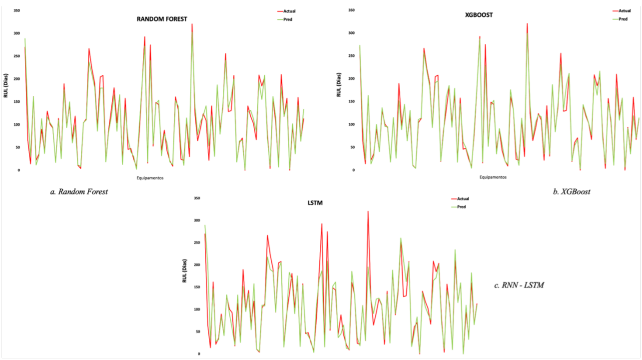

Figure 5: Visualization of Predicted X Actual RUL Values by implemented algorithm.

Figure 6 exhibits the spreads of predicted values by the implemented models. As one can see in item (b), the XGBoost model demonstrates a large concentration of the prediction points, pointing to its higher accuracy regarding the RUL prediction process. Contrastingly, item (c), whose model is based on the Recursive Neural Network - LSTM, demonstrates a greater variation of the predicted RUL values around the trend line, evidencing its inferior performance compared to the other implemented models.

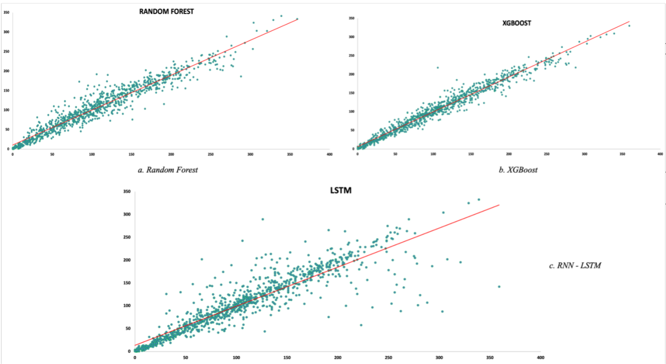

Figure 6: Overview of the dispersion of RUL Values Predicted by the Models.

Ultimately, the analysis of two metrics for evaluating regression forecast models is paramount to identify the RUL forecast model with the best performance in this study. These metrics are the Coefficient of Determination - R^2 and the Root Mean Square Error - RMSE.

The coefficient of determination, also referred to as R^2, is a statistical measure that states how well the regression model is fitted to the observed data. It ranges from 0 to 1 and represents the proportion of the variability in the dependent variable that can be explained by the independent variable. An R^2 value close to 1 suggests that the model explains most of the variability in the data, while one close to 0 indicates that the model does not explain the variability in the data well.

The coefficient of determination is extensively employed in regression analysis and can be calculated through different methods, including the sum of squares method and the maximum likelihood method [6]. Nonetheless, it is worth remembering that R^2 alone is not at all sufficient to gauge the model's appropriateness, and additional statistical tests should be performed to guarantee that the model is both reliable and valid.

The RMSE (Root Mean Square Error) metric is one of the most used performance measures in regression problems. As stated by [17], the RMSE is calculated from the square root of the mean square errors between the model predictions and the measured values from the test base.

RMSE metric is useful as it gives more significance to larger errors, an important consideration in many applications. Also, the RMSE is easy to interpret as it shares the same unit as the response variable.

Figure 7, below, represents the RMSE and R2 values for the implemented models based on Random Forest, XGBoost and LSTM algorithms, respectively. It can be noted that the model deployed using the XGBoost algorithm yielded the best RMSE (13.94) and R2 (0.96) results.

Furthermore, Figure 5 graphically depicts these results, emphasizing that the R2 is given in percentage terms, in which the RUL prediction model applied through the algorithm XGBoost accounts for 96% of the variability of the data used in the study.

	Conjunto de Dados de Teste	
Modelo	RMSE	R^2
Random Forest	19,82	0,92
XGBoost	13,94	0,96
RNN - LSTM	28,74	0,83

Quadro 3 – Valores de RMSE e R^2 por Modelo.

Figure 7: RMSE and R2 values.

Figure 8: R2 values and RMSE Models Compare.

In conclusion, regarding the RMSE and R2 metrics, and the obtained results related to the evaluation of the regression models used herein, the RUL Prediction Model implemented through the XGBoost algorithm can be used. Notwithstanding, the results achieved through the Random Forest and LSTM models are also proven to be relevant, chiefly considering their coherent and perfectly acceptable performances in realistic scenarios they might eventually be applied to.

In terms of the usage of statistical process control charts for continuous monitoring of equipment variables, Figure 6 illustrates such element, in which the points above and below the upper and lower limits (red traced lines), respectively, raise alerts indicating possible abnormalities in the equipment's operation.

The construction of the control chart adopts the approach of [19], who proposed the use of control limits to track the mean and variance of the process. In Shewhart's view, control limits are established based on the standard deviation of the process, meaning that any point outside these limits signals a significant change in the process mean or variation.

Figure 9 graphical representation demonstrates the monitoring of the variable by its average value at each time interval, thereby monitoring the equipment's behavior in its current operation cycles.

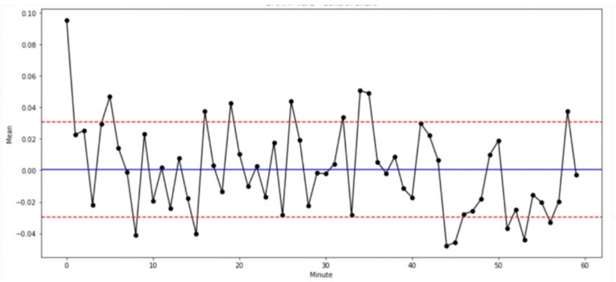

Figure 9: Equipment Control Chart.

It is worth emphasizing that the control charts are designed for each individual variable or characteristic that is desired to be monitored in the respective industrial equipment. In the present study, assuming the approach centered on the energy meter equipment, there are a total of 10 control charts, one per variable monitored in the energy meter. The choice of which variables will be monitored via statistical process control charts must also take into account the feasibility of automating the equipment itself, once each variable being tracked generates the required technical infrastructure for this purpose, involving the acquisition and installation of a growing number of sensors for the equipment that lacks this feature already integrated.

5 Conclusions and Future Works

The use of machine learning techniques to estimate the remaining lifetime of equipment broadens the asset management possibilities in industrial environments, reduces costs associated with unscheduled shutdowns in the production system, and also improves the planning process of the overall production chain.

In this study the RUL prediction models and statistical process control charts were associated, so as to consolidate a broader solution for equipment management in a productive environment. For the RUL prediction model, the results are robust concerning precision, being totally proven the viability of using this type of technology in the industrial environment. For the data sets used in this study, the XGBoost algorithm presented the highest accuracy in RUL value prediction. Moreover, statistical process control charts enable the real-time verification of equipment operation, providing an immediate controlling element to all monitored processes.

In the present study it was evaluated the implementation of RUL prediction models applying three machine learning algorithms: Random Forest, XGBoost and LSTM, under the characteristics of the energy meter equipment. As part of future work, RUL prediction model implementations can be conducted with different algorithms than the ones discussed here. A different perspective can be offered to implement models that contemplate a different group of equipment rather than the energy generators examined in this study.

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