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# Machine Learning Technics for Remaining useful Life Prediction using Diagnosis Data: a Case Study of a Jaw Crusher

Mariya Guerroum[1], Mourad Zegrari[2], Malek Masmoudi[3], Mouna Berquedich[4], Abdelhafid Ait Elmahjoub[5]
[1,2,5]*Laboratory of Complex Cyber Physical Systems (CCPS) - The National Higher School of Arts and Crafts (ENSAM)-Sciences Faculty Ben M'Sik, Hassan II University, Casablanca, Morocco*
[3]*University of Sharjah, College of Engineering, Sharjah, UAE*
[4]*Green Tech Institute- Mohammed VI Polytechnique University, Benguerir, Morocco*

***Abstract*— Predictive maintenance currently involves digital transformation with all the technologies developed to serve the latter. This maintenance strategy is believed to be an efficient solution to end late/early intervention issues. It is for this reason that machine health state monitoring by Remaining Useful Life prognosis is very crucial. However, in the literature, most studies focus on failure diagnosis more than the system's Remaining Useful Life. In addition, to prepare models to serve the prognosis, the use of actual machinery data is critical to assure the later scalability of the application. The literature about predictive maintenance has often evaluated data-driven approaches with machine learning techniques processing simulated Data rather than real ones. To tackle this problem, the authors propose a continuity of previous work treating a jaw crusher default diagnosis in the context of the ore mining industry. The RUL of the crusher components is estimated upon completion of the fault diagnosis data. Smart sensors Data have been pre-processed to serve the evaluation of four regression machine learning models: Bayesian Linear Regression, Poisson Regression, Neural Network Regression, and Random Forest. Poisson regression and Neural Network required data normalization in this case study to improve their performance. Linear regression methods proved their inability to forecast the machine degradation state, while the bagging ensemble method, Random Forest, was able to track the actual values. This paper aims to enhance the Prognosis and Health Management of the machine while contributing to the literature enhancement on failure prognosis using real industrial data.**

***Keywords*— Data-driven approach, Industry 4.0, Machine learning, Predictive Maintenance, RUL prognosis, Smart sensors.**

## I. INTRODUCTION

Rotating machines play a vital role in the manufacturing industry. In the ore treating facilities, machines make it possible to produce the right quality at the right time. This challenge is continuous and requires machine availability around the clock to keep up with the steering demand.

For a process where machines must be working 24/7 and undergoing rough conditions, bearings suffer from severe degradation over time.

Predictive Maintenance (PdM) anticipates possible flaws based on degradation development trends and indicates the best moment for an ideal intervention [1], [2]. For this reason, the prognosis of rotating machines' health state has been the focal point of research in recent years. Hence, the importance of the Remaining Useful life (RUL) was highlighted in several works as the predictable metric for the health state prognosis. The RUL could serve risk management on equipment. Indeed, the concept of risk on equipment before discovering failure signals and the RUL are closely correlated [3]. Since then, Machine learning technics were associated with the RUL prognosis to serve PdM in time. This ambition can only be met with a data-driven strategy to approach the system of interest. The prognosis and health management (PHM) idea has become an essential trend in the context of smart manufacturing and Big data from industry with the advent of "Industry 4.0." [4], [5]. Big data analytics have become the foundation for manufacturing areas such as forecasting, proactive maintenance, and automation [6],[7].

In the context of predictive maintenance integration under the “Industry 4.0” tide, [8]'s research is developed on the basis of an IoT structure collecting vibrations signals for failure detection and forecasting. Moreover, authors in [9] presented a Deployment of a Smart and Predictive Maintenance System in an industrial metal stamping machine using IoT and machine learning.

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As per the literature, Linear regression, Support Vector Machines, Decision Trees, and Random Forest algorithms are the most commonly used ML technics in predictive maintenance [4]. In the review work of 34 Predictive maintenance studies conducted by [10], Random forest was declared the most frequently adopted algorithm, followed by Support vector machine and Artificial Neural Network. Also, authors in [11] compared the results of a proposed multi-stage Remaining Useful Life prediction system with Linear regression, Convolutional Neural Network, Long Short Term Memory, and Support vector Regression using sensory data from real manufacturing systems. The authors introduced a manufacturing system based on a balanced random survival forest. This non-parametric machine learning approach can combine complicated dynamic correlations underlying shop floor data streams to provide a long-term prognosis of machine breakdowns, which was introduced by the authors in [12],[13].

In addition, an approach for RUL estimation using Recurrent Neural Networks (RNNs)was proposed by [14] to tackle some practical challenges when using data-driven approaches in predictive maintenance. Authors claimed that it is difficult to build physics-based models for health degradation analysis in complex machines with several components. Degradation trends tend to be non-exponential, plus the unavailability of sensor data due to unstable communication networks or other damages.

However, in the literature, failure prediction has not been addressed enough, while failure detection and diagnosis had more attention [10]. Nevertheless, there is proof that Machine Learning-based failure prediction models work well for several systems. Despite the significant work implemented as lab prototypes, few industrial implementations are reported in the literature, e.g., actual industrial data [15].

This paper investigates algorithms to perform RUL prediction in the mining industry's fixed installations. Data from the Authors' previous related work on fault diagnosis collected from smart sensors implemented on a jaw crusher [16] was combined with maintenance reports on actual interventions. Figure 1 presents the stages of the Predictive maintenance process where Prognosis comes after diagnosis in the Data analysis step. In this paper, the following Machine learning models were tested on Microsoft Azure ML studio to precise which technic is the most suitable in the mining context of big data: Poisson Regression, Bayesian Linear Regression, Neural Network Regression, and RF.

SVR and LSTM were omitted since the ML studio platform does not support them. In the remaining of this paper, materials and methods are presented. Followed by results and discussion, and finally, a conclusion and perspective.

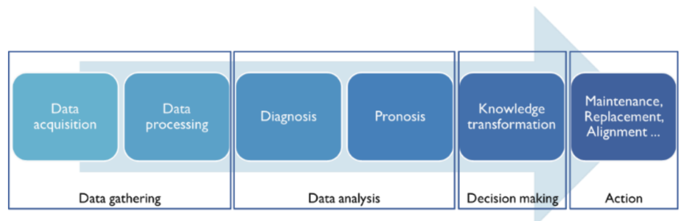


**FIGURE 1 PREDICTIVE MAINTENANCE PROCEDURE STEPS [16]**

## II. MATERIALS AND METHODS

### *A. Presentation of the jaw crusher machine*

The system under consideration is a jaw crusher that treats sterile after screening (class > 90 mm). This machine smashes the blocks to break them up under 250 mm size. The sterile is then transferred via the trash disposal conveyor. This equipment is located on the extracted phosphate physical treatment facilities line. Only the rotational portions of this machine are addressed in the scope of this research. Table I shows the jaw crusher components used in a mining production line. The jaw crusher can be divided into two parts: driving and driving. On the first hand, two electric motors and two mechanical bearings operate the crusher drive pulley in the driving section. On the second hand, two bearings on the central axis hold the driving pulley in place.

Figure 2 represents a diagram of the transmission chain from the electric motors to the crusher movable jaw connecting rods as previously described.

**TABLE I**
**JAW CRUSHER COMPONENTS' LISTE [16]**

| Component | Designation |
|---|---|
| Comp1 | Left electric motor |
| Comp2 | Right electric motor |
| Comp3 | Front bearing on left engine side |
| Comp4 | Front bearing on right engine side |
| Comp5 | Right bearing of the central axis |
| Comp6 | Left bearing of the central axis |

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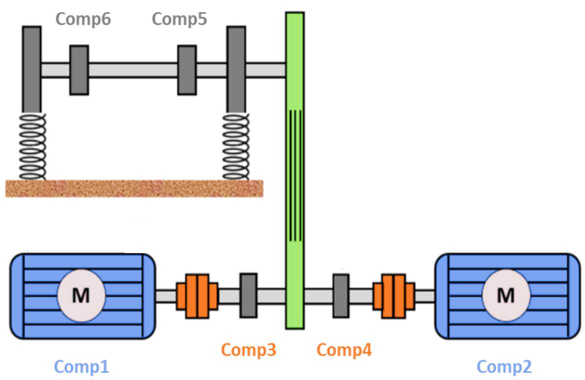


**FIGURE 2 KINEMATIC DIAGRAM OF THE JAW CRUSHER [16]**

Overall, the crusher's operating conditions are harsh given the load applied to it and the contaminated environment in which it functions. Additionally, the system's complexity has risen since each part of the crusher needs to be studied as an independent part of a whole. In addition, given that its primary function of reducing the size of mining waste is variable, modeling the jaw crusher is complicated, if not impossible. As a result, the load put on the machine is unpredictable and variable. As a result, the authors have decided to handle the equipment using a data-driven strategy rather than a model-driven one to acquire an overview of its state of health.

### *B. Instrumentation and Methodology*

In this case study, the overall vibratory displacement values in mm / s, acceleration in g, and temperature with a frequency of 4 hours are collected from the wireless smart sensors implemented on the 6 components. The data is saved in the cloud and exported in CSV format. Over 20 months, 14673 registrations were recorded. The data is then cleaned and processed by removing records created while the system was shut down. In addition, before continuing with the ML model building, weekly fault diagnostic reports are used to analyze the acquired sensor data. Figure 3 depicts the data flow of the proposed approach.[16] Moreover, it was noticed that the most common faults at the crusher level are structure defects, misalignments, lubrication deficiencies, bearing problems, and fixing concerns. Smart sensors are used to collect the crusher's components signals. Jointure of the smart sensors data and diagnosis reports made it possible to add features such as downtime and runtime to achieve the RUL calculation. In this study, two types of failures were considered. According to the diagnosis reports, alignment correction was performed at both electrical motors and front bearings left and right. In addition, all the mechanical bearing were greased. As for the other defaults no further intervention was reported. These assumptions lead to deal only with greasing and alignment failures while excluding the remaining other crusher defects for field information lack.

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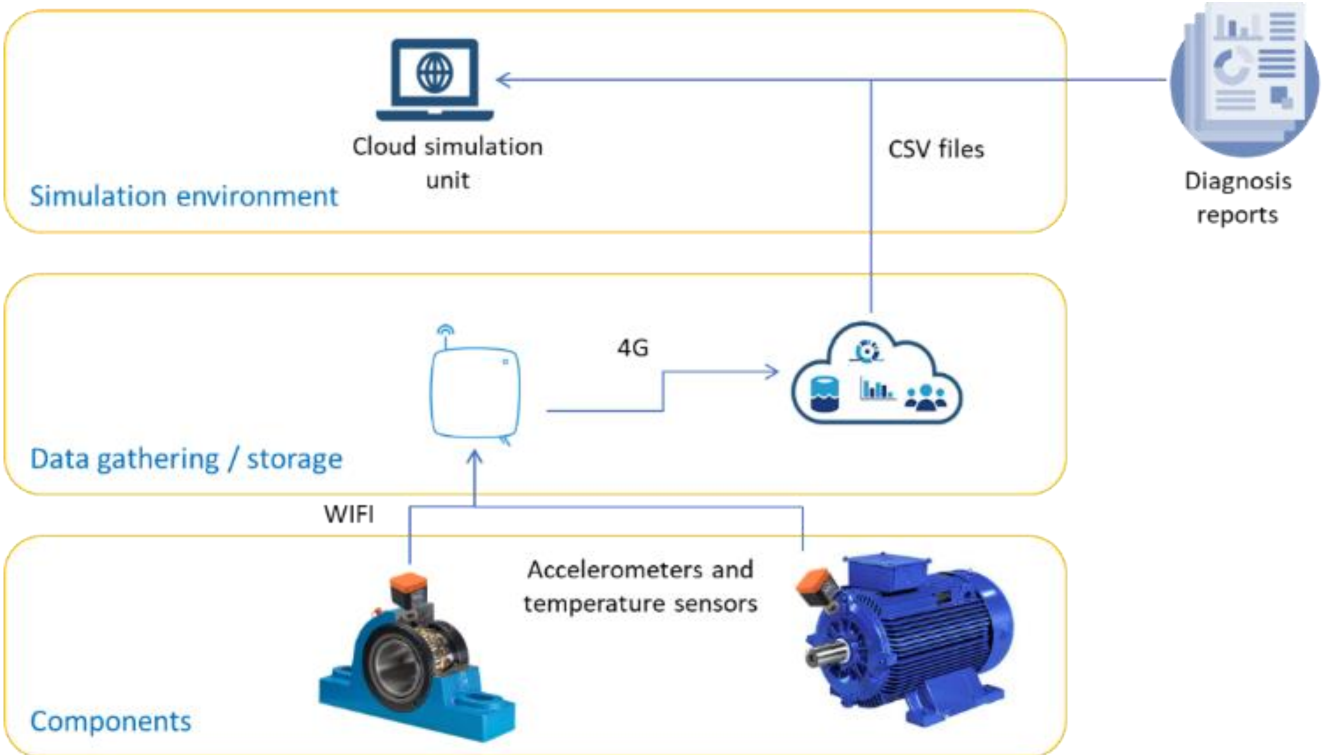


**FIGURE 3 DATA FLOW DIAGRAM [16]**

A data-driven approach was used to predict the remaining useful life before the next failure. Infact, predicting the class of an instance as a failure or regular operation is insufficient in predictive maintenance whereas appropriately estimating the remaining time far before the probable breakdown is more important. Therefore, the problem was handled as a regression model rather than a classification task. In the following, hyperparameters, also known as machine learning multiple configurations are studied to comprehend the predictive modeling issue. Matching the right hyperparameters and the algorithms help optimize a model. According to the literature, hyperparameter optimization can be used to regulate the learning process. Different search algorithms, including grid and random search, can be used to carry out this optimization [17].

For each component, multiple models were built, mainly by evaluating four algorithms: Random Forest, Neural Network, Poisson Regression and Bayesian Linear Regression. These algorithms were considered for regression applicability, prediction power evaluation and scalability in high-dimensional data.

Another reason for these algorithms is the ability to fit the application in the matter of Data type and volume, needed prediction interval, and historical availability. Data were normalized for the Bayesian linear Regression and the neural Network models to avoid overfitting issues.

The development environment is Microsoft Azure machine learning platform where input dataset was divided using the 60-20-20% train-test-evaluate ratio. To tune the model hyperparameter, the adopted parameter sweeping mode was random with 50 runs as a maximum number for cost computation optimization and increasing efficiency.

The following settings were found to be best under the required conditions after examining numerous alternative possibilities inside the hyperparameter sweeping for the models. The chosen regularization weight of the Bayesian Linear was 1. Poisson Regression model sweeps results showed an optimization tolerance of 3e-06, a L1Weight of 0.023, a L2 weight of 0.106 and a memory Size of 44. By the same token, the neural network algorithm learning rate of 0.01 proved to be fit to de dataset while the Loss function and the number of iterations were varying according to the component as listed in Table1.

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Last, Random Forest was set to a bagging resampling method, 8 decision trees with 128 as the number of random splits per node.

**TABLE II**
**ANN REGRESSION HYPERPARAMETERS SWEEP RESULTS**

| Component | LossFunction | Iterations number |
|---|---|---|
| Comp1 | CrossEntropy | 464 |
| Comp2 | CrossEntropy | 493 |
| Comp3 | CrossEntropy | 498 |
| | SquaredError | 494 |
| Comp4 | CrossEntropy | 499 |
| | CrossEntropy | 472 |
| Comp5 | CrossEntropy | 473 |
| Comp6 | CrossEntropy | 462 |

After evaluating the most extensively used ML algorithms for signal-based predictive maintenance, the precision calculation must be highlighted to assess the algorithm. Several metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R-squared ($R^2$) were used to evaluate the model.

MAE determines how well forecasts match actual results. To avoid negative and positive residuals canceling each other out, the average error is calculated by taking the average of all residuals. MAE is defined by Eq. 1, where the symbol $\hat{y}_t$ denotes the predicted value of the models and the actual value of the test dataset is denoted by the symbol $y_t$.

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|y_t - \hat{y}_t| \qquad (1)$$

For the prediction accuracy evaluation, the RMSE is a single value that summarizes the model's Error. The RMSE ignores over and under prediction through difference squaring, as shown by Eq.2.

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)} \qquad (2)$$

$R^2$ measures the model's ability to predict and ranges from 0 to 1. $R^2$ denotes the model's attribute variability minimization. In contrast to the MAE measure, a higher $R^2$ value indicates a better overall fit for the model. $R^2$ is defined as follows, as seen in Eq. 3.

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{n}(y_t - \frac{1}{n}\sum_{t=1}^{n} y_t)^2} \qquad (3)$$

## III. RESULTS AND DISCUSSION

In this section, the models training results are presented and discussed. The evaluation metrics of each Machine learning model are grouped in TABLE III. For a better interpretation, figure 4 enables the comparison of components' $R^2$ measure. As a result, the best performance was obtained using Random Forest model with a $R^2$ score of at least 0.9176(comp 4 for RUL to greasing failure) and at most 0.9903 (comp 3 for RUL to alignment failure). By contrast, the neural network model, recorded different ratings for each instance. This model demonstrated outstanding performance in Alignment failure in components 3 and 4 vs components 1 and 2, where the precision did not surpass 0.56 $R^2$. Regarding the linear regression models, Poisson Regression and Bayesian Linear Regression showed a poor performance not exceeding $R^2$ of 0.3354, specially for RUL to greasing related failure of components 5 and 6.


FIGURE 4 ML MODELS R-SQUARED SCORE COMPARISON OF THE JAW CRUSHER COMPONENTS

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TABLE III
MACHINE LEARNING REGRESSION MODELS METRICS

| Component | Default | Algorithm | MAE | RMSE | $R^2$ |
|---|---|---|---|---|---|
| Comp1 | Alignment | Bayesian Linear Regression | 0.6973 | 0.8653 | 0.2596 |
| | | Poisson Regression | 290.8621 | 363.7549 | 0.2772 |
| | | Neural Network Regression | 0.4961 | 0.6678 | 0.5589 |
| | | Random Forest Regression | 30.8548 | 104.4739 | 0.9404 |
| Comp2 | Alignment | Bayesian Linear Regression | 0.6678 | 0.8169 | 0.3354 |
| | | Poisson Regression | 288.8864 | 350.1983 | 0.3411 |
| | | Neural Network Regression | 0.4984 | 0.6677 | 0.5560 |
| | | Random Forest Regression | 29.5879 | 68.1115 | 0.9751 |
| Comp3 | Greasing | Bayesian Linear Regression | 0.7755 | 0.9228 | 0.1300 |
| | | Poisson Regression | 181.8412 | 228.6540 | 0.4260 |
| | | Neural Network Regression | 0.3243 | 0.4990 | 0.7225 |
| | | Random Forest Regression | 21.1459 | 60.9879 | 0.9626 |
| | Alignment | Bayesian Linear Regression | 0.7435 | 0.9114 | 0.1890 |
| | | Poisson Regression | 452.7349 | 559.3382 | 0.1732 |
| | | Neural Network Regression | 0.0208 | 0.0521 | 0.9973 |
| | | Random Forest Regression | 11.8345 | 61.6702 | 0.9903 |
| Comp4 | Greasing | Bayesian Linear Regression | 0.7708 | 0.9119 | 0.1504 |
| | | Poisson Regression | 232.3633 | 278.2426 | 0.1500 |
| | | Neural Network Regression | 0.2425 | 0.4307 | 0.7933 |
| | | Random Forest Regression | 23.8209 | 90.4781 | 0.9176 |
| | Alignment | Bayesian Linear Regression | 0.7352 | 0.9104 | 0.1908 |
| | | Poisson Regression | 474.1094 | 605.8081 | 0.0653 |
| | | Neural Network Regression | 0.0171 | 0.0406 | 0.9983 |
| | | Random Forest Regression | 14.0363 | 72.2812 | 0.9867 |
| Comp5 | Greasing | Bayesian Linear Regression | 0.7775 | 0.9365 | 0.1263 |
| | | Poisson Regression | 278.3077 | 335.3647 | 0.1420 |
| | | Neural Network Regression | 0.3222 | 0.4914 | 0.7553 |
| | | Random Forest Regression | 19.6136 | 60.5517 | 0.9720 |
| Comp6 | Greasing | Bayesian Linear Regression | 0.8160 | 0.9727 | 0.0575 |
| | | Poisson Regression | 294.7092 | 351.6171 | 0.0568 |
| | | Neural Network Regression | 0.2885 | 0.4474 | 0.7971 |
| | | Random Forest Regression | 21.7020 | 62.1571 | 0.9705 |

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Figures 5, 6, 7, 8, 9, 10, and 11 illustrate the comparison of the models' performance using randomly picked data points from the evaluation set (20% of the original Data). It is obvious on the figures that the results obtained by Random Forest model followed by Neural Network Regression are the closest predictions to the actual values.

Due to the non-linear nature of the crusher model, the linear regression techniques performed badly. These algorithms failed to detect any variation in the data and could not outperform forecasting the sample dataset's mean RUL.

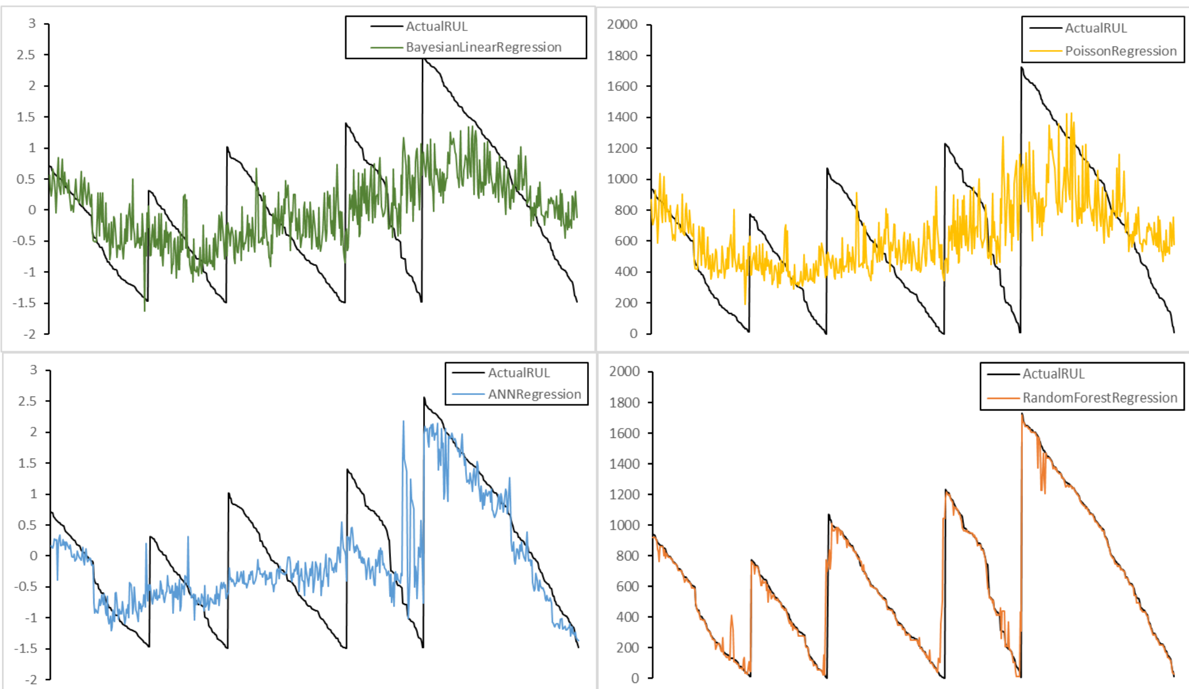


**FIGURE 5 : COMP1 ACTUAL RUL TO ALIGNMENT DEFAULT VS PREDICTIONS (A) BAYESIAN LINEAR REGRESSION (B) POISSON REGRESSION (C) ANN REGRESSION (D) RANDOM FOREST REGRESSION**

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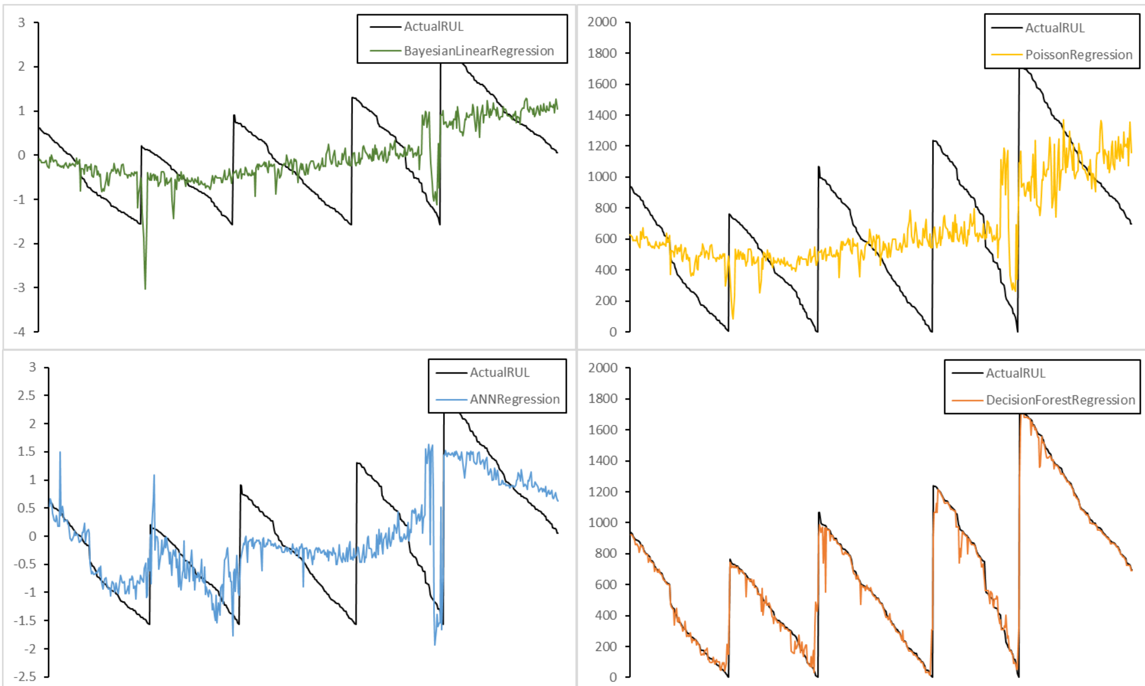


**FIGURE 6: COMP2 ACTUAL RUL TO ALIGNMENT DEFAULT VS PREDICTIONS (A) BAYESIAN LINEAR REGRESSION (B) POISSON REGRESSION (C) ANN REGRESSION (D) RANDOM FOREST REGRESSION**

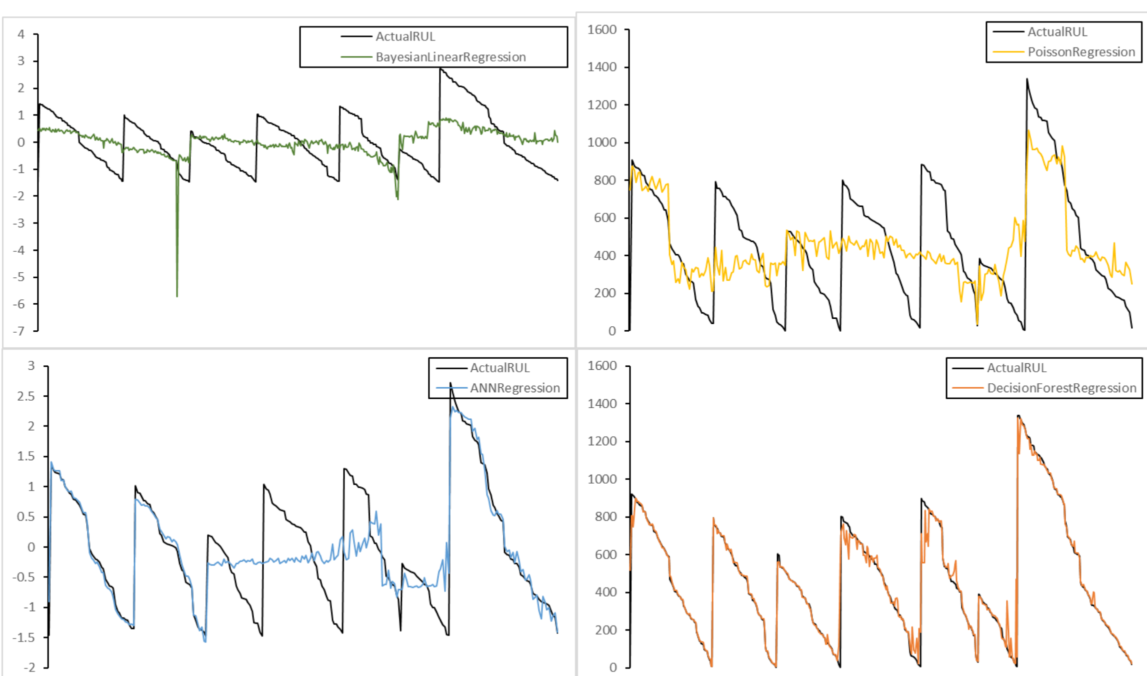


**FIGURE 7: COMP3 ACTUAL RUL TO GREASING DEFAULT VS PREDICTIONS (A) BAYESIAN LINEAR REGRESSION (B) POISSON REGRESSION (C) ANN REGRESSION (D) RANDOM FOREST REGRESSION**

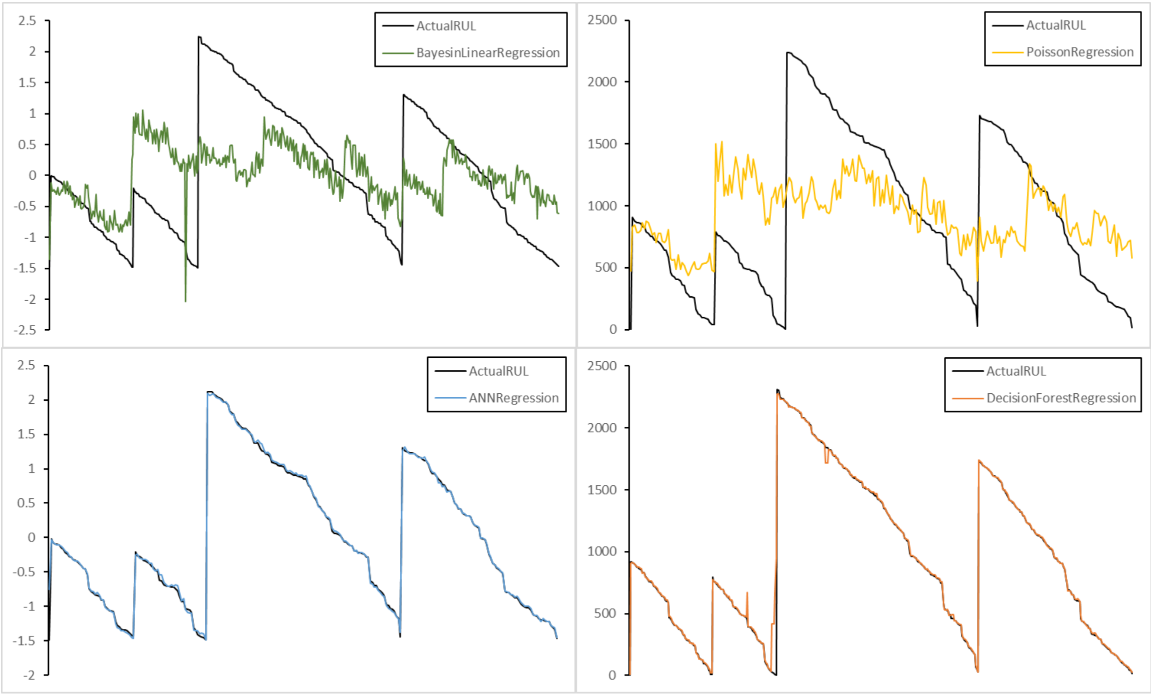


**FIGURE 8: COMP3 ACTUAL RUL TO ALIGNMENT DEFAULT VS PREDICTIONS (A) BAYESIAN LINEAR REGRESSION (B) POISSON REGRESSION (C) ANN REGRESSION (D) RANDOM FOREST REGRESSION**

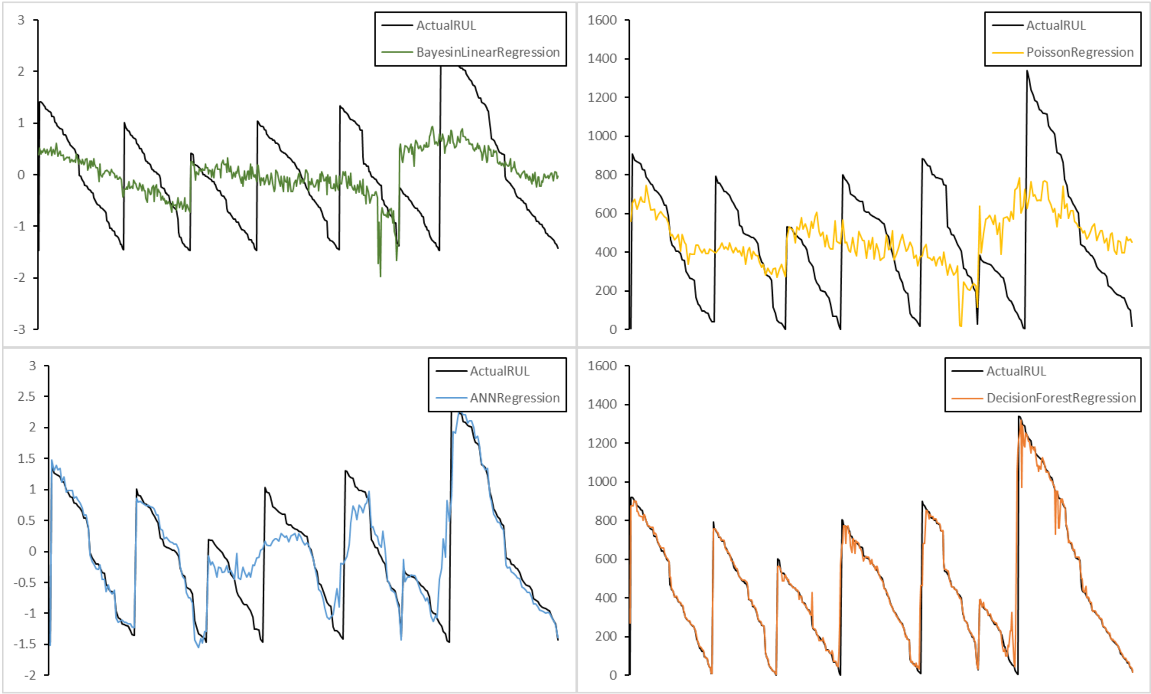


**FIGURE 9: COMP4 ACTUAL RUL TO GREASING DEFAULT VS PREDICTIONS (A) BAYESIAN LINEAR REGRESSION (B) POISSON REGRESSION (C) ANN REGRESSION (D) RANDOM FOREST REGRESSION**

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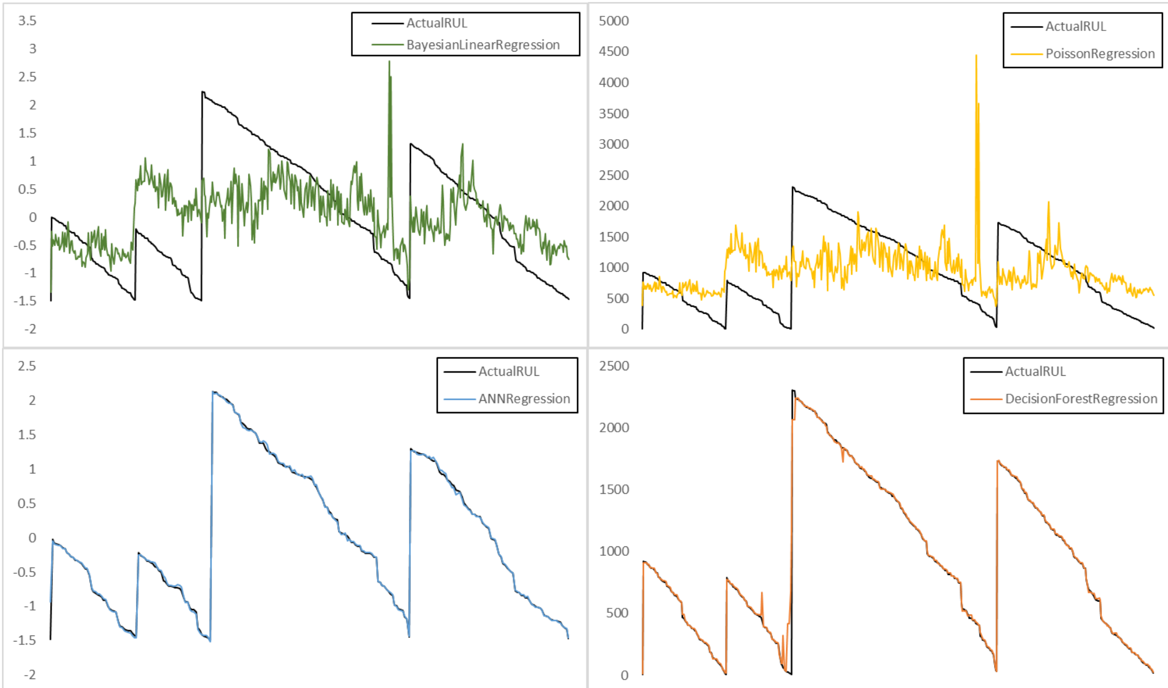


FIGURE 10: COMP4 ACTUAL RUL TO ALIGNMENT DEFAULT VS PREDICTIONS (A) BAYESIAN LINEAR REGRESSION (B) POISSON REGRESSION (C) ANN REGRESSION (D) RANDOM FOREST REGRESSION

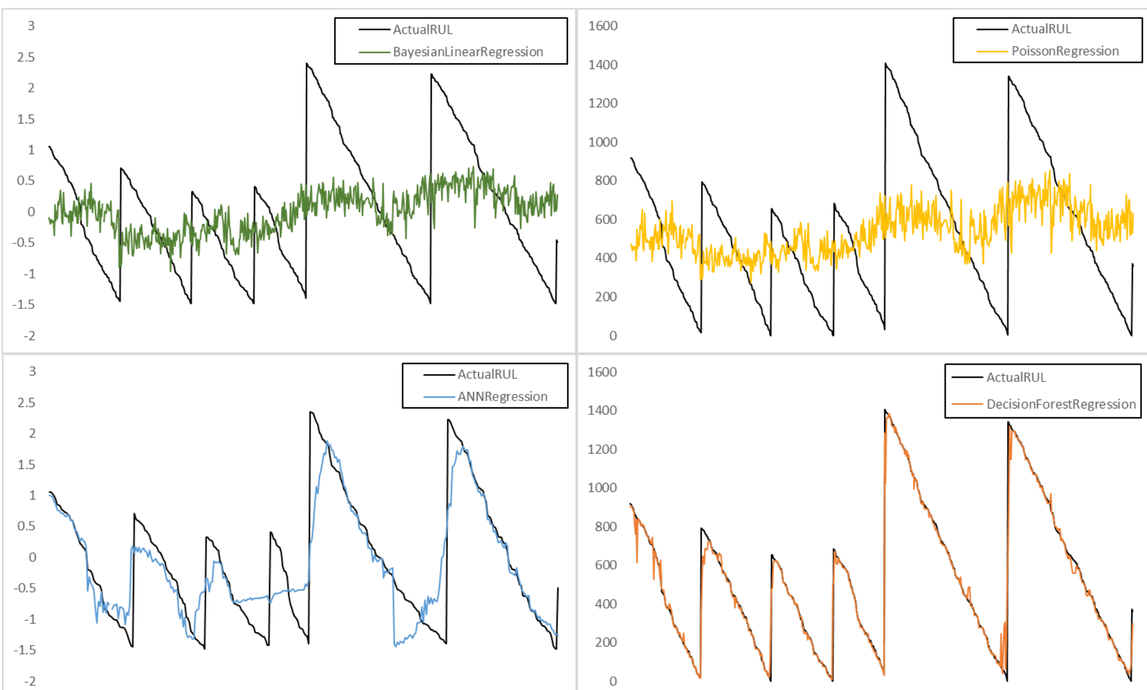


FIGURE 11:COMP5 ACTUAL RUL TO GREASING DEFAULT VS PREDICTIONS (A) BAYESIAN LINEAR REGRESSION (B) POISSON REGRESSION (C) ANN REGRESSION (D) RANDOM FOREST REGRESSION

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EXPLORING RESEARCH AND INNOVATIONS

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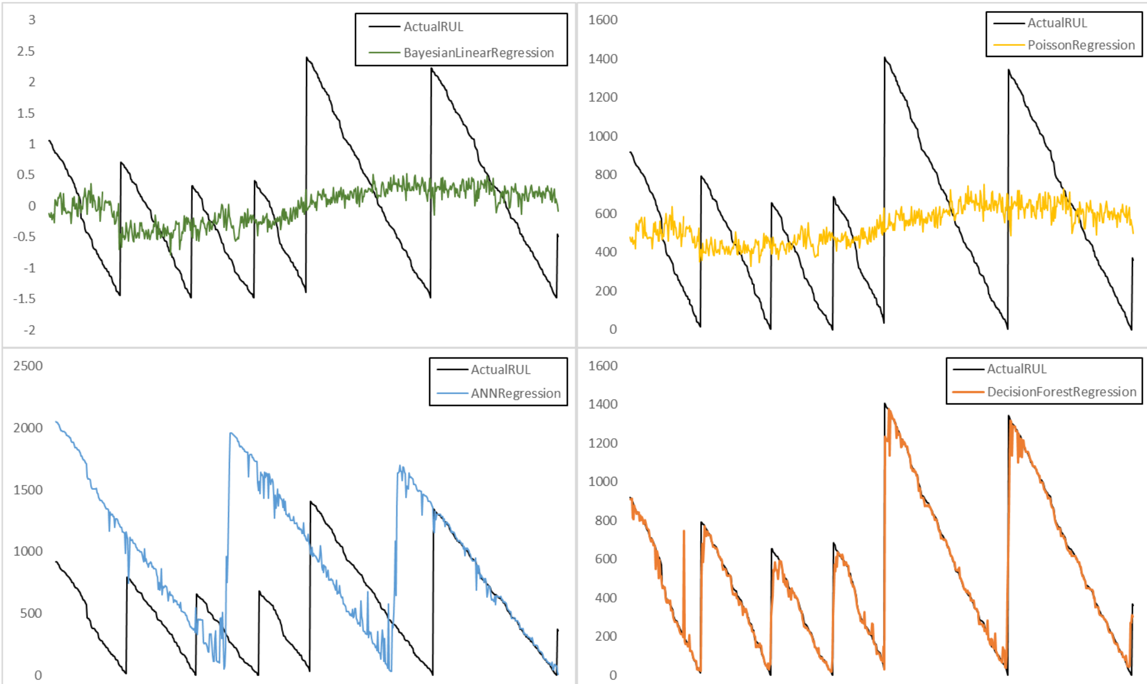


**FIGURE 12: COMP6 ACTUAL RUL TO GREASING DEFAULT VS PREDICTIONS (A) BAYESIAN LINEAR REGRESSION (B) POISSON REGRESSION (C) ANN REGRESSION (D) RANDOM FOREST REGRESSION**

Different machine learning models were investigated to test the approach performance in the RUL prediction. The machine learning techniques are employed because of their applicability and cost effectiveness.

The findings confirmed the literature affirmation showing that models built using Random Forest performed better than those built using just the Neural Network Regressor and Linear Regression algorithms [10] despite the applied data normalization and the hyperparameters tuning attempts.

Thus far, this research has added to the literature on developing machine learning models based on actual data gathered from installed intelligent sensors on the complex Jaw crusher machine. Additionally, this machine learning approach is used in the ore mining industry, where there has not yet been a similar application. It is commonly known that the ore mining industry is a harsh environment where old-fashioned practices are preferred, such as running to failure. Corrective Maintenance activities inflict additional and unexpected costs. The impact is further huge in the case of continuous process production industries as assets are influenced and the production plan.

Another traditional maintenance approach is periodic maintenance ahead of planned maintenance based on the manufacturer's recommendations which do not prevent late interventions. The gap lies in the inability to consider the totality of the production chain and underestimating the system's complexity.

So, this work's motivation consists of performing prognosis using diagnosis data to fulfill the PdM process. It is also crucial to emphasize that this artificial intelligence method was developed using accurate data, making it scalable and effective in the field of significant amounts of data. One should not deny this approach's important role in investing more in IoT sensors implementation serving predictive maintenance and other production-oriented purposes. Conversely, the race to implement digital transformation has promoted the usage of IoT platforms to deliver real-time data for preventative maintenance. It is the case of this study where Data from rotating parts of the jaw crusher are delivered to forecast the system's right intervention time. This strategy aim is to enhance assets and production continuity and quality.

Regardless, this study was limited as the data were collected from only one machine. Nonetheless, this machine's rotating and other equipment parts are alike, making this approach possible to generalize over fixed installations. Furthermore, such a system could also be implemented in other ore mining fixed installations. Due to the rarity of the other failure categories, the RUL prediction could only accurately anticipate two types of failure: greasing and alignment. However, this approach could be customized with minor modifications to fit new rotating machines applications datasets.

## IV. Conclusion And Perspectives

In this paper, Machine learning models were developed for estimating the RUL of a previous fault diagnosis case study of an ore mining industry equipment based on IoT sensors data and diagnosis reports. According to the maintenance reports, only alignment and greasing related failures were fixed at the study's data acquisition time range. As a result, each component's remaining useful life for the two failures was anticipated. Thus, Bayesian Linear Regression, Poisson Regression, Neural Network Regression and Random Forest algorithms were evaluated in the context of this work using the Microsoft Azure ML Studio. To meet this objective Data was preprocessed by removing records during the jaw crusher downtime. As well as that, each component was treated individually. Components Datasets were normalized and went through hyperparameter tuning processes in the case of Neural Network and Poisson Regression to improve their performances. Afterward, Data were split into training test and evaluation sets. Random Forest outperformed other algorithms with an average $R^2$ of 0.96 followed by Neural Network with an average score of 0.78 $R^2$. Unlikely, Linear Regression algorithms techniques were found to be insufficient in this scenario due to the nonlinearity of the data. Machine learning (ML) approaches have mostly been incorporated into data-driven initiatives. They require less historical data, are simpler and less expensive, and are more relevant while offering a compromise between complexity, cost, precision, and application [18].

This study would contribute to the body of literature in the context of the ore mining sector digital transformation because big data analytics will be a crucial foundation for forecasting manufacture, the fleet of machines, and preventive maintenance [9].

Authors plan to extend work on other failure types. In addition, there is an ambition to develop and redefine spare parts acquisition strategy and optimize maintenance activities by incorporating Predictive maintenance into the mining facilities. This goal will enable us to fulfill the specifications listed in the modeling of the authors' PdMSys, a predictive maintenance system for mining facilities[19].

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