Data-Driven Remaining Useful Life Estimation Approach for Neutron Generators in Multifunction Logging-While-Drilling Service

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ABSTRACT

This paper introduces a data-driven approach for estimating the remaining useful life of the neutron generator component in logging-while-drilling tools. The approach builds on identification of the incipient failure modes of the neutron generator and constructing a health indicator that serves as a statistical representation of the component's deterioration over time. Afterwards, a K-nearest neighbors algorithm is trained to establish the relationship between the extracted health indicator values and the corresponding remaining useful life. The effectiveness of the presented approach is verified through the utilization of real-world data gathered from oil well drilling operations. The study is part of a long term project aimed at developing a digital fleet management system for drilling tools.

1. INTRODUCTION

The multifunction logging-while-drilling (LWD) tool shown in Fig. 1 is an industry-leading formation evaluation technology developed for oil well drilling applications (SLB, 2023).

Figure 1. Multifunction LWD service

During the drilling operations, this LWD tool collects information related to formation evaluation as well as equipment diagnostics, and some of this information is transmitted in real time via mud pulses, depending on the operational requirements. The full quantity of raw information is stored in a memory board for additional analysis upon the tool returning to surface after completing drilling operations.

This multifunction LWD tool integrates functionalities that were previously achieved by two or three LWD tools, resulting in significantly reduced drilling rig operating time, fewer electrical and communication failures due to physical tool-to-tool connections, and improved geological data quality from simultaneous and co-located measurements.

One of the other critical factors that places the technology ahead of all other competitors is the inclusion of a pulsed neutron generator (PNG), as shown in Fig. 2. The PNG is an electron neutron generator that produces high-energy neutrons five times higher in energy than conventional americium-beryllium chemical sources. The PNG produces neutrons by particle fusion reaction. Multiple security locking logic has been added to the PNG firmware and hardware and is contained in operation manuals, making the use and transportation of the PNG safe. The high-energy neutron emission also allows for a variety of additional and advanced formation measurements for the customer.

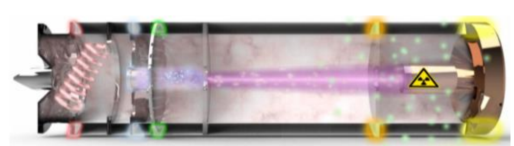

Figure 2. Pulsed neutron generator

The electrical and physical complexity of the PNG system makes it very demanding for a technician to become proficient in maintaining and troubleshooting the system and a failure of analysis would potentially result in critical field operation failures and jeopardize the company's reputation. Therefore, developing an automated fault diagnosis and degradation assessment tool to determine the health status of PNGs accurately and consistently is essential. This assessment tool can significantly reduce the potential for human error and enable users to make efficient and effective decisions (Zhan, Ahmad, Heuermann-Kuehn, & Baumann, 2010) (Isermann, 2006). This paper will focus on building data-driven remaining useful life estimation (RUL) for PNG systems, so appropriate actions can be taken for preventative replacement of the asset. The novelty and academic contributions of this study are highlighted by the fact that there has been no prior work related to RUL prediction for PNG systems, making this research a pioneering effort in the field.

The next section of this paper provides a detailed overview of the PNG system and discusses previous work and research relevant to this study. Research problem is formulated in the following section. The next two sections present the modeling approach and experimental results, respectively. A conclusions section completes the paper.

2. Pulsed Neutron Generator System

2.1. Description

For many years, the oil and gas industry has employed high-energy neutron generators in neutron-gamma-ray or neutron-neutron logging (Tittle, 1961). These generators offer several advantages over conventional chemical sources, including the ability to deactivate the PNG and eliminate radiation risks when not in use downhole. Additionally, the generators enable precise control over neutron output, facilitating more accurate measurements of formation properties.

In the field of nuclear well logging, achieving accurate formation measurements hinges on emitting neutron pulses to irradiate the Earth's formations and detecting the resulting radiation from the interaction between the Earth's formation atoms and the emitted neutrons. Understanding the characteristics of the neutron pulse, including its output and timing, is crucial for achieving precision. Ideally, the neutron pulse should exhibit a substantially square wave shape. The PNG, depicted in Fig. 3, proves instrumental in overcoming these technical challenges and facilitating the generation of desirable neutron pulses. Serving as a stand-alone particle accelerator, the PNG utilizes fusion reactions to produce neutrons.

Conducting a failure investigation and root cause analysis revealed two major failure modes of the PNG:

1. Internal cathode wire discontinuity due to overheating
2. Reduced neutron generation flux due to doped target wear

These failure modes can potentially compromise the functionality of the PNG and even lead to the failure of the LWD tool.

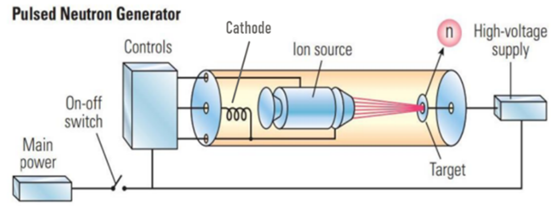

Figure 3. PNG architecture

2.2. Previous Work and Research

In prior research, a data-driven fault detection model for the PNG subsystem was introduced (Mosallam, Laval, Youssef, Fulton, & Viassolo, 2018). This approach involved creating a univariate representation known as a health indicator (HI). Subsequently, a classifier utilizing the decision tree method was trained to distinguish healthy and failed runs of PNGs. The method demonstrated high accuracy, providing quick and precise assessment for maintenance and field engineers.

Following that, a data-driven fault diagnostics method for the PNG system was introduced, specifically focusing on the detection of failures associated with the power supply boards (Mosallam, Kang, Youssef, Laval, & Fulton, 2023). This work complements the previously published fault detection model for the PNG subsystem (Mosallam et al., 2018) by providing detailed information indicating which electronic board or boards failed. The method extracts features from data channels capturing fault symptoms and builds support vector classifier models for each board. Experimental results showed an average accuracy of about 99% for all boards, reducing troubleshooting time and enabling automatic triggering of maintenance procedures for faulty boards.

The latest publication concentrated on the data-driven degradation modeling of the PNG system, emphasizing one of its incipient failure modes (Mosallam, Youssef, et al., 2023). The method extracts HI values from data channels quantifying component health degradation utilizing a random forest classification model. Experimental results demonstrate an average accuracy of 90.4%. The algorithm enables the identification of degradation stage of the PNG, empowering better planning for the equipment usage and avoidance of the failure during downhole operations.

However, in order to foster decision-making even more precisely, the necessity for a RUL estimation persists. This paper focuses on predicting the reduction of neutron generation flux due to doped target wear over time and determining the remaining useful time of the system. Integrating RUL estimation will enable proactive maintenance planning, better decision-making on well sites, and future manufacturing forecasts and equipment delivery optimization based on worldwide RUL of active PNGs.

3. Problem Formulation

The main objective of prognostics is to minimize the equipment or system downtime by forecasting the RUL of the system (or critical components of the system), as shown in Fig. 4. The RUL prediction methods can be broadly classified into three categories: physics model based, data-driven, and hybrid (Medjaher, Tobon-Mejia, & Zerhouni, 2012)(Lei et al., 2018). Physics model based methods use mathematical models to describe the system's or component's physical behavior and predict its RUL. Although these methods require a deep understanding of the failure mechanisms and effective estimation of model parameters, they can provide accurate RUL estimation. On the other hand, data-driven methods use pattern recognition algorithms to learn patterns from historical data and make RUL predictions. The data-driven methods do not require a comprehensive understanding of the system failures but require high-quality data. Hybrid methods combine the strengths of both methods to improve RUL predictions.

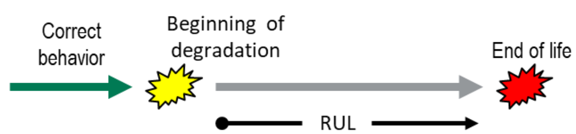

Figure 4. RUL forecast schematic

The PNG system being studied is highly complex, which limits the use of physics model-based and hybrid methods for predicting the PNG's (or PNG component's) RUL. Thus, the goal is to create a data-driven prognostic model that incorporates data related to the incipient failure modes of the PNG target. This model will estimate the target's RUL along with its confidence level as shown in Fig. 5.

There are two primary methods for building data-driven prognostic models: direct RUL mapping and cumulative degradation prognostics (Mosallam, Medjaher, & Zerhouni, 2016). The direct RUL mapping approach uses empirical models to directly correlate sensor data with the end of life (EOL) value, eliminating the need to determine the health status of the monitored component (see Fig. 6).

In contrast, the cumulative degradation prognostics approach uses empirical models to describe the system's degradation progression. This degradation information can then be used to estimate the health status of the system and predict the RUL based on the system's expected future behavior (see Fig. 7).

This study introduces a novel approach for predicting RUL using the direct RUL mapping approach. The primary objective is to establish a model that effectively captures the correlation between sensor measurements and end-of-life states, thereby enabling RUL prediction without relying on predefined alarm thresholds. Predefined alarm thresholds do not effectively capture the correlation between sensor measurements and EOL states, which can lead to less accurate predictions of RUL. The proposed method builds on the extraction of health indicators from historical training data, which serve as foundational reference models. Upon encountering new data, the approach employs a K-nearest neighbors (KNN) classifier to identify the most closely resembling HI within the database, subsequently leveraging it as a reliable RUL predictor.

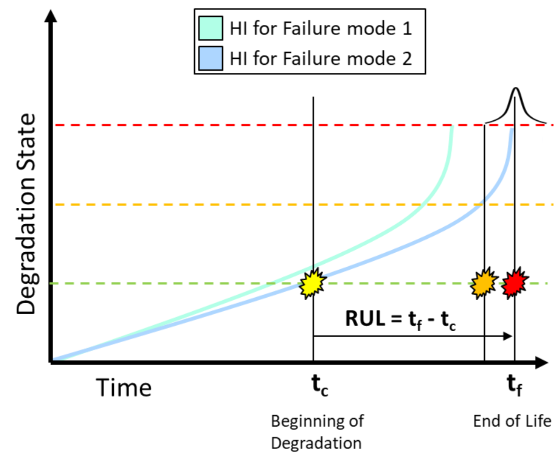

Figure 5. HIs for a system with two different failure modes

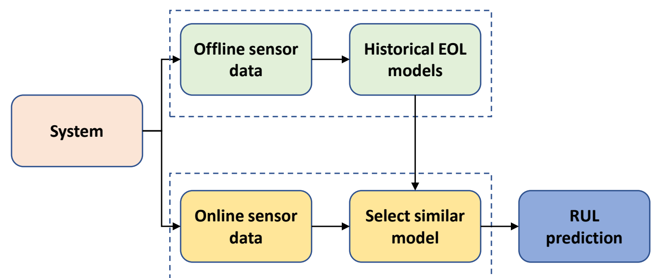

Figure 6. Direct RUL mapping approach

4. Proposed Method

The objective of the proposed method is to construct an HI based on sensor data that efficiently captures the PNG deterioration information. The HI values with RUL assignment are then modeled using a machine learning algorithm, which can estimate the RUL of the PNG. The proposed method is divided into four main steps: channel selection, preprocessing, HI construction, and modeling.

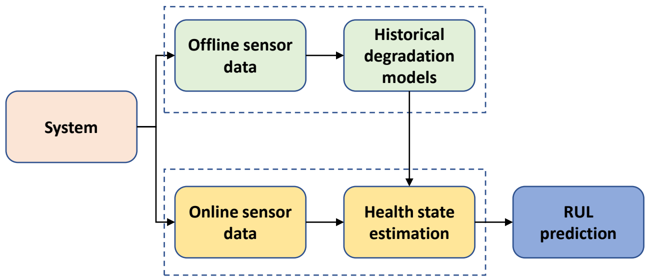

Figure 7. Cumulative degradation approach

4.1. Channel Selection

As highlighted in Section 1, the LWD tool generates a substantial number of high-resolution data channels during each drilling operation, leading to millions of data points. However, not all of these channels contribute information pertaining to the degradation of PNG over time. Enhancing the efficiency and precision of the HI involves the removal of irrelevant data channels. The selection of pertinent data channels relies on the expertise of subject matter experts with domain knowledge in nuclear physics and instrumentation. This process is crucial for optimizing the relevance of the data considered for the HI.

For the target failure mode, the following two data channels were selected:

- BLD: The internal high voltage in the PNG's minitron that enables the particles' acceleration to the target. The higher the BLD, the better the fusion reaction.
- BEAM: The particle beam current. The higher the BEAM, the higher the neutron emission.

Raw data for BLD and BEAM channels are presented in Fig. 8. The HI will be constructed using the data from the channels after the preprocessing step that will be described in the upcoming subsection. Note that the duration of each run is different according to the drilling job requirements, and the data of the sixth and eighth run before EOL are missing.

4.2. Preprocessing

The LWD data acquisition system commences recording data as soon as a field engineer initializes it for the forthcoming drilling operation (or run). The LWD tool follows the subsequent steps:

1. Tool initialization: the field engineer configures the acquisition parameters for the upcoming job, formats the tool memory, and begins the tool recording.
2. Shallow hole test: the field engineer confirms that the tool is functioning as expected inside the well before deploying the tool to the full well depth.

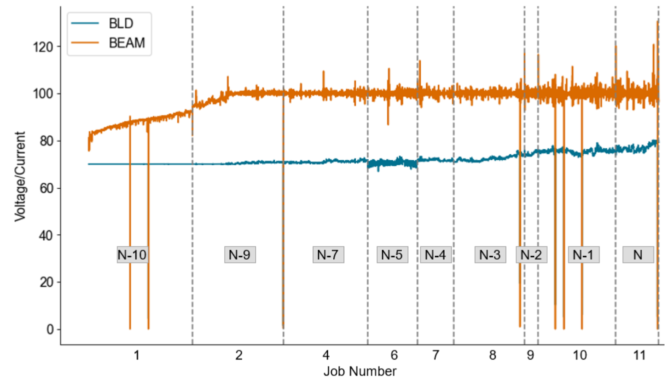

Figure 8. Raw data of the selected channels of eleven consecutive runs before EOL, where N denotes the last run, N-1 denotes the first run before EOL, N-2 denotes the second run before EOL, and so on.

3. Casing logging for caliper calibration: The field engineer calibrates the tool's ultrasonic measurement by using the known internal diameter of the metal casing connecting the rig to the wellbore and the known drilling fluid properties.
4. Drilling operation: The field engineer places the tool behind the drill bit for measurement acquisition during the physical drilling of the well.

For each run, the data collected during the initial three steps lack information pertaining to PNG degradation and are consequently excluded. Additionally, during periods when the PNG does not fire, the firmware generates dummy records to fill data channel gaps, known as missing values. All missing values must be disregarded as they do not provide any insights into faults. The duration of each drilling job varies. Let T represent the duration of a given drilling job. Consequently, the next step is undertaken to facilitate the extraction of a consistent statistical representation of the signal. Each time series of BLD and BEAM, denoted as

$$X = [x_1, \ldots, x_T]$$

and

$$Y = [y_1, \ldots, y_T]$$

respectively, generated throughout the run is segmented into $N = 200$ windows, determining the window size based on the duration of the run

$$w = \left\lfloor \frac{T}{N-1} \right\rfloor,$$

where each of $1, \ldots, N-1$ windows are of window size w and the last window is of a size $T \mod N-1$. Within each of 200 windows the minimal mode of each channel is extracted. To define the process of extracting the minimal mode, the function $g(Z)$ is denoted as the minimum of the mode of

Z, and is expressed as:

$$g(Z) = \min(\text{mode}(Z)).$$

For BLD channel, the minimal mode is extracted as follows:

$$x'_{i+1} = \begin{cases} g([x_{iw+1}, \ldots, x_{(i+1)w}]), & \text{if } i \in \{0, \ldots, N-2\} \\ g([x_{iw+1}, \ldots, x_T]), & \text{if } i = N-1 \end{cases}$$

resulting in

$$X' = [x'_1, \ldots, x'_N].$$

The same process is applied to BEAM channel, with the formula given by:

$$y'_{i+1} = \begin{cases} g([y_{iw+1}, \ldots, y_{(i+1)w}]), & \text{if } i \in \{0, \ldots, N-2\} \\ g([y_{iw+1}, \ldots, y_T]), & \text{if } i = N-1 \end{cases}$$

resulting in

$$Y' = [y'_1, \ldots, y'_N].$$

Finally, a median filter is applied to the sequence X' and Y' to smooth the signals, with $\tilde{X}$ and $\tilde{Y}$ denoting the smoothed X' and Y', respectively. Fig. 9 presents the raw signals of BLD and BEAM shown in Fig. 8 after preprocessing.

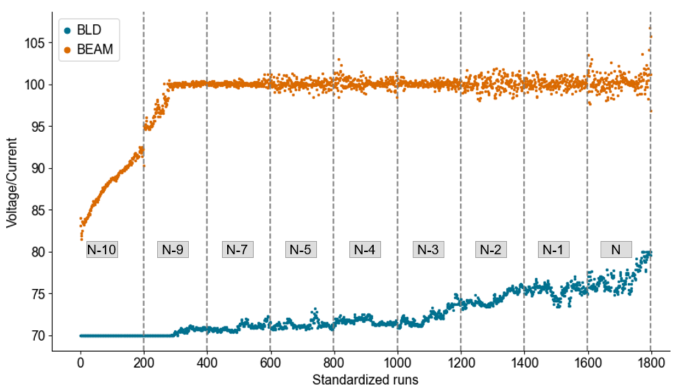

Figure 9. Preprocessed BLD and BEAM signals

4.3. Health Indicator Construction

In this algorithm step, an HI is constructed using the preprocessed data. The main objective of deriving this HI is to represent the system's degradation in a 1D array format. The HI is extracted as a result of element-wise addition of the preprocessed BLD and BEAM signals, which can be represented by the formula

$$HI = \tilde{X} + \tilde{Y}.$$

The decision to extract the HI by summing two channels comes from the fact that this approach ensures the HI has several key characteristics necessary for effectively monitoring health status of the PNG. These include sensitivity to degradation, monotonicity, predictive power, noise robustness, and consistency across conditions. Additionally, this method is computationally efficient and easily interpretable. Fig. 10 presents the HI values constructed using the Fig. 9 example data.

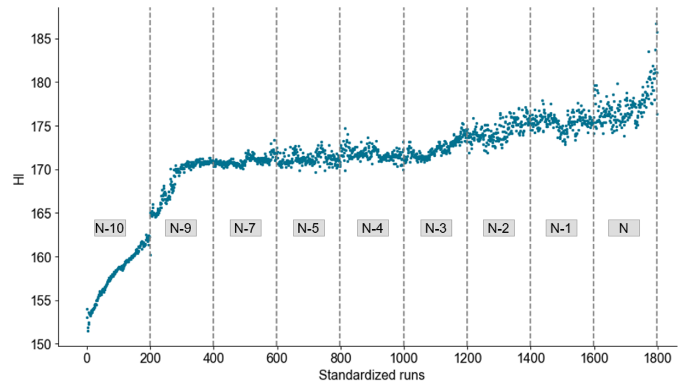

Figure 10. Constructed HI

It is important to highlight that the input data utilized reflects the incipient failure mode. Consequently, the resulting HI acts as a numerical gauge of the system's condition in a monotonic manner. Put simply, the HI offers a numerical representation of the system's health, enabling further analysis or decision-making processes.

4.4. Modeling

The HI constructed from the data collected during each drilling job results in 1D array representation, independent of the actual run duration. Thus, the RUL estimation problem can be converted into a regression problem if the array of each run has RUL assigned. To accomplish that, the usage of the PNG in hours estimated for each run is used, and respectively summed up over a lifespan. The formula for the RUL assignment is the following:

$$RUL_t = EOL - t, \forall EOL > t, \tag{1}$$

where t is the current time. The RUL labels serve as a target variable for each run. Specifically, this paper uses a KNN classifier to establish the relationship between the input HI values and their corresponding RUL i.e., $RUL_t = f(X_t)$, where

$$X_t = [x_{1,t}, x_{2,t}, ...x_{200,t}] \tag{2}$$

5. Experimental Results

A dataset containing operational data from 89 different LWD tool runs in different locations was collected to validate the proposed method. The dataset consists of historical runs from 16 different PNGs that reached the EOL. However, each PNG can operate different number of runs and the data availability highly varies between the PNGs. As mentioned in Section 2.2, in the previous work, the health state estimation model was developed (Mosallam, Youssef, et al., 2023). This algorithm is applied for the PNG and enables distinguishing five degradation states: healthy, lightly degraded, moderately degraded, severely degraded and EOL. The dataset utilized for estimating the RUL differs from that used in previous studies, primarily due to an increased number of EOL cases captured in the current research. Previously, without a health state estimation model, the usage of the PNG until late stages of degradation was scarcely feasible, rendering RUL estimation impossible at that time. It is important to note that the main focus of this work is to predict the RUL when the PNG's degradation has already started, ad therefore, we train the model only from a certain degradation state. The RUL estimation is thus performed for the four stages of the PNG degradation being lightly degraded, moderately degraded, severely degraded or reaching EOL.

To assess the performance of the proposed method, the mean absolute percentage error (MAPE) evaluation metric is calculated. Let RUL_i be the actual remaining useful life and RUL_i^* be the predicted remaining useful life for $i = 1, \ldots, n$ where n is the total number of runs performed by all PNGs. The MAPE is defined as follows:

$$MAPE(\%) = \frac{100\%}{n} \cdot \sum_{i=1}^{n} \left| \frac{RUL_i - RUL_i^*}{RUL_i} \right| \qquad (3)$$

To assess and compare the performance of the models, as well as to validate their ability to generalize the learned patterns, the dataset was split into a training set of 14 PNGs corresponding to 75 runs, and a test set of 2 PNGs resulting in 14 runs. Additionally, a specialized form of k-fold cross-validation is employed in the training phase. This method involves iterating through the PNGs, with each iteration leaving out one PNG for validation along with all its corresponding runs while training the model on the runs from the remaining $k - 1$ PNGs. This approach allows for efficient validation of how the model performs across various stages of PNG degradation, reducing the bias in performance estimation.

To select the best-performing model, two groups of algorithms were tested to estimate the RUL of the PNG: regressors and classifiers (Mosallam, 2014). The following algorithms were evaluated within each group: KNN, decision tree, random forest, and gradient boosting. Additionally, hyperparameter tuning was conducted to determine the best-performing algorithm.

The two best-performing algorithms: KNN and gradient boosting regressor (GBR) were selected for the further evaluation based on the overall MAPE presented in the Table 1. The selection of the single, most-suitable and best-performing algorithm is done based on both the MAPE overall and the MAPE calculated across various RUL intervals presented in Table 2. This approach ensures that the chosen model accurately predicts system behavior not only throughout its operational lifespan but also specifically as it approaches EOL conditions.

Table 1. MAPE of the LOOCV set for the trained algorithms

Algorithm name	**MAPE (%)**
K-Neighbors Classifier (K=2)	16.64 %
Gradient Boosting Regressor	17.26 %
K-Neighbors Classifier (K=3)	17.57 %
Random Forest Regressor	17.67 %
K-Neighbors Regressor (K=3)	17.78 %
K-Neighbors Regressor (K=2)	17.91 %
K-Neighbors Regressor (K=4)	18.40 %
K-Neighbors Classifier (K=4)	18.69 %
Random Forest Classifier	21.54 %
Decision Tree Classifier	21.92 %
Decision Tree Regressor	25.82 %
Gradient Boosting Classifier	30.18 %

Table 2. MAPE of the RUL intervals for the best performing algorithms

RUL interval	**GBR MAPE (%)**	**KNN MAPE (%)**
(0, 100]	26 %	13 %
(100, 200]	20 %	19 %
(200, 300]	16 %	20 %
(300, 400]	21 %	22 %
(400, 500]	8 %	11 %
(500, 600]	13 %	10 %
(600, 700]	6 %	5 %
(700, 800]	6 %	13 %

Taking into consideration the results of overall MAPE and MAPE calculated for the specified intervals, the KNN model outperforms other algorithms. The accuracy of prediction for the RUL in the interval $(0, 100]$ is significantly higher for KNN with $k = 2$, which is crucial as the PNG approaches the EOL. As previously stated, the objective is not solely to reduce the overall MAPE, but also to ensure the accuracy of predictions as the PNG approaches the end of its lifespan. The final phase of model validation involves training the model on the entire training set and evaluating its performance on the left-out test set. The MAPE for the test set is showcased in Table 3, confirming the consistent performance of both models.

Table 3. MAPE of the test set for the best-performing algorithms

Algorithm name	**MAPE (%)**
K-Neighbors Classifier (K=2)	16.24 %
Gradient Boosting Regressor	11.85 %

In conclusion, the KNN algorithm outperformed the GBR and other algorithms, as evidenced by the LOOCV outcomes and its superior accuracy in predicting the RUL of PNGs as they approach the end of their lifespans. Furthermore, the KNN algorithm demonstrated strong performance on the test set, and offers greater explainability than GBR due to its straightforward methodology and direct reliance on training data points. Therefore, this model got selected for the implementation. Fig. 11 presents the RUL estimated by KNN model for all the available runs for one of the PNGs, resulting in MAPE of 11.1%.

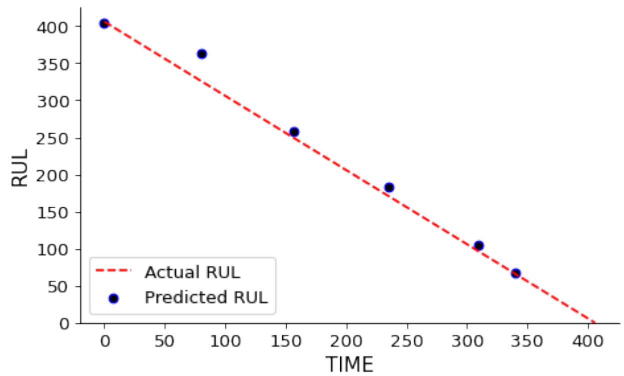

Figure 11. KNN prediction for selected PNG

6. Conclusions

This paper has presented a data-driven approach for RUL estimation of the PNG system in LWD tools. The method provides a quantitative measure of the component's deterioration by extracting the HI from BLD and BEAM data channels related to identified incipient failure mode of PNG. These HI values are used to build a KNN classification model to estimate the PNG RUL, which has been deployed as part of the health analyzer software for the LWD tool. Experimental results on actual operational data collected from the field resulted in the MAPE for LOOCV of 16.6%, and MAPE for the test set of 16.2%, demonstrating the effectiveness of the method. This method can assist maintenance engineers in promptly determining the PNG's remaining operational lifespan, reducing troubleshooting time; enable automatic triggers for maintenance activities for replacing faulty nuclear components; and improve decision making. Regarding future endeavors, there are intentions to address the second incipient failure mode of the PNG, with the aim of improving the prognostics model for the PNG.

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Biographies

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