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Data-Driven Multi-Failure Degradation Modeling for Neutron Generators in Logging-While-Drilling Service

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This article introduces an innovative, data-driven strategy for modeling the deterioration of the neutron generator component within logging-while-drilling tools. The research commences by identifying the initial failure modes of the neutron generator and creating a health indicator (HI) to quantify the component's health status. The derived HI can be employed for further analysis and decision-making. Subsequently, a decision tree classifier is trained to establish the connection between the obtained HI values and the corresponding degradation level labels. The proposed approach is verified using real data obtained from oil well drilling operations. The experimental findings affirm its efficacy in precisely categorizing the health condition of the neutron generator component. This study is part of a prolonged initiative aimed at developing a digital fleet management system for drilling tools.

Keywords: Prognostics, Health State Estimation, Oil and Gas, Nuclear Subsystems

1. Introduction

The multifunction logging-while-drilling (LWD) tool depicted in Fig. 1 represents a cutting-edge technology specifically designed for oil well drilling applications SLB (2023).

Fig. 1.: Multifunction LWD service

This versatile tool delivers an integrated set of functions, including formation evaluation, well placement, and drilling optimization measurements, all encapsulated within a single housing. Notably, it incorporates a crucial subsystem known as the pulsed neutron generator (PNG) as shown in Fig. 2, a self-contained particle accelerator employing fusion reactions to generate neutrons. The PNG eliminates the need for an americium-beryllium chemical source, reducing health and safety risks during transportation and well site operations, while also enabling diverse and advanced measurements for customers.

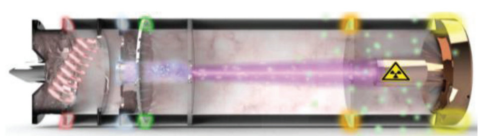

Fig. 2.: Pulsed neutron generator

During each drilling operation, the LWD tool collects a wealth of data, including drilling and formation information from clients and diagnostic data from original equipment manufacturers. This information is transmitted in real-time via mud pulses and stored in high-resolution on two built-in memory boards for additional analysis upon completion of drilling operations. Integrating functions from two or three LWD tools reduces drilling rig operating time, minimizes electrical and communication failures, and enhances geological data quality through simultaneous measurements.

However, the PNG, being a highly complex and sensitive device, must operate under harsh environmental conditions. The electrical and physical complexity of the tool introduces potential failure modes, some of which are challenging to reproduce at the maintenance base and may only manifest in extreme downhole environments. Furthermore, the intricacies of the PNG system make training technicians for proficient maintenance and troubleshooting a time-consuming and costly process. Field engineers often face decisions on whether to rerun the tool under time constraints when it must operate multiple times without returning to the maintenance base.

Given the essential role of the PNG and taking into consideration its complexity, the development of an automated health assessment tool is crucial to accurately and consistently determine the health status of PNGs and mitigate potential negative consequences. This assessment tool not only reduces the potential for human error but also empowers users to make efficient and effective decisions Zhan et al. (2010) Isermann (2006).

The subsequent part of this paper is dedicated to providing an overview of previous work and research pertaining to the PNG system. Subsequently, the paper will delve into a detailed examination of the PNG system and its incipient failure modes. Following this exploration, the next section will articulate the formulation of research problems. Subsequent sections will then proceed to discuss the degradation modeling approach and present the experimental results. The paper will conclude with a final section summarizing the key findings.

2. Pulsed Neutron Generator System: Previous Work and Research

In prior research, a data-driven fault detection model for the PNG subsystem was introduced Mosallam et al. (2018). This approach utilized a univariate representation known as a health indicator (HI) with a decision tree classifier trained to distinguish healthy and failed PNG runs.

Subsequently, a fault diagnostics method for the PNG system was developed, specifically targeting failures associated with power supply boards Mosallam et al. (2023). This work complemented the earlier fault detection model for the PNG subsystem Mosallam et al. (2018) by pinpointing which electronic board or boards failed. Features were extracted from data channels reflecting fault symptoms, and support vector classifier models were built for each board. Experimental results achieved an average accuracy of approximately 99%, significantly reducing troubleshooting time and enabling automatic maintenance triggers for faulty boards.

A later publication focused on data-driven degradation modeling for the PNG system, addressing one of its incipient failure modes: the reduction of neutron generation flux due to doped target wear over time Mosallam et al. (2023). HI values were extracted from data channels to quantify component health degradation, with a random forest classifier achieving an average accuracy of 90.4%.

Building on this, the necessity for remaining useful life (RUL) estimation was addressed in subsequent research. Also targeting the reduction of neutron generation flux due to doped target wear, this study estimated the system's remaining useful time Sobczak-Oramus et al. (2024). Experimental results showed a mean absolute percentage error of 16%. Integrating RUL estimation facilitated proactive maintenance planning, improved wellsite decision-making, and optimized manufacturing forecasts and equipment delivery based on the worldwide RUL of active PNGs.

Despite these advancements, the PNG system includes two incipient failure modes that can compromise its functionality. This paper aims to construct a data-driven health state estimation targeting the second failure mode: internal cathode wire discontinuity caused by overheating. Integrating degradation modeling for both failure modes will assist maintenance engineers in promptly assessing the PNG's health state and anticipating maintenance needs.

3. Pulsed Neutron Generator System Description

For numerous years, the oil and gas industry has employed high-energy neutron generators in neutron-gamma-ray or neutron-neutron logging, a practice well-documented by 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, they enable precise control over neutron output, facilitating more accurate measurements of formation properties.

In the realm 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, is 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.

This paper focuses on the early failure modes of the PNG. Two major failure modes are identified after a failure investigation and root cause analysis. These failure modes include:

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

These two failure modes can potentially compromise the functionality of the PNG and even cause the LWD tool failure. As previously mentioned, the health state estimation method for the target wear failure mode has been described in Mosallam et al. (2023). In the following sections, a method to model the cathode degradation responsible for the first failure mode will be presented, complementing the previous published work.

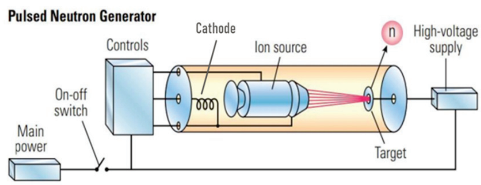

Fig. 3.: PNG architecture

4. Problem Formulation

The primary aim of prognostics is to minimize equipment or system downtime by anticipating the remaining useful life of the system or critical components, as illustrated in Fig. 4. RUL prediction methods are broadly categorized into three groups: physics model-based, data-driven, and hybrid approaches Lei et al. (2018). Physics model-based methods employ mathematical models to articulate the physical behavior of the system or component and forecast its RUL. While these methods demand a profound understanding of failure mechanisms and precise estimation of model parameters, they can yield accurate RUL estimations. In contrast, data-driven methods leverage pattern recognition algorithms to discern patterns from historical data and formulate RUL predictions. Although data-driven methods don't necessitate an exhaustive understanding of system failures, they do require high-quality data. Hybrid methods amalgamate the strengths of both approaches to enhance RUL predictions.

The PNG system under examination exhibits a high level of complexity, thereby constraining the applicability of physics model-based and hybrid methods for predicting the remaining useful life of the PNG or its components. Consequently, the objective is to develop a data-driven prognostic

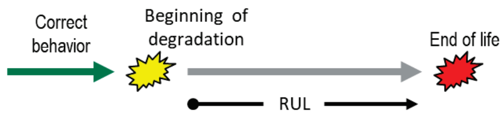

Fig. 4.: RUL forecast schematic

model that integrates information pertaining to the incipient failure modes of the PNG target. This model aims to provide estimations of the target's RUL along with corresponding confidence levels, as illustrated in Fig. 5.

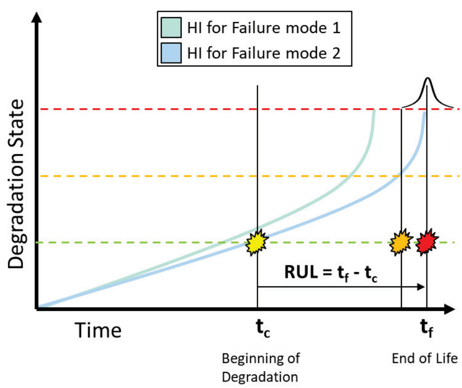

Fig. 5.: HIs for a system with two different failure modes

There are two primary methods for building data-driven prognostic models; i.e., direct RUL mapping and cumulative degradation prognostics Mosallam et al. (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).

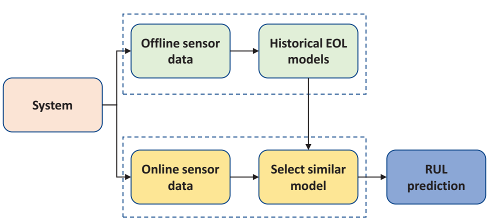

Fig. 6.: Direct RUL mapping approach

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).

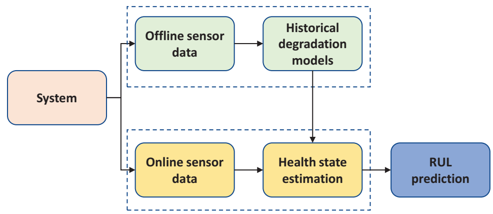

Fig. 7.: Cumulative degradation approach

The direct RUL mapping approach relies significantly on the availability of EOL data to construct the prognostic model. In the case of PNG, EOL data are constrained due to early maintenance. Furthermore, instances of EOL for the cathode degradation failure mode are even scarcer, as the target often degrades before the cathode, further limiting these cases. Considering the previously mentioned challenges, the direct RUL mapping approach is deemed unsuitable for this scenario. Instead, prioritizing the development of a health state estimation model for the PNG will furnish maintenance engineers with valuable insights to strategize efficient and cost-effective maintenance activities. A comprehensive explanation of this proposed method is outlined in the subsequent section.

5. The Proposed Method

The proposed method aims to construct a HI from sensor data that captures PNG degradation information. The labeled HI values are then modeled using a machine learning model, which can effectively discriminate between different degradation states of the PNG. The proposed method is divided into four main steps; i.e., channel selection, preprocessing, HI construction, and modeling, as shown in Fig. 8. The process is happening iteratively, until the modeling results are satisfying.

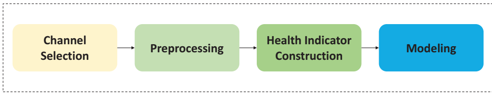

Fig. 8.: Proposed method flowchart

5.1. *Channel Selection*

As highlighted in Section I, the LWD tool accumulates 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 (SMEs) 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 cathode failure mode, initially the following two data channels were selected:

- ICAT: Cathode's electrical current.
- VCAT: Cathode's electrical voltage.

Fig. 9 and Fig. 10 show respectively the raw ICAT and VCAT channel data that will be used to construct the HI. Note that the duration of each run is different according to the job requirements, and the data of the sixth, ninth and eleventh run before EOL are missing.

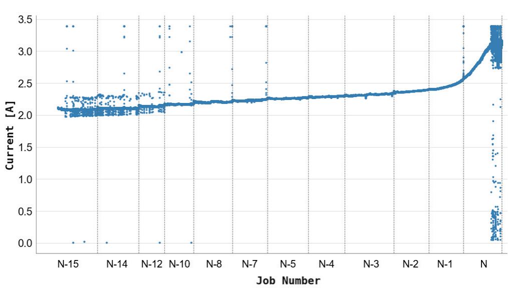

Fig. 9.: Raw data of ICAT channel of fifteen consecutive runs before EOL, where N denotes the last run, N-1 denotes the first run before EOL, N-2 denotes the second run before EOL, and so on.

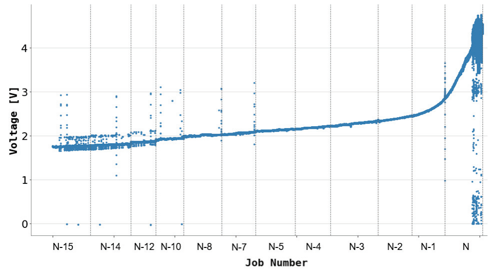

Fig. 10.: Raw data of VCAT channel of fifteen consecutive runs before EOL, where N denotes the last run, N-1 denotes the first run before EOL, N-2 denotes the second run before EOL, and so on.

5.2. *Preprocessing*

The LWD data acquisition system begins to record data once a field engineer initializes it for the upcoming drilling job and follows the 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.
(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 first three steps do not hold information about the PNG degradation and are thus removed. Furthermore, in the state when the PNG does not fire, the firmware generates some dummy records to fill the gaps in the data channels, which are discarded because they do not contain any information about the faults. The next step is the outlier filtering. The Hampel filter is applied to smooth the signals with the window size equal to 10% of each job's length. This process helps to remove the data that are obscuring the pattern of degradation. By using a gradual filtering approach, the Hampel filter can effectively account for the natural progression of voltage and current levels, while still eliminating short-term anomalies that may misrepresent the true degradation trend. This ensures that the underlying trend of degradation is preserved for HI construction. The preprocessed ICAT signal, originally shown in Fig. 9, is presented in Fig. 11.

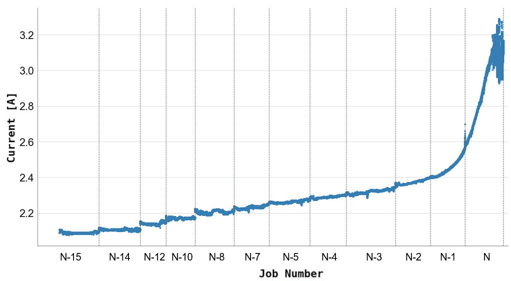

Fig. 11.: Preprocessed ICAT signal

5.3. *Health Indicator Construction*

In this algorithm step, a HI is derived using the preprocessed data. The main objective of generating this HI is to represent the system's degradation level in a 1D array format. Due to the observed differences in the voltage and current levels in the beginning of life of different PNGs, the explicit values of voltage and current cannot be used as an indicator. However, it is visible at the Fig. 11 that the value of current is growing much faster when the PNG is reaching the EOL, than in its beginning of life. The same applies to the voltage. Taking that fact into consideration, the rate of change of the signal remains our focus for the HI creation. For each drilling job, the third degree polynomial $y = f(X)$ is fitted to the preprocessed signal, where $X = [x_1, ..., x_n]$ and n is the number of observations in the signal in the current job. Afterwards, the rate of change of the signal is calculated following the formula:

$$\Delta = \frac{f(x_n) - f(x_1)}{x_n - x_1}. \tag{1}$$

Described process of the rate of change extraction is applied for ICAT, VCAT and their multiplication, which stands for the power of cathode. Fig. 12 shows the constructed HI using the preprocessed ICAT data show in Fig. 11.

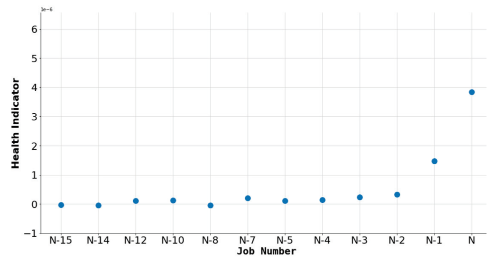

Fig. 12.: HI constructed using ICAT signal

It is worth noting that the input data used represents the incipient failure mode. As such, the generated HI serves as a quantitative measure of the system's current health in a monotonic manner. More simply, HI provides a numerical representation of the system's health that can be used for additional analysis or decision-making.

5.4. *Modeling*

HI constructed from the data collected during each drilling job results in 1D array representation, independent of the actual run duration. Thus, the health state estimation problem can be converted into a classification problem if the array of each run is labeled. To accomplish that, the SME identifies three degradation states the PNG undergoes throughout its lifecycle through failure analysis; i.e., healthy, severely degraded, and EOL. These degradation states serve as class labels for each run, enabling accurate degradation level classification of each run's data using a classification model. Specifically, this paper uses a decision tree classifier to establish the relationship between the input HI values and their corresponding labels; i.e., $y = f(X)$, where

$$X = \Delta \tag{2}$$

and

$$y = \begin{cases} 0 & \text{when } X \text{ is labeled as healthy.} \\ 1 & \text{when } X \text{ is labeled as severely degraded.} \\ 2 & \text{when } X \text{ is labeled as EOL.} \end{cases} \tag{3}$$

6. Experimental Results

A dataset containing operational data from 69 different LWD tool runs in different locations was collected to validate the proposed method. The dataset consists of historical runs from 7 different PNGs. Each run was analyzed and labeled by the SME. More specifically, as summarized in Table 1, there are 61 runs labeled as healthy, four as severely degraded, and four as EOL. Fig. 13 shows the label assignments performed by the SME for the HI shown in Fig. 12.

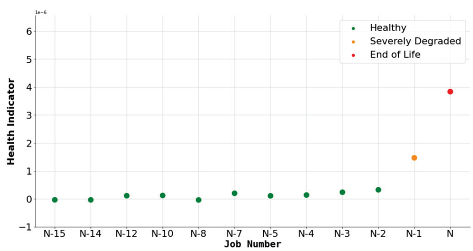

Fig. 13.: Label assignments for the degradation states performed by the SME

Due to highly imbalanced classes, several procedures were performed to correctly evaluate the model performance and obtain reliable results. Therefore, the balanced accuracy and F1-score per class metrics are applied to ensure reliable results in spite of the class imbalance. Let $C = \{0, 1, 2\}$ be the set of the labels assigned for the PNG health states. The formulas for the performance evaluation metrics are the following:

$$balanced\ accuracy = \frac{\sum_{c \in C} recall(c)}{\#C} \tag{4}$$

$$F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}, \tag{5}$$

$$recall = \frac{True\ Positives}{True\ Positives + False\ Negatives} \tag{6}$$

$$precision = \frac{True\ Positives}{True\ Positives + False\ Positives}. \tag{7}$$

Additionally, a leave-one-out cross-validation (LOOCV) method is used. This method provides low-biased performance metrics results compared with using a single test dataset Witten et al. (2011). Hyperparameter tuning was conducted for several classifiers to determine the best classification algorithm, including logistic regression, support vector classifier, k-neighbors classifier, decision tree classifier, random forest classifier, and gradient boosting classifier. All those methods were applied to three HIs constructed based on ICAT, VCAT and ICAT·VCAT values and the results were compared to choose the best performing HI and classification algorithm. The highest balanced accuracy per HI is presented in Table 2.

Table 1.: Number of drilling runs per degradation state used in LOOCV.

Degradation State	Number of Samples
Healthy	61
Severely Degraded	4
EOL	4

The HI constructed from the ICAT signal using the decision tree classifier outperformed the other algorithms; thus, this HI was implemented.

The LOOCV process yielded an F1-score of 100% for each class and a balanced accuracy of 100%. Additionally, the algorithm was validated 18 months after deployment using operational data from 73 drilling operations, with the corresponding confusion matrix shown in Table 3. This validation achieved a balanced accuracy of 96%, with F1-scores of 100% for the healthy, 94% for the severely degraded, and 86% for the EOL class. The model's primary objective is to prevent PNG failures by accurately identifying severely degraded and EOL states. Notably, all cases of those were correctly classified into one of these two categories, demonstrating the model's effectiveness in identifying critical degradation stages.

Table 2.: LOOCV balanced accuracy per HI.

Health Indicator	Balanced Accuracy (%)
ICAT rate of change	100
VCAT rate of change	83
ICAT · VCAT rate of change	83

Table 3.: Validation Confusion Matrix.

		Predicted		
		Healthy	S. Deg.	EOL
Actual	Healthy	50	0	0
	S. Deg.	0	15	2
	EOL	0	0	6

7. Conclusion

This paper introduces a data-driven approach to model the degradation of cathode components in the PNG system of LWD tools. The methodology involves identifying incipient failure modes associated with the PNG, extracting HI values from the ICAT data channel to quantify the component's health degradation over time. Utilizing these HI values, a decision tree classification model is trained to estimate the PNG degradation state after each drilling operation. Results from real operational data collected in the field demonstrate the method's effectiveness, with an average balanced accuracy of 100% across all degradation states. The trained machine learning model is integrated into the LWD tool's health analyzer software, which is widely utilized by field and maintenance engineers globally. This approach proves instrumental in reducing troubleshooting time and automatically initiating maintenance activities, preempting downhole failures related to highly degraded nuclear components. Future efforts aim to estimate the precise remaining useful life for PNG considering cathode degradation failure mode.

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