

Predictive Maintenance of High-Voltage Railway Equipment Using Machine Learning: A Case Study on Pantograph and Auxiliary Converter Units in a 3 kV DC Rail System [†]

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Abstract

In 3 kV DC systems, the pantograph–catenary interface and auxiliary converter unit (ACU) are among the critical high-voltage subsystems, where electrical transients and thermal overload conditions frequently lead to service disruptions. This paper presents a case study on the application of machine-learning-based predictive maintenance to a 3 kV DC electric train, with a specific focus on the pantograph and ACU. A 2-year period of operational data collected from a passenger rail fleet was analysed using a hybrid data sampling strategy to capture both operational conditions and events associated with failures. Logistic Regression (LR), and Random Forest (RF) were trained and evaluated using standard performance metrics. The RF model achieved superior predictive performance, with an accuracy of approximately 93%, a precision of 0.91, a recall of 0.88, and an F1-score of 0.89, outperforming the baseline across all metrics. The analyses demonstrated that anomalies in electrical arcing, line voltage, and ACU current and temperature frequently preceded recorded fault events, confirming that failures arise from subsystems interactions and that it is critical for such parameters to be monitored. The results demonstrate the technical feasibility and practical value of integrating machine learning into EMU maintenance practice, enabling earlier detection of degradation, more targeted interventions, and a transition towards condition-based maintenance.

Keywords: predictive modelling; PdM; sensor-based maintenance; fault detection; condition monitoring; electric multiple unit (EMU); pantograph; rolling stock maintenance; 3 kV DC trains



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1. Introduction

Electric multiple units (EMUs) operating in dense urban and commuter networks are particularly sensitive to maintenance performance, as failures in critical subsystems can propagate quickly into service delays, cancellations, and safety risks. This research is a case study of a Metrorail 3 kV DC EMU fleet, where traditional maintenance strategies implemented are reactive (corrective) and time-based preventive. While these strategies are easier to implement, they do not detect equipment failures before they occur, which is not ideal for some of the critical subsystems such as pantographs and auxiliary converter units (ACUs). As a result, faults occur unexpectedly in service, leading to service disruptions impacting passenger experience. However, predictive maintenance enabled by artificial

intelligence (AI) and machine learning (ML) enables condition-based management of rail assets. By continuously analysing sensor data, ML models can detect changes in operating conditions and identify patterns that precede faults, allowing interventions to be optimally scheduled with clear intervention objectives. This study is pursued to demonstrate the potential of data-driven models specifically focusing on pantograph and converter systems of 3 kV DC EMUs.

This paper addresses this gap by training and evaluating a predictive maintenance framework for the pantograph and ACU of a specific fleet of EMUs using supervised machine learning. The study leverages operational data of a period between 2023 and 2024 collected from a South African Metrorail operator. Two ML models, Logistic Regression and Random Forest, are trained on the resulting dataset after systematic preprocessing, including handling missing data, normalisation, and class imbalance mitigation. The main objective of this paper is to demonstrate that PdM can be implemented on high-voltage equipment such as pantographs and ACUs.

1.1. Railway Maintenance Background

In the railway industry, the evolution and modernisation of maintenance strategies are vital and reflect the industry's shift towards proactive solutions for improved operational efficiency, safety, and the reliability of assets [1]. In the field of rolling stock, the implementation of maintenance strategies, particularly those that integrate monitoring models, has evolved from being a best practice to an essential requirement [2]. This necessity arises from the complex interaction between environmental factors, mechanical components, and electronic systems, which collectively influence the safety and reliability of railway operations [3]. Ideally, a system is expected to function flawlessly throughout its designed lifespan before inevitably experiencing failure as a result of wear and tear. However, practical experience diverges from this ideal scenario, illustrating maintenance as a comprehensive suite of activities aimed not just at repairing or extending the life of a system but crucially at maintaining its performance to meet its designed functions throughout its operational life [4,5].

1.2. Predictive Maintenance for Electric Train High-Voltage Equipment

Predictive maintenance for high-voltage railway equipment has increasingly been adopted as a practical pathway for shifting maintenance practices from corrective or periodic/ time-based interventions toward condition-based decision-making [6]. This transition is particularly relevant for critical subsystems in 3 kV DC electric multiple units (EMUs), such as pantographs and auxiliary converter units (ACUs), where faults often develop progressively under dynamic operating conditions [7].

Within the pantograph–catenary interface, research has consistently shown that arcing activity, voltage dips, and variations in contact force provide measurable indicators of contact instability, wear, or mechanical misalignment [8,9]. Supervised learning models, including RF, have demonstrated strong performance in detecting fault conditions, particularly in datasets where failures are rare and class imbalance is significant.

2. Predictive Maintenance Implementation Approach

The method was designed to ensure that the application of AI-driven PdM to railways was addressed thoroughly by regarding the correlation between research objectives, data collection procedure, model development and evaluation methods. The research project is centered around applying ML algorithms to analyse data and forecast equipment malfunctions before they occur.

2.1. Data Collection

Sensor data used in this study was collected from the case study operator, from the pantograph and the auxiliary converter unit (ACU) of the EMU. The pantograph was monitored for pressure and vibration to assess its performance and contact stability. The ACU was monitored for current, temperature, and air flow to ensure stable support for non-propulsion systems.

The period of the data collected was two years in order to include seasonal patterns, operational fluctuations and different system states. As a result of the limited number of failure cases, extra synthetic failure data was generated to facilitate model learning of correct failure patterns. A hybrid data sampling strategy was employed, combining periodic sampling at fixed 15 min intervals with event-based sampling.

2.2. Machine Learning Model Development

The core analytical technique used for this investigation was machine learning, which can be framed as a five-step lifecycle—data collection, data modelling, data preparation, model building and training, and model deployment.

Operational data was pre-processed, structured into training and validation sets, and then fed into machine learning frameworks, Logistic Regression and Random Forest, which were incrementally trained and tested to ensure robustness, accuracy, and the ability to generalise across unseen conditions. The data was split into training and validation components, with 80% used in training the model and 20% in validating it. This model was not validated in any real-life environment nor redeployed to the live train monitoring and event logging platform where the original data was collected.

3. A Case Study: 3 kV DC Pantograph and ACU

This section provides a summary of the observation from analysis, simulation and modelling activities that were performed to develop the intelligent PdM model for using the data collected. The paper investigates the ability to predict failures of components relative to operational and environmental conditions of a number of key sub-systems such as the pantograph and auxiliary converter unit (ACU).

3.1. Pantograph

The pantograph serves as a vital electromechanical interface on any electric multiple unit (EMU), ensuring continuous electrical contact with the overhead catenary system and thereby facilitating reliable power transmission to both propulsion and auxiliary systems. Electrical arcing, a common phenomenon during dynamic conditions such as acceleration, braking, or transitions between catenary subsections, manifests as transient voltage drops and contributes to progressive wear of pantograph and contact wire components. In the case of this 3 kV DC EMU system, the arcing frequency is formulated to quantify the rate at which the pantograph experiences electrical arcing.

This formulation of the arcing frequency (f_{arc}) is mathematically expressed as the number of arc events (N_{arc}) detected within a specified time period (T), as shown below:

$$f_{\text{arc}} = \frac{N_{\text{arc}}}{T} \quad (1)$$

where N_{arc} is the number of detected real events defined in terms of threshold voltage dips, current derivatives and a signal processing algorithm.

3.1.1. Descriptive Statistics

Table 1 is a compilation of statistical information related to essential operational variables for the pantograph. The measured standard deviation of ± 50 A reveals a nearly

constant current budget among different operational modes. In particular, the low current levels around 74 A are probably due to idle/coast conditions, and the peaks above 530 A suggest high traction loads during acceleration phases or when traversing steep gradients. Such transient peak currents may also be associated with regenerative braking events, reflecting the bidirectional energy flow characteristic of modern EMU power systems. These observations therefore establish a criterion for threshold-based anomaly detection, permitting the integration of probabilistic forecasting techniques to prevent major breakdowns.

Table 1. Descriptive statistics—pantograph/Line.

Parameter	Mean	Std Dev	Min	Max
Line Current	299.99 A	50.05	73.96	534.72
Line Voltage	3000.26 V	149.95	2292.76	3723.21
Arc Frequency	0.3 Hz	0.3	0	3.72
Pressure	7.50 bar	0.50	5.18	9.68

3.1.2. Pantograph Trends from Observed Data

Figure 1 below shows the frequency of overhead electrical arcs on a particular pantograph on Train_1 over the period of two (2) years.

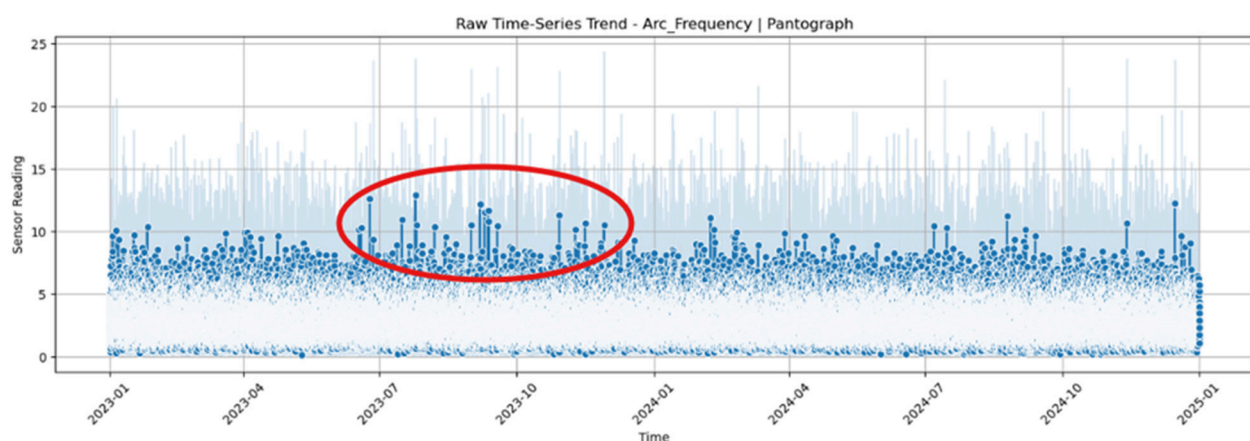


Figure 1. Raw time series (2023–2024) for pantograph electrical arcing occurrences.

When line voltage measurements were observed, they indicated to be clustering around the nominal supply of 3000 V DC, with occasional spikes above 3200 V and dips below 2800 V. These voltage spikes and dips were often synchronised with spikes in arc frequency.

The correlation between pantograph pressure and electrical arcing is also observed in Figure 2 below. The majority of the pantograph pressure measurements are within the normal operating range of 7.0 to 8.5 bar, indicating consistent performance under normal conditions. However, significant increases in arcing frequency, occasionally exceeding 10 Hz, frequently align with periods of reduced pantograph pressure.

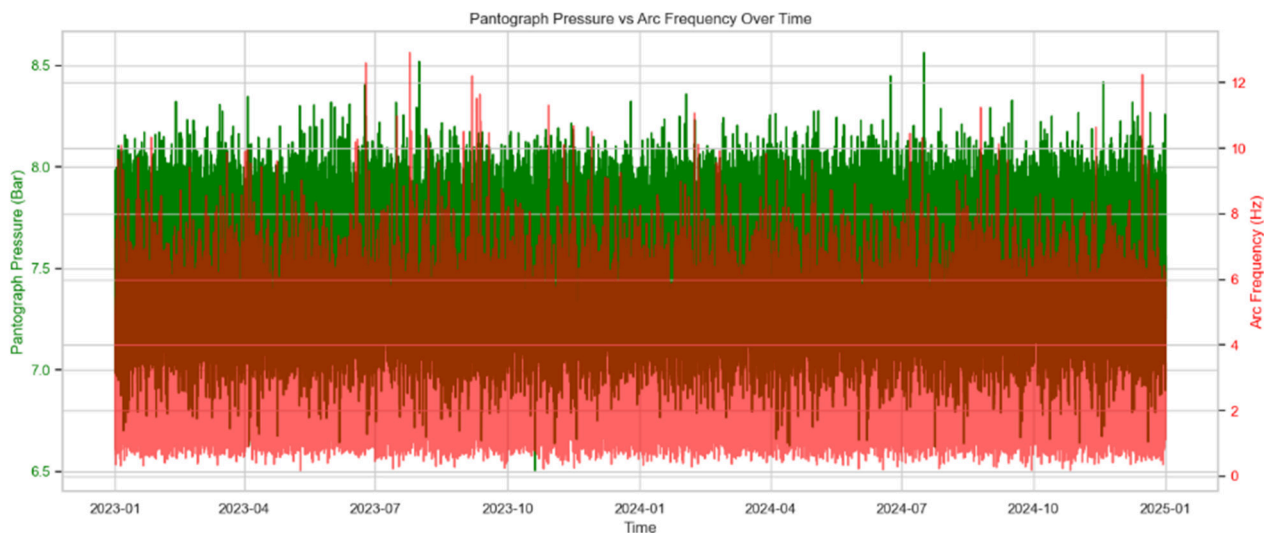


Figure 2. Pantograph pneumatic pressure vs electrical arcing.

3.2. Auxiliary Converter Unit Pre-Analysis

The auxiliary converter unit (ACU) in electric trains is essential for supplying medium (400 VAC) and low (110 VDC) voltages to the auxiliary subsystems. The ACU ensures the seamless operation of these subsystems, which are vital for passenger comfort and safety. To enhance reliability, the ACU is equipped with sensors to monitor key parameters, air flow, current, and temperature.

Descriptive Statistics

Table 2 shows the ACU's operational characteristics through descriptive statistics. Air flow measurements indicate a generally stable cooling performance. While temperature readings suggest moderate thermal variability. It is observed that spikes in current and temperature, particularly during also peak conditions or periods of reduced air flow, suggest potential stress points, as shown in Figure 3. These patterns emphasise the importance of integrated monitoring to identify anomalies and inform maintenance strategies, ensuring reliability and preventing failure events in service. Furthermore, failures in the auxiliary converter unit (ACU) seem not to predominantly occur at the extreme limits of the measured parameters but are more commonly observed during typical operational variations.

Table 2. Descriptive statistics—ACU.

Parameter	Mean	Std Dev	Min	Max
Current	299.87 A	49.99	64.14	551.62
Temperature (°C)	64.99 °C	9.99 °C	21.04 °C	112.46 °C
Air Flow	1.20	0.20	0.25	2.24

The pattern indicates that failures may stem not only from extreme values but also from intricate interactions among multiple variables or fleeting anomalies that are not immediately evident when examining individual parameter extremes. These findings highlight the critical need for advanced, multi-sensor data analytics and integrated cross-parameter monitoring to enhance predictive maintenance and early fault detection.

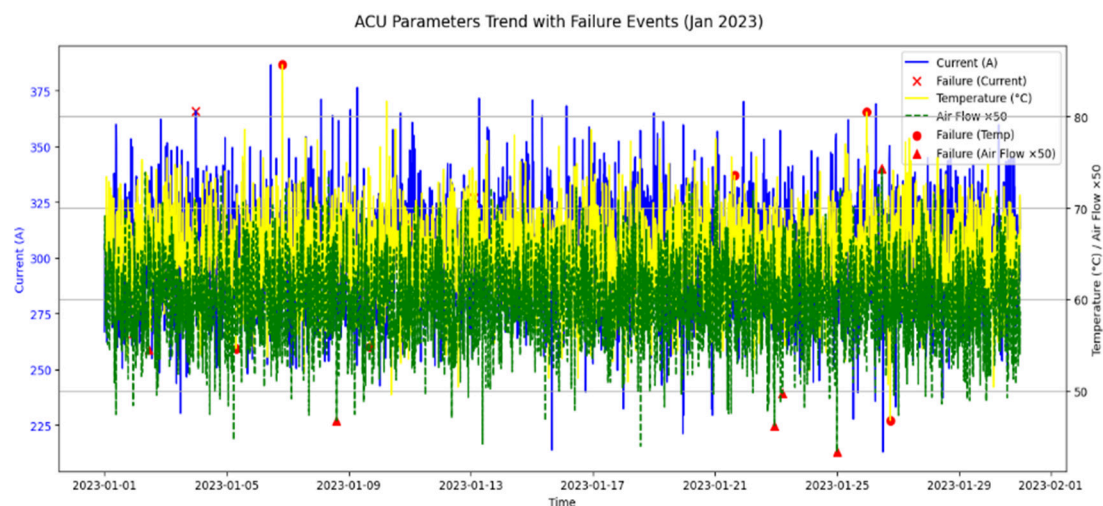


Figure 3. A one-month view for ACU analysis with fault indicators.

3.3. Model Training and Dataset Partitioning

For data pre-processing before the actual model training, several steps of data processing were performed to optimise the integrity and comparability of all variables. This data preparation process ensured that the final dataset was structured into machine learning dataframes, which lead to the training of accurate and explainable predictive models for railway maintenance applications (See Table 3).

Table 3. Data partitioning.

Subset	Purpose	Percentage
Training	Model learning and tuning	80%
Testing	Model validation	20%

3.4. Model Development and Evaluation

3.4.1. Logic Regression Predictive Model

Figure 4 shows the classification report of the Logistic Regression predictive model. The report highlighted high performance for class 0, which was the class allocated to operational data, with a perfect precision of 1.000, high recall (0.980), and an F1-score of 0.990. However, a significant weakness was observed in detecting class 1, which was allocated to represent fault events. This class recorded a precision of only 0.040 with a considerably low F1-score of 0.076, though the recall was good, which indicated that every actual failure was correctly classified as such.

Figure 5a below shows the confusion matrix of the Logistic Regression, which confirmed that while almost all operational events are correctly classified, a significant number (13,721) of failures are incorrectly detected as fault events, though all actual failures are detected, with no actual fault event incorrectly classified. The results demonstrated a high sensitivity (recall) for actual faults but with a higher rate of falsely reporting a fault. The ROC curve in Figure 5b further illustrates the overall discriminative ability of the model, at an AUC of 0.990, which indicates that the model was highly capable of distinguishing failure versus non-failure events under the chosen threshold.

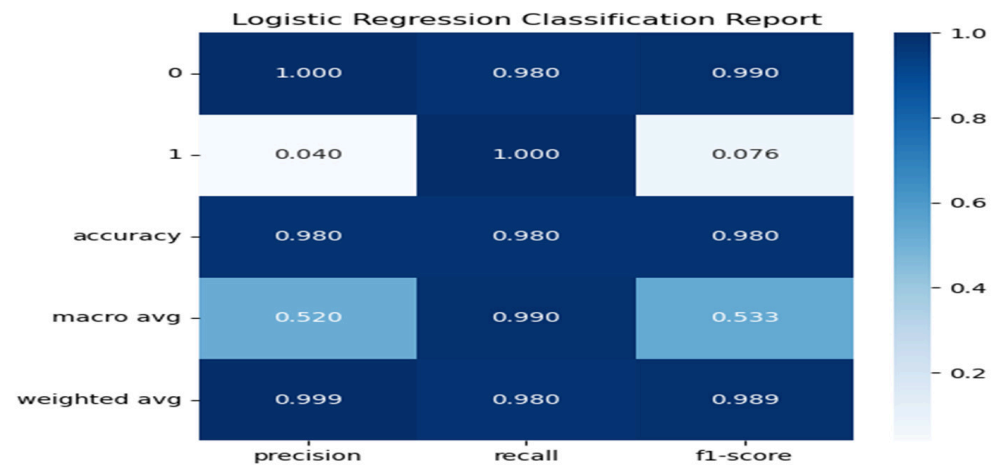


Figure 4. Logistic Regression classification report.

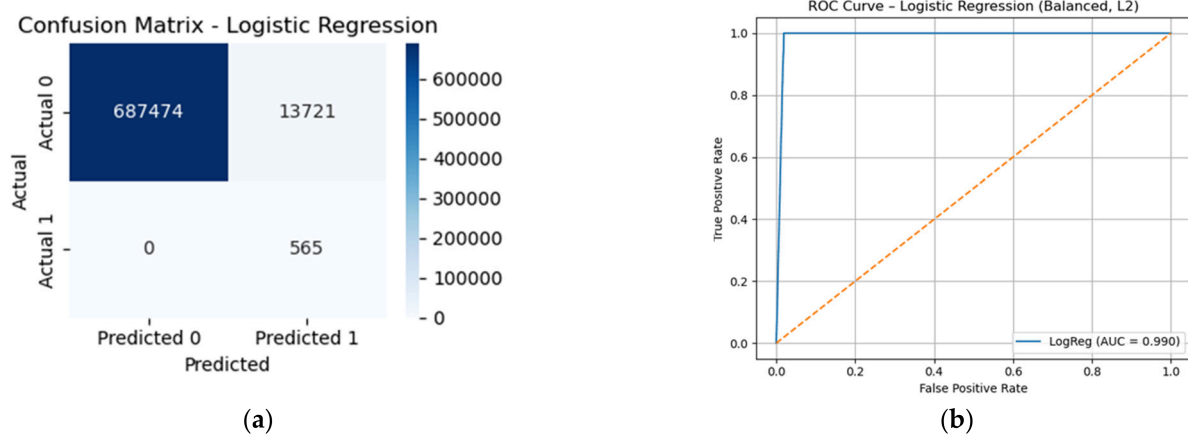


Figure 5. LR performance: (a) confusion metric and (b) ROC-AUC.

The report indicated that the model, in the framework in which it was implemented, achieved the objective of high failure recall, which is necessary for predictive maintenance, ensuring that the actual fault events are correctly detected. However, it was quite a significant shortfall that the model showed low precision and over-predictive tendencies for the failure events, which led to a high number of failure alerts.

3.4.2. Random Forest Classifier Predictive Model

The RF algorithm was configured with an initial set of 400 decision trees, a maximum depth of 14, and balanced class weights to counter the inherent class imbalance observed between failure events and operational events. The model was trained using five-fold cross-validation, which ensured statistical robustness and reduced overfitting tendencies by testing the algorithm's generalisation capacity across multiple subsets of the data. The model achieved an overall classification accuracy of approximately 95 percent, with a precision of 0.86 and recall of 0.94, resulting in an F1-score of 0.92, as illustrated in Figure 6.

For RF, an ROC curve, with an ROC-AUC value of 0.991, which further confirmed the model's discriminative power, was observed, with the area under the curve approaching unity, illustrating reliable performance across a range of decision thresholds. These metrics collectively demonstrate Random Forest's ability to discriminate between normal operating states and fault events.

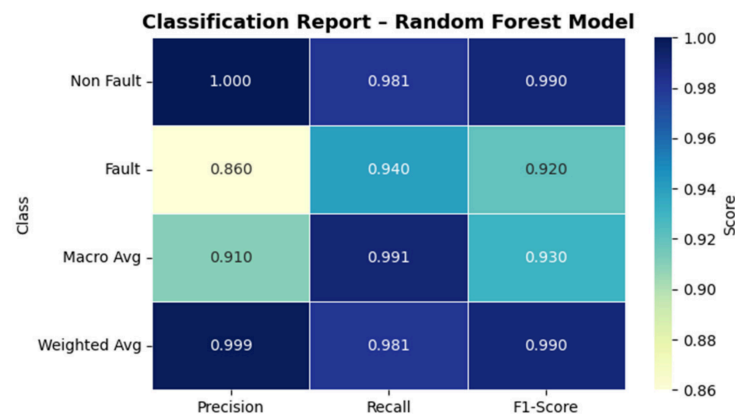


Figure 6. RF classification report.

The RF confusion matrix analysis revealed a strong diagonal dominance, with 687,912 actual non-faults (operational events) and 8797 actual faults correctly identified, while 132 non-failure events and 27 faults were incorrectly classified. This indicated high predictive accuracy for both failure and non-failure classes, with relatively insignificant incorrect classification. This pattern validates the effectiveness of the class weight balancing strategy, which compensated for the scarcity of failure events within the dataset.

3.4.3. Comparative Evaluation of the Models

The comparative results, as presented in Table 4, consistently demonstrate that Random Forest outperforms LR across all quantitative performance metrics. The ensemble design of RF allows for recognition of complex non-linear patterns, integrating electrical, thermal, and mechanical parameters. Consequently, the RF model was formally adopted as the preferred algorithm for subsequent predictive maintenance deployment considerations.

Table 4. Comparative evaluation of the models.

Criterion	Logistic Regression	Random Forest
Accuracy	0.86	0.93
Precision	0.79	0.91
Recall	0.72	0.88
F1-score	0.75	0.89
ROC-AUC	0.91	0.991
Interpretability	High	Moderate
Handling of non-linearity	Limited	Strong
Robustness to complexity and Imbalance	Moderate	High

4. Simulation Results Discussion

The LR baseline provided an interpretable reference but demonstrated limited capability in predicting the non-linear interactions inherent in high-voltage railway systems. The RF classifier achieved superior performance, with an accuracy of 0.93, a precision of 0.91, a recall of 0.88, and an F1-score of 0.89. These results confirm the suitability of ensemble learning for predictive maintenance in environments characterised by noise, transient disturbances, and complex parameters.

The findings demonstrate that predictive maintenance for high-voltage railway equipment can be effectively implemented using machine learning when multi-parameter data is available. The strong relationship between pantograph electrical arcing and line voltage

stability confirms that pantograph monitoring provides direct insight into traction power quality and current collection health.

5. Conclusions

This paper presents a machine-learning-based predictive maintenance framework for high-voltage railway equipment, focusing on pantograph and auxiliary converter unit behaviour in an EMU fleet operating under a 3 kV DC traction supply. RF model achieved superior prediction performance and is recommended, in comparison to LR, as a suitable modelling approach for practical predictive maintenance implementation in DC railway environments.

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Abbreviations

ACU	Auxiliary Converter Unit
AI	Artificial Intelligence
CM	Corrective Maintenance
EMU	Electrical Multiple Unit
ET	Electric Train
LR	Logistic Regression
ML	Machine Learning
PdM	Predictive Maintenance
PM	Preventive Maintenance
PRASA	Passenger Rail Agency
RF	Random Forest
TBM	Time-Based Maintenance

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