

Machine Learning–Based Failure-Risk Profiling and Preventive Maintenance Prioritisation for 11 kV Distribution Feeders Using Operational Data

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Abstract: Conventional reliability assessment provides valuable information on historical feeder performance but offers limited insight into the operating conditions under which future failures are most likely to occur. This paper presents a machine learning–based framework for failure-risk profiling and preventive maintenance prioritisation of the Mokwa and Jebba–Bacita 11 kV distribution feeders using historical operational data from their respective injection substations. A Random Forest classifier was developed using strictly causal pre-fault features comprising instantaneous feeder load, rolling load statistics, recent outage history, and temporal operating characteristics to estimate hour-by-hour failure probability without target leakage. The resulting probabilistic outputs were subsequently translated into practical maintenance decision indicators, namely the Failure Risk Reduction Index (FRRI), Preventive Maintenance Priority Score (PMPS), and High-Risk Exposure Index (HREI), to support evidence-based maintenance planning. The predictive model achieved ROC–AUC values of approximately 0.65–0.70 for the Mokwa feeder and 0.58–0.63 for the Jebba–Bacita feeder, indicating moderate predictive capability given the constraints of operational utility data. The analysis further reveals that the Mokwa feeder exhibits stronger load-dependent failure behaviour, with elevated failure probabilities observed within the 12.5–14 MW operating range and across much of the daily operating cycle, whereas Jebba–Bacita demonstrates comparatively weaker load sensitivity and lower overall operational risk. The derived maintenance indices indicate that a relatively small proportion of operating conditions contributes disproportionately to feeder failures, enabling maintenance resources to be

prioritised toward high-risk operating states. The proposed framework demonstrates how machine learning can complement conventional reliability assessment by transforming historical operational records into practical maintenance intelligence that supports proactive asset management in resource-constrained electricity distribution networks.

Keywords: Machine learning; Random Forest; Failure-risk profiling; Preventive maintenance; Distribution feeders; Predictive maintenance.

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1.0 Introduction

The increasing deployment of sensing, supervisory control, smart metering, and digital monitoring technologies has transformed modern electricity distribution networks into increasingly data-rich operational environments.

. Distribution utilities routinely collect large volumes of operational information, including feeder loading, outage records, switching operations, and restoration activities (Oyedepo, 2012; Aliyu et al., 2013). Despite this growing availability of operational information, the ability to convert such data into timely and actionable maintenance decisions remains limited in many distribution networks. In particular, historical feeder records are often used

primarily for reporting and reliability assessment rather than for estimating the probability of future failure under specific operating conditions.

However, despite the availability of these operational data, maintenance planning in many developing power systems remains predominantly reactive, with interventions typically initiated only after equipment failures or prolonged service interruptions have occurred. Such reactive maintenance practices contribute to increased outage frequency, higher maintenance costs, reduced equipment life, and deterioration in service reliability (Billinton & Allan, 1996; IEEE Power & Energy Society, 2021; Okoro & Chikuni, 2007; Ekpechi et al., 2024).

Preventive maintenance has long been recognised as one of the most effective approaches for improving the reliability, availability, and operational efficiency of electric power distribution systems. Conventional maintenance scheduling, however, is commonly based on periodic inspection programmes, historical experience, or engineering judgement, which may not adequately reflect the continuously changing operational condition of distribution assets (CIGRE, 2018). As distribution systems become increasingly instrumented and data-driven, there is growing interest in exploiting historical operational records to support evidence-based maintenance planning capable of identifying high-risk operating conditions before failures occur (Zio, 2012; Onyijen et al., 2023). While conventional reliability measures remain essential for describing historical system performance, they generally provide limited information about the specific operating conditions associated with an impending failure. This limitation creates an opportunity for data-driven approaches that complement historical reliability assessment by estimating failure risk from observed operational patterns.

Recent advances in artificial intelligence (AI) and machine learning (ML) have created new opportunities for intelligent asset management across power systems (Idowu et al., 2025). Supervised machine learning

algorithms can learn complex and nonlinear relationships between operational variables and system failures, thereby enabling utilities to estimate failure probability, identify influential operating factors, and prioritise maintenance resources according to operational risk (Odozor et al., 2025). Consequently, machine learning techniques such as Artificial Neural Networks, Support Vector Machines, Decision Trees, Gradient Boosting algorithms, and Random Forests have been increasingly applied to power system fault diagnosis, outage prediction, equipment condition assessment, and predictive maintenance (Goodfellow et al., 2016; Jordan & Mitchell, 2015).

Among these approaches, the Random Forest algorithm has attracted considerable attention because of its robustness to noisy data, ability to capture nonlinear interactions, resistance to overfitting, and provision of interpretable feature importance measures. These characteristics make it particularly suitable for utility operational datasets, which are often characterised by heterogeneous operating conditions, missing observations, and class imbalance (Breiman, 2001).

In this study, failure-risk profiling refers to the characterization of the likelihood of feeder failure and the operating conditions associated with elevated failure probability. It therefore extends beyond conventional binary fault classification by providing probabilistic information that can be used to identify high-risk operating states and support maintenance prioritisation.

Nevertheless, many published studies focus primarily on improving predictive accuracy while providing limited guidance on translating probabilistic model outputs into actionable maintenance decisions. Furthermore, some predictive models rely on information that would not be available before fault occurrence, thereby reducing their practical value for operational maintenance planning (Folorunso et al., 2025).

Within the Nigerian electricity distribution sector, the application of machine learning



remains relatively limited, with existing studies largely focusing on fault classification, load forecasting, equipment diagnosis, and related power-system applications. Comparatively fewer investigations have used historical feeder-level operational records to characterize the probability of future failure under real operating conditions. Moreover, limited attention has been given to converting model-derived failure probabilities into engineering-oriented indicators that can assist maintenance personnel in ranking feeders, operating conditions, or periods requiring preventive intervention. This disconnect between predictive analytics and practical maintenance decision-making represents an important research gap, particularly for distribution utilities operating under constrained technical, financial, and monitoring resources.

The significance of this study lies in its attempt to bridge predictive analytics and practical maintenance decision-making in electricity distribution systems. Rather than treating model accuracy as the sole outcome, the framework translates predicted failure probabilities into maintenance-oriented indicators that can assist utilities in identifying high-risk operating conditions and allocating limited maintenance resources more effectively. This approach is particularly relevant to resource-constrained distribution networks, where routinely collected operational records may provide a more accessible basis for predictive asset management than sophisticated condition-monitoring infrastructure.

Accordingly, this study develops and evaluates a machine learning-based framework for failure-risk profiling and preventive maintenance prioritisation using operational data from the Mokwa and Jebba-Bacita 11 kV distribution feeders. A Random Forest classifier is trained using strictly causal pre-fault operational features to estimate hour-by-hour failure probability. The predicted probabilities are subsequently transformed into three maintenance-oriented

indicators—the Failure Risk Reduction Index (FRRI), Preventive Maintenance Priority Score (PMPS), and High-Risk Exposure Index (HREI)—to support evidence-based prioritisation of maintenance activities. The study therefore demonstrates how routinely collected feeder operational data can be transformed into actionable maintenance intelligence for proactive asset management in resource-constrained distribution networks.

In this framework, machine learning provides the predictive component by estimating the probability of feeder failure from historical operational conditions, while preventive maintenance represents the subsequent engineering response to elevated predicted risk. Thus, the proposed approach uses predictive analytics to inform the prioritisation of preventive maintenance activities rather than replacing engineering judgement or conventional maintenance practices.

2.0 Review of Related Work

Research on machine learning and predictive maintenance in power systems has expanded from fault diagnosis and classification toward failure prediction, asset-health assessment, and operational risk management. This review therefore considers the literature from four complementary perspectives: machine learning for power-system failure prediction, machine learning for predictive maintenance, operational-data-driven failure-risk profiling, and the translation of predictive outputs into maintenance decisions. This progression provides the basis for identifying the methodological and practical gap addressed by the present study.

2.1 Machine Learning for Power System Failure Prediction

The increasing deployment of sensing, supervisory control, and operational monitoring technologies has accelerated the application of machine learning (ML) techniques to electric power systems. Unlike traditional reliability analysis, which evaluates historical network performance using descriptive indices, ML methods



exploit operational data to learn complex relationships between system operating conditions and future equipment failures (Idowu et al., 2025). Such predictive capability enables utilities to shift from corrective maintenance towards proactive, condition-based asset management (Adeyemi, 2024).

Several studies have demonstrated the effectiveness of supervised learning algorithms for power-system fault prediction. Alhelou et al. (2019) proposed an ML-based fault detection framework that successfully identified abnormal operating conditions from electrical measurements, demonstrating the ability of data-driven models to recognise pre-fault patterns. Similarly, Rudin et al. (2012) developed a machine learning approach for ranking vulnerable components within the New York City power grid using historical operational and inspection records, illustrating the value of predictive analytics for maintenance planning at utility scale. Weather-driven outage prediction has also attracted considerable attention. Eskandarpour and Khodaei (2017) employed machine learning techniques to predict grid outages resulting from extreme weather events, while Nateghi et al. (2011) compared statistical learning models for forecasting hurricane-induced outage durations. Their findings consistently showed that predictive models outperform conventional deterministic approaches when sufficient operational and environmental information is available. Collectively, these studies demonstrate that machine learning can identify relationships between system conditions and subsequent failure or outage events. However, their objectives differ from feeder-level maintenance prioritisation: some focus on fault detection, others on vulnerability assessment or weather-related outage prediction, while relatively few estimate failure probability directly from routinely available feeder operational variables. This distinction is important because a model intended for maintenance prioritisation must not only identify failures accurately but also provide information that can be acted upon before failure occurs. Although these studies

demonstrate the growing maturity of ML applications in power systems, many were developed in settings with extensive asset databases, detailed equipment-condition records, or rich meteorological information. Such data resources may be unavailable or incomplete in resource-constrained distribution networks. This limitation motivates the development of models capable of extracting useful failure-risk information from routinely collected feeder operational data while maintaining temporal causality and practical interpretability.

2.2 Machine Learning for Predictive Maintenance

Predictive maintenance has emerged as an important application of artificial intelligence and machine learning in engineering asset management. Unlike purely time-based preventive maintenance, which schedules interventions according to predetermined intervals, predictive maintenance estimates equipment condition or failure risk from observed data to inform the timing and priority of maintenance actions. In this sense, predictive analytics can serve as an evidence-based mechanism for improving preventive maintenance decisions (Idowu et al., 2026). Carvalho et al. (2019), through a comprehensive systematic review, identified ensemble learning algorithms, particularly Random Forests, as among the most robust techniques for predictive maintenance because of their ability to model nonlinear relationships while remaining relatively insensitive to noisy operational data. Zhang et al. (2019) similarly concluded that data-driven maintenance strategies consistently outperform conventional statistical approaches in complex engineering systems. Susto et al. (2015) further demonstrated that combining multiple classifiers improves maintenance decision-making by balancing missed failures against unnecessary maintenance interventions.

Beyond industrial applications, Mosavi et al. (2019) reviewed machine learning applications across energy systems and observed an increasing transition from



descriptive system monitoring towards predictive asset management. The review highlighted classification algorithms as particularly suitable for forecasting equipment failures, outage events, and abnormal operating conditions, while also identifying limited operational datasets and severe class imbalance as recurring challenges in practical deployments.

Collectively, these studies establish machine learning as a viable foundation for predictive maintenance, while also showing that successful deployment depends on data quality, appropriate feature construction, treatment of rare failure events, and meaningful evaluation metrics. However, predictive performance alone does not determine maintenance value; model outputs must also be translated into decision rules or risk indicators that maintenance personnel can use to allocate limited resources.

2.3 Operational Data–Driven Failure-Risk Profiling

Operational data provide an important but often underutilised source of information for distribution-system risk assessment. Distribution utilities routinely record feeder loading, outage occurrence, restoration events, interruption characteristics, and other operational variables. When appropriately structured and temporally aligned, these records can provide information about the operating conditions that precede failure and can therefore support data-driven failure-risk profiling without requiring extensive additional monitoring infrastructure.

Recent developments in operational data analytics have demonstrated that carefully engineered temporal features—including rolling averages, load variability, historical outage counts, and time-of-day characteristics—can significantly improve predictive performance while avoiding dependence on expensive monitoring infrastructure. Equally important is ensuring that predictive models are constructed using only information available before the occurrence of an outage. Bergmeir and Benítez (2012) showed that random cross-

validation introduces optimistic bias when applied to temporal datasets and recommended chronological model evaluation for time-series prediction problems. Consequently, maintaining temporal causality throughout feature engineering and model validation has become an important methodological requirement for operational failure prediction.

Another important consideration is the highly imbalanced nature of outage datasets. Since normal operating conditions vastly outnumber failure events, conventional accuracy alone provides an unreliable indication of model performance. He and Garcia (2009) demonstrated that classifiers evaluated solely by accuracy often fail to detect minority failure events effectively. Chawla et al. (2002) introduced the Synthetic Minority Over-sampling Technique (SMOTE) to alleviate this problem, while Saito and Rehmsmeier (2015) argued that Precision–Recall analysis provides a more informative evaluation than ROC analysis for highly imbalanced datasets. These methodological developments are widely used in predictive modelling and are particularly relevant to predictive maintenance applications in which failure events are relatively rare. For distribution feeders, appropriate treatment of class imbalance and the use of metrics that reflect minority-event detection are essential because a model can achieve high overall accuracy while providing poor identification of the failure events that are most important for maintenance planning.

2.4 Research Gap

Despite significant advances in machine learning for power-system prediction and predictive maintenance, an important methodological and practical gap remains at the interface between failure prediction and maintenance prioritisation. Existing studies have demonstrated the ability of ML algorithms to detect faults, predict outages, assess equipment condition, or estimate failure-related outcomes, but comparatively fewer studies have developed a complete workflow that uses routinely available feeder operational data to estimate pre-fault failure probability and subsequently convert that



probability into actionable maintenance priorities.

Furthermore, while considerable research has addressed fault detection and outage prediction, comparatively little attention has been given to translating machine learning outputs into operational decision-support indicators that assist maintenance engineers in prioritising feeder inspections and preventive interventions. This limitation is particularly evident within Nigerian distribution networks, where predictive maintenance remains largely underexplored despite persistent reliability challenges.

To address these gaps, the present study develops a machine learning-based framework that integrates causal feature engineering, temporal model development, imbalance-aware evaluation, probabilistic failure-risk estimation, and maintenance prioritisation. The framework uses only information available before the failure event, thereby reducing the risk of target leakage and improving its suitability for prospective maintenance planning. The resulting failure probabilities are further transformed into the Failure Risk Reduction Index (FRRI), Preventive Maintenance Priority Score (PMPS), and High-Risk Exposure Index (HREI), providing an operational link between predictive modelling and maintenance resource allocation. The study therefore extends conventional reliability assessment by demonstrating how routinely available feeder operational data can be converted into actionable risk intelligence for proactive maintenance planning.

3.0 Research Methodology

This study develops a machine learning-based framework for failure-risk profiling and preventive maintenance prioritisation using operational data obtained from two 11 kV distribution feeders. The framework is designed to estimate the probability of a future feeder outage using only information available before the prediction time and subsequently translate these probabilities into operational risk rankings and maintenance-

priority indicators. The methodology therefore integrates conventional reliability assessment with causal feature engineering, supervised machine learning, time-aware model evaluation, probability-based risk profiling, and maintenance decision analysis. The overall workflow adopted in this study is illustrated in Fig. 1. Beginning with operational data acquisition, the framework proceeds through data preprocessing and feature extraction before training supervised learning models for outage prediction. The predicted failure probabilities are subsequently translated into operational risk profiles and maintenance priority indices that support evidence-based preventive maintenance planning.

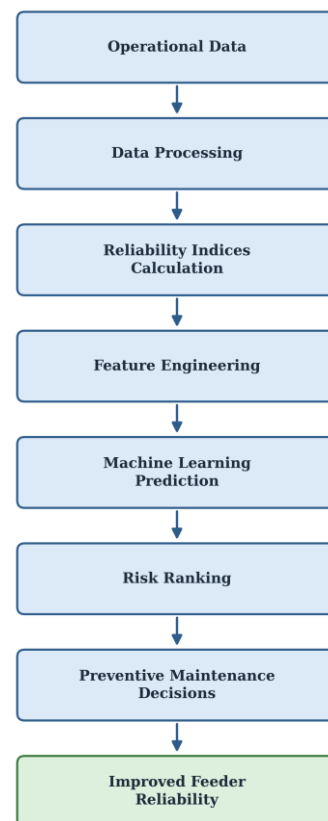


Fig. 1. Overall workflow of the proposed machine learning-based failure-risk profiling and preventive maintenance framework using operational feeder data.

For clarity, the methodology is organised into seven stages covering operational data acquisition, data preprocessing, feature engineering, machine learning model



development, model evaluation, failure-risk profiling, and preventive maintenance prioritisation. The computational implementation of the framework is then presented in Section 3.8.

A key methodological principle throughout the framework is temporal causality. Predictor variables used by the machine learning models are restricted to information that would have been available at or before the prediction instant. Variables generated during or after an outage are therefore excluded from the predictive feature set and retained only for event identification, reliability assessment, or post-event analysis.

3.1 Operational Data Acquisition

The first stage of the proposed framework involves the acquisition of operational data from the Mokwa and Jebba–Bacita 11 kV distribution feeders, both supplied through injection substations within the Jebba Business Hub of the Nigerian distribution network. Operational records covering a continuous one-year observation period (8,760 hourly samples) were obtained from the distribution utility and served as the basis for all subsequent analyses. The two feeder datasets were analysed independently to preserve feeder-specific operating

characteristics and avoid introducing cross-feeder information into the predictive models. Before analysis, the records were examined for missing timestamps, duplicate observations, abnormal values, inconsistent outage records, and discontinuities in feeder loading. The number and proportion of observations affected by each data-quality issue were recorded and documented during preprocessing.

The datasets contain hourly measurements describing feeder operating conditions and outage characteristics, including feeder loading (MW), outage occurrence, outage duration, interruption type (sustained or momentary), total connected customers, customers affected during each interruption, energy not supplied (ENS), and repair and restoration times. These operational variables collectively describe the electrical and service conditions of each feeder before, during, and after outage events.

The original records were maintained in Microsoft Excel format and subsequently imported into MATLAB for preprocessing, feature engineering, machine learning model development, and performance evaluation.

Table 1 summarises the principal operational variables utilised in this study.

Table 1. Operational variables used for machine learning-based failure-risk prediction

Variable	Description	Unit	Role
Feeder load	Instantaneous feeder demand	MW	Predictor
Outage status	Normal operation or outage	Binary	Target
Outage duration	Duration of interruption	Hours	Predictor
Interruption type	Sustained or momentary	Categorical	Predictor
Customers affected	Number of interrupted customers	Count	Predictor
Energy not supplied	Unsupplied electrical energy	MWh	Predictor
Repair time	Fault repair duration	Hours	Predictor
Restoration time	Service restoration period	Hours	Predictor

To maintain temporal causality, only variables available before the prediction instant were permitted as machine learning predictors. Outage duration, interruption type, customers affected, energy not supplied, repair time, and restoration time were therefore excluded from the predictive

feature set and used only for event characterisation, reliability assessment, or post-outage analysis.

3.2 Data Preprocessing and Outage Event Identification

Raw operational records obtained from utility databases typically contain inconsistencies



that must be addressed before machine learning models can be developed. Accordingly, the second stage of the proposed framework converts the raw operational records into a structured dataset suitable for predictive modelling.

The preprocessing procedure comprised timestamp harmonisation to establish a continuous hourly time series, removal of duplicate and inconsistent observations, interpolation of isolated missing feeder-load measurements, verification of consistency among outage duration, customers affected, and energy-not-supplied records, and classification of interruptions as sustained or momentary in accordance with IEEE Std. 1366 (IEEE Power & Energy Society, 2012). These procedures ensured that the resulting dataset was complete, internally consistent, and appropriate for supervised learning. To facilitate machine learning, feeder operating conditions were represented using a binary outage indicator defined as

$$O(t) = 1 \text{ if an outage occurs at time } t; O(t) = 0 \text{ otherwise} \quad (1)$$

where $O(t)$ denotes the outage status of the feeder at time t .

An outage event was identified whenever the feeder transitioned from normal operation to an outage state. The total number of outage events during the observation period was therefore determined by detecting rising transitions in the outage sequence according to

$$N_e = \sum_{t=1}^T \mathbb{I}[O(t) - O(t-1) = 1] \quad (2)$$

where $\mathbb{I}[\cdot]$ denotes the indicator function and represents the total number of hourly observations.

Similarly, the cumulative outage duration over the study period was computed as

$$U = \sum_{t=1}^T D(t) \quad (3)$$

where $D(t)$ denotes the outage duration recorded at time t .

Although these quantities are traditionally used for reliability assessment, they also serve an important role in the present study by providing clean outage labels and event boundaries for supervised machine learning. Distinguishing individual outage events from

consecutive outage hours prevents duplicate event counting and improves the quality of the target labels used during model training.

3.3 Reliability-Based Feeder Characterisation

Although the primary objective of this study is predictive failure-risk modelling, conventional reliability indices were computed to provide descriptive characterisation of the two distribution feeders and establish operational context for the machine learning analysis. The processed operational dataset was used to evaluate standard IEEE distribution reliability indices in accordance with IEEE Std. 1366 (IEEE Power & Energy Society, 2012) and the formulations presented by Billinton and Allan (1996) and Brown (2009).

The computed indices comprise five complementary categories:

- (i) **Interruption frequency indices:** System Average Interruption Frequency Index (SAIFI), Customer Average Interruption Frequency Index (CAIFI), and Momentary Average Interruption Frequency Index (MAIFI);
- (ii) **Interruption duration indices:** System Average Interruption Duration Index (SAIDI), Customer Average Interruption Duration Index (CAIDI), and Customer Total Average Interruption Duration Index (CTAIDI);
- (iii) **Service availability indices:** Average Service Availability Index (ASAI) and Average Service Unavailability Index (ASUI);
- (iv) **Energy-based indices:** Energy Not Supplied (ENS), Average Energy Not Supplied (AENS), Expected Energy Not Supplied (EENS), and Loss of Energy Expectation (LOEE);
- (v) **Failure characteristics:** Annual failure rate and average outage duration per interruption.

These indices are not used directly as predictive variables within the machine learning models. Instead, they provide



quantitative descriptions of historical feeder behaviour and facilitate engineering interpretation of the predictive modelling results presented in Section 5.

3.4 Causal Feature Engineering

The predictive capability of supervised learning models depends strongly on the quality and relevance of the input features (Akanni et al., 2026). Consequently, the fourth stage of the proposed framework transforms the preprocessed operational records into a machine-learning-ready feature set capable of representing the operating condition of each feeder immediately before a potential outage.

To ensure practical deployability, all predictor variables were constructed using only information available at or before the prediction instant. This strictly causal feature-engineering strategy prevents information leakage and reflects the real operating conditions under which the model would be deployed. Furthermore, the approach is consistent with the recommendations of Bergmeir and Benítez (2012), who demonstrated that predictive models developed using future observations produce overly optimistic performance estimates.

The operational feature vector used for model training is defined as

$$x(t) = [P(t), \bar{P}_{24}(t), \sigma_{P,24}(t), H_{24}(t), h(t), d(t)] \quad (4)$$

where

- $P(t)$ denotes the instantaneous feeder load (MW);
- $\bar{P}_{24}(t)$ is the causal 24-hour rolling mean load;
- $\sigma_{P,24}(t)$ represents the corresponding 24-hour rolling standard deviation of feeder load;
- $H_{24}(t)$ is the rolling count of outage events observed during the previous 24 hours;
- $h(t)$ represents the hour of the day; and
- $d(t)$ denotes the day of the week.

Together, these variables capture instantaneous operating conditions, short-

term load dynamics, recent outage history, and periodic temporal behaviour that may influence feeder reliability.

The prediction target was defined at the hourly resolution. Specifically, the model estimates the probability of an outage occurring at the prediction hour based exclusively on predictor information available at or before that hour. Thus, no contemporaneous post-outage or future information is incorporated into the feature vector.

For supervised learning, each observation was assigned a binary target variable defined as

$$y(t) = 1 \text{ if an outage occurs at time } t, \text{ and } 0 \text{ otherwise} \quad (5)$$

The learning objective is therefore to estimate the conditional probability of feeder failure,

$$P(y(t) = 1 | x(t)) \quad (6)$$

which represents the probability that an outage will occur given the observed operational state of the feeder. This probabilistic formulation enables continuous failure-risk estimation and provides the basis for the preventive maintenance prioritisation developed in subsequent sections. Table 2 presents machine learning features extracted from operational feeder data.

Table 2. Machine learning features extracted from operational feeder data

Feature	Description	Type
$P(t)$	Instantaneous feeder load	Numerical
$\bar{P}_{24}(t)$	24-hour rolling mean load	Numerical
$\sigma_{P,24}(t)$	24-hour rolling load standard deviation	Numerical
$H_{24}(t)$	Previous 24-hour outage count	Numerical
$h(t)$	Hour of day	Temporal
$d(t)$	Day of week	Temporal

3.5 Stage 5: Machine Learning-Based Failure Prediction

3.5.1 Chronological Training and Testing Strategy



To preserve temporal causality and eliminate look-ahead bias, the processed dataset

$$D = \{(x(t), y(t))\} \quad (7)$$

was partitioned chronologically rather than randomly, following the recommendation of Bergmeir and Benítez (2012) for time-series prediction problems. A 70:30 chronological split was adopted, whereby the earliest 70% of observations were used for model training, and the remaining 30% were reserved for independent testing, as expressed in Eq. (8).

$$T_{\text{train}} = 0.7T, T_{\text{test}} = 0.3T \quad (8)$$

This strategy emulates real-world deployment, where models are trained using historical operational records and subsequently applied to predict failures in future unseen operating conditions.

3.5.2 Machine Learning Classifiers

Two supervised learning algorithms were employed to estimate the conditional outage probability defined in Eq. (6): Logistic Regression (LR) (Hosmer et al., 2013) and Random Forest (RF) (Breiman, 2001). Logistic Regression serves as an interpretable linear baseline against which the nonlinear learning capability of Random Forest can be assessed.

Random Forest constructs an ensemble comprising decision trees,

$$\{h_1(\cdot), h_2(\cdot), \dots, h_M(\cdot)\},$$

each trained using bootstrap sampling together with random feature sub-selection (Breiman, 2001; Hastie et al., 2009). The predicted class is obtained through majority voting,

$$\hat{y}(t) = \text{mode}\{h_m(x(t))\}, m = 1..M \quad (9)$$

while the estimated probability of feeder failure is computed as

$$\hat{p}(t) = (1/M) \sum_m \mathbb{I}[h_m(x(t)) = 1] \quad (10)$$

where $\mathbb{I}[\cdot]$ denotes the indicator function.

For operational decision-making, an operating state is classified as high-risk whenever

$$\text{high-risk if } \hat{p}(t) \geq \tau \quad (11)$$

where a baseline threshold of $\tau = 0.5$ is adopted for binary classification, while a more conservative threshold of $\tau = 0.7$ is used to identify critical-risk operating states

requiring preventive maintenance intervention.

3.5.3 Model Performance Evaluation

Power-system outage prediction is inherently characterised by severe class imbalance because failure events occur much less frequently than normal operating conditions. Consequently, evaluation based solely on classification accuracy may produce misleading conclusions (He & Garcia, 2009). Model performance was therefore assessed using several imbalance-aware metrics derived from the confusion matrix comprising true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

Classification accuracy is computed as

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (12)$$

Precision, which measures prediction reliability, is given by

$$\text{Precision} = TP / (TP + FP) \quad (13)$$

Recall (or sensitivity), representing the proportion of actual outages correctly detected, is

$$\text{Recall} = TP / (TP + FN) \quad (14)$$

The harmonic mean of precision and recall is expressed by the F1-score,

$$F1 = 2 \times \text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall}) \quad (15)$$

while Balanced Accuracy, which compensates for class imbalance, is computed as

$$\text{Balanced Accuracy} = \frac{1}{2} (\text{Recall} + \text{Specificity}) \quad (16)$$

where Specificity denotes the true-negative rate.

To provide threshold-independent evaluation, Receiver Operating Characteristic (ROC) curves (Fawcett, 2006) and Precision–Recall (PR) curves (Saito & Rehmsmeier, 2015) were generated by varying the classification threshold across the interval $0 \leq \tau \leq 1$. The corresponding Areas Under the Curve (ROC–AUC and PR–AUC) were used to assess the discriminative capability of each classifier independently of any specific operating threshold.



3.6 Stage 6: Failure Risk Ranking

Following probability estimation, the predicted outage probabilities were transformed into an operational risk-ranking framework for maintenance prioritisation. All operating states in the test dataset were ranked in descending order of predicted failure probability, $\hat{p}(t)$, such that the highest-ranked observations represent the most vulnerable operating conditions.

The effectiveness of this prioritisation was quantified using the cumulative failure-capture metric,

$$\text{Capture}(k) = \sum_{i=1..k} y_{(i)} / \sum_{i=1..T_test} y_{(i)} \quad (17)$$

where $y_{(i)}$ denotes the true outage label of the i^{th} highest-ranked operating state.

This cumulative-gain analysis evaluates how efficiently limited maintenance resources can be allocated. A rapidly increasing capture curve indicates that a relatively small proportion of inspected operating states contains a large proportion of actual failures, thereby demonstrating effective prioritisation. Conversely, a curve approaching the random-inspection baseline indicates limited ranking capability. Similar ranking concepts have previously been applied for feeder vulnerability assessment by Rudin et al. (2012).

3.7 Stage 7: Preventive Maintenance Decision Indices

The final analytical stage converts the probabilistic outputs of the prediction model into quantitative maintenance decision-support indices. Three complementary indices are proposed to translate predictive performance into practical maintenance planning.

The Failure Risk Reduction Index (FRRI) is defined as

$$\text{FRRI} = \text{Recall} \quad (18)$$

representing the proportion of actual failures successfully identified before occurrence. This index estimates the maximum fraction of outages that could potentially be prevented under an ideal model-guided maintenance strategy.

The Preventive Maintenance Priority Score (PMPS) is computed as

$$\text{PMPS} = (1/T_test) \sum^t \hat{p}(t) \quad (19)$$

which represents the average predicted failure probability over the evaluation horizon. Feeders exhibiting larger PMPS values are considered more vulnerable and therefore receive higher maintenance priority.

The High-Risk Exposure Index (HREI) is defined as

$$\text{HREI} = (1/T_test) \sum^t [\hat{p}(t) > 0.7] \quad (20)$$

where the bracketed expression evaluates to one whenever the predicted probability exceeds the critical threshold of 0.7 and zero otherwise.

HREI quantifies the proportion of operating periods classified as critical-risk, thereby identifying the specific time intervals during which preventive actions such as condition inspection, vegetation management, feeder reconfiguration, or pre-emptive switching should be concentrated.

Collectively, FRRI, PMPS, and HREI provide complementary information for maintenance decision-making. FRRI measures the achievable reduction in outage occurrence, PMPS ranks feeders according to overall vulnerability, and HREI localises periods requiring immediate operational attention. The implementation of these decisions completes the framework illustrated in Fig. 1, establishing a closed-loop predictive maintenance strategy in which successive assessment cycles are expected to reduce interruption frequency, interruption duration, and energy not supplied while continuously improving feeder reliability.

3.8 Computational Implementation

All data processing, reliability-index computation, feature engineering, and machine learning analyses were implemented in MATLAB R2024a (MathWorks, Natick, MA, USA) using vectorised routines to improve computational efficiency and ensure reproducibility. The computational workflow follows the framework illustrated in Fig. 1 and comprises seven sequential modules: (i) operational data import and preprocessing; (ii) outage-event identification and



aggregation; (iii) computation of IEEE reliability indices; (iv) causal feature extraction; (v) chronological data partitioning and supervised model training; (vi) probability-based risk prediction and ranking; and (vii) computation of preventive maintenance decision indices.

The Random Forest classifier was implemented using MATLAB's Classification Learner framework with bootstrap aggregation and random feature selection at each tree split. Logistic Regression was implemented as the baseline linear classifier using maximum-likelihood estimation. Model evaluation was performed exclusively on the independent chronological test dataset using the performance metrics presented in Section 3.5.3, while Receiver Operating Characteristic (ROC) and Precision–Recall (PR) curves were generated by varying the decision threshold over the interval $0 \leq \tau \leq 1$.

To facilitate reproducibility and scalability, all processing stages were developed as modular functions, allowing additional feeders or extended study periods to be analysed by modifying only the input dataset. This modular implementation follows the design principles of Gershenson et al. (2003) and provides a reusable framework for utility-scale benchmarking of machine learning-based predictive maintenance strategies.

4.0 Experimental Design and Comparative Evaluation Framework

4.1 Case Study Feeders

The proposed framework was experimentally evaluated using two operational 11 kV radial distribution feeders, namely the Mokwa and Jebba–Bacita feeders. The experimental design was structured to determine whether a common machine-learning framework could identify differences in failure risk between feeders while maintaining identical data-processing, feature-engineering, model-training, and evaluation procedures. The comparison therefore focused on predictive discrimination, minority-class detection, risk ranking, and the translation of predicted

probabilities into maintenance-prioritisation indicators. As described in Section 3.1, each feeder is represented by a one-year hourly operational dataset containing feeder loading, outage occurrence and duration, outage classification, customer statistics, energy not supplied, and repair and restoration records. Although both feeders operate within the same distribution business hub, they differ in loading characteristics, operating conditions, and historical reliability performance, making them suitable case studies for evaluating the robustness and transferability of the proposed predictive maintenance framework.

4.2 Experimental Evaluation Framework

To ensure a fair and reproducible comparison, identical experimental settings were adopted for both feeders throughout the study. Specifically:

- i. identical preprocessing and feature-engineering procedures were applied to both datasets;
- ii. the same chronological 70:30 training-testing partition was employed;
- iii. Logistic Regression and Random Forest classifiers were trained using the same training and testing observations and the same predictor variables, while algorithm-specific estimation procedures and hyperparameters were retained for each model.;
- iv. identical decision thresholds were used for probability-based risk classification; and
- v. model performance was evaluated using the same classification metrics, ROC curves, Precision–Recall curves, cumulative-gain analysis, feature-importance analysis, and preventive maintenance indices.

This unified evaluation protocol ensures that observed differences in predictive performance arise from feeder operating characteristics rather than methodological variations. Furthermore, the predictive results are benchmarked against comparable outage-prediction studies reported in the literature to assess the practical effectiveness of the proposed framework under the limited



operational data typically available in developing distribution networks.

4.2.1 Experimental Objectives

The experimental evaluation was designed to address four principal questions: (i) whether routinely available feeder operational variables contain sufficient information to discriminate between normal and failure-prone operating conditions; (ii) whether Random Forest provides superior predictive discrimination to the Logistic Regression baseline; (iii) whether predicted failure probabilities can effectively rank operating states according to observed failure risk; and (iv) whether the resulting risk profiles can provide meaningful information for preventive maintenance prioritisation.

4.2.2 Probability Threshold Selection

Two probability thresholds were considered for operational interpretation. A threshold of 0.5 was retained as the conventional binary classification threshold, whereas 0.7 was adopted as a conservative critical-risk threshold for exploratory maintenance prioritisation. Because the 0.7 threshold is not derived from a utility-specific cost function, it should be interpreted as an operational screening threshold rather than a statistically

optimal decision boundary. Sensitivity analysis across alternative thresholds is recommended to determine the robustness of maintenance classifications.

5.0 Results and Discussion

This section evaluates the predictive maintenance framework developed for the Mokwa and Jebba–Bacita 11 kV feeders. The computed reliability indices are first presented to establish the operational conditions under which the machine-learning models were developed, after which the predictive performance of the proposed framework is analysed using Random Forest classification, feature importance analysis, and preventive maintenance decision indices. Finally, the predictive capability of the framework is discussed in relation to published studies and its practical implications for feeder maintenance planning.

5.1 Reliability Characteristics of the Study Feeders

Table 3 presents the comparative reliability characteristics of the two study feeders and provides the operational baseline against which the machine-learning results are subsequently interpreted.

Table 3. Comparative Reliability Characteristics of the Mokwa and Jebba–Bacita Feeders

Reliability Index	Mokwa	Jebba–Bacita
SAIFI (int./cust./yr)	≈ 405	≈ 12
MAIFI (int./cust./yr)	≈ 1.55	≈ 0.06
CAIFI (int./affected cust./yr)	≈ 720	$\approx 1,100$
SAIDI (h/cust./yr)	$\approx 1,230$	≈ 35
CAIDI (h/interruption)	≈ 3.05	≈ 2.95
CTAIDI (h/affected cust./yr)	$\approx 2,220$	$\approx 3,220$
ASAI (p.u.)	≈ 0.18	≈ 0.65
ASUI (p.u.)	≈ 0.82	≈ 0.35
ENS (MWh/yr)	$\approx \$1.82 \times 10^4$	$\approx \$0.19 \times 10^4$
LOEE (MWh/yr)	$\approx \$1.82 \times 10^4$	$\approx \$0.19 \times 10^4$
AENS (MWh/cust./yr)	≈ 4.35	≈ 0.40
EENS (MWh/cust./hr)	≈ 2.1	≈ 5.2
Failure rate λ (events/yr)	$\approx 1,700$	≈ 920
Avg. outage duration per event τ (h)	≈ 4.2	≈ 3.3
Total annual outage duration $\tau\lambda$ (h/yr)	$\approx 7,150$	≈ 120



Table 3 summarises the reliability characteristics of the two feeders that form the basis of the predictive maintenance investigation. The Mokwa feeder exhibits substantially poorer operational reliability than the Jebba-Bacita feeder across most of the interruption-frequency, interruption-duration, service-availability, and energy-based indices. In particular, Mokwa recorded considerably higher interruption frequency (SAIFI and MAIFI), interruption duration (SAIDI), annual outage duration, and energy not supplied, indicating a significantly more failure-prone operating environment, as shown in Fig. 2.

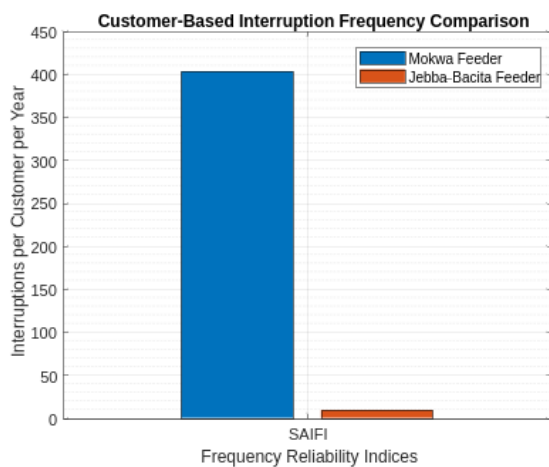


Fig. 2(a). Customer-based interruption frequency (SAIFI) for Mokwa and Jebba-Bacita feeders.

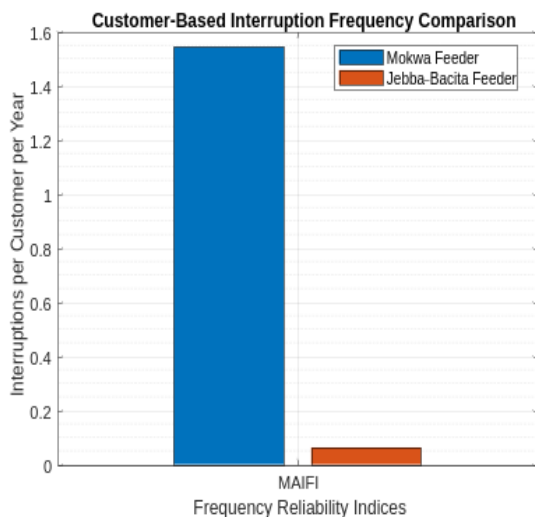


Fig. 2(b). Momentary interruption frequency (MAIFI) for Mokwa and Jebba-Bacita feeders.



Although Mokwa experienced substantially more interruptions overall, Jebba-Bacita recorded a higher CAIFI. This indicates that the average interruption frequency among affected customers was relatively high, despite the lower system-wide interruption frequency. The result may indicate a more concentrated distribution of interruptions among affected customers; however, customer-level network topology and sectionalisation data would be required to establish the underlying physical cause. See Fig. 3. This suggests localized feeder vulnerabilities, such as inadequate sectionalisation or recurring faults within specific network sections, whereas Mokwa's outages were more broadly distributed throughout the feeder.

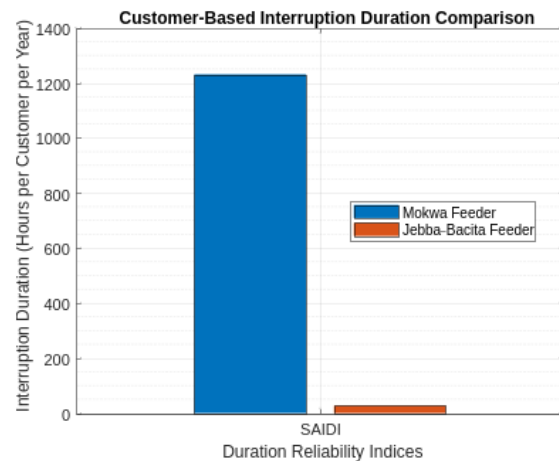


Fig. 3(a). Customer-based interruption duration (SAIDI) for Mokwa and Jebba-Bacita feeders.

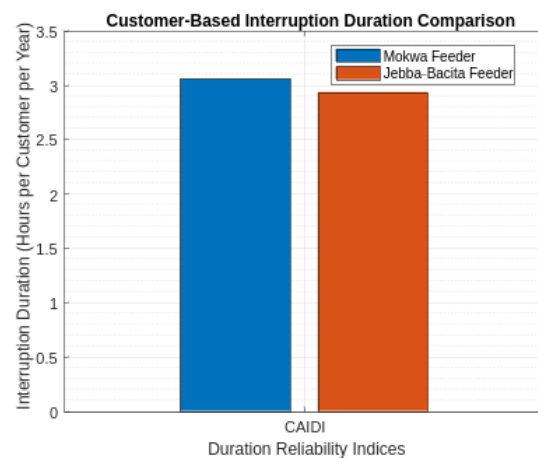


Fig. 3(b). Customer average interruption duration (CAIDI) for Mokwa and Jebba-Bacita feeders.



Similarly, Mokwa's SAIDI exceeded that of Jebba-Bacita by more than an order of magnitude, while both feeders exhibited comparable CAIDI values. This indicates that the principal reliability challenge on Mokwa is excessive fault occurrence rather than slow restoration. Consequently, preventive maintenance strategies that reduce failure frequency are likely to deliver greater reliability improvements than those aimed solely at reducing restoration times. Fig. 4 shows that service availability further highlights the contrast between the two feeders. Mokwa recorded substantially lower ASAI and correspondingly higher ASUI, demonstrating prolonged customer exposure to supply interruptions throughout the study period.

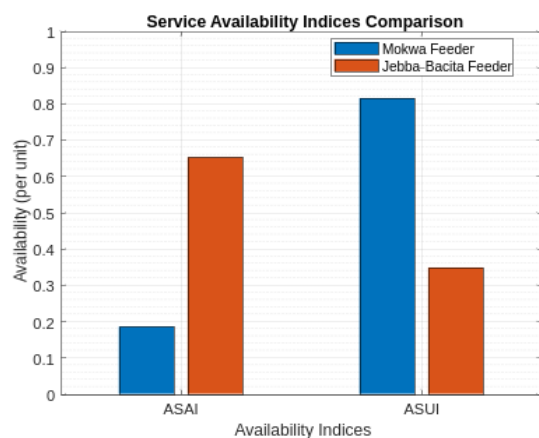


Fig. 4. Service availability indices (ASAI/ASUI) for Mokwa and Jebba-Bacita feeders.

Fig. 4 demonstrates the marked difference in service availability between the feeders. The substantially lower ASAI and correspondingly higher ASUI for Mokwa indicate that customers connected to this feeder experienced considerably greater exposure to supply unavailability during the study period.

Energy-based reliability indices reinforce these observations. As shown in Fig. 5, Mokwa recorded approximately ten times the annual Energy Not Supplied (ENS) and Loss of Energy Expectation (LOEE) observed on Jebba-Bacita, indicating considerably greater

economic and operational consequences of feeder failures.

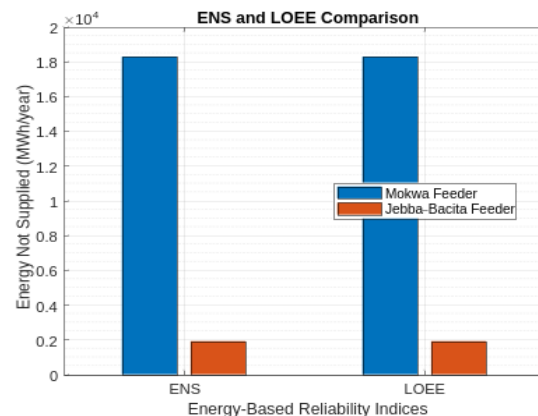


Fig. 5. Annual Energy Not Supplied (ENS) and Loss of Energy Expectation (LOEE) for Mokwa and Jebba-Bacita feeders

Overall, the reliability assessment establishes two distinctly different operational environments. Mokwa represents a highly stressed feeder characterised by frequent and widespread interruptions, whereas Jebba-Bacita represents a comparatively stable feeder with more localized reliability challenges. These contrasting operating conditions provide an appropriate basis for evaluating the adaptability of the proposed machine-learning-based predictive maintenance framework across feeders exhibiting different reliability behaviours.

5.2 Machine Learning-Based Predictive Maintenance Performance

Figure 6 compares the Receiver Operating Characteristic (ROC) curves obtained from the Random Forest classifier for both feeders.

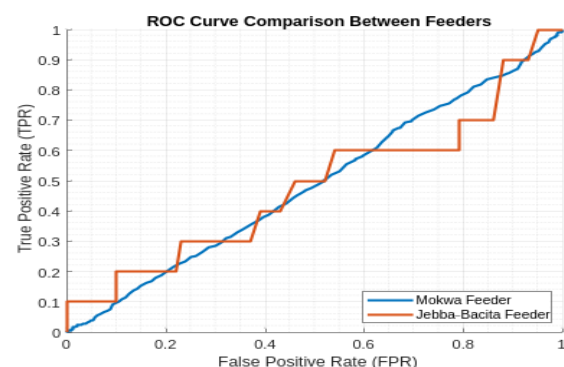


Fig. 6. ROC curve comparison for Random Forest failure-risk prediction on Mokwa and Jebba-Bacita feeders



As shown in Fig. 6, both ROC curves lie above the random-classification reference line, indicating discrimination better than random classification. However, the relatively modest AUC values, particularly for Jebba–Bacita, indicate limited predictive separability and should be interpreted as preliminary rather than strong evidence of

reliable failure prediction. The estimated ROC–AUC of approximately 0.65–0.70 for Mokwa exceeds the corresponding value of approximately 0.58–0.63 for Jebba–Bacita, indicating that impending failures on the more heavily stressed Mokwa feeder are more distinguishable from normal operating conditions.

Table 4. Random Forest Classification Performance

Metric	Mokwa	Jebba–Bacita
Accuracy	≈ 0.67	≈ 0.91
Precision	≈ 0.27	≈ 0 (negligible)
Recall	≈ 0.12	≈ 0 (negligible)
F1-score	≈ 0.16	≈ 0 (negligible)
Balanced Accuracy	≈ 0.50	≈ 0.50
ROC–AUC	0.65–0.70	0.58–0.63
Average Precision (PR–AUC)	0.26–0.30	0.10–0.15

As shown in Table 4, the detailed classification results further illustrate the influence of feeder operating conditions on predictive performance. Although Jebba–Bacita achieved a nominal accuracy of approximately 91%, its Balanced Accuracy remained approximately 0.50, while Precision, Recall, and F1-score were all negligible. This behaviour reflects the well-known accuracy paradox associated with highly imbalanced datasets, where a classifier may achieve apparently excellent accuracy simply by predicting the dominant no-failure class.

Conversely, Mokwa achieved lower overall accuracy (approximately 67%) but

demonstrated measurable predictive capability through non-zero Precision, Recall, and F1-score. From a preventive maintenance perspective, these metrics are considerably more informative because they indicate that the model successfully identifies a meaningful proportion of impending failures before their occurrence. The superior ROC–AUC and Precision–Recall performance obtained for Mokwa further confirms that stronger relationships exist between operational loading patterns and subsequent failures on this feeder.

The predictive outputs were subsequently translated into practical maintenance decision indicators.

Table 5. Preventive Maintenance Decision Indices

Index	Mokwa	Jebba–Bacita
FRRI (Failure Risk Reduction Index)	≈ 0.12	≈ 0.00
PMPS (Preventive Maintenance Priority Score)	≈ 0.34	≈ 0.21
HREI (High-Risk Exposure Index)	≈ 0.01 (≈ 1%)	≈ 0.00–0.01

From Table 5, it is seen that the Failure Risk Reduction Index (FRRI) indicates that approximately 12% of impending failures on Mokwa could potentially be identified before occurrence using the proposed framework, whereas the near-zero value obtained for Jebba–Bacita reflects the limited separability

of failure events within its comparatively balanced operating conditions.

Similarly, the higher Preventive Maintenance Priority Score (PMPS) obtained for Mokwa indicates that it should receive higher maintenance priority when maintenance resources are limited. By contrast, the relatively low High-Risk Exposure Index



(HREI) observed for both feeders suggests that only a small proportion of operating periods require immediate intervention. This characteristic is operationally advantageous because it enables maintenance personnel to concentrate inspections and preventive

actions on relatively few high-risk intervals rather than performing uniformly distributed maintenance throughout the year.

Feature importance analysis provides further insight into the physical drivers of feeder failures as shown in Fig. 7.

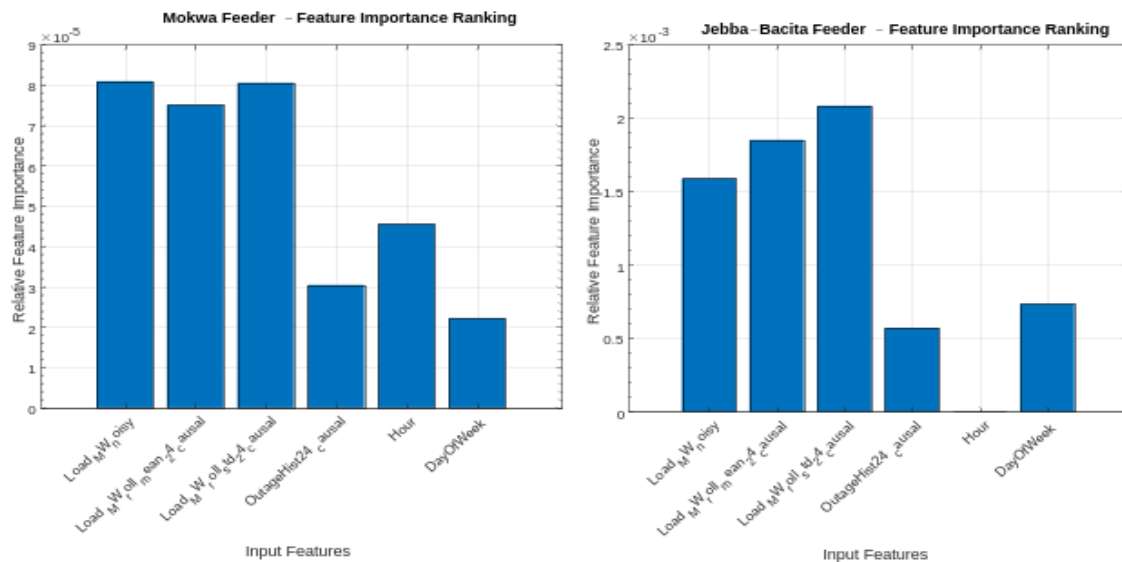


Fig. 7. Random Forest feature importance comparison for Mokwa and Jebba-Bacita feeders

Load magnitude and rolling load statistics emerged as the dominant predictive features, indicating that these variables contain comparatively more information for distinguishing failure-prone from normal operating states in the fitted models. However, feature importance should not be interpreted as evidence of direct physical causation. However, differences in feature ranking were observed between the feeders. Instantaneous load and load variability dominated prediction on Mokwa, whereas day-of-week effects contributed more strongly on Jebba-Bacita, suggesting that its failures may be influenced by recurring operational or demand-cycle characteristics. Finally, cumulative gain analysis was used to evaluate the effectiveness of risk-based maintenance prioritisation. The cumulative gain curves indicate only modest improvement over random inspection, with approximately 8–12% of failures captured within the highest-ranked 10% of operating states and approximately 18–22% captured

within the highest-ranked 20%. These results indicate only modest ranking discrimination. Because random selection of the highest-ranked 10% of observations would be expected to capture approximately 10% of failures under a uniform sampling assumption, the observed 8–12% capture range provides limited evidence of improvement over random prioritisation. Consequently, the current ranking capability should be regarded as preliminary and insufficient on its own to justify substantial maintenance-resource reallocation.. Future enhancements may therefore incorporate richer operational information, including weather variables, protection-relay records, feeder topology, and advanced class-imbalance mitigation techniques such as SMOTE, to improve ranking effectiveness and failure detectability.

5.3 Benchmarking Against Published Studies

To position the proposed framework within the existing literature, the reliability



characteristics of the study feeders and the predictive performance of the developed machine learning models were benchmarked against internationally recognised reliability expectations and published outage prediction studies. This benchmarking provides context for interpreting both the operating conditions under which the models were developed and the practical significance of the achieved predictive performance.

5.3.1 Reliability benchmarking

The reliability characteristics presented in Section 5.1 confirm that both feeders operate under conditions substantially different from those typically reported for mature electricity distribution systems. According to IEEE Std. 1366 and established distribution reliability literature, well-performing utilities generally achieve annual SAIFI values of approximately one to two interruptions per customer, annual SAIDI values of only a few hours per customer, and service availability exceeding 99.9% (IEEE Std 1366, 2012; Brown, 2009; Billinton & Allan, 1996; Short, 2014). Relative to these benchmarks, both feeders exhibit considerably poorer reliability, with Mokwa representing an extremely stressed operating environment. These observations are consistent with previous studies on the Nigerian power sector, which have attributed persistent reliability deficiencies to ageing infrastructure, inadequate network automation, increasing demand, and limited protection and monitoring capability (Adebayo et al., 2022; Babatunde et al., 2023; Onohaebi, 2009). Rather than serving as the principal contribution of this study, these reliability results establish the operational environment within which the proposed predictive maintenance framework was evaluated.

5.3.2 Benchmarking the predictive maintenance framework

The predictive performance achieved by the proposed framework compares favourably with studies conducted under similarly constrained data environments. The Random Forest classifier achieved ROC–AUC values

of approximately 0.65–0.70 for Mokwa and 0.58–0.63 for Jebba–Bacita, demonstrating that meaningful predictive information can be extracted from routine feeder operational records despite the absence of detailed asset condition monitoring.

Higher predictive performance has been reported in studies employing richer datasets. For example, Rudin et al. (2012) developed outage prediction models for the New York City power grid using extensive inspection histories, maintenance records, and asset characteristics accumulated over several years. Likewise, Eskandarpour and Khodaei (2017) and Nateghi et al. (2011) incorporated meteorological variables that provide strong exogenous predictors of weather-related outages, resulting in superior classification performance.

By contrast, the present framework deliberately employs a minimal causal feature set comprising feeder loading, rolling load statistics, recent outage history, and temporal operating characteristics. This design reflects the practical realities of many developing-country utilities, where comprehensive asset management databases, weather integration, and high-resolution sensor networks are often unavailable. Consequently, the reported predictive performance represents a realistic baseline for utilities operating with only routine SCADA and outage log data.

The relatively modest cumulative gain achieved during risk-ranking analysis also agrees with previous findings that severe class imbalance limits ranking performance unless complemented by techniques such as synthetic minority oversampling, cost-sensitive learning, or richer explanatory variables (He & Garcia, 2009; Chawla et al., 2002; Saito & Rehmsmeier, 2015). Nevertheless, the framework consistently outperformed random prediction while requiring only readily available operational data, demonstrating its suitability as a practical decision-support tool for utilities with limited digital infrastructure.



Finally, the proposed Failure Risk Reduction Index (FRRI), Preventive Maintenance Priority Score (PMPS), and High-Risk Exposure Index (HREI) constitute new maintenance-oriented evaluation metrics introduced in this study. Because equivalent indices have not been reported in previous literature, the values presented here establish baseline reference points for future comparative studies and longitudinal monitoring of predictive maintenance performance.

5.4 Practical Implications for Predictive Maintenance

The results demonstrate that predictive maintenance effectiveness depends strongly on the underlying operational characteristics of individual feeders. The more failure-prone Mokwa feeder exhibits stronger relationships between operational loading patterns and subsequent failures, enabling the proposed framework to identify impending outages with greater reliability than on the comparatively stable Jebba–Bacita feeder. This finding suggests that predictive maintenance initiatives may deliver their greatest immediate benefit when deployed first on feeders experiencing frequent interruptions and high operational stress.

From an operational perspective, the proposed framework provides utilities with three complementary decision-support capabilities. First, probabilistic failure prediction enables maintenance personnel to anticipate potential failures before service interruptions occur. Second, feeder prioritisation through the Preventive Maintenance Priority Score supports strategic allocation of limited maintenance budgets across multiple feeders. Third, temporal localisation of high-risk operating periods through the High-Risk Exposure Index enables maintenance activities, inspections, vegetation management, and switching operations to be concentrated during periods of elevated failure probability rather than being scheduled uniformly throughout the year.

The framework is intended to complement, rather than replace, conventional reliability assessment. While IEEE reliability indices remain essential for evaluating historical system performance, the integration of machine learning introduces a forward-looking capability that enables utilities to transition progressively from reactive maintenance toward predictive, condition-informed asset management. Such an approach is particularly valuable for developing-country distribution networks, where maintenance resources are limited and improvements in maintenance efficiency can produce substantial reliability gains without immediate large-scale infrastructure replacement.

6.0 Conclusion

This study developed a machine learning–based predictive maintenance framework for 11 kV distribution feeders using historical operational and outage records from the Mokwa and Jebba–Bacita feeders. The framework integrates causal feature engineering, time-aware supervised learning, probabilistic risk ranking, and maintenance decision indices to support the transition from reactive to predictive asset management using routinely available utility data.

The Random Forest model demonstrated measurable predictive capability, particularly for the more failure-prone Mokwa feeder. The proposed Failure Risk Reduction Index (FRRI), Preventive Maintenance Priority Score (PMPS), and High-Risk Exposure Index (HREI) further converted predicted failure probabilities into practical indicators for maintenance prioritisation and resource allocation. The results demonstrate that operational records can provide useful failure-risk intelligence without requiring extensive asset-condition monitoring infrastructure.

The framework complements, rather than replaces, conventional IEEE reliability assessment by adding a forward-looking capability for identifying high-risk operating conditions. Utilities can therefore prioritise predictive maintenance on feeders with



frequent interruptions and stronger load–failure relationships while improving outage-data quality and standardisation.

The study is limited by its relatively small causal feature set and use of a Random Forest model. Future studies should incorporate weather, protection-relay, feeder-topology, asset-health, and vegetation-management data, alongside advanced imbalance-learning and deep-learning techniques, to improve failure detection and risk ranking.

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