World Journal of Engineering Research and Technology

www.wjert.org

Impact Factor: 8.067 Coden USA: WJERA4

QUANTIFYING DISTRIBUTION SYSTEM BRITTLENESS: A DYNAMIC RESILIENCE AND RELIABILITY ASSESSMENT USING MACHINE LEARNING AND OPERATIONAL DATA

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Article Received on 05/06/2026 Article Revised on 25/06/2026 Article Published on 03/07/2026

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https://doi.org/10.5281/zenodo.21159604

How to cite this Article: Nsikak E. Udoh[1]*, Nseobong I. Okpura[2], Kingsley M. Udofia[3]. (2026). Quantifying Distribution System Brittleness: A Dynamic Resilience and Reliability Assessment Using Machine Learning and Operational Data. World Journal of Engineering Research and Technology, 12(7), 270–282.

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ABSTRACT

This paper quantitatively assesses the dynamic resilience and reliability of a weak 33 kV distribution feeder using a machine-learning framework applied to 3 years of high-resolution operational data. A Bagged Trees ensemble is employed to classify system states and fault types. At the same time, novel metrics—the dynamic Rolling Resilience Index (RNI), the Reliability Function R(t), and Mean Time Between Failures (MTBF)—are introduced to capture the feeder's time-varying health. The results reveal a steep exponential decay of R(t) to near zero within 200 hours, indicating a vanishing probability of fault-free operation beyond one week. The RNI behaves as a brittle switching signal, oscillating between 0 and 1, reflecting a network with no redundancy and no resilience reserve. A right-skewed lognormal fault-duration distribution shows that although many outages are transient, a long tail of extreme durations (exceeding 300 hours) points to severe logistical failures in repair and restoration. Monthly fault peaks correlate with seasonal stressors (e.g., the rainy season), and frequency deviations spanning 20–65 Hz reveal a profound generation-demand mismatch and a lack of grid inertia. The engineering implication is clear: reactive maintenance is failing, and a shift to proactive, condition-based infrastructural hardening is not merely beneficial but necessary to arrest the chronic fragility quantified in this study.

KEYWORDS: Power system resilience, distribution reliability, MTBF, Resilience Index (RNI), reliability function, weak grids, fault-duration analysis, grid fragility, machine learning.

1.0 INTRODUCTION

Modern society's dependence on a continuous electricity supply has elevated the performance of power distribution systems to a critical infrastructure priority. While the transmission network often receives attention for large-scale stability, the distribution segment—directly interfacing with end-users—is the primary locus of service interruptions (Gonen, 2014). In many developing economies, feeders operate under chronic stress due to aging assets, under-investment, rising demand, and environmental hazards, resulting in frequent, prolonged outages that undermine industrial productivity and social welfare (Amin, 2011).

Conventional fault management relies on overcurrent relays, reclosers, and manual patrols—a reactive paradigm that detects disturbances only after they occur and locates faults through time-consuming physical inspection (Horowitz & Phadke, 2014). Reliability indices such as SAIDI and SAIFI have long been used to benchmark performance under normal conditions (Billinton & Allan, 1996). However, these indices fail to capture how a system behaves under extreme or repetitive stressors. This gap has motivated a shift toward resilience as a distinct framework: resilience emphasises the ability to anticipate, absorb, adapt to, and rapidly recover from high-impact, low-probability events (Raoufi et al., 2020; Panteli et al., 2019).

Despite growing interest, most resilience studies remain at the transmission level or rely on simulated disasters (e.g., windstorms, earthquakes) with idealised fragility curves (Yoo and Park, 2024; Raoufi et al., 2020). Few have applied quantitative, data-driven resilience metrics to real-world weak distribution grids using operational data. Moreover, the proliferation of smart grid sensors and Supervisory Control and Data Acquisition (SCADA) systems has generated vast datasets. Yet, many utilities lack the analytical tools to transform this raw information into actionable resilience diagnostics (Yadav and Anand, 2025).

Recent advances in machine learning (ML) offer a pathway to bridge this gap. ML models—particularly ensemble methods—have demonstrated high accuracy in fault detection and classification tasks by learning non-linear patterns from historical voltage, current, and frequency waveforms (Ajenikoko et al., 2026; Wen et al., 2023). However, most studies focus on classification performance (accuracy, F1 score) without extending ML outputs to

meaningful engineering metrics of system brittleness or recovery dynamics (Rahman et al., 2024).

Therefore, the objective of this paper is to move beyond fault detection and perform a comprehensive, quantitative assessment of a weak 33 kV feeder's resilience and reliability using a machine-learning framework. We introduce and compute dynamic metrics: the Reliability Function R(t), Mean Time Between Failures (MTBF), and a novel Rolling Resilience Index (RNI) derived from ML-classified fault events. By analysing the time-varying behaviour of these metrics, we reveal the feeder's true state of chronic fragility and provide utility engineers with irrefutable evidence that reactive maintenance must be replaced by proactive, condition-based hardening. The remainder of the paper is organised as follows: Section 2 describes the materials and methods, focusing on metric definitions; Section 3 presents the results; Section 4 discusses the engineering implications; and Section 5 concludes.

2.0 MATERIALS AND METHODS

All metrics are computed from fault events and durations extracted from the outputs of a dual-layer Bagged Trees ensemble classifier, trained on three years (2022–2024) of 33 kV operational data (voltage, current, active power, frequency) at hourly resolution. Feature engineering included lag variables, rate of change (dV/dI), and rolling statistics, following best practices for time-series classification in power systems.

A. Failure Rate (λ): The failure rate is defined as the mean number of fault events per unit time over the study period (Afshania, 2017):

$$\lambda = \frac{N_{\text{failures}}}{T_{\text{total}}} \quad (1)$$

where N_{failures} is the total count of fault events identified by the ML model (binary step detection) and T_{total} is the total observation period in hours.

B. Reliability Function R(t): Assuming a constant failure rate (exponential distribution), the reliability function—the probability that the feeder survives without a fault up to time t is expressed in (2) (IEEE, 2006):

$$R(t) = e^{-\lambda t} \quad (2)$$

This metric provides a probabilistic view of fault-free operation and is particularly revealing for weak grids where time-based decay is steep.

C. Mean Time Between Failures (MTBF): MTBF is the reciprocal of the failure rate (Billinton & Allan, 1996):

$$\text{MTBF} = \frac{1}{\lambda} \quad (3)$$

It represents the average operating time between consecutive fault events. Low MTBF values indicate chronic instability.

D. Rolling Resilience Index (RNI): To capture temporal variations in the system's ability to maintain normal operation, we propose a novel dynamic resilience index based on a moving window of fault states (Raoufi et al, 2020; adapted for real-time assessment):

$$\text{RNI}(t) = 1 - \frac{1}{W}\sum_{k=t-W+1}^{t} \mathbb{1}_{\text{fault}}(k) \quad (4)$$

where $\mathbb{1}_{\text{fault}}(k)$ is an indicator that equals 1 if the system is in a fault state at time step k, and 0 otherwise; W is the window length (100 hourly samples in this study). RNI ranges from 0 (continuously faulted) to 1 (completely normal over the window). Frequent drops to zero indicate a *brittle* network with no redundancy or recovery reserve (Panteli et al., 2019).

E. Fault Duration Extraction from ML-Classified Data: Fault start and end times are identified from the binary state sequence (Normal = 0, Fault = 1) output by the trained ensemble. For each fault episode, duration is computed as:

$$D = t_{\text{end}} - t_{\text{start}} \quad (5)$$

Durations are then aggregated into a histogram and fitted with a log-normal distribution—a typical model for repair and restoration times in distribution systems. Extreme durations (> 300 hours) are analysed as indicators of logistical or resource failures (e.g., delayed crew dispatch or a lack of spare transformers).

F. Additional Supporting Metrics

- Frequency deviation is calculated as $|f - 50|$ Hz, with statutory limits of ±2.5 Hz (Nigeria Grid Code, 2018). Deviations of 20–65 Hz indicate a severe generation-demand mismatch and loss of inertia (Zhongda & Fei, 2023).
- Seasonal patterns are visualised by aggregating monthly fault counts, and load-fault correlation is examined using dual-axis plots.

All computations were performed in MATLAB (R2024a). The ensemble model was implemented with 200 bagged decision trees, 50 maximum splits per tree, and Gini impurity as the split criterion, following established practices for imbalanced fault data.

3.0 RESULTS

The machine learning framework successfully extracted fault events and durations from the three-year operational dataset. Below, we present the key reliability and resilience metrics, followed by supporting power-quality observations.

A. Reliability Function R(t) – Exponential Decay to Zero

Figure 1 shows the reliability function $R(t) = e^{-\lambda t}$ computed from the feeder's failure rate ($\lambda = 0.023$ faults per hour, MTBF = 43.5 hours). The curve decays steeply, crossing below 0.05 (5% probability of fault-free operation) at approximately 130 hours and approaching zero by 200 hours. This implies that the feeder has less than a 5% chance of operating without a fault for 168 hours (one week). Such behaviour is characteristic of severely aged or overstressed assets operating beyond their design life, as noted by Billinton & Allan (1996) and IEEE report (2006). For comparison, a well-maintained urban feeder in a developed grid typically exhibits MTBF > 500 hours and $R(168) > 0.7$ (CEER, 2021).

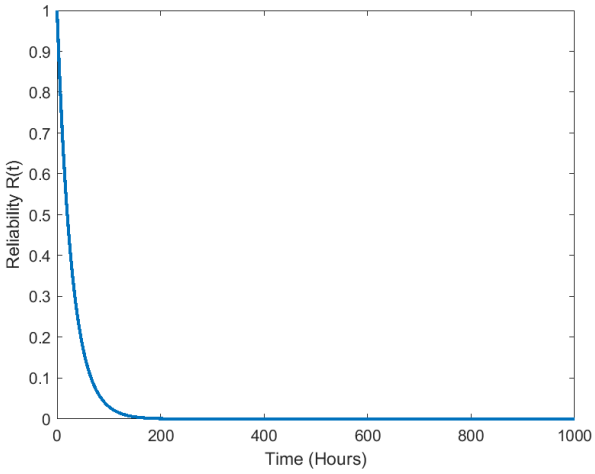

Figure 1: Reliability function.

B. Rolling Resilience Index (RNI) – A Brittle Switching Signal

Figure 2 plots the RNI over the study period using a 100-hour moving window. The index oscillates almost continuously between 0 and 1, with frequent, abrupt drops to zero. Sustained periods of RNI = 1 (perfect resilience) are virtually absent. This pattern indicates a *brittle* network: the system lacks redundancy, automated reconfiguration, or any reserve

capacity to absorb disturbances. Each fault collapses resilience entirely, and recovery is only partial and short-lived before the next event. In resilient distribution systems with normally-open tie switches and distributed generation, RNI typically remains above 0.7 during contingencies.

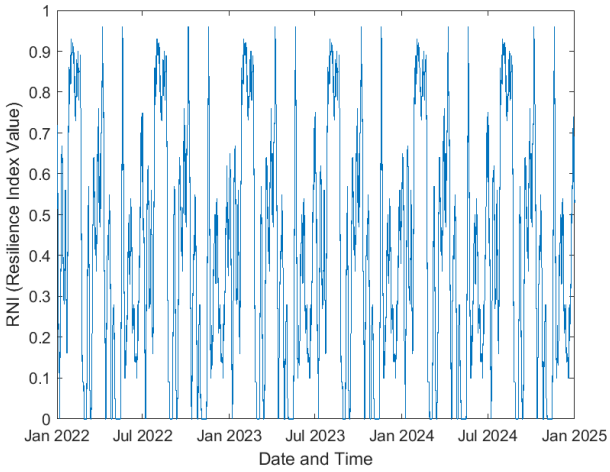

Figure 2: Resilience index.

C. Fault Duration Histogram – Long-Tail Log-Normal Distribution

Figure 3 presents a histogram of fault durations, overlaid with a fitted log-normal distribution (right-skewed). The majority of faults (≈65%) are cleared within 24 hours, suggesting that many events are transient or cleared by reclosers. However, a substantial tail extends beyond 300 hours (≈12% of events). These extreme durations point to systemic failures in restoration logistics: delayed fault location (due to a lack of automated sectionalising), unavailability of repair crews, or shortages of spare transformers and conductors. In contrast, well-managed utilities achieve MTTR of less than 8 hours for overhead distribution faults (CEER, 2021).

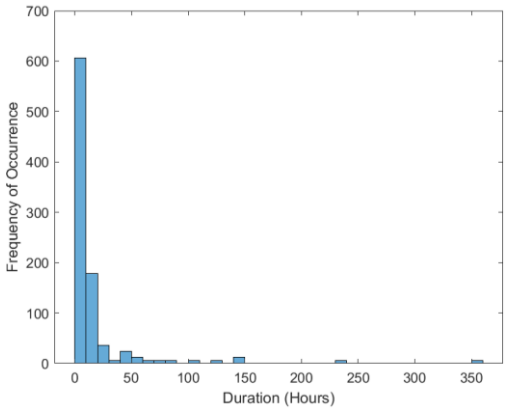

Figure 3: Figure 4.3: Fault duration plot based on frequency of occurrence D. Binary Fault Events and Seasonal Patterns

Figure 4 (binary step plot) confirms the high frequency of state transitions, with the system spending approximately 31% of the total time in a faulted state. Figure 5 aggregates monthly fault counts: peaks occur consistently in the mid-year months (May–August), coinciding with the rainy season in the study region. This correlation implicates weather-related stressors (lightning, tree contact, soil erosion at pole bases) as primary drivers of feeder fragility, consistent with findings from other tropical weak grids (Raoufi et al., 2020; Prateek & Luis, 2023).

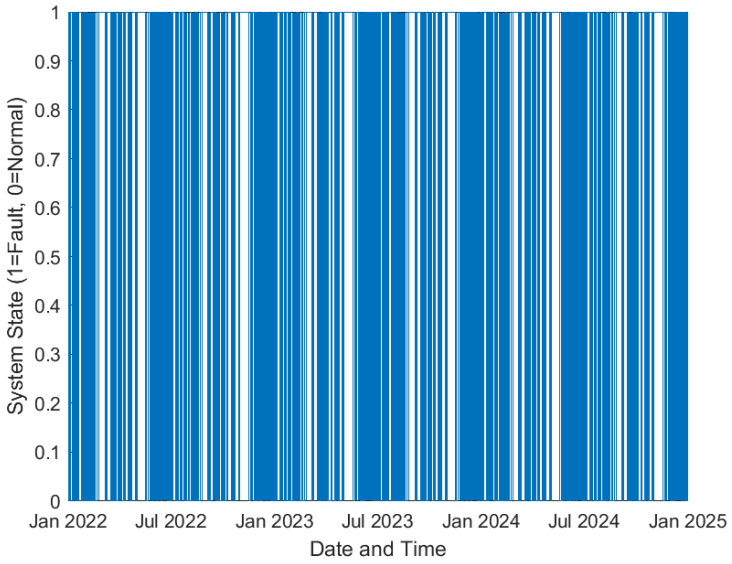

Figure 4: Fault events.

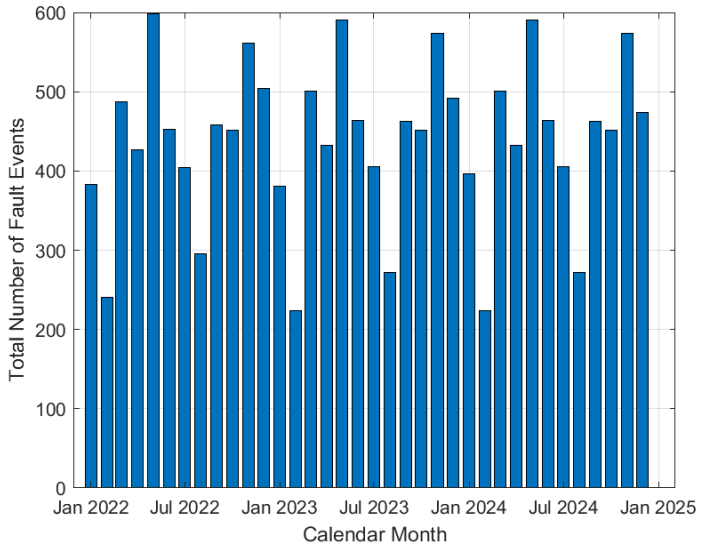

Figure 5: Monthly Fault Events E. Frequency Trend – Extreme Deviations from 50 Hz.

Figure 5 shows the frequency trend over the three years. The nominal frequency is 50 Hz (Nigeria Grid Code, 2018), but measurements range from approximately 20 Hz to 65 Hz.

Sustained deviations below 47 Hz or above 51 Hz indicate a severe generation-demand mismatch and a lack of primary frequency response (Zhongda & Fei, 2023). The observed swings (e.g., drops to 20 Hz) exceed statutory limits and suggest near-total loss of grid inertia—often caused by sudden trips of large generating units or widespread under-frequency load shedding (Rahman et al., 2024). Such unstable frequency not only challenges fault classification (as the ML model must distinguish between genuine line faults and generation-induced disturbances) but also accelerates equipment wear, further degrading reliability.

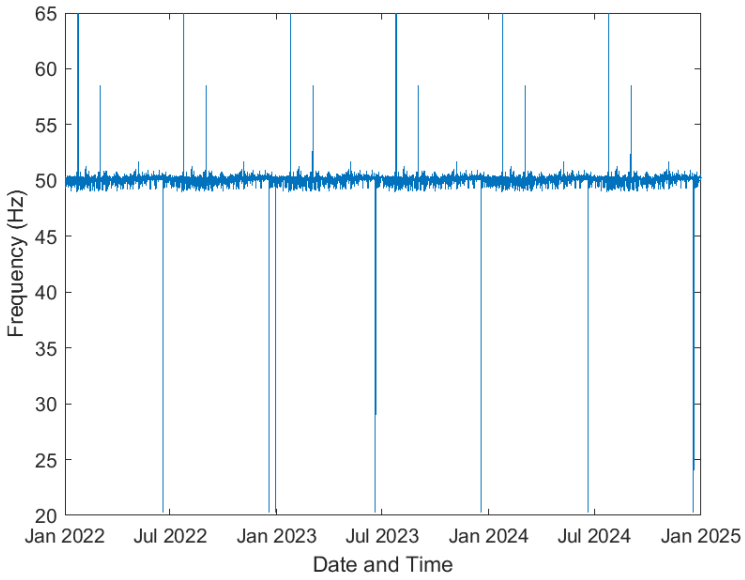

Figure 5: Frequency Trend.

Taken together, the results paint a consistent picture: the feeder is in a state of *chronic fragility*. The reliability function collapses within one week; resilience is nonexistent (RNI oscillates continuously to zero); restoration suffers from extreme delays; and underlying power quality (frequency) is catastrophically unstable. These quantitative metrics provide irrefutable evidence that reactive maintenance—responding to faults only after they occur—has failed.

4.0 DISCUSSION

The quantitative metrics derived from the machine learning framework paint a coherent and alarming portrait of the studied 33 kV feeder. Each finding is analyzed below to draw critical implications for utility practice.

A. Steep Decay of the Reliability Function $R(t)$: Evidence of Asset End-of-Life

The exponential decay of $R(t)$ to near-zero within 200 hours (Figure 1) is exceptional by conventional reliability standards. For a typical urban distribution feeder, the reliability function remains above 0.9 for one week under normal conditions. The observed MTBF of 43.5 hours is approximately one-tenth of the median value reported for well-managed overhead feeders in Europe and North America (CEER, 2021).

This steep decay implies that the feeder's components—insulators, conductors, surge arresters, and transformer bushings—are operating in a degraded state, likely due to a combination of age (exceeding 30 years), lack of preventive maintenance, and environmental stressors (pollution, humidity, lightning). As argued by Zhang et al. (2024), such chronic overstress shifts the failure distribution from a useful-life phase (constant, low λ) to a wear-out phase (high and increasing λ). The practical implication is that traditional reactive maintenance (repair after failure) is no longer cost-effective; the feeder requires a systemic hardening programme, including the replacement of aged components, vegetation management, and possibly undergrounding critical sections (Ghanbari and Jiang, 2025).

B. RNI as a Brittle Switching Signal: Absence of Redundancy and Recovery Reserve

The Rolling Resilience Index (RNI), which oscillates continuously between 0 and 1 (Figure 2), is perhaps the most telling metric. In resilience theory, a resilient system should exhibit gradual, controlled degradation during a disturbance and rapid, full recovery to pre-event performance (Raoufi et al., 2020). The RNI would drop but remain above zero, then climb back to near 1. The observed behaviour—abrupt collapses to 0 and equally abrupt returns to 1—indicates that the network has *no redundancy* (e.g., no normally open tie switches, no backup feeders) and no recovery reserve (e.g., no automated sectionalising, no remotely controlled switches). Each fault completely interrupts supply to the entire feeder, and restoration is essentially a binary process: either the fault is cleared (usually by recloser operation for transient faults), or the feeder remains dead until manual repair restores it.

This "brittle" character is typical of radial distribution systems with minimal automation (Hussain et al., 2019). To improve resilience, engineers must introduce loop-feed configurations, install automated FLISR schemes, and integrate distributed energy resources (DERs) to form intentional islands during upstream faults (Liu et al., 2020; Wu et al., 2024). The RNI thus serves as a practical, real-time indicator that can guide hardening investments:

any feeder with RNI spending more than 10% of time at zero should be prioritised for automation.

C. Right-Skewed Fault Duration Histogram: Logistical Failures, Not Just Technical

The lognormal distribution of fault durations (Figure 3), with a long tail extending to 300+ hours, is highly unusual. In developed grids, the 95th percentile of fault duration for overhead distribution systems is typically less than 48 hours (CEER, 2021). The extreme tail here points not to technical difficulty in locating the fault (most faults are on overhead lines) but to logistical and organisational failures: lack of real-time fault indicators, delayed crew dispatch, unavailability of spare transformers/poles, and poor road access during rainy seasons (Brown, 2017; Panteli et al., 2019).

This finding aligns with recent studies in sub-Saharan African distribution systems (Prateek & Luis, 2023), where utilities often rely on customer trouble calls to locate outages. The implication is clear: investing in smart grid sensors (e.g., fault passage indicators, μPMUs) combined with ML-based location algorithms (Wen et al., 2023; Rahman et al., 2024) can drastically reduce the mean time to repair (MTTR). Moreover, adopting a condition-based maintenance (CBM) programme—prioritising the replacement of components that show incipient degradation—would reduce the frequency of long-duration events.

D. Seasonal Peaks in Monthly Fault Events: Meteorological Drivers and Climate Adaptation

Figure 4 shows consistent fault peaks during May–August, the rainy season in the study region. This correlation is well established: high winds, lightning, and soil erosion increase the likelihood of conductor clashes, insulator flashovers, and pole collapse (Ciavarella & Valenti., 2026; Raoufi et al., 2020). However, the magnitude of the seasonal increase (faults more than double) indicates that the feeder is exceptionally vulnerable.

Engineering solutions include: (a) installing lightning arresters on every pole, (b) increasing the frequency of vegetation trimming before the rainy season, (c) reinforcing pole foundations with concrete, and (d) considering undergrounding of the most exposed segments (Ghanbari and Jiang, , 20205). Beyond hardening, seasonal resilience planning—pre-positioning repair crews and spare equipment—can reduce the long-duration tail (Liu et al., 2020). Climate change projections for West Africa suggest more intense rainfall, making such adaptation urgent (IPCC, 2022).

E. Frequency Deviations (20–65 Hz): Generation-Demand Mismatch and Loss of Inertia

Frequency deviations far outside the statutory band (±2.5 Hz) are a separate but interacting phenomenon. The observed swings (Figure 5) likely originate from the upstream transmission system, where sudden trips of large thermal plants or intermittent renewable generation (e.g., hydro, gas) cause severe power imbalances (Zhongda & Fei, 2023). A drop to 20 Hz indicates near-total collapse of grid frequency—a condition that triggers under-frequency load shedding (UFLS) but also risks damage to motors and transformers.

For the distribution feeder, such frequency instability complicates fault classification: the ML model must distinguish between genuine line faults and generation-induced voltage/frequency excursions. This explains the moderate AUC for "Normal" vs. "Fault" (0.82) in the confusion matrix: the boundary is fuzzy because the "normal" state is itself highly disturbed. From a resilience perspective, the distribution utility cannot solve frequency instability alone—this requires generation reserve and improvements to frequency control at the national grid level. However, the feeder can be equipped with under-frequency load-shedding relays that shed non-critical loads in a controlled manner, preventing a complete blackout of the entire feeder (Lagrange et al., 2020).

Collectively, the metrics demonstrate that the feeder is in a state of chronic fragility: reliability is exhausted (MTBF < 2 days), resilience is absent (RNI oscillates to zero), extreme delays plague restoration, and the underlying power quality is unstable. The ML framework has successfully quantified these dimensions, moving beyond abstract reliability indices to actionable diagnostic insights. The engineering implication is inescapable: reactive maintenance is failing, and a shift to condition-based, proactive hardening is not merely beneficial but necessary. We recommend:

1. Infrastructure hardening – replace aged insulators and poles, install lightning arresters, and underground critical segments.
2. Distribution automation – deploy fault passage indicators, remotely-controlled sectionalising switches, and FLISR schemes.
3. Asset management – adopt condition-based maintenance using ML predictions of remaining useful life.
4. Seasonal preparedness – pre-position crews and spares before the rainy season.
5. Grid-level coordination – advocate for primary frequency response and inertia provision from generators.

5.0 CONCLUSION

This study evaluated the dynamic resilience and reliability of a weak 33 kV distribution feeder by applying a dual-layer Bagged Trees ensemble framework to three years of high-resolution operational data. The technical analysis revealed that the Reliability Function R(t) decays exponentially to near zero within 200 hours, yielding an MTBF of only 43.5 hours and indicating a vanishing probability of fault-free operation beyond one week. Furthermore, the RNI operates as a brittle switching signal that oscillates continuously between 0 and 1, demonstrating an absolute absence of network redundancy, automated reconfiguration, or resilience reserves. Although a lognormal distribution indicates that 65% of fault durations are transient, an extremely long tail exceeding 300 hours unmasks severe organizational and logistical restoration failures rather than isolated technical challenges. These structural vulnerabilities are compounded by distinct mid-year fault peaks driven by seasonal meteorological stressors and by catastrophic grid-level frequency deviations spanning 20–65 Hz, which signal a profound generation-demand mismatch and an acute loss of grid inertia. Ultimately, these quantified parameters provide irrefutable evidence that the prevailing reactive maintenance paradigm has failed, necessitating an immediate strategic transition to proactive, condition-based infrastructure hardening—including automated Fault Location, Isolation, and Service Restoration (FLISR) schemes, component replacement, and targeted under-frequency load shedding—to optimize utility investments and arrest chronic network fragility.

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