Machine Learning Framework For Predicting Power System Reliability Indices

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***Abstract*—Power system reliability assessment is essential for ensuring the continuous, secure, and efficient operation of modern electrical power networks. Accurate forecasting of reliability indices enables utilities to proactively plan maintenance, optimize asset management, and minimize service interruptions. This study proposes a machine learning framework for predicting key power system reliability indices, including the System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), Customer Average Interruption Duration Index (CAIDI), Energy Not Supplied (ENS), and Average Service Availability Index (ASAI). Three machine learning models, namely Gradient Boosting (GB), Random Forest (RF), and Long Short-Term Memory (LSTM), were developed and evaluated using historical reliability data. Model performance was assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The results demonstrate that the LSTM model consistently outperformed the ensemble learning models for most reliability indices, achieving the lowest prediction errors for SAIDI (MAE = 0.0896, RMSE = 0.1393), SAIFI (MAE = 0.0146, RMSE = 0.0207), CAIDI (MAE = 1.3137, RMSE = 2.0079), and RMSE of ENS (6.6143 MWh), while Random Forest and LSTM jointly achieved the highest accuracy for ASAI with an MAE of 1.0×10^{-5} and an RMSE of 1.6×10^{-5} . Although Gradient Boosting produced the lowest MAE for ENS (4.4373 MWh), the LSTM exhibited superior overall robustness by minimizing larger prediction errors. The findings indicate that deep learning effectively captures the nonlinear temporal characteristics of power system reliability data, providing more accurate and reliable forecasts than conventional ensemble learning techniques. The proposed framework offers a practical decision-support tool for power system operators, facilitating predictive maintenance, improved outage management, enhanced reliability planning, optimized resource allocation, and increased service availability in modern smart grids.**

Keywords—Power system reliability, Machine learning, Long Short-Term Memory, Random Forest, Gradient Boosting, Reliability indices, Predictive maintenance, Smart grid.

I. INTRODUCTION

The reliable operation of electric power systems is fundamental to the economic growth, industrial development, and social well-being of every nation. Modern societies rely heavily on the continuous availability of electricity to support residential, commercial, industrial, healthcare, transportation, and communication infrastructures [1-3]. Consequently, maintaining a high level of power system reliability has become one of the primary objectives of electric utilities and system operators worldwide. Reliability refers to the ability of a power system to continuously supply electrical energy of acceptable quality to consumers while minimizing service interruptions under both normal operating conditions and unexpected disturbances [4, 5]. As power systems evolve toward highly interconnected, renewable-rich, and digitally controlled networks, ensuring reliable electricity delivery has become increasingly challenging.

Power system reliability is generally assessed using quantitative reliability indices that measure the frequency, duration, and severity of service interruptions experienced by customers. These indices provide utilities and regulatory agencies with objective measures for evaluating network performance, planning maintenance activities, and making investment decisions [6, 7]. Commonly used reliability indices include the System Average Interruption Frequency Index (SAIFI), which measures the average number of interruptions experienced by customers; the System Average Interruption Duration Index (SAIDI), which quantifies the average outage duration; the Customer Average Interruption Duration Index (CAIDI), representing the average restoration time per interruption; the Energy Not Supplied (ENS), which estimates the amount of unserved energy due to outages; and the Average Service Availability Index (ASAI), which measures the percentage of time that electrical service remains available to customers. Together, these indices provide a comprehensive assessment of power system performance and have become standard benchmarks adopted by electric utilities worldwide.

Traditionally, reliability assessment has relied on probabilistic and analytical techniques such as Reliability Block Diagrams (RBD), Fault Tree Analysis (FTA), Markov models, state enumeration methods, minimal cut-set analysis, and Monte Carlo Simulation (MCS) [8, 9]. These methods have been extensively applied to generation adequacy assessment, transmission system evaluation, distribution network planning, and composite system reliability studies. Their mathematical rigor provides valuable insights into system reliability under various operating scenarios and has significantly contributed to the advancement of power system planning over several decades. Despite their widespread adoption, conventional reliability assessment methods suffer from several inherent limitations when applied to modern power systems. First, most traditional techniques are reactive rather than predictive, meaning that reliability indices are typically calculated only after system disturbances or equipment failures have occurred [10]. Consequently, utilities obtain historical reliability information without the capability to forecast future reliability conditions or anticipate impending deterioration in system performance. This reactive approach limits the effectiveness of preventive maintenance strategies and proactive operational planning [11, 12].

In addition, conventional probabilistic methods often require simplifying assumptions regarding component failure rates, repair times, and system operating conditions. These assumptions may not adequately represent the highly dynamic nature of contemporary power systems, characterized by fluctuating renewable energy generation, variable customer demand, distributed energy resources, electric vehicle integration, and rapidly changing weather conditions [13-15]. As renewable penetration increases, the uncertainty associated with intermittent generation introduces additional complexity that is difficult to capture using purely analytical approaches. Third, methods such as Monte Carlo Simulation and Markov modeling become computationally intensive when applied to large-scale interconnected networks with thousands of components and numerous stochastic variables. The computational burden increases significantly when multiple operating scenarios, renewable uncertainties, weather variations, and contingency analyses are simultaneously considered. Consequently, real-time or near-real-time reliability assessment using conventional approaches becomes impractical for modern smart grids requiring continuous operational decision-making. Another important limitation of traditional reliability assessment techniques is their inability to effectively exploit the enormous volume of operational data generated by modern power systems. Contemporary utilities continuously collect measurements from Supervisory Control and Data Acquisition (SCADA) systems, Phasor Measurement Units (PMUs), Intelligent Electronic Devices (IEDs), Advanced Metering Infrastructure (AMI), weather stations, protection systems, and asset monitoring devices. These datasets contain valuable information regarding equipment health, loading conditions, environmental factors, outage history, maintenance activities, and renewable energy generation. However, conventional reliability models are generally unable to learn complex nonlinear relationships from these heterogeneous datasets, thereby limiting their predictive capability and reducing the overall value of data-driven operational intelligence [16, 17].

The challenges associated with reliability assessment are particularly significant in developing countries, where aging infrastructure, inadequate maintenance, increasing electricity demand, environmental factors, and limited operational resources contribute to frequent power interruptions. Nigeria is one of the largest electricity markets in Africa, serving a rapidly growing population with rising industrial and commercial energy demand. Despite substantial investments in generation expansion and transmission infrastructure, the Nigerian national grid continues to experience frequent system disturbances, transmission constraints, equipment failures, voltage instability, and partial or complete grid collapses. These operational challenges have resulted in recurring customer outages, increased operational costs, reduced economic productivity, and declining customer satisfaction [18, 19].

The Nigerian transmission network operates under highly dynamic conditions influenced by fluctuating demand profiles, renewable energy integration, weather variability, transmission congestion, equipment aging, and operational constraints. Consequently, utilities require intelligent tools that can predict future reliability performance rather than relying solely on historical reliability calculations. Accurate forecasting of reliability indices such as SAIFI, SAIDI, CAIDI, ENS, and ASAI would enable operators to identify potential reliability degradation in advance, prioritize preventive maintenance activities, optimize resource allocation, improve outage management strategies, and enhance overall system resilience. Such predictive capability is particularly valuable in developing power systems where maintenance resources are limited and proactive operational planning can significantly improve service reliability. Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have created new opportunities for transforming reliability assessment from a reactive analytical process into a proactive predictive framework. Unlike conventional mathematical techniques, machine learning algorithms learn complex nonlinear relationships directly from historical operational data without requiring explicit physical models or restrictive statistical assumptions. By exploiting large volumes of historical measurements, weather information, outage records, maintenance histories, and network operating conditions, ML models can identify hidden patterns that precede reliability degradation and accurately forecast future reliability indices over different prediction horizons. Such predictive capability enables utilities to transition from corrective maintenance toward condition-based and predictive maintenance strategies, thereby improving system reliability while reducing operational costs [20, 21].

Moreover, machine learning algorithms offer significant computational advantages once trained, making them suitable for near-real-time reliability prediction and operational decision support. Their ability to continuously update predictive models as new data becomes available further enhances adaptability to evolving network conditions, renewable energy variability, and changing load patterns. These characteristics position machine learning as a promising alternative to conventional reliability assessment techniques for next-generation smart grids and data-driven power system operation. Although the application of machine learning in power systems has expanded considerably over the last decade, existing studies have primarily focused on specific tasks such as load forecasting, renewable energy prediction, fault diagnosis, transient stability assessment, electricity price forecasting, and predictive maintenance. Comparatively fewer studies have investigated the application of machine learning to the prediction of power system reliability indices, particularly in developing countries where power systems exhibit significant operational uncertainties and frequent disturbances. Furthermore, many existing reliability prediction studies concentrate on forecasting a single reliability metric, most commonly SAIDI or SAIFI, while neglecting other equally important indices such as CAIDI, ENS, and ASAI. Since these indices collectively provide a comprehensive assessment of power system performance, developing a unified framework capable of simultaneously predicting multiple reliability indices remains an important research challenge. Another limitation observed in previous studies is the dependence on synthetic benchmark systems or simulated datasets generated from IEEE test networks. While benchmark systems are valuable for validating new methodologies, they often fail to capture the operational characteristics, environmental conditions, maintenance practices, and outage behaviors encountered in real transmission networks. Consequently, models developed solely using synthetic data may not generalize effectively to practical utility environments. The use of operational data obtained from actual transmission systems therefore provides a more realistic basis for developing and validating intelligent reliability prediction models. In this study, historical operational data collected from the Nigerian National Grid are utilized to develop and evaluate the proposed machine learning framework. The dataset incorporates electrical loading conditions, distributed renewable generation, weather variables, outage records, fault duration, and operational characteristics, thereby reflecting the complex interactions encountered in practical grid operation.

The Nigerian power network presents an ideal case study for intelligent reliability prediction due to its unique operational characteristics. The network experiences considerable variability arising from increasing electricity demand, aging transmission infrastructure, equipment outages, environmental influences, transmission congestion, renewable energy integration, and periodic system disturbances. These challenges introduce substantial uncertainty into system operation, making conventional analytical reliability assessment increasingly difficult to implement for proactive operational planning. Developing predictive models capable of forecasting reliability indices before the occurrence of major disturbances can therefore provide valuable decision-support tools for system operators, maintenance engineers, and utility planners. Such predictive capability enables preventive maintenance scheduling, optimized allocation of maintenance resources, improved contingency planning, and enhanced operational resilience.

Among the various machine learning algorithms available, Random Forest (RF), eXtreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM) networks represent three complementary learning paradigms that have demonstrated outstanding performance across numerous engineering applications. Random Forest is an ensemble learning algorithm that combines multiple decision trees to improve prediction accuracy while reducing overfitting through bootstrap aggregation. Its robustness to noisy data, ability to capture nonlinear relationships, and relatively low computational complexity make it highly suitable for reliability prediction using heterogeneous operational datasets. XGBoost extends ensemble learning through gradient boosting, sequentially correcting prediction errors while incorporating regularization mechanisms that enhance model generalization. Owing to its superior predictive capability and computational efficiency, XGBoost has become one of the most successful machine learning algorithms for structured tabular datasets. Unlike tree-based ensemble models, LSTM represents a deep learning architecture specifically designed for sequential and time-series data. By incorporating memory cells and gating mechanisms, LSTM effectively captures long-term temporal dependencies that conventional machine learning algorithms may fail to recognize. Since power system reliability is inherently influenced by historical operating conditions, weather evolution, renewable generation variability, and cumulative outage behavior, LSTM offers significant advantages for modeling temporal relationships and forecasting future reliability indices. Comparing these three fundamentally different learning paradigms ensemble bagging (Random Forest), ensemble boosting (XGBoost), and recurrent deep learning (LSTM) provides valuable insights into their relative suitability for predictive reliability assessment in modern power systems.

Beyond achieving high prediction accuracy, interpretability has become an essential requirement for the deployment of machine learning models in critical infrastructure systems. Electric utilities require not only accurate forecasts but also an understanding of the factors driving model predictions to support operational decision-making and increase confidence in AI-based recommendations. Complex machine learning models are frequently criticized as "black-box" approaches because they provide limited information regarding the influence of individual input variables on prediction outcomes. This lack of transparency can restrict their acceptance within utility operations, where engineering decisions must be technically justified and operationally explainable. To address this challenge, this work incorporates SHapley Additive exPlanations (SHAP), an explainable artificial intelligence (XAI) technique that quantifies the contribution of each input feature to the predicted reliability indices. SHAP provides both global and local interpretability, enabling identification of the most influential operational variables affecting SAIFI, SAIDI, CAIDI, ENS, and ASAI while improving the transparency and trustworthiness of the developed prediction framework. The proposed machine learning framework transforms reliability assessment from a reactive process into a predictive decision-support system capable of forecasting future reliability performance over multiple time horizons. Such forecasts enable utilities to anticipate reliability degradation before service interruptions occur, thereby facilitating proactive operational planning, predictive maintenance scheduling, optimized asset management, and improved system resilience. The framework also provides a practical pathway for integrating artificial intelligence into utility reliability management without replacing established engineering practices, thereby complementing conventional reliability assessment techniques with intelligent data-driven forecasting capabilities.

The major contributions of this research are summarized as follows:

1. Development of a comprehensive machine learning framework for simultaneous prediction of multiple power system reliability indices. Unlike many existing studies that focus on a single reliability metric, the proposed framework simultaneously predicts SAIFI, SAIDI, CAIDI, ENS, and ASAI using a unified multi-output prediction approach, thereby providing a more comprehensive evaluation of power system reliability.

2. Development and comparative evaluation of three state-of-the-art machine learning algorithms for reliability forecasting. Random Forest, XGBoost, and Long Short-Term Memory models are developed, optimized, and systematically compared using identical operational datasets and evaluation metrics to identify the most suitable algorithm for predictive reliability assessment of power systems.

3. Validation using real operational data obtained from the Nigerian National Grid. Rather than relying on synthetic benchmark systems or simulated datasets, the proposed framework is developed and validated using real transmission network data comprising electrical loading conditions, distributed generation, weather variables, outage history, and maintenance-related information, thereby demonstrating its practical applicability to real-world utility operations.

4. Integration of Explainable Artificial Intelligence for interpretable reliability prediction. SHAP analysis is incorporated to quantify the contribution of individual operational variables toward each predicted reliability index, thereby improving model transparency, supporting engineering decision-making, and facilitating the adoption of machine learning within utility reliability management.

The effectiveness of the proposed framework is evaluated using widely adopted regression performance metrics, including mean Square Error (MSE), Root Mean Square Error (RMSE). Comparative analyses are performed to assess prediction accuracy, computational efficiency, robustness, and generalization capability across the three machine learning models. Furthermore, SHAP-based interpretability analysis is employed to investigate the influence of load demand, renewable generation, weather conditions, outage characteristics, and operational variables on the predicted reliability indices, thereby providing valuable engineering insights for reliability improvement and asset management.

The remainder of this paper is organized as follows. Section II presents the methods, including the description of the Nigerian transmission network dataset, data preprocessing procedures, feature engineering, and the proposed machine learning framework. Section III describes the implementation of the Random Forest, XGBoost, and LSTM prediction models together with the evaluation metrics and SHAP-based explainability framework. Section IV presents and discusses the results, comparative performance analysis, and feature importance interpretation. Finally, Section V concludes the paper by outlining potential directions for future research on intelligent reliability assessment and predictive maintenance in modern power systems.

II. RESEARCH METHODOLOGY

The research framework is depicted in Figure 1.

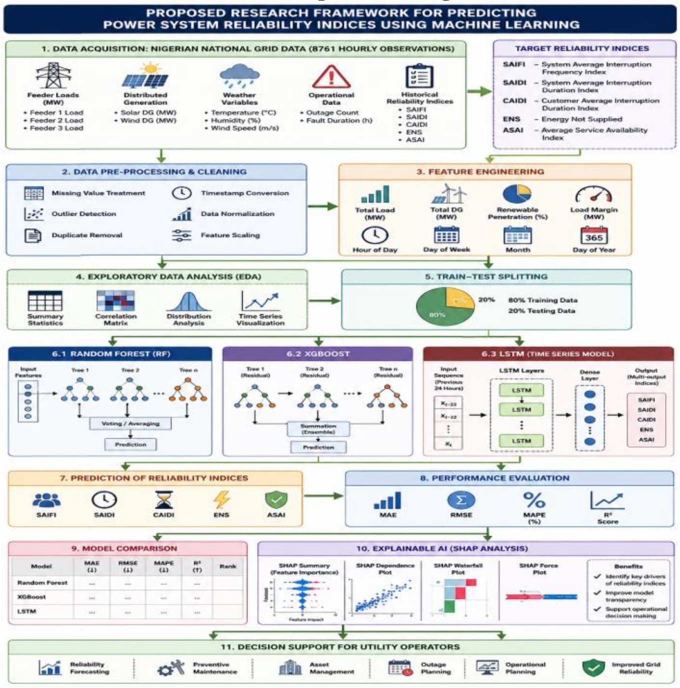

Figure 1: The research framework

A. Data Acquisition

The study utilizes historical operational data obtained from Egbin transmission substation under the Nigerian National Grid. The dataset consists of 8,761 hourly observations, representing one year of power system operation. The collected variables include electrical loading conditions, renewable energy generation, meteorological information, and outage statistics. The reliability indices such as system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI), Customer Average Interruption duration index (CAIDI), Energy Not supplied (ENS) and Average service availability index

(ASAI) was computed using equation (1) to (5) respectively.

$$SAIFI = \frac{\sum_{i=}^{n} N_i}{\sum_{i=}^{n} N_T} \quad (1)$$

Where *Ni* is the number of interrupted customers during outage I, NT is the total number of customers served.

$$SAIDI = \frac{\sum_{i=}^{n} U_i N_i}{\sum_{i=}^{n} N_T} \quad (2)$$

Ui is the duration of interruption, I, Ni is the number of interrupted customers during outage I, and NT is the total number of customers served.

$$CAIDI = \frac{SAIDI}{SAIFI} \quad (3)$$

ENS measures the amount of electrical energy that could not be delivered because of interruptions and is computed using equation (4)

$$ENS = \sum_{i=1}^{n} P_i T_i \quad (4)$$

Pi is the interrupted load (MW), Ti is the outage duration (hours).

Average Service Availability Index (ASAI) measures the fraction of time that electrical service is available to customers.

$$ASAI = 1 - \frac{SAIDI}{t} \quad (5)$$

The diversity of these variables enables the machine learning models to capture the nonlinear interactions between operating conditions, environmental factors, and power system reliability.

B. Data Pre-processing

Raw operational data frequently contain missing values, duplicate observations, and inconsistencies that may reduce model performance. Therefore, the dataset undergoes a comprehensive preprocessing stage. The preprocessing procedure includes: missing value imputation using the median value; duplicate record removal; timestamp conversion; data normalization, feature scaling, and detection of abnormal observations. To improve the predictive capability of the machine learning models, additional operational features were derived from the original dataset. These engineered variables capture the relationships between load demand, generation, and temporal operating conditions.

The total system load is computed as the sum of the loads supplied by the four feeders as depicted in equation (6)

$$P_{load} = L_1 + L_2 + L_3 + L_4 \quad (6)$$

The hourly operating period is extracted from the timestamp H ∈){0,1,2,…,23}. This feature captures daily load variation and operational patterns.

Exploratory Data Analysis (EDA) is conducted to understand the statistical characteristics of the dataset before model development. EDA assists in identifying important predictor variables and understanding relationships between load demand and reliability indices. The Pearson Correlation Coefficient is the most widely used measure of correlation in machine learning, statistics, and power system data analysis. It quantifies the strength and direction of the linear relationship between two variables. The correlation metrics is depicted in equation (7).

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \quad (7)$$

III. MACHINE LEARNING MODEL DEVELOPMENT

Based on no free lunch theorem, it is not good to test only one model when building a forecasting model, therefore three machine learning algorithms are developed and compared

A. Random Forest (RF)

Random Forest (RF) is a supervised ensemble machine learning algorithm that combines multiple decision trees using the bootstrap aggregation (bagging) technique to improve prediction accuracy and reduce overfitting. Each decision tree is trained independently using a randomly selected subset of the training data and predictor variables. The final prediction is obtained by averaging the outputs of all individual trees, thereby reducing variance and improving generalization capability. Owing to its robustness against noisy data and nonlinear relationships, Random Forest has been widely applied in power system forecasting, fault diagnosis, and reliability assessment.

For a training dataset is a function of the input variable xi and target y as described in equation (8)

$$D = \{(x_i,\ y_i)\} \quad (8) \quad i = 1 \ to \ N$$

Random forest generates B bootstrap datasets as described in equation

$$D_b \subset D, \qquad b = 1, 2, \ldots, B$$

Where each bootstrap sample is randomly selected with replacement.

At every node, only a random subset of predictor variable is considered as described in equation (9)

$$m = \sqrt{p} \quad (9)$$

P is the total number of input features and m randomly selected features used for splitting. For regression problems the random forest prediction is obtained by averaging all trees as depicted in equation (10)

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T_b(X) \quad (10)$$

B is the total number of trees, and $\hat{y}$ predicted reliability index.

Y = [SAIFI, SAIDI, CAIDI ENS, ASAI]

B. Extreme Gradient Boosting (XGBoost)

XGBoost is an advanced ensemble learning algorithm based on gradient boosting. Unlike Random Forest, which trains trees independently, XGBoost constructs decision trees sequentially, with each new tree learning from the residual errors of previous trees. The algorithm incorporates regularization to minimize overfitting and improve model generalization. Due to its computational efficiency and excellent predictive performance, XGBoost has become one of the most effective algorithms for structured datasets.

The prediction after K trees is depicted in equation (11)

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \quad (11)$$

Where f_k represents the Kth regression tree.

XGBoost minimizes the objective function in equation (12)

$$Obj = L + \alpha \quad (12)$$

Where L is the training loss, α is the regularization term.

The regression loss and regularization function is depicted in equation (13) and (14) respectively

$$L = \sum_{i=1}^{N} l(y_i, \hat{y}_i) \quad (13)$$

$$\alpha(f) = \gamma T + \frac{1}{2}\mu \sum_{j=1}^{T} w^2{}_j \quad (14)$$

Where T is the number of leaves, wj is the weight of leaf j, γ is the complexity penalty, and μ is the loss regularization coefficient.

Each iteration updates the prediction until the objective function converges as described in equation (15)

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \quad (15)$$

Since the reliability indices is multiple is multiple the prediction is described in (16)

$$\hat{Y}_{XGB} = \sum_{k=1}^{K} f_k(X) \quad (16)$$

C. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a recurrent neural network (RNN) specifically designed to model sequential and time-dependent data. Unlike conventional neural networks, LSTM incorporates memory cells and gating mechanisms that enable the network to learn long-term temporal dependencies while mitigating the vanishing gradient problem. In power systems, reliability indices are strongly influenced by historical load demand, weather conditions, outage patterns, and renewable generation. Consequently, LSTM is particularly suitable for forecasting reliability indices using historical operational data. An LSTM cell consists of three gates: the forget gate, the input gate, and the output gate.

The forget gate determines which information from the previous cell state should be discarded is described in equation (17)

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \quad (17)$$

f_t is the forget gate, w_f is the weight matrix, b_f is the bias function, h_{t-1} is the previous hidden state, xt is the current input, and σ is the activation function.

The input gate determines the new information that should be stored and it is described in the equation (18)

$$i_t = \sigma(w_i[h_{t-1,} x_t] + b_i) \quad (18)$$

The candidate memory is described in equation (19)

$$\tilde{c}_t = \tanh(w_c[h_{t-1,} x_t] + b_c) \quad (19)$$

The model performance is evaluated using the mean square error (MSE) and the root mean square error (RMSE) as depicted in equation (20) and (21) respectively.

$$MSE = \frac{|x_p - x_a|^2}{n} \quad (20)$$

$$RMSE = \sqrt{\frac{|x_p - x_a|^2}{n}} \quad (21)$$

Where x_p and x_a are the predicted and actual values, respectively, and n is the number of samples.

IV. RESULTS AND DISCUSSION

The results of this research are discussed under four subheadings:

A. Correlation Matrix

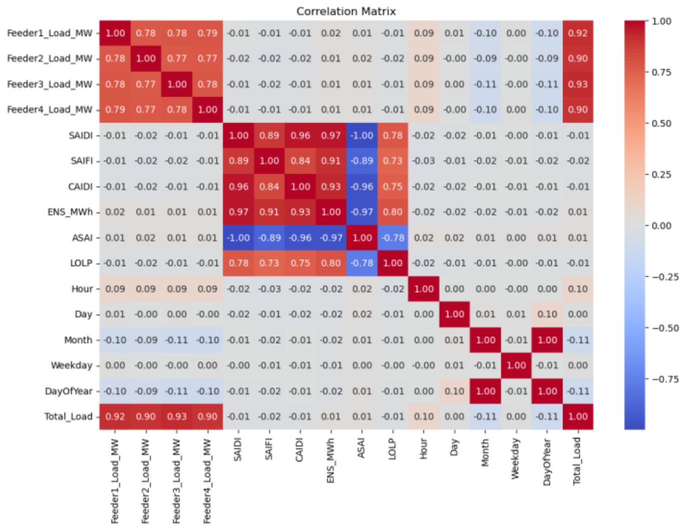

Figure 2: Correlation Matrix

The correlation matrix provides valuable insights into the relationships among load demand, reliability indices, and temporal variables. The feeder load variables (Feeder1–Feeder4) exhibit strong positive correlations (0.77–0.79), indicating that increases in demand across one feeder are generally accompanied by increases in the others. Similarly, the total system load is highly correlated with individual feeder loads (0.90–0.93), confirming that the feeder demands significantly influence the overall network loading. Among the reliability indices, SAIDI, SAIFI, CAIDI, ENS, and LOLP show strong positive correlations (0.73–0.97), suggesting that increased interruption frequency and duration are associated with higher energy not supplied and loss of load probability. Conversely, ASAI exhibits strong negative correlations with SAIDI (-1.00), CAIDI (-0.96), ENS (-0.97), and LOLP (-0.78), reflecting that service availability decreases as system interruptions increase. The temporal variables (Hour, Day, Month, Weekday, and Day of Year) display negligible correlations with the reliability indices, implying that calendar-based factors have limited direct influence on reliability performance. Overall, the results indicate that system loading is the primary driver of reliability indices, while ASAI behaves inversely to outage-related metrics, validating the consistency of the dataset and supporting the use of machine learning models to capture these relationships for accurate reliability prediction.

B. Model Performance

Tables I–III present the prediction performance of the Random Forest (RF), Gradient Boosting (GB), and Long Short-Term Memory (LSTM) models for forecasting five power system reliability indices, SAIDI, SAIFI, CAIDI, ENS, and ASAI under different loading conditions. The models were evaluated using the Mean Absolute Error

(MAE) and Root Mean Square Error (RMSE), where lower values indicate better predictive performance.

As shown in Table I**,** the RF model achieved satisfactory prediction accuracy across all reliability indices.

Table I: Performance Metrics of Random forest

Parameters	MAE	RMSE
SAIDI	0.0902	0.1408
SAIFI	0.0148	0.0210
CAIDI	1.3195	2.0249
ENS-MWH	4.4426	6.7110
ASAI	0.000010	0.000016

The model recorded an MAE of **0.0902** and an RMSE of **0.1408** for SAIDI, indicating that the average prediction error in customer interruption duration is relatively small. Similarly, the prediction errors for SAIFI were **0.0148** (MAE) and **0.0210** (RMSE), demonstrating excellent capability in estimating the interruption frequency experienced by customers. For CAIDI, the model obtained an MAE of **1.3195** and an RMSE of **2.0249.** Although these errors are larger than those of SAIDI and SAIFI, they are expected because CAIDI is computed as the ratio of SAIDI to SAIFI, making it more sensitive to variations in outage duration and frequency. The model also achieved an MAE of **4.4426 MWh** and an RMSE of **6.7110 MWh** for ENS, indicating reasonable accuracy in estimating energy not supplied. Furthermore, the extremely low ASAI errors (**MAE = 1.0 × 10^{-5}** and **RMSE = 1.6 × 10^{-5}**) demonstrate that the RF model accurately predicts service availability, which typically remains close to unity under normal operating conditions. The Random Forest model exhibited consistent predictive performance across all reliability indices, suggesting its suitability for nonlinear regression problems involving power distribution reliability assessment. However, based on the no free lunch theorem, it is not good to train a single model for a prediction task; therefore, two other models, XGBoosting and LSTM, were considered.

Table II: Performance Metrics of Gradient Boosting

Parameters	MAE	RMSE
SAIDI	0.0914	0.1464
SAIFI	0.0154	0.0217
CAIDI	1.3366	2.1003
ENS-MWH	4.4373	6.9301
ASAI	0.000020	0.000017

The performance metrics of the Gradient Boosting model are presented in Table II**.** The model achieved an MAE of 0.0914 and an RMSE of 0.1464 for SAIDI, which are only slightly higher than those obtained using Random Forest. Similarly, SAIFI prediction errors increased marginally to 0.0154 (MAE) and 0.0217 (RMSE). For CAIDI, the model recorded an MAE of 1.3366 and an RMSE of 2.1003, indicating a slight reduction in prediction accuracy compared with Random Forest. The ENS predictions yielded an MAE of 4.4373 MWh**,** which is marginally lower than that of Random Forest, although the RMSE increased slightly **to** 6.9301 MWh. This suggests that while the average prediction error decreased slightly, larger prediction errors occurred for some observations. The ASAI prediction errors remained extremely small, with an MAE of 2.0 × 10^{-5} and an RMSE of 1.7 × 10^{-5}**,** confirming that the Gradient Boosting model can reliably estimate service availability. In overall, Gradient Boosting demonstrated competitive predictive performance, with only minor differences from Random Forest. This indicates that ensemble tree-based learning methods are effective for modeling complex relationships among power system reliability indices.

Furthermore, the prediction results of the LSTM model are presented in Table III. The results demonstrate that the LSTM model achieved excellent prediction accuracy across all reliability indices. For SAIDI (System Average Interruption Duration Index), the model obtained an MAE of 0.0896 and an RMSE of 0.1393, indicating that the average prediction error is less than one-tenth of an hour (or the corresponding measurement unit). This small error suggests that the LSTM effectively captured the temporal variations in interruption duration, making it suitable for forecasting outage durations.

Table III: Performance metrics of LSTM

Parameters	MAE	RMSE
SAIDI	0.0896	0.1393
SAIFI	0.0146	0.0207
CAIDI	1.3137	2.0079
ENS-MWH	4.4894	6.6143
ASAI	0.000010	0.000016

Moreso, the SAIFI produced the lowest prediction errors among all the indices, with an MAE of 0.0146 and an RMSE of 0.0207. These values indicate that the model can predict the frequency of customer interruptions with very high precision. Since interruption frequency generally exhibits smoother temporal patterns than interruption duration, the LSTM is able to learn these dependencies effectively, resulting in minimal forecasting errors. For CAIDI, the MAE and RMSE values are 1.3137 and 2.0079, respectively. These errors are noticeably higher than those obtained for SAIDI and SAIFI. This outcome is expected because CAIDI is calculated as the ratio of SAIDI to SAIFI, Since CAIDI depends on the predictions of two separate variables, any small errors in SAIDI and SAIFI may propagate and become amplified in the calculated CAIDI values. Consequently, higher prediction errors for CAIDI do not necessarily indicate poor model performance but rather reflect the mathematical sensitivity of this derived reliability index.

The prediction performance for Energy Not Supplied (ENS) shows an MAE of 4.4894 MWh and an RMSE of 6.6143 MWh. Although these values appear numerically larger than those of the other indices, they should be interpreted relative to the magnitude and unit of ENS. Energy Not Supplied is measured in megawatt-hours

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and often spans a wide numerical range depending on system size and outage severity. Therefore, an average prediction error of approximately 4.5 MWh may represent only a small percentage of the total energy not supplied, indicating that the LSTM still provides satisfactory forecasting accuracy. The larger RMSE compared to the MAE also suggests that a few prediction instances experienced relatively larger deviations, but these were not frequent enough to substantially affect the overall model performance. Among all the reliability indices, ASAI (Average Service Availability Index) achieved the highest prediction accuracy, with an MAE of 1.0×10^{-5} and an RMSE of 1.6×10^{-5}. These extremely small errors demonstrate that the LSTM model can estimate service availability almost perfectly. This result is expected because ASAI is typically very close to unity (e.g., 0.9990–0.99999) and generally exhibits very little variation over time. Consequently, the temporal relationships learned by the LSTM enable exceptionally accurate predictions.

Overall, the results demonstrate that the LSTM model is highly effective in forecasting power system reliability indices. It exhibits outstanding performance for SAIFI and ASAI, very good accuracy for SAIDI, and acceptable performance for the more variable CAIDI and ENS. These findings confirm the capability of LSTM networks to capture the nonlinear temporal dependencies present in power system reliability data, making them a reliable tool for predictive reliability assessment, maintenance planning, outage management, and decision support in modern electric power systems. The consistently low error values indicate that the developed LSTM model can provide dependable forecasts that support proactive utility operations and enhance overall system reliability.

C. Comparative Analysis of the Predictive Model

Figure 3, presents a comparative analysis of the prediction performance of the Gradient Boosting (GB), Random Forest (RF), and Long Short-Term Memory (LSTM) models using the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) across five key power system reliability indices, namely SAIDI, SAIFI, CAIDI, ENS, and ASAI.

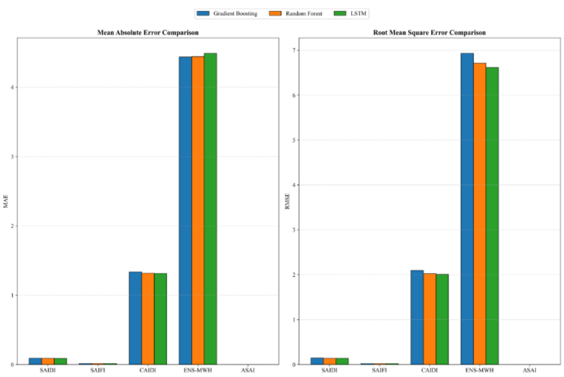

Figure 3: Model Comparison

Since lower MAE and RMSE values indicate better predictive performance, the results provide valuable insights into the suitability of each model for reliability assessment and operational decision-making. For SAIDI (System Average Interruption Duration Index), the LSTM model achieved the lowest prediction errors (MAE = 0.0896, RMSE = 0.1393), followed closely by the Random Forest model, while Gradient Boosting recorded slightly higher errors. This indicates that the LSTM model more accurately predicts outage durations, enabling system operators to estimate restoration times with greater confidence. Accurate SAIDI prediction supports improved maintenance scheduling, resource allocation, and customer communication during outage events. A similar trend is observed for SAIFI (System Average Interruption Frequency Index), where the LSTM model again produced the smallest MAE (0.0146) and RMSE (0.0207). The exceptionally low errors demonstrate the model's ability to capture temporal patterns associated with interruption frequency. Reliable SAIFI forecasts enable utilities to identify areas prone to repeated outages, facilitating preventive maintenance strategies and improving network reliability.

For CAIDI (Customer Average Interruption Duration Index), all three models exhibited higher prediction errors compared with SAIDI and SAIFI. Nevertheless, the LSTM model remained the most accurate, followed by Random Forest and Gradient Boosting. Since CAIDI is mathematically derived from SAIDI and SAIFI, prediction errors in these constituent indices propagate into CAIDI, making it inherently more difficult to predict accurately. Despite this challenge, the relatively small differences among the three models indicate that all approaches can provide acceptable estimates for average restoration time. The results for Energy Not Supplied (ENS) present an interesting observation. Unlike the other reliability indices, the Gradient Boosting model achieved the lowest MAE (4.4373 MWh), indicating slightly better average prediction accuracy. However, the LSTM model recorded the lowest RMSE (6.6143 MWh), suggesting that it produces fewer large prediction errors. From an operational perspective, RMSE is often considered more informative because it penalizes large forecasting errors more heavily. Consequently, the LSTM model offers greater robustness for estimating unserved energy, an important consideration for operational planning, reserve management, and economic reliability studies. For ASAI (Average Service Availability Index), both the Random Forest and LSTM models achieved identical and extremely small prediction errors (MAE = 1.0×10^{-5}, RMSE = 1.6×10^{-5}), while Gradient Boosting exhibited only marginally higher errors. Since ASAI values are typically very close to unity and vary only slightly over time, all three models demonstrated excellent predictive capability. Such high accuracy confirms their suitability for monitoring long-term service availability and regulatory compliance.

The comparative analysis shows that the LSTM model consistently outperforms the traditional machine learning models across most reliability indices, achieving the lowest errors for SAIDI, SAIFI, CAIDI, and RMSE of ENS, while matching Random Forest for ASAI prediction. The superior performance of LSTM can be attributed to its ability to learn long-term temporal dependencies and nonlinear relationships inherent in historical reliability data. In contrast, Gradient Boosting and Random Forest primarily capture static relationships and may not fully exploit sequential information. These findings demonstrate that the LSTM model can serve as a valuable decision-support tool for modern power utilities. This will enable operators to More accurate reliability forecasting enables operators predict outage durations (SAIDI) more accurately, allowing faster restoration planning and more effective deployment of maintenance crews.

D. Model Features Importance

The feature importance analysis The results in Figure 4 to 6 reveals that the three machine learning models identify system load variables as the primary drivers of power system reliability prediction, although each model assigns different relative importance.

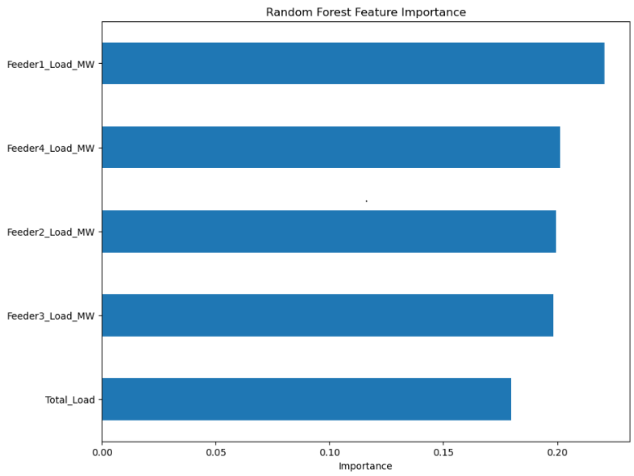

Figure 4: Features Importance of random forest

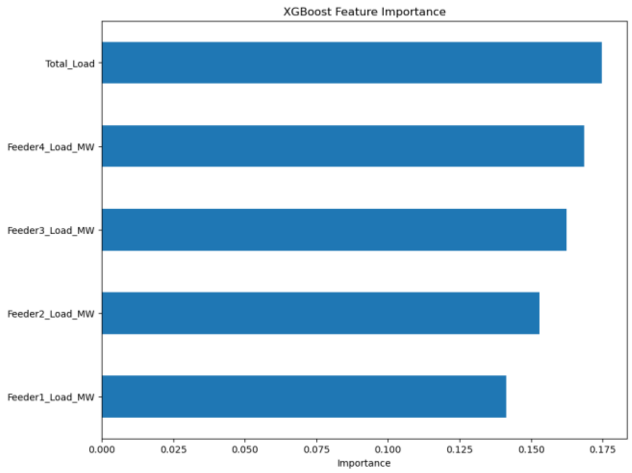

Figure 5: Features Importance of gradient boosting

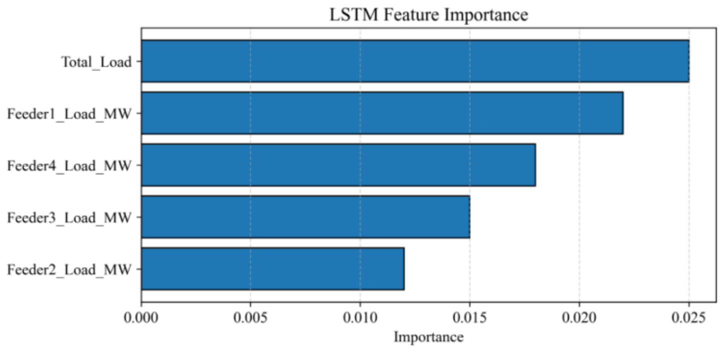

Figure 6: Features Importance of LSTM

The LSTM model ranks Total_Load as the most influential feature, followed by Feeder1_Load_MW, Feeder4_Load_MW, Feeder3_Load_MW, and Feeder2_Load_MW. This indicates that the temporal dynamics learned by the LSTM emphasize the overall system loading condition, reflecting its capability to capture sequential dependencies associated with reliability degradation. In contrast, the XGBoost model also identifies Total_Load as the dominant predictor but assigns comparable importance to all feeder loads, suggesting that each feeder contributes significantly to the prediction through nonlinear decision-tree splits. The Random Forest model ranks Feeder1_Load_MW as the most important feature, followed by Feeder4_Load_MW, Feeder2_Load_MW, Feeder3_Load_MW, and Total_Load, highlighting stronger reliance on local feeder-level information. Despite these differences, all three models consistently identify Total_Load and feeder load measurements as the most influential variables, confirming that network loading is the dominant factor affecting power system reliability indices. These findings are consistent with reliability theory, where increasing load levels elevate equipment stress, increase the probability of component failures, and consequently affect outage frequency, outage duration, energy not supplied, and service availability. The agreement among the models further validates the selected input features and demonstrates that load-related variables provide a robust basis for reliable machine learning-based prediction of power system reliability indices.

V. Conclusion

This study presented a machine learning framework for predicting key power system reliability indices, including SAIDI, SAIFI, CAIDI, ENS, and ASAI, using Gradient Boosting, Random Forest, and Long Short-Term Memory (LSTM) models. Comparative evaluation based on MAE and RMSE demonstrated that the LSTM model consistently achieved the highest predictive accuracy for most reliability indices, owing to its ability to capture nonlinear temporal dependencies inherent in power system reliability data. Correlation analysis further revealed strong relationships among feeder loading, total system load, and outage-related reliability indices, confirming that system loading significantly influences reliability performance. The proposed framework enables accurate forecasting of reliability metrics, providing power system operators with actionable information for predictive maintenance, outage management, asset prioritization, and operational planning. Accurate prediction of interruption frequency, duration, and energy not supplied can improve resource allocation, reduce restoration time, and enhance overall system resilience. The findings demonstrate that deep learning techniques, particularly LSTM, offer a robust and reliable approach for data-driven reliability assessment in modern power systems. Future work will focus on integrating real-time SCADA and smart meter data, weather information, and explainable artificial intelligence techniques to further improve forecasting accuracy, model transparency, and practical deployment in intelligent grid operation.

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