Machine Learning Model Implementation for Predicting Essential Transmission Line Outage via Reliability Index

Sujit Pani†, **Dipu Sarkar**, and **Ch Sekhar Gujjarlapudi**, Non-members

ABSTRACT

Currently, electric power transmission systems are operating at maximum loading capacities, frequently operating near their stability thresholds with minimal security margins. In such scenarios, monitoring of important lines for a particular loading level has become a crucial factor in ensuring the efficient operation of contemporary power systems. Thus, precisely assessing reliability for different line outage conditions is an important task for a power engineer. This paper concentrates on presenting the most recent machine learning (ML) techniques, like gradient boosting (GB), K- Nearest Neighbour (KNN), and linear regression (LR), utilized to determine the reliability index for different outage conditions. Out of the 3 ML techniques, GB demonstrated the best performance with an R_2 score of 0.9309, a mean absolute error (MAE) of 0.2503, a mean squared error (MSE) of 0.1497, and a root mean squared error (RMSE) of 0.3869.

Keywords: Power system reliability, Line outage, Machine learning, Gradient boosting

1. INTRODUCTION

In power system domains, the variety and quantity of failures are increasing rapidly due to emerging technologies, renewable source integration complexity, and component downsizing. For this reason, in order to satisfy client requirements, design engineers are giving more attention to the analysis of functional performance as well as the reliability, availability, maintainability, and safety of power system components. Once the system reliability analysis has been done, the designers can determine which component of the system is the least reliable in order to increase the uniformity of the system as a whole.

In this respect the conventional model techniques are highly computational and might not be able to satisfy the needs of real-time applications. They are based on the fundamental mathematical reliability analysis of a power system. So, in order to enable online decision-making, researchers have moved to machine learning (ML) approaches. With sufficient training, a data-based model may generate correct predictions from measurements it hasn't been exposed to previously, which is the generalization ability of the ML technique.

Balli Reddy et al. [1] employed a probabilistic technique, based on probability theory, to evaluate reliability indices by taking into account the likelihood of an event occurring for a power network. Hu, Bo, et al. [2] proposed the k-means algorithm to expedite the reliability assessment process for an uncertain price-based demand response model. Teixeira et al. [3] used the hybrid reliability indices by means of sequential Monte Carlo simulation, which serve as the foundation for the power system's performance assessment. Li et al. [4] proposed a sequential Monte Carlo simulation-based approach intended for assessing the reliability of energy supply.

Adinolfi et al. [5] suggested a planning tool for overhead distribution line reliability assessment and congestion predictions. A wind power generation system's stochastic production simulation and reliability analysis were conducted using the stochastic simulation algorithm by Liu et al. [6]. A multi-situation risk-oriented clustering method that takes renewable energy into account was anticipated by Yang et al. [7]. Prajapati et al. [8] examines quantifiable effects of energy storage system ability on power system network reliability and congestion relief. Li et al. [9] examines the dependability of large–scale grid-connected battery energy storage systems and how it affects power networks' overall reliability while taking battery deterioration and thermal runaway propagation into account. David C. Yu et al. [10] showed an approach of Bayesian networks to the problem of reliability calculation. G. C. Oliveira et al. [11] explained a model used for multi-area generation system reliability evaluation. R. N. Allan et al. [12] summarized a few of the constraints that presently occur in the generation data. Hou K et al. [13] showed an approach of an effectual reliability assessment scheme aimed at several energy systems built on shadow price. D. Urgun, C. Singh et al. [14] present an algorithm that provides an efficient method for gathering training samples and training convolutional neural networks to calculate power system reliability indices based on deviations in system parameters. Yarramsetty, C., et

Manuscript received on April 7, 2025; revised on June 30, 2025; accepted on July 18, 2025. This paper was recommended by Associate Editor Chawasak Rakpenthai.

The authors are with Department of Electrical and Electronics Engineering, NIT Nagaland, Dimapur, India.

†Corresponding author: sujitpani2010@gmail.com

Digital Object Identifier: 10.37936/ecti-eec.2525233.258445

al. [15] demonstrated an approach using deep learning & Monte Carlo simulation to improve the reliability evaluation of composite power systems. This method addresses the computational challenges of recurring optimal power flow solutions and reliability assessments in large integrated power grids, as highlighted by Gayatri S. Palit et al. [16].

Transmission lines are a vital component of the power grid, linking generation facilities to distribution systems and end users. A failure in a key transmission line can result in serious consequences, including power flow disruptions, overloading of neighboring lines, voltage instability, cascading failures, and even widespread blackouts. The ML model introduced in this study provides improved predictions for critical transmission line outages. Specifically, it delivers more accurate assessments of various reliability indices such as average customer curtailment index (ACCI), average energy not supplied (AENS), interruption energy assessment rate (IEAR), average service availability index (ASAI), average service unavailability index (ASUI), customer average interruption duration index (CAIDI), system expected energy not supplied (EENS), system average interruption duration index (SAIDI), and system average interruption frequency index (SAIFI) for both single and multiple transmission line failures.

Following the literature review in Section 1, Section 2 outlines the fundamental theoretical concepts and various reliability indices. Section 3 details the core framework of the proposed model along with an overview of the ML techniques utilized in this study. Section 4 introduces the different hierarchical ML models and explains the processing of utility data. To identify the most robust model among the three algorithms and performance evaluation. Finally, it summarizes the key findings and concludes the paper.

2. POWER SYSTEM RELIABILITY

Power system reliability is a synonym for demonstration of quality and consistency. Power systems are vulnerable to flaws such as human error and lightning, as well as system abnormalities such as control mistakes, protection system failures, and communication system failures. Even though most modern systems have a number of protection mechanisms in place to help them prevent unforeseen circumstances and power outages, emergencies and malfunctions still happen to power systems. Ensuring power reliability is crucial for both design and operation. Therefore, reliability analysis is a crucial aspect in every stage of power system planning, design, & operation. The possible catastrophes and effects of transmission line failures are identified, examined, and assessed in a transmission line risk reliability evaluation. It can support the transmission system operator in bettering emergency response plans, allocating resources optimally, and setting priorities for maintenance tasks. The following conventional reliability indices are presently used for power system analysis: Let us assume that rt = restoration time; Ni = the total number of users interrupted; NT = total number of customers served; T is the time period under study state; Ci is the cost associated with interruption i; Ei energy is not supplied during interruption i.

2.1 Customer Average Interruption Duration Index

CAIDI is a useful tool for both utility companies and regulatory authorities to assess the reliability and quality of electricity distribution services, driving continuous improvement efforts to better serve consumers and ensure critical infrastructure resilience.

$$\text{CAIDI} = \frac{\sum \text{Duration of Interruptions}}{\text{Number of Customers Affected}}$$

$$\text{CAIDI} = \frac{\sum r_t \times N_i}{\sum N_i} \quad \text{hrs./Customer Interruptions} \tag{1}$$

2.2 System Average Interruption Duration Index

The SAIDI is a critical metric that helps utility companies and regulatory authorities gauge the reliability and quality of electricity distribution services. By monitoring SAIDI values and taking proactive measures to improve system performance, utilities can enhance customer satisfaction and contribute to the overall resilience of the power grid.

$$\text{SAIDI} = \frac{\sum \text{Duration of Interruptions}}{\text{Total Number of Customers Served}}$$

$$\text{SAIDI} = \frac{\sum r_t \times N_i}{\sum N_T} \quad \text{hrs./Customer.yr.} \tag{2}$$

2.3 System Average Interruption Frequency Index

It is an important indicator for utility companies and regulatory organizations assessing the reliability and performance of electricity distribution systems. By monitoring SAIFI values and implementing efforts to reduce interruption frequency, utilities can increase customer happiness while also contributing to the overall resilience of the power grid. It is calculated as

$$\text{SAIFI} = \frac{\sum \text{Number of Interruptions}}{\text{Total Number of Customers Served}}$$

$$\text{SAIFI} = \frac{\sum N_i}{\sum N_T} \quad \text{f./Customer.yr.} \tag{3}$$

2.4 Average Service Availability Index

The ASAI remains a crucial metric that helps organizations assess the availability and reliability of their services. By monitoring ASAI values and implementing measures to enhance service availability, organizations can strengthen customer relationships and maintain a competitive edge in the marketplace.

$$\text{ASAI} = \frac{\sum \text{Available Time}}{\text{Total time in period}}$$
$$\text{ASAI} = 1 - \left[\frac{\sum r_t \times N_i}{\sum N_T \times T}\right] \text{ P.U.} \tag{4}$$
$$\text{ASAI} = \left[\frac{8760 - \text{SAIDI}}{8760}\right]$$

2.5 Average Service Unavailability Index

A crucial indicator for evaluating the dependability and resilience of services offered by businesses in a range of sectors is the ASUI. It is a quantitative measure of the average length and frequency of service disruptions or unavailability over a certain period of time, as opposed to the ASAI, which quantifies the percentage of time a service is available.

$$\text{ASUI} = \frac{\sum \text{Service Unavailable}}{\text{Total time in period}}$$
$$\text{ASUI} = 1 - \text{ASAI}$$
$$\text{ASUI} = \frac{\sum r_t \times N_i}{\sum N_T \times T} \text{ P.U.} \tag{5}$$

2.6 System Expected Energy Not Supplied

It is a fundamental metric that helps utility companies and regulatory authorities assess the reliability and performance of energy delivery systems. By quantifying the estimated energy not supplied, organizations can make informed decisions to enhance service reliability, minimize disruptions, and meet the energy needs of customers effectively.

$$\text{EENS} = \sum \text{EENS}_i \quad \text{MW hour/year} \tag{6}$$

2.7 Average Energy Not Supplied

AENS is a significant performance indicator in the context of electrical power systems, particularly in evaluating the reliability and robustness of power supply networks. AENS quantifies the amount of electrical energy that is not delivered to consumers due to outages and interruptions in the power supply over a specific period.

$$\text{AENS} = \frac{\sum \text{Number of Average Unsupplied Energy}}{\text{Total Number of Served Customers}}$$
$$\text{AENS} = \frac{\sum \text{EENS}_i}{\sum N_T} \quad \text{MW.hour/Customer.year} \tag{7}$$

2.8 Average Customer Curtailment Index

The ACCI is a critical metric for evaluating the reliability and quality of power supply from the perspective of individual customers. By monitoring and managing ACCI, utility companies can enhance service reliability, improve customer satisfaction, and comply with regulatory standards.

$$\text{ACCI} = \frac{\text{Total Number of Unsupplied Energy}}{\text{Total Number of Interrupted Customers}}$$
$$\text{ACCI} = \frac{\sum \text{ENS}_i}{\sum N_i} \quad \text{kVA / Customer} \tag{8}$$

2.9 Interruption Energy Assessment Rate

The Interruption Energy Assessment Rate (IEAR) is a critical metric used in the energy sector to quantify the economic impact of power interruptions on both utility companies and their customers. It provides a standardized way to evaluate the financial consequences of energy not supplied due to outages, facilitating better decision-making in power system planning and reliability improvement efforts.

$$\text{IEAR} = \frac{\sum (C_i * E_I)}{\sum E_i} \quad \text{Rs. / kW / hour} \tag{9}$$

3. ML APPLIED TO RELIABILITY ANALYSIS

The goal of the present study is to build up an ML model to determine the most essential lines in the power network through the reliability index by line outage condition for a particular system.

Fig. 1 exhibits the block diagram of the intended working architecture. In the first stage, the input features data set was separated into training & testing data sets. Before the first stage, the input data set was pre-processed for duplication or missing values. In the second stage, the training data was given to ML algorithms to train the models. In the third stage, based on the training data, the validation of ML algorithms was tested using the testing data. In the final stage, performance evaluation of different ML algorithms is evaluated using the R_2 score, MAE, MSE, and RMSE.

3.1 Gradient Boosting

Breiman [17] first described the gradient boosting (GB) technique, highlighting its function as an optimization method on a suitable loss function. Friedman later expanded on this concept, developing an advanced variant of GB [18]. In this technique, several simple methods known as the "weak learner" are combined, and an improved accuracy prediction model known as the "strong learner" is obtained. The GB technique is a numerical optimization methodology that discovers an additive model for loss function minimization. This algorithm iteratively adds one more decision tree to optimally reduce the loss function. Basically, first one decision tree is added, and then in each step more decision trees are added to minimize the loss function. Since GB iteratively corrects the errors of previous models, it shares the main advantage of other boosting algorithms: the ability to learn complex patterns from input data. However, this technique can lead to overfitting and model noise if the input data is noisy [19], [20]. It is particularly effective for applications involving small datasets [21].

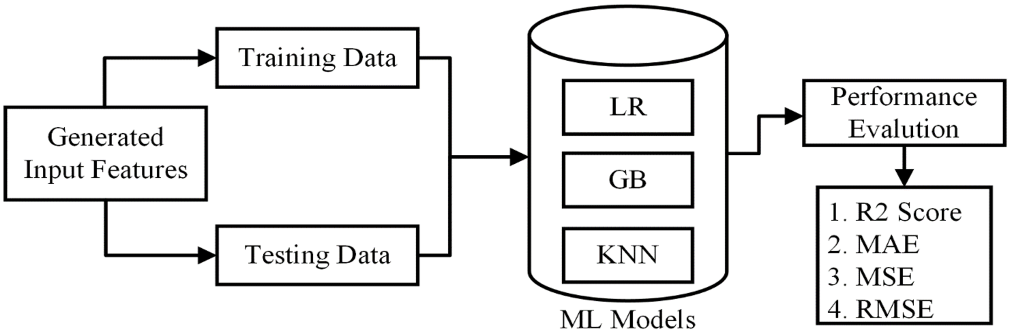

***Fig. 1**: Flowchart of Predict Essential Transmission Line Outage by ML Algorithm.*

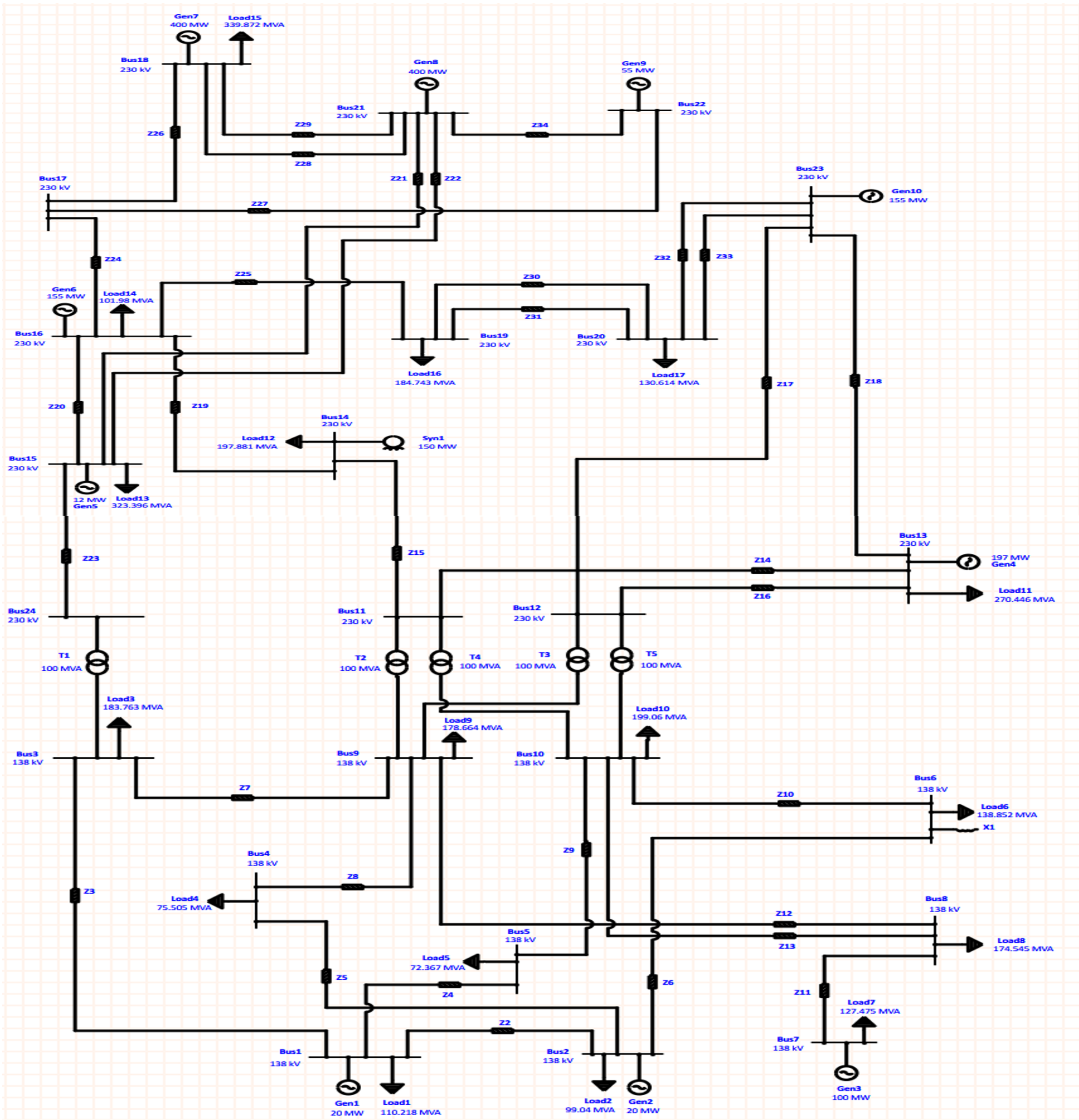

***Fig. 2**: Reliability Test of IEEE 24 Bus.*

3.2 K- Nearest Neighbour

According to [23], K-means is among the easiest unsupervised learning algorithms for tackling clustering problems. This algorithm classifies a particular data set into a predetermined quantity of clusters (k clusters) in a straightforward manner. The K-means algorithm stays particularly useful when labeled data is not presented [22]. Additionally, the general method of transforming

***Table 1**: Sample of Training Data Set.*

Cases	Line Outage Conditions	Power loss		Reliability indices									
		Active Power Loss (MW)	Reactive Power Loss (MVAR)	ACCI (MVA / Customer)	AENS (MW hr*. / Customer) yr.)	ALII (p.u.* (KVA))	ASAI (p.u.*)	ASUI (p.u.*)	CAIDI (hr.* / Customer interruption)	CTAIDI (hr.* / Customer. yr.)	EENS (MW hr.* / yr*.)	SAIDI (hr.* / Customer / yr.*)	SAIFI (f/Customer / yr.*)
Case I	No Line Outage	51.246	454.77	2325.991	50933.47	13.62	0.9652	0.03482	22.388	305.018	916802.5	305.018	13.624
Case II	2, 6, 9	52.141	463.80	2130.009	49025.88	12.48	0.9664	0.03355	23.495	293.935	882465.90	293.9346	12.5107
Case III	2, 4, 6, 12	54.602	476.60	2046.562	48209.66	11.99	0.9670	0.03299	24.045	289.035	867773.90	289.0346	12.0207
Case IV	1,2,5,6,19, 22	100.661	862.49	1958.542	46954.03	11.47	0.9678	0.03219	21.416	281.941	845172.60	281.9413	11.5473

p.u. *= Per Unit, hr.*= hour, yr.* = year

rough heuristics into highly accurate prediction rules involves the use of a "weak" learning algorithm. This algorithm is capable of constantly identifying classifiers ("rules of thumb") that perform marginally more reliably than random, with a precision of approximately 55%. By applying a boosting algorithm to sufficient data, it is possible to construct a single classifier with a significantly higher accuracy, potentially reaching 99% [24].

3.3 Linear Regression

LR is one of the easiest and most commonly used approaches in supervised learning. It is principally applied to regression problems relating to continuous data. The core objective of this algorithm is to establish a linear association amongst the input features and the output target based on existing data. It does so by fitting a straight line that best represents the relationship between these variables. If the data exhibits a linear trend between the input features and the output target value, LR becomes a suitable choice for modelling. The strength of this method lies in its interpretability and ease of application. It adopts that changes in the input variables lead to proportional changes in the output. As a result, LR is most effective for problems where a linear correlation exists between the dependent and independent variables [25].

4. SIMULATIONS AND RESULT ANALYSIS

In this context, the IEEE 24 bus system is considered a test system. The ETAP software was used to assist with the network modeling. As illustrated in Fig. 2, the transmission system consists of 24 load/generation buses with 38 lines and transformers. The transmission line has two voltage levels: 230 kV and 138 kV. Figure 2 displays the 230 kV system with 230 kV / 138 kV connecting stations in buses 11, 12, & 24, while the lower part of

***Table 2**: Result analysis of ML algorithms.*

Parameter / Algorithm	R_2 SCORE	MAE	MSE	RMSE
GB	0.9309	0.2503	0.1497	0.3869
LR	0.8036	0.44	0.4259	0.6526
KNN	0.7829	0.4867	0.4708	0.6861

Fig. 2 displays the 138 kV system with 138 kV / 230 kV connecting stations in buses 3, 9, & 10. There are 38 lines in the system, and two buses connect them via a single sectionalizing switch. By switching OFF, an offline outage scenario can be performed in the network. In these different outage conditions, the different reliability indices are observed, and the dataset is formed. The dataset contains the line connections information (line outages), system losses (active & reactive power), as well as the corresponding different reliability index. Three distinct algorithms were employed. LR, GB, & the KNN Algorithm are three of them.

A small amount of sample dataset, which is prepared for training the ML model, is illustrated in Table 1. Table 1 presents the power loss & reliability indices for various line outage scenarios. The IEEE 24-bus system comprises thirty-eight lines. For instance I, where no line outage is considered, the power loss & reliability index is evaluated via ETAP software. In Cases II to IV, three distinct line outage circumstances are examined, & the corresponding real, reactive loss & reliability index are noted.

4.1 Evaluation of ML models

For the MSE GB algorithm, given the minimum value of 0.1497, the performance of LR in terms of MSE reported 0.4259. The KNN algorithm reported 0.4708 for MSE. On the other hand, the RMSE value reported the least value

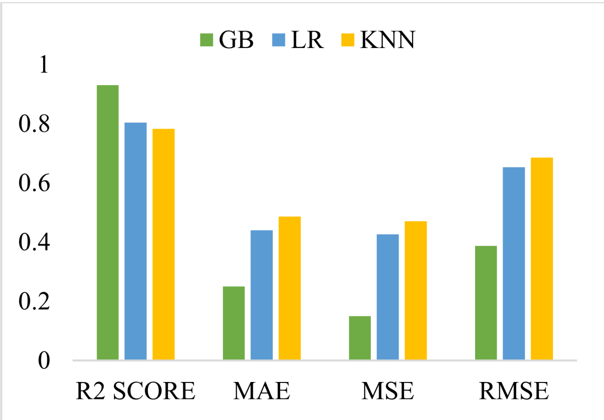

***Fig. 3**: Performance evaluation of three ML models.*

of 0.3869 for GB, 0.6526 for LR, and 0.6861 for KNN. The following Fig. 3 shows the performance evaluation of the three algorithms for different parameters.

Table 2 reported the performance evaluation of 3 different types of ML algorithms. The GB algorithm performance was reported to be the best out of 3 different algorithms in terms of R_2 score, with 0.9309. 0.8036 reported the R_2 score for the LR algorithm. The performance of KNN with respect to the R_2 score was reported as 0.7829. The value of MAE reported 0.2503, 0.44, and 0.4867 for GB, LR, and KNN, respectively, out of all the values, GB is given the lowest value of 0.2503. Figure 3 represents the comparison of performance of 3 ML algorithms.

Unlike LR, which assumes linearity and struggles with outliers, GB uses robust loss functions and regularization to handle noise and prevent overfitting. Furthermore, Compared to KNN, which is computationally expensive and sensitive to irrelevant features, GB offers scalability, native categorical feature support, and implicit feature selection. It can manage the high-dimensional datasets and imbalanced data, making it ideal for complex analytical tasks where accuracy is prioritized over interpretability. The ideal value of the R_2 score is 1, whereas MAE, MSE, and RMSE are 0. GB outperforms LR and KNN due to its ensemble method, integrating weak decision trees to capture complex, non-linear relationships without manual feature engineering.

5. CONCLUSION

Either technical failure or natural disaster-related line failures are erratic and require more maintenance. Thus, this research suggests a method for assessing the reliability of transmission lines that takes into account the most important line outage, which leads to severe impact on the entire network. This approach develops an ML-based reliability model that takes into account the different line outage conditions that will affect the system. The approach successfully evaluates the reliability of a power system under the effects of outage conditions due to disaster or any technical reason, as demonstrated by the findings. The evaluation metrics indicate that the R_2 score is close to the ideal value, suggesting that the model explains most of the variance in the target variable. The MAE value reflects high prediction accuracy, while the MSE signifies strong model performance. Additionally, the RMSE value indicates a good model fit. These results show that the GB model performs better compared to the other two models. This model may be utilized for future planning purposes or transmission line risk mitigation for power systems.

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Sujith Pani was received his B. Tech degree from West Bengal University of Technology, Nadia, West Bengal, India in Electrical and Electronics Engineering. He received his M.Tech. degree with specialization in West Bengal University of Technology, Nadia, West Bengal, and pursuing his Ph.D. from the Department of Electrical and Electronics Engineering, National Institute of Technology, Nagaland, India. His areas of interest are Power system planning, security, and reliability.

Dipu Sarkar received his B. Tech in Electrical Engineering in 2003 from University of Kalyani, W.B., India. He received his M. Tech. with specialization of electrical power systems from University of Calcutta, India, in 2007 and his PhD from the Department of Electrical Engineering, Bengal Engineering and Science University, Shibpur, India (presently known as Indian Institute of Engineering Science and Technology [IIEST]) in 2013. Currently he is working as an Associate Professor in the Department of Electrical and Electronics Engineering of National Institute of Technology, Nagaland, India. His fields of interest are power systems operation and control, power systems stability, soft computational applications in power systems, and smart grids, Grid integrated renewable Energy, Service Restoration and Protective Relay Coordination.

Ch Sekhar Gujjarlapudi was received his B. Tech degree from Acharya Nagarjuna University, Guntur, Andhra Pradesh, India in Electrical and Electronics Engineering. He received his M.Tech. degree with specialization in Power Electronics from JNTUK, Kakinada, India, and pursuing his Ph.D. from the Department of Electrical and Electronics Engineering, National Institute of Technology, Nagaland, India. His areas of interest are Special Electrical Machines, Smart Grid, Grid integrated Renewable Energy, Data Science, and Industrial Internet of Things.