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Power System contingencies Ranking using Machine Learning

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Abstract

Power system contingency is a critical concern in ensuring the security, stability and efficiency of electrical grids. Contingency analysis, which evaluates the potential impact of various contingencies on power system operation, plays a crucial role in maintaining reliability. Traditional methods for contingency analysis often rely on deterministic or probabilistic approaches such as Newton Raphson Load Flow (NRLF), although it is accurate but may have limitations in time consuming or computational efficiency. This paper proposes a novel approach utilizing machine learning techniques for power system contingencies ranking. Firstly, calculate performance indices; active power (PIP) and reactive power (PIV) performance index for each line outage condition using NRLF in Matlab. Then, analysis compared the performance of various regression models including Gradient Boosting Regressor, Random Forest, KNN, Decision Tree Regressor, and SVM on predicting two target variables, PIP and PIV. Finally, R-squared scores were used to evaluate model performance. The ranking is made in descending order of most severe contingencies line that has high value of performance index. The proposed methodology is validated through case studies on standard IEEE 14-bus test systems, demonstrating its capability for practical application in power system operation and planning.

Keywords

Performance indices, contingencies ranking, Newton Raphson Load Flow (NRLF), Matlab, Machine learning

1. Introduction

Power system security is crucial for maintaining the reliability and stability of electrical grids[1]. It's essentially the ability of the system to withstand disturbances or contingencies without compromising safety, reliability, or customer service. These disturbances could range from equipment failures to extreme weather events or even malicious attacks. Ensuring power system security involves careful planning, monitoring, and response mechanisms. This includes factors like maintaining proper voltage and frequency levels, managing power flows, and having contingency plans in place for various scenarios. Inadequate security can indeed lead to catastrophic failures, blackouts, or other disruptions, which can have serious consequences for both the grid operators and end consumers. Therefore, investing in measures to enhance power system security is essential for maintaining a safe, reliable, and economically viable electricity supply [2]. . In summary, power system security is essential for ensuring that operating conditions remain within tolerable ranges. To achieve long-term reliability and safety: I. Proper design with security as a primary concern is crucial. II. Regular monitoring during operation to maintain parameters within acceptable ranges is imperative. III. Good engineering practices, supported by advanced analysis tools, are necessary to achieve these goals. IV. Environmental changes continually refine the requirements for power system security analysis and assessments, prompting evolution in analysis tools. By addressing these points, power systems can sustain reliability and safety over the long run [3]. The prediction of changes in line flow resulting from generator or transmission line outages is facilitated by distribution factors, as discussed in references [4]-[5]. The utilization of AC power flow analysis is elaborated upon in [5]. This method offers valuable insights into how alterations in the network configuration affect the distribution of power flows throughout the system. Through AC power flow analysis, engineers can anticipate and manage potential overloads or imbalances in the grid, contributing to enhanced system security and reliability. Contingency analysis involves the selection and screening of potential contingencies.[6] elaborates on complete bounding methods employed for AC contingency screening, aiming to reduce computational barriers. These methods provide efficient ways to assess the impact of various contingencies on power system operation without exhaustive calculations. By bounding the potential outcomes, these techniques streamline the analysis process, enabling quicker and more effective decision-making for ensuring grid security and reliability. The main objective of this paper of this paper is to propose a machine learning-based methodology to enhance contingency ranking in power systems using the Newton-Raphson load flow method, aiming to improve system reliability and decision-making capabilities.

The process of contingency analysis in power systems[7][8][9][10]. Let's summarize the steps: I. Contingency Creation: This is where we identify all possible contingencies that could occur in a power system. It involves creating lists of these contingencies, which could include events line outages only. II. Contingency Selection: Once you have a list of possible contingencies, you need to select the most severe ones to analyze further. This step involves assessing the impact of each contingency on the power system, particularly focusing on potential violations such as bus voltage or power limits. You calculate an index to determine the severity of each contingency, and then prioritize them based on this severity index. The goal is to identify the most critical contingencies that need immediate attention. III. Contingency Evaluation: In this final step, you develop strategies to mitigate the effects of the most severe contingencies. This could involve taking necessary control actions, such as adjusting generator outputs or reconfiguring the network, to ensure the system remains stable and within operational limits. Additionally, you might implement security measures to prevent similar contingencies in the future. The Performance Index (PI) method is used to quantify the severity of each contingency and rank them accordingly, aiding in the decision-making process during steps 2 and 3. This systematic approach helps power system operators anticipate and prepare for potential disruptions, ensuring the reliability and stability of the electrical grid.[1].

The Newton-Raphson (NR) method indeed offers significant flexibility and generality in analyzing power systems. Here's a breakdown of its key features and applications:

I. representational needs within power systems, such as on-load tap changing (OLTC) and phase-shifting devices, area interchanges, functional loads, and remote voltage control. This means it can handle a wide range of system configurations and control devices, making it versatile for different operational scenarios.

II. Optimization of Power System Operation: NR load flow serves as a central method for optimizing power system operation. By iteratively solving the load flow equations, the NR method helps in determining optimal operating conditions, such as generator outputs and voltage levels, to minimize system losses or meet other operational objectives[11].

III. Sensitivity Analysis: The NR method enables sensitivity analysis, allowing engineers to assess how changes in system parameters or operating conditions affect system performance. This is crucial for understanding the impact of uncertainties and making informed decisions about system design and operation [12].

IV. System-State Assessments: NR load flow facilitates system-state assessments by providing insights into the steady-state conditions of the power system. Engineers can use this information to identify potential issues such as voltage violations, line overloads, or voltage stability problems.

V. Modeling of Linear Networks: While the NR method is an iterative nonlinear technique, it is also used as the basis for linearizing power system models in certain analysis methods. Linearized models are valuable for stability analysis, small-signal analysis, and control design.

VI. Evaluation of Security: The NR method helps in evaluating the security of power systems by identifying critical contingencies and assessing their impact on system stability and reliability. This is essential for ensuring the robustness of the grid against potential disturbances or faults.

VII. Transient Stability Analysis: Although NR load flow primarily deals with steady-state conditions, it is often used as part of transient stability analysis techniques. By providing initial conditions for dynamic simulations, the NR method contributes to assessing the system's ability to withstand and recover from transient disturbances.

VIII. Online Computation: The NR formulation is well-suited for online computation, allowing for real-time monitoring and control of power systems. This enables operators to quickly respond to changing conditions and maintain grid stability and reliability.

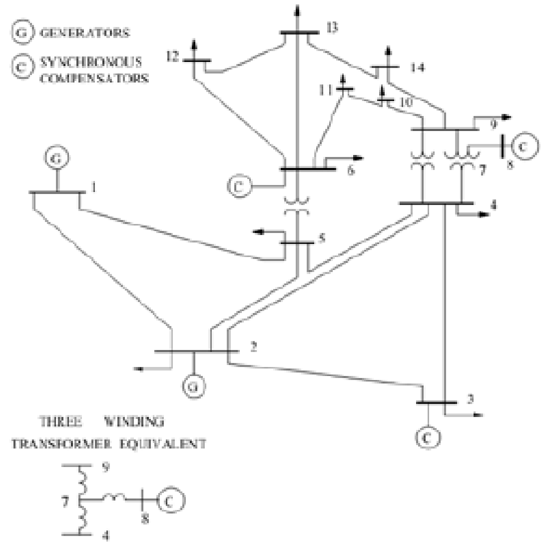

Figure 1: IEEE 14 Bus single line daigram

2. Methodology

The algorithm for contingency analysis using Newton-Raphson load flow [6] solution can be summarized as follows: 1. Data Input: Read the line data and bus data of the given power system. 2. Base Case Load Flow Analysis: Perform a load flow analysis using NRLF without considering any line contingencies to establish a base case. 3. Line Contingency Simulation: Simulate a line outage or contingency by removing a line from the system and proceed to the next step. 4. Load Flow Analysis with Contingency: Conduct a load flow analysis for the system with the specific line outage. Calculate the active power flow in the remaining lines and determine the maximum active power flow (Pmax). 5. Active Power Performance Index (PIP): Calculate the active power performance index, which indicates the violation of active power limits in the system model under the specific contingency. 6. Voltage Calculation: Calculate the voltages at all load buses affected by the line contingency. 7. Voltage Performance Index (PIV): Compute the voltage performance index, indicating the violation of voltage limits at the load buses due to the line contingency. 8. Overall Performance Index (OPI): Compute the overall performance index by adding the active power performance index (PIP) and the voltage performance index (PIV) for each line outage. 9. Repeat for All Line Outages: Repeat steps 3 to 8 for all line outages in the system to obtain PIP and PIV for each contingency. 10. Rank Contingencies: Rank the contingencies based on the overall performance index (OPI), calculated from the values of the performance indices obtained in the previous steps. This algorithm allows for the systematic assessment and ranking of line contingencies based on their impact on the system's performance, enabling effective mitigation strategies to be implemented.

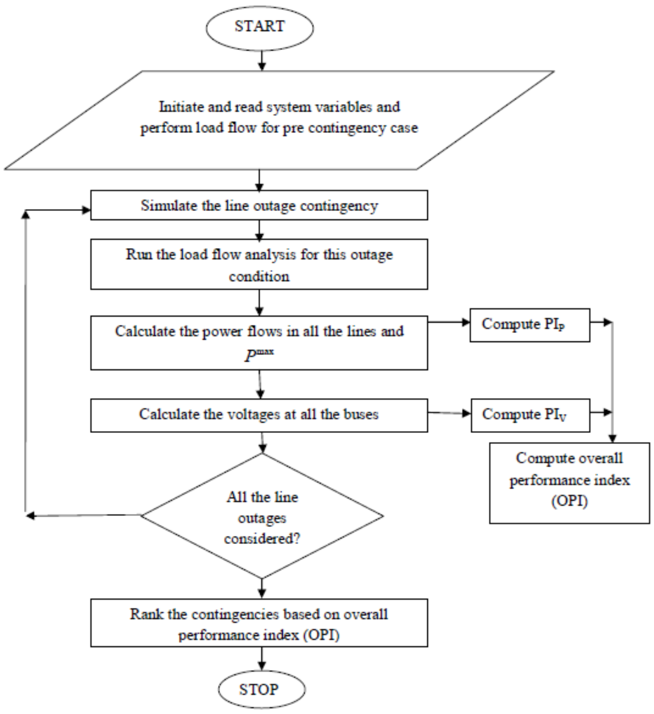

Figure 2: algorithm for contingency analysis using N-R load flow

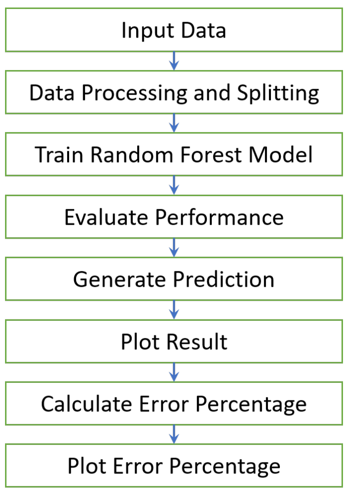

Figure 3: General outline of Methodology

2.1 Newton Raphson Load Flow Method

The NR method is used to calculate load flow of transmission line because X/R is greater than 1 which means inducatance loss can not be neglected. It offers significant flexibility and versatility, allowing for convenient and effective integration of various representational requirements. These include load tap changing, phase-shifting devices, area interchanges, functional loads, and remote voltage control. The NR load flow method serves as a fundamental technique for optimizing power system operation, conducting sensitivity analyses, assessing system states, modeling linear networks, evaluating security, and analyzing transient stability. It is particularly suitable for online computation. The NR formulation is essential for systems with significant angle variations across lines and for control devices that impact reactive and real power.

I. Formulation of Power flow equation: The power flow equations for active power P and reactive power Q at bus i are typically formulated as:

$$P_i = V_i \sum_{i=1}^{n} |V_i||V_j|(G_{ij}\cos(\theta_{ij}) + B_{ij}\sin(\theta_{ij})) \tag{1}$$

$$Q_i = V_i \sum_{i=1}^{n} |V_i||V_j|(G_{ij}\sin(\theta_{ij}) - B_{ij}\cos(\theta_{ij})) \tag{2}$$

II. Initail Guess: Initially, an initial guess for the voltage magnitudes V_i and phase angle θ_i at all buses in the system is assumed.

III. Linearization of Power FLow Equations:The power flow equations are linearized around the initial operating point using Taylor series expansion to obtain a linear approximation. This linearization process results in linear equations for incremental changes in voltage magnitudes and phase angles.

IV. Jacobian Matrix Calculation : The Jacobian matrix, denoted as J, is calculated based on the linearized power flow equations. The Jacobian matrix represents the sensitivity of power flow equations with respect to changes in voltage magnitudes and phase angles.

V. Power Residual Calculation : Power residuals, denoted as ΔP and ΔQ are calculated as the difference between scheduled and calculated values of active and reactive power injections at each bus, respectively.

$$\Delta P_i = P_{i,scheduled} - P_i \tag{3}$$

$$\Delta Q_i = Q_{i,scheduled} - Q_i \tag{4}$$

VI. Update voltage phasors : Using the Jacobian matrix and power residuals, incremental changes in voltage magnitudes ΔV_i and phase angle θ are calculated using the following linear system of equations:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = J \begin{bmatrix} \Delta \Theta \\ \Delta V \end{bmatrix} \tag{5}$$

VII. Update Voltage magnitude and Phase angles: The voltage magnitudes V_i and phase angles θ_i at all buses are updated using the calculated incremental changes:

$$V_i^{new} = V_{i_{old}} + \Delta V_i \tag{6}$$

$$\theta_i^{new} = \theta_i^{old} + \Delta\theta_i \tag{7}$$

Finally, the converged solution is validated to ensure that it satisfies all system constraints and operating limits.

This iterative process continues until the solution converges to an acceptable accuracy level. The NR method is widely used for solving power flow problems in power system analysis due to its efficiency and effectiveness.

2.2 Approach For Contingencies Ranking

Contingency ranking in power systems involves the systematic evaluation of potential disruptions or failures within the system and their respective impacts. By simulating various contingencies, such as line outages or equipment failures, the robustness and resilience of the power grid can be assessed. This process aids in identifying critical contingencies that may lead to adverse consequences, such as voltage instability or excessive power flows. By prioritizing contingencies based on their potential impact, system operators can proactively implement mitigation strategies to enhance system reliability and resilience. Additionally, continuous monitoring and analysis of contingencies play a crucial role in maintaining the stability and security of power systems, especially in the face of evolving operational conditions and emerging challenges.

In this section, we delve into the Newton-Raphson method applied to contingency ranking within power systems. This approach has been explored across IEEE 14-bus systems. The outcomes derived from this method are subsequently utilized to compute performance indices, namely the active power performance index and voltage power performance index. These indices serve as critical metrics for evaluating system performance under different contingencies. Contingencies are prioritized based on their overall performance index, with higher values indicating greater severity, and are arranged in descending order accordingly.

2.2.1 Active power performance index PI_p

The Active Power Performance Index (PIP) is a crucial metric used to evaluate the degree of line overloads within a power system. It provides insights into the extent to which power lines are operating beyond their capacity. The PIP is calculated using the following formula:

$$PI_p = \sum_{i=1}^{L} \left(\frac{W}{2n}\right)\left(\frac{P_i}{P_i^{\max}}\right)^{2n} \tag{8}$$

where, P_i represents the active power flow on line i, $P_i^{\max}$ is the Maximum capacity of line i, n is the penalty function (equal to 1), L is the total number of lines in the system and w is weighting factor nearly equal to 1. The maximum active power flow $P_{\max}$ is calculated as :

$$P_{\max} = \left(\frac{V_i * V_j}{X_{ij}}\right) \tag{9}$$

where, V_i and V_j are the voltages at buses i and j obtained from NRLF method and X_{ij} represents the reactance between buses i and j.

2.3 Reactive Power Performance Index PI_v

It provides insights into the extent to which power lines are operating beyond their reactive power capacity. The PI_v is calculated using the following formula:

$$PI_v = \sum_{i=1}^{N_{pq}} \left(\frac{W}{2n}\right)\left[\frac{(|V_i| - |V_i^{sp}|}{V_i^{\max} - V_i^{\min}}\right]^{2n} + \sum_{i=1}^{N_G} \left(\frac{W}{2n}\right)\left[\frac{Q_i}{Q_i^{\max}}\right]^{2n} \tag{10}$$

where, $V_i^{\max}$ and $V_i^{\min}$ are the maximum and minimum of i^{th} bus voltage, $|V_i^{sp}|$ is the specified magnitude of voltage of i^{th} bus, n is the penalty factor (taken as 1), N_{pq} is total number of buses in that system.

2.4 Overall Performance index

OPI serves as a valuable tool in contingency analysis, enabling efficient decision-making and risk management in power system operations. It combines various performance indices, such as the Active Power Performance Index (PI_p) and Reactive Power Performance Index (PI_v) , to provide a holistic assessment of the impact of contingencies on system operation. Mathematically,

$$OPI = PI_p + PI_v \tag{11}$$

Typically, higher values of the OPI indicate greater severity of contingencies. By considering both active and reactive power aspects, the OPI offers a balanced evaluation of system performance under different conditions.

3. Contingencies Ranking using Machine Learning Approach

This paper explores using machine learning to assess electrical network security, focusing on simulating different network operating conditions. It discusses training ML algorithms per contingency for predicting network failures and analyse the predictability of contingencies. Results suggest that ML tools' predictive power is influenced by training data distribution. Various efficient algorithms and methodologies based on graph theory, matrix properties, or stochastic processes have been proposed to handle the challenges of contingency analysis. Machine learning techniques have gained popularity for power flow predictions due to their practicality and adaptability, particularly in real-time power management systems like digital twin-based applications. This paper focuses on the application and limitations of ML techniques in contingency analysis and introduced a novel ML-based tool to provide new power flow data for both training and testing purposes [13]. In this paper five types of model are tested for training which are described below:

I. Gradient Boosting:Gradient Boosting is an ensemble learning technique that builds a series of weak learners (typically decision trees) sequentially, with each subsequent tree learning from the errors of the previous one [14]. Mathematical Formula: The prediction F(x) for a given input x is computed as the sum of predictions from all individual weak learners:

$$F(X) = \sum_{i=1}^{N} f_i(x) \tag{12}$$

Where fi(x) is the is the prediction of the i- th weak learner, and N is the total number of weak learners.

II. Random Forest Regressor: Random Forest is another ensemble learning method that builds multiple decision trees independently and averages their predictions to reduce overfitting [15] [16] [17].

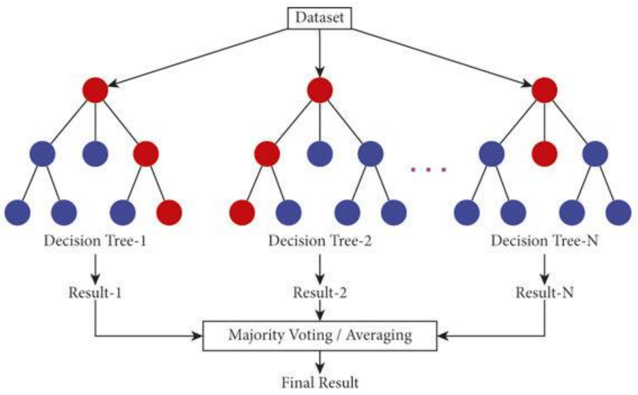

Figure 4: Illustration of Random Forest trees

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} f_i(x) \quad (13)$$

where fi(x) is the prediction of the i-th decision tree, and N is the total number of trees in the forest.

III. Support Vector Machine: SVM is a supervised learning algorithm used for classification and regression tasks. In regression, SVM aims to find the hyperplane that best fits the data points[18].

$$\min_{w},_b \frac{1}{2} = |w|^2 + C\sum_{i=1}^{n} \max(0, |y_i, -(w.x_i + b)| - \epsilon \quad (14)$$

w is the weight vector, b is the bias term, C is the regularization parameter, and ε is the margin parameter

IV. K-Nearest Neighbours (KNN): K-Nearest Neighbours is a non-parametric and instance-based learning algorithm used for classification and regression tasks. It predicts the target variable by averaging the values of its k nearest neighbours [19] [20] [21].

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} \hat{y}_i(x) \quad (15)$$

where y_i represents the target value of the i-th nearest neighbour.

V. Decision Tree is a tree-like model where each internal node represents a feature, each branch represents a decision based on that feature, and each leaf node represents the outcome (prediction) [22].

$$\text{imppurity}(D) = \sum_{i=1}^{N} p_i(1-p_i) \quad (16)$$

3.1 Model Training and Evaluation:

Data Splitting: The dataset was split into training and testing sets using an 80-20 split, with 80% of the data used for training and 20% for testing. The result from NR method (Changing loading from 75% to 125% is used as dataset. **Splitting Function:** The train test split function from the model selection module was utilized for data splitting. **Environment:** Model training and evaluation were conducted using Google Colab, a cloud-based Jupyter notebook environment, to leverage high-performance computing resources. **Model Fitting:** The training data were used to fit the models using the selected algorithms. **Hyperparameter Tuning:** Techniques such as Grid Search Cross-Validation were employed for hyperparameter tuning to optimize the models. **Performance Evaluation:** Model performance was evaluated using the coefficient of determination (R-squared) on the testing set to assess predictive accuracy. **Prediction:** The trained models were then used to make predictions on the testing set.

4. Results and Discussion

4.1 Results obtained from Newton Raphson Load flow

Contingencies ranking based on total performance indices is done using NRLF. The result obtained after using newton Raphson load flow method for IEEE 14 bus system is shown in table 1. The total performance indices for all possible (N-1) contingencies are computed. Then using these data to train machine learning and calculating result for other bus data. 14 bus system consists of 4 generator buses, 9 load buses and 1 slack bus.This system has 20 transmission line where single respective line outage is consider for each line contingency.

Table 1: Performance index and contingency ranking using NRLF

O.L.N	PI_p	PI_v	OPI	Rank
1	0.196294	3.945016	4.14131	1
2	0.058422	2.728651	2.787073	3
3	0.073697	2.669195	2.742892	4
4	0.058797	1.922092	1.980889	11
5	0.055592	2.254917	2.310509	6
6	0.050223	1.881235	1.931458	14
7	0.054105	2.036255	2.09036	7
8	0.060753	1.662663	1.723416	19
9	0.047595	1.76152	1.809115	18
10	0.068953	3.363528	3.43248	2
11	0.047677	2.011383	2.05906	8
12	0.047968	1.771293	1.819261	16
13	0.050026	1.927438	1.977464	12
14	0	0	0	20
15	0.061787	2.497595	2.559382	5
16	0.047946	1.763482	1.811428	17
17	0.049211	1.934753	1.983964	10
18	0.047434	1.961641	2.009075	9
19	0.047644	1.807943	1.855588	15
20	0.048094	1.894945	1.943038	13

From the Table 1, The Active Power Performance Indices and Voltage Performance Indices for line outage is 0.196294 and 3.945 is highest than any other contingency. Also Overall performance index (OPI) is highest. Hence we conclude that line outage-1 is highest severity case followed by line outage 10, 2, 3, 15, 5,7,11, 13, 20,6,19, 12, 16, 9, 8 and 14 respectively in descending order. For line outage-14, the active power performance index and reactive power performance index is zero because when that line is outage then it leads to outage of generator hence this line is discarded.

4.2 Results Obtained from machine learning

section, performance indices from machine learning approach is presented for 5 models. The main objective is to calculate indices for different bus value after trained it by the result from Newton Raphson Method.

I. Results of performance indices using Decision Tree Method: Figure 4,5,6,7 shows the results of PI_p, PI_v, OPI and Error from decision tree method.

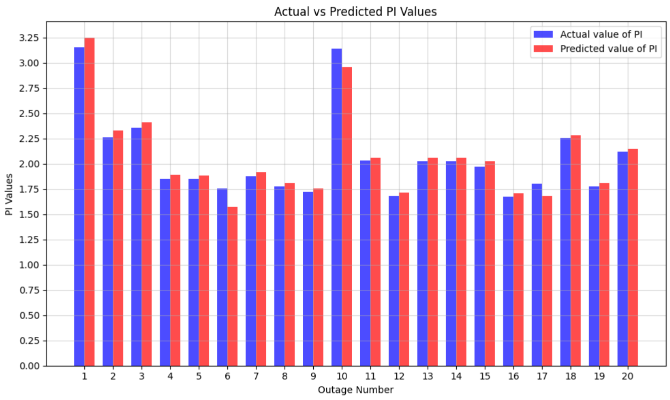

Figure 5: Value of OPI index using decision tree method

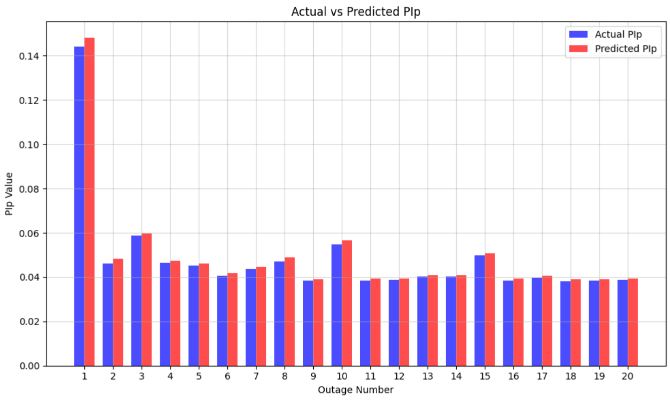

Figure 6: Value of PI_p index using decision tree method

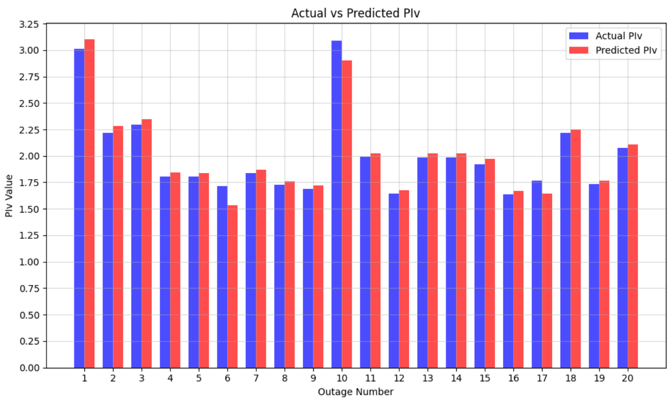

Figure 7: Value of PI_p index using decision tree method

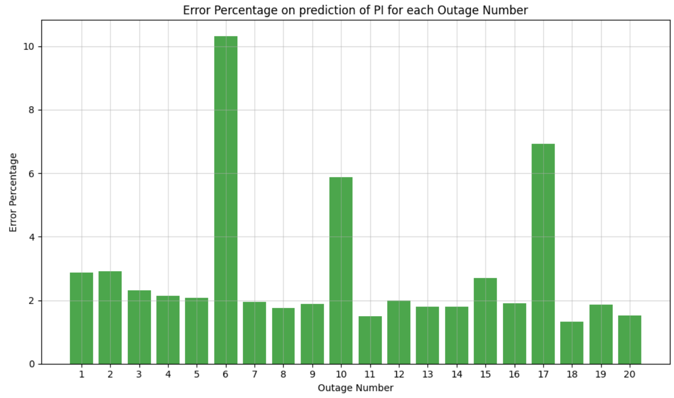

Figure 8: Error Percentage on predtiction of PI for each outage number

II. Results of performance indices using SVM method. Figure 8, 9, 10, 11 shows the results of PI_p, PI_v, OPI and Error from SVM method.

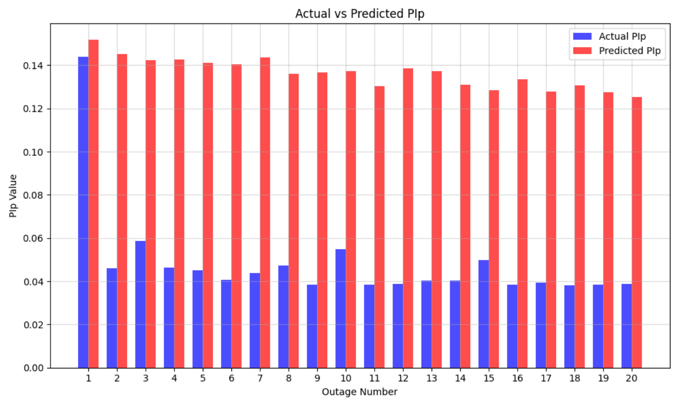

Figure 9: value of PI_p index using SVM method

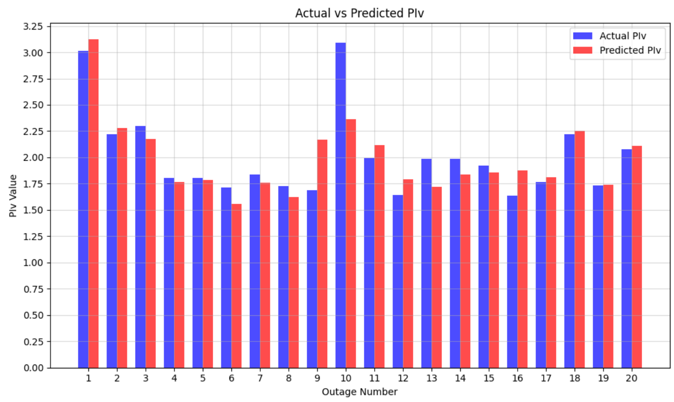

Figure 10: value of PI_v index using SVM method

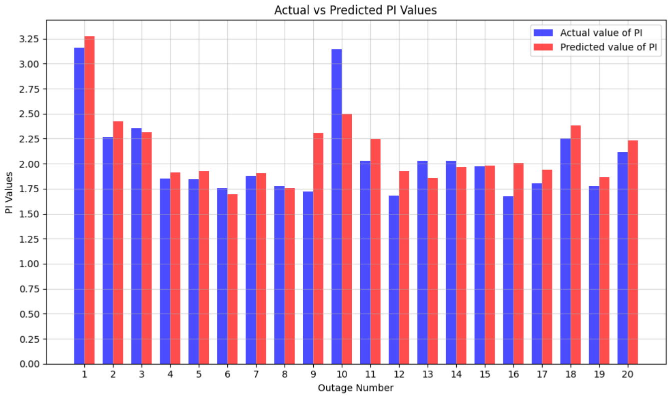

Figure 11: Value of OPI indices using SVM method

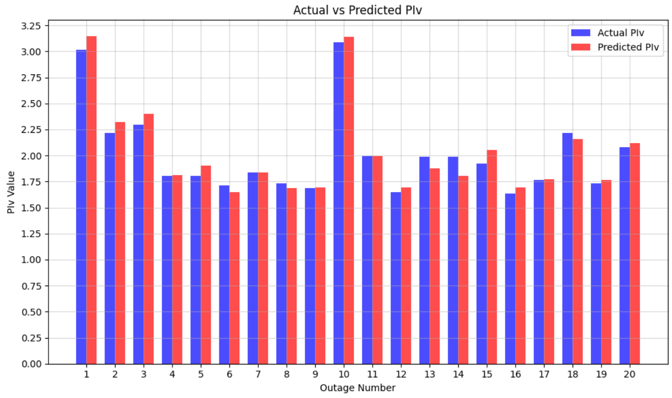

Figure 14: value of PI_v index using Gradient Boosting method

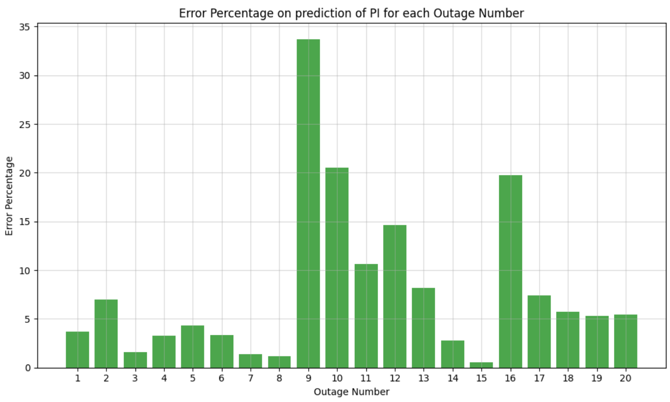

Figure 12: Error percentage on prediction of PI for each outage line using SVM method

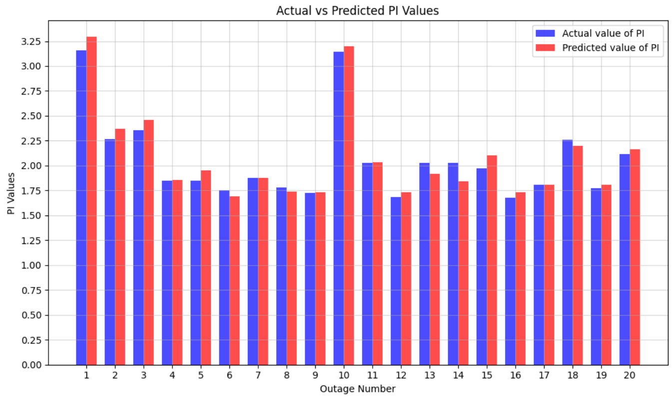

Figure 15: Value of OPI using Gradient Boosting Method

III. Results of performance indices using Gradient Boosting method. Figure 12,13,14,15 shows the results of PI_p, PI_v, OPI and Error from Gradient Boosting method.

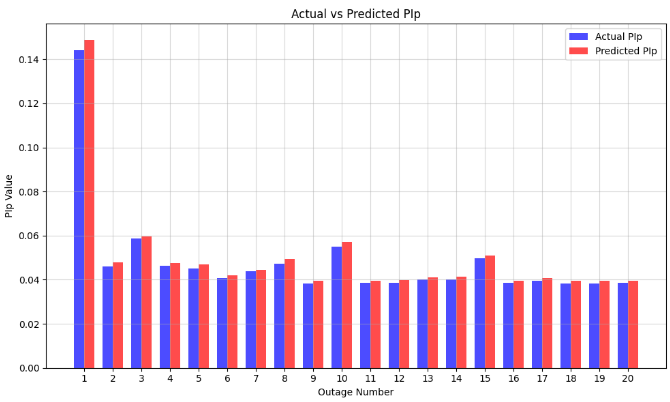

Figure 13: value of PI_p index using Gradient Boosting method

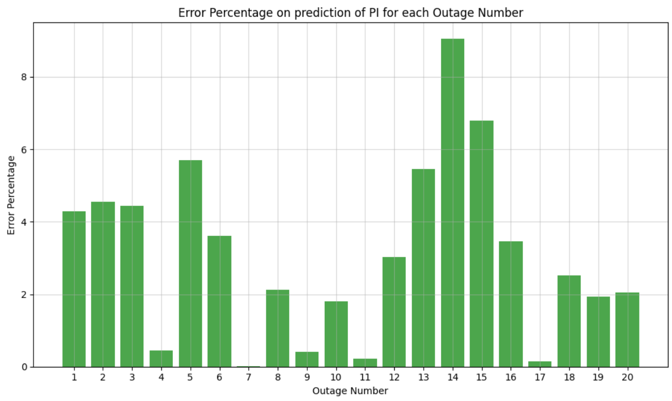

Figure 16: Error percentage on prediction of PI for each outage line using Gradient Boosting Method

IV. Results of performance indices using KNN method.

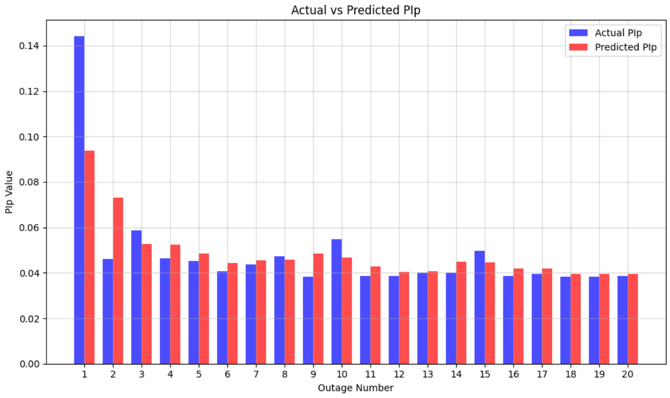

Figure 17: value of PI_p index using KNN method

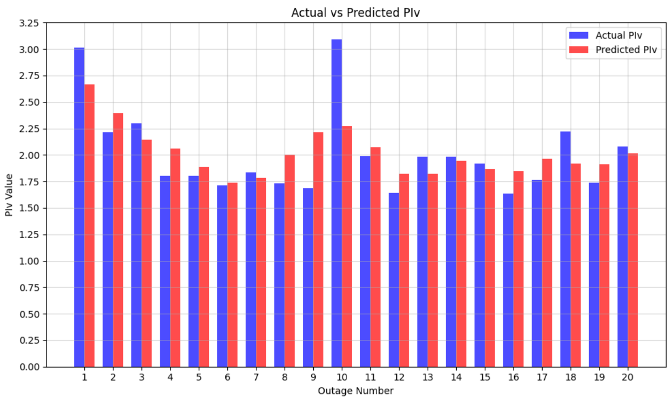

Figure 18: value of PI_v index using KNN method

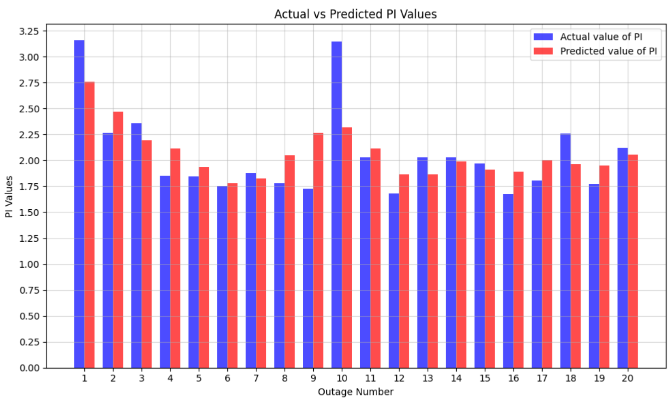

Figure 19: value of OPI index using KNN method

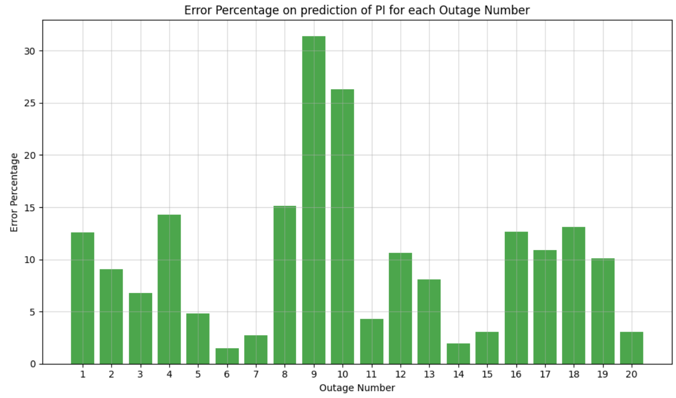

Figure 20: Error percentage prediction of OPI for each outage number using V method

V. Results of performance indices using Random forest method. Figure 20,21,22 and 23 shows the results of PI_p, PI_v, OPI and Error from Random Forest method.

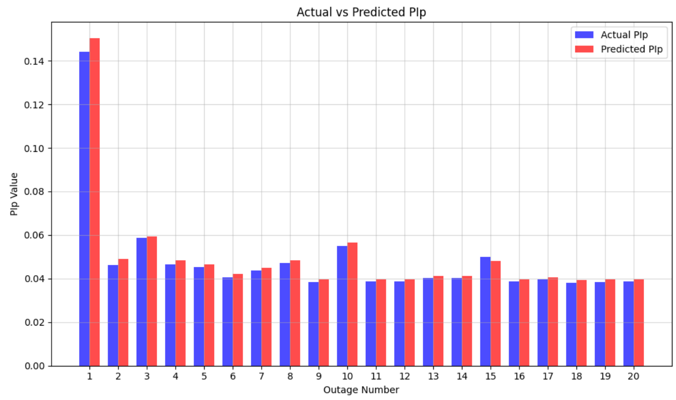

Figure 21: value of PI_p index using Random Forest method

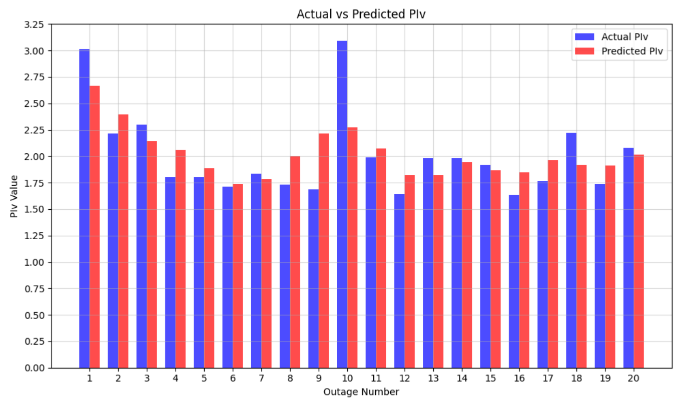

Figure 22: value of PI_v index using Random Forest method

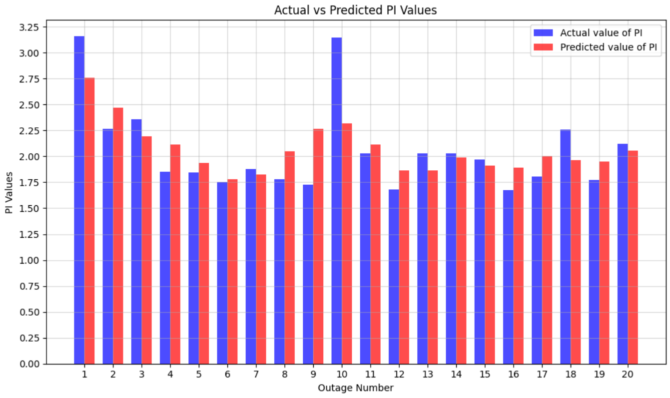

Figure 23: CValue of OPI index using Random Forest Method

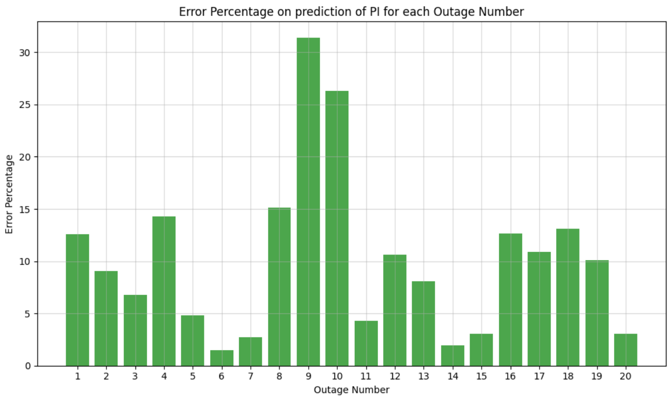

Figure 24: Error percentage on prediction PI for each outage case

- Performance Assessment: The performance of each model was assessed based on the R-squared score obtained on the testing set.
- Visualization: Actual vs. predicted values were visualized using bar plots to compare the predictive capabilities of the models.
- Further Analysis: Additional analysis was conducted to understand the strengths and weaknesses of each algorithm in predicting the target variables 'Piv' and 'Pip'.

Through extensive experimentation and analysis, we evaluated the performance of each model based on metrics such as R-squared score and predictive accuracy shown in table 2.

R Squared Error obtained while calculating PI_p and PI_v by using above method is shown in Table 2:

Table 2: R squared Error in ML methods

Model Name	PI_v	PI_p
Gradient Boosting Regressor	0.957456118	0.994412534
Random Forest	0.9586081	0.992687211
KNN	0.505518816	0.650856696
Decision Tree Regressor	0.963404296	0.996176729
SVM	0.67293019	-14.78624804

Our results indicated that ensemble methods such as Gradient Boosting and Decision tree Regressor outperformed other models in terms of predictive accuracy and robustness. These models demonstrated the ability to effectively rank contingencies in power systems, providing valuable insights for system operators and planners.

5. Conclusion

our study highlighted the importance of considering model interpretability, computational efficiency, and generalization capability when selecting machine learning models for real-world applications in power systems. While complex models like SVM and neural networks offer high predictive power, simpler models like Decision Trees and KNN provide better interpretability and computational efficiency.

Overall, our findings contribute to the growing body of research on leveraging machine learning techniques for contingency ranking in power systems. By accurately assessing the severity of potential contingencies, our approach facilitates proactive decision-making and enhances the resilience of power infrastructure against disruptions. Future research directions may focus on exploring hybrid models and incorporating additional features to further improve contingency ranking accuracy in power systems.

6. Recommendation

The above Result and conclusion show that the contingency ranking of IEEE 14 bus system using ANN method which gives accurate result in compare to other analytical method. This method can be further implemented in INPS which help in power system security and reliability.

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