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Original Article

A Data-Driven Approach to Power System Contingency Analysis Using Support Vector Machines

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Abstract *- Power system security is one of the most considerable studies to understand the vulnerability of various contingencies occurring on the system. In this paper, the contingency ranking is performed for single-line outages. Among the increments of the load variation for cases like only active power loading, only reactive power loading, and both the active and reactive power loadings are considered to create various scenarios using the Active Power Performance Index (APPI). These scenarios have been classified through a Support Vector Machine Classifier (SVMC) to observe the impacts of line outage. The data has been generated using MATLAB software for the UPSEB Indian Utility 75-bus system. Python programming is used to classify using SVMC.*

Keywords *- Active Power Performance Index, Contingency analysis, Data analysis, Machine Learning, Support Vector Machine Classifier.*

1. Introduction

The power system is a combination of various independent and dependent variables. These variables are driven through the generation, transmission, and distribution. These subsystems need to maintain stability under any unwanted scenarios. These unwanted or unpredictable scenarios are contingencies that occur in the system. The contingencies may be, viz., single transmission line outage, double transmission line outage, generator outage, transformer outage, and so on. Most of the predominant contingencies are N-1, which occurs very frequently for any natural disaster or even during maintenance. During these situations, the most dangerous transmission line needs to be identified and ranked as that particular line needs to be secured first, for which there should be any preventive action to be taken to maintain the stability and also to uphold the reliability of the system. Machine learning is one such technique that is the most dominant for the prediction of unknown situations based on the training provided.

Among many machine learning algorithms, Support Vector Machine Classifier (SVMC) is proven for its effective classification of the provided data. The severity of the transmission lines needs to be classified based on the various classes provided. The SVMC has the capability to classify the unknown values based on the severity or the class mentioned for a particular transmission line. The contingency ranks can be classified based on the type of class observed. The foundation of N-1 contingency analysis is the requirement that the system continue to function in the event that only one transmission component fails, in order to keep the grid secure [1]. Key indicators for identifying risky operating situations and facilitating accurate choices include quantitative performance indices, including heat limits, voltage aberrations [2, 3].

The indicators help operators avoid cascade outages and maintain continuous service. To strengthen resilience, advanced contingency planning procedures, such as corrective gearbox switching and fast system recovery approaches, have been employed [4, 5]. Due to the fast growth of machine learning, the integration into power systems has increased rapidly, and the data analysis of such complex and high-dimensional data is being conducted [6–7]. Based on many techniques in machine learning, SVM is widely used for various IEEE standard test systems for ranking the contingencies and contingency screening [8]. The SVM has the capability to reduce unwanted data and predict an appropriate and accurate output when compared to other conventional methods [9–10].

The voltage and the reactive power through the line loading index have been classified by the SVM in the combination of other techniques with an accuracy of 99% [11]. And also, the combination with fuzzy-neural classification, the line outage analysis has been performed effectively. The single-line outage and the double-line outage are carried for the large-scale power systems and are computed with combinational topologies with neural networks [12]. A Radial-Basis Function Support Vector Machine (RBF-SVM) paired with a Back-Propagation (BP) neural network accurately identified transmission-line fault types with up to 100% accuracy in experimental test systems [13]. Other works have focused on transmission outage prediction based on weather, vegetation, and climatic factors—where ML models, including logistic regression and ensemble learning, successfully improved outage risk modeling in overhead systems.

Moreover, reinforcement-learning-based controllers have been developed to support remedial action selection under contingency conditions, adding an intelligent layer to traditional SCADA systems [14]. Despite these advances, challenges remain: ML-based models must be scalable, interpretable, and adaptable to evolving grid topologies, renewable integrations, and dynamic loading conditions [15]. Hybrid frameworks combining PV and wind forecasting with severity classification, such as transformer-based and ensemble architectures, have shown resilience to data variability and missing inputs [16]. There is an increasing demand to fuse existing performance indices with feature-selection mechanisms, ensuring robust and explainable contingency screening.

2. Contingency Analysis and Ranking

Contingency analysis is one of the important studies in power systems. This is observed through the security of the transmission line and various component outages in the system. As shown in Figure 1, the study is done to identify the line, evaluate the transmission line, and also to rank the same for any contingency. The stability of the system can be analyzed based on the single-line outage condition. The complete analysis is carried out based on the type of contingency scenario, severity evaluation, and the assessment of the contingency. The severity evaluation can be done based on the type of index used to compute, and the mitigating methodology can also be provided if needed.

Though the analysis of contingency is prioritized, handling the large bus system using traditional methods is still complex. Based on various performance indices and computational methods used, rankings and the performance measures may vary as per the requirements. In this paper, ranking is performed based on the value of the Active Power Performance Index (APPI). The analysis is considered based on the data obtained by the index, and a support vector machine is used for the ranking methodology.

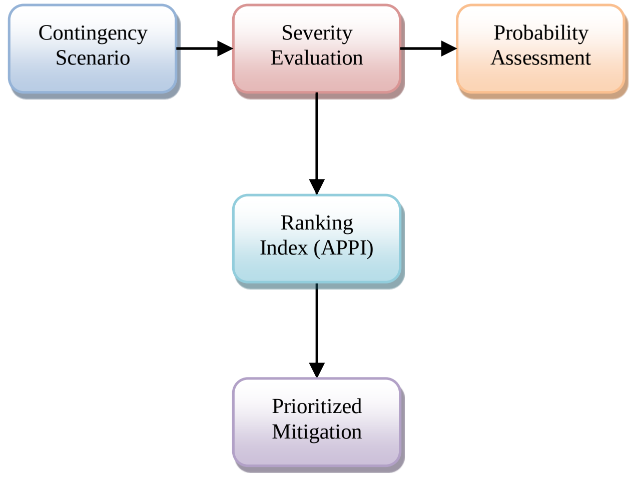

Fig. 1 Contingency analysis

2.1. Active Power Performance Index (APPI)

The Active Power Performance Index, as in (1), was used to do the contingency ranking based on the real/Active Power Performance Index (APPI) flow in the transmission line (APPI). The line that is overloaded will have the highest APPI rating. The transmission line with the highest APPI rating will be the one that has to be safeguarded first to avoid a systemic breakdown.

$$APPI = \sum_{r=1}^{L_N} \left(\frac{u}{2n}\right)\left\{\frac{P_l}{P_l^{max}}\{\}^{2n}\right\} \tag{1}$$

Where, P_l = Power flow through line l, P_l^{max} = Maximum capacity of power flow through the line l, L_N = Number of transmission lines, u= Real non negative weighting factor (i.e. 1), n = Exponent of penalty function (i.e. 1), $P_l^{max \frac{V_i \times V_j}{X}}$, V_i= voltage at bus i, V_j = Voltage at bus j, X = Reactance of the line between bus i and bus j.

3. Support Vector Machine

Power Systems is a huge network that transports the essential needs of clients situated in remote locations. Transferring data from generation stations across long distances while avoiding disruptions such as breakdowns, overloading, overvoltage, and so on is a critical task for a power system engineer in real life. In a power system, generating disruptions has serious consequences, which can lead to the system failing to meet demand. Machine Learning Algorithm has a significant impact on solving this type of problem by prediction. Support Vector Machines (SVM) frequently employ standardisation as a data pre-processing approach to rescale a dataset's characteristics. This improves the SVM algorithm's performance and guarantees that all the features are on a similar scale.

Additionally, standardisation reduces the amount of memory needed to hold the data. The kernel type that was chosen is linear. The linear kernel is a type of kernel function that is often utilised in SVM to tackle linearly separable issues. It computes the dot product of input data points in the original feature space, without explicitly translating to a higher-dimensional feature space.

$$\text{Standardization}=\frac{\text{original data value-mean}}{\text{standard deviation}} \quad (2)$$

Where,

$$\text{Mean}=\frac{\text{sum of all the observations}}{\text{number of observations}}$$

$$\text{Standard deviation} = \sum\sqrt{\frac{(\text{original value-mean})^2}{\text{samplecount}}}$$

The linear kernel function is given as follows: $K(x,x')=x \cdot x'$, where x and x′ represent the input data points and represents the dot product. The linear kernel simply computes the dot product (a measure of similarity or correlation) between the input data points.

Because it does not require any expensive computations or explicit feature mapping, the linear kernel is efficient and computationally inexpensive. It is useful for linearly separable problems for which a hyperplane may be utilised to divide data points from distinct classes.

4. Proposed Methodology

4.1. Contingency Ranking using APPIs

The results and discussion may be presented separately, or in one combined section, and may optionally be divided into headed subsections. For an Indian Utility 75 Bus system, the N-1 transmission line contingencies are performed for all 98 lines, and the severity of the lines is identified based on contingency ranking. Based on the computation of APPI, the contingencies are ranked.

The computational methodology is as follows.
Step 1: Consider the complete data of the system, viz., bus, line data.
Step 2: Execute the load flow with and without line outage contingency.
Step 3: N-1 line outage is performed.
Step 4: APPI is computed for each line outage.
Step 5: High-severity lines need to be ranked.

4.2. Severity Classification

The methodology delineates a comprehensive machine learning pipeline designed for evaluating contingency severity within the UPSEB-75 bus power system using a Support Vector Machine (SVM) model. The process commences with the initialization phase, where data on the voltage magnitude, voltage angle, active power flow, reactive power flow, and transmission line reactance are considered for power system operation. This is followed by the generation of a machine learning dataset through N-1 contingency analysis, which simulates single-component failures to assess system resilience under contingency conditions. Once the dataset is prepared, the data is standardized or normalized to get all the prescribed data into a simple, compatible level. One of the hyperparameters, i.e., the linear kernel function, improves the observation.

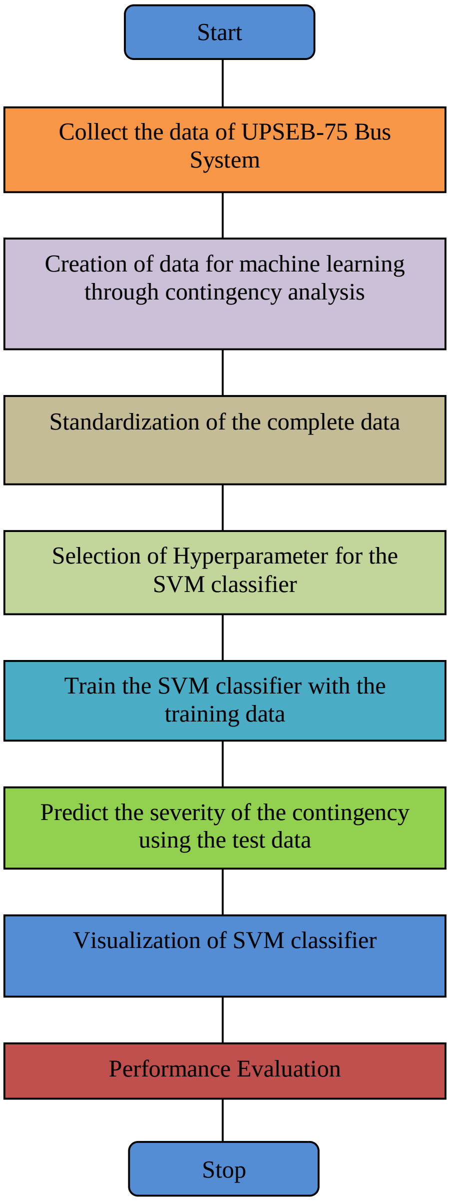

Fig. 2 Severity classification based on contingency analysis

The SVMC is trained based on the input data to understand the difference between Non_Severe, Semi_Severe, and Severe operating conditions. This stage is important to understand and enable the classifier to predict the new data sets. There are 14 lines associated with the generator bus (L-G). 1 line associated with the slack bus (L-S). 83 lines are associated with the load bus (L-L). The data is generated through the actual system loading condition.

The performance of the classifier is quantitatively measured using a standard evaluation metric, i.e., as accuracy, which helps to validate its robustness. The workflow concludes with the completion phase, establishing a structured and repeatable framework for critical contingency analysis in power systems, supporting enhanced reliability and operational decision-making. The Severity Classification based on Contingency Analysis is shown in Figure 2.

5. Results and Discussions

From the N-1 contingency analysis, the most severe lines were identified that make the system unstable. Contingency Analysis performed through a single transmission line outage. After performing N-1 transmission line contingency on all 98 transmission lines, only 70 lines are considered for further analysis, as these lines converge post-contingency. The following Table 1 shows the converged lines that are considered for further analysis.

The analysis of the proposed methodology is carried out in various loading conditions, i.e., active power, reactive power, and both active and reactive power loading conditions. As described in Section 4, the data is generated through the following cases. Each case is observed through the system loading condition and the type of loading condition. The actual percentage of system loading is considered.

Case I: Single line outage with Pd load variation
Case II: Single line outage with Qd load variation
Case III: Single line outage with both Pd & Qd load variation

Table 1. Converged lines after N-1 transmission line contingency

S. No.	Line No	From bus	To bus		S. No.	Line No	From bus	To bus
1	2	17	16		36	58	31	32
2	3	22	25		37	59	35	36
3	4	23	24		38	60	46	37
4	5	26	27		39	61	19	36
5	6	29	30		40	62	17	35
6	7	36	37		41	64	40	48
7	8	38	39		42	65	74	41
8	9	45	44		43	66	74	41
9	25	16	46		44	67	74	73
10	26	16	50		45	68	26	22
11	27	17	19		46	69	29	22
12	28	17	23		47	70	26	41
13	29	23	29		48	71	48	49
14	31	19	26		49	72	49	40
15	32	47	50		50	73	38	29
16	33	47	67		51	74	38	22
17	34	24	27		52	75	18	47
18	35	24	54		53	76	30	65
19	39	25	43		54	77	41	42
20	41	54	28		55	78	42	74
21	42	28	43		56	80	23	74
22	43	28	56		57	81	24	67
23	44	56	30		58	82	18	68
24	45	30	57		59	83	18	71
25	46	53	30		60	84	27	68
26	47	53	61		61	85	27	71
27	48	30	61		62	87	43	58
28	49	57	58		63	88	43	56
29	50	57	59		64	89	55	44
30	51	59	39		65	90	73	45
31	52	39	31		66	94	21	65
32	54	54	63		67	95	21	30
33	55	55	63		68	96	28	55
34	56	61	62		69	97	35	41
35	57	62	32		70	98	39	32

5.1. APPI without Single Transmission Line Outage

The following Figure 3 shows the Active Power Performance Index (APPI) value for various loading conditions, i.e., active power, reactive power, and both active and reactive power loading without a single line transmission outage. The APPI value is less than 1 under three different loadings, indicating that the system is stable and operating within its operating limits.

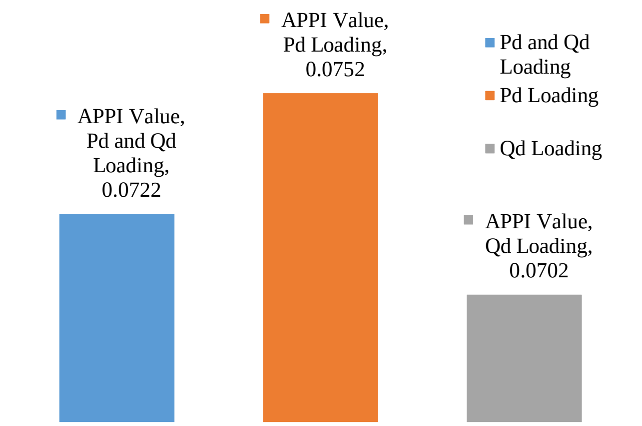

Fig. 3 APPI value for various loading conditions without contingency

5.2. APPI with Single Transmission Line Outage

Contingency Ranking performed through a single transmission line outage is done based on the Active Power Performance Index (APPI) when both active and reactive power system loading are done under loading cases under transmission line outage. An APPI value greater than 1 at the 67th line indicates that the 67th line outage makes the system unstable.

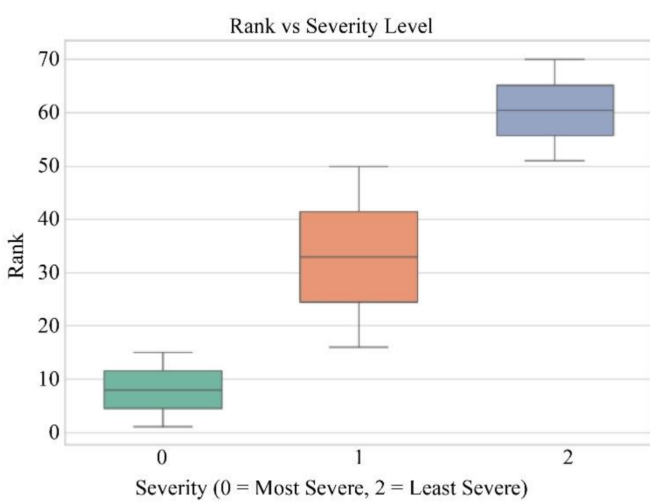

Fig. 4 Classification of rank based on severity

Figure 4 presents the classification of contingency ranks based on severity levels derived from machine learning analysis. The ranking process incorporates metrics such as line outage impact and APPI, enabling the segmentation of scenarios into three categories: most severe, moderately severe, and least severe. The classification aids in prioritizing the most critical contingencies that may jeopardize system security. Each rank corresponds to a distinct severity class, making this visualization essential for contingency ranking and risk-informed decision-making in operational planning. The figure validates the model's ability to distinguish effectively between varying degrees of system threat.

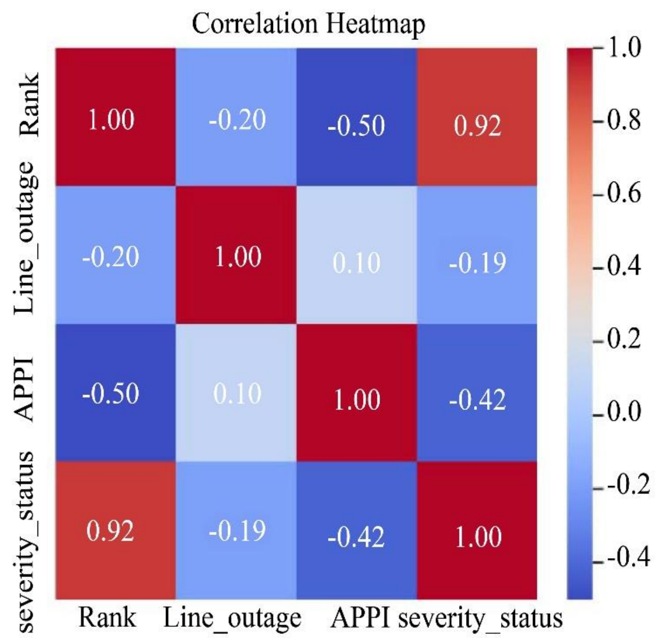

Fig. 5 The correlation under Pd & Qd loading conditions

Figure 5 demonstrates the correlation matrix for key variables under combined active (Pd) and reactive (Qd) power loading scenarios. The matrix quantifies the linear relationships between inputs (Rank, Line Outage, APPI) and output (Severity). Positive and negative correlations are color-coded to reflect the strength and direction of each association. Strong correlations highlight significant dependencies, offering valuable insights into variable influence on system behavior. This analysis assists in variable selection and dimensionality reduction for machine learning tasks. The figure serves as a diagnostic tool to understand how variations in power demand influence critical performance indicators and system security.

5.3. Classification of the Severity of Lines using SVM

The following condition is considered to classify the three different classes based on the Active Power Performance index ranking. The classification of the ranks is given in Table 2 below.

Table 2. Class classification for SVM

S.No.	Severity	Ranks	Class
1.	Severe condition	Ranks 1 to 15	0
2.	Semi-Severe condition	Ranks 16 to 50	1
3.	Non-Severe condition	Ranks 51 to 70	2

5.3.1. Single Line Outage with Pd Load Variation

The proposed SVM methodology is used to assess the severity of single-line outage events under full Pd loading conditions. Seventy percent of the dataset was utilized for training, and the remaining 30 % served as a test set to evaluate model performance. Figure 6 depicts the scatter plot of three severity categories-Severe, Semi-Severe, and Non-Severe after dimensionality reduction via principal component analysis. The SVM constructs two hyperplanes to form decision surfaces that effectively separate the three classes. These decision boundaries define the classification regions corresponding to each severity level. The accuracy of class separation demonstrates the classifier's capability to distinguish between varying outage severities under full Pd loading. This analysis confirms that the proposed SVM model provides robust and reliable classification of single-line outage severity, enabling rapid identification and categorization of critical system events.

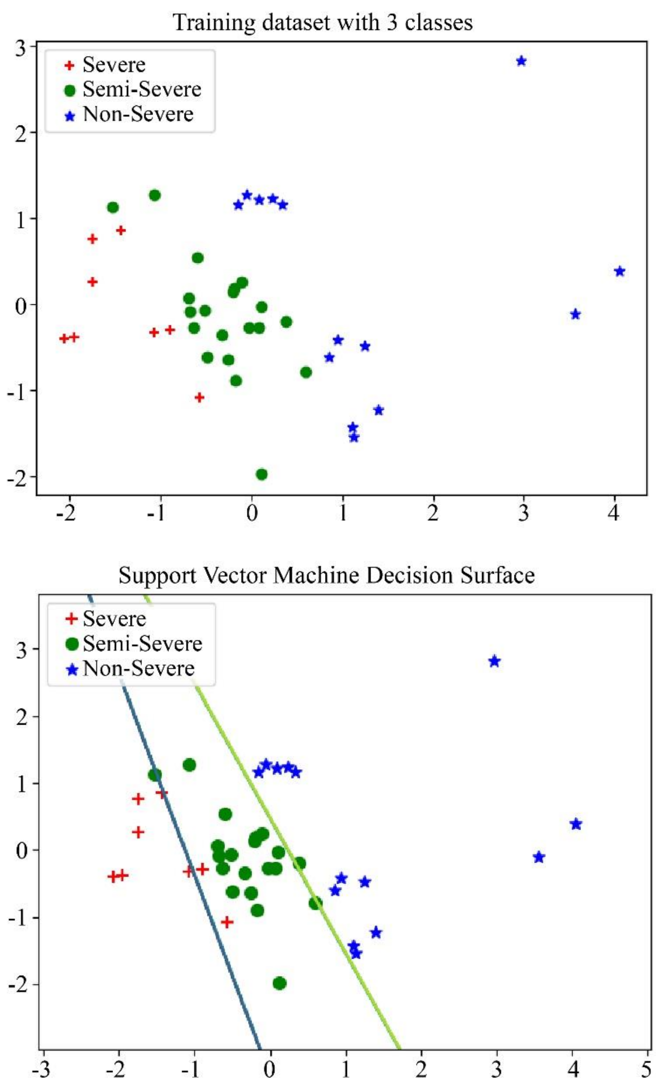

Fig. 6 Scatter plot and the hyperplanes generated for Pd loading trained data

5.3.2. Single Line Outage with Qd Load Variation

In this case, a single line outage by varying the Qd loading conditions was done. The SVM classifier model has been trained with 60% of the dataset, and the remaining data has been used for testing the model's performance, that is, for prediction.

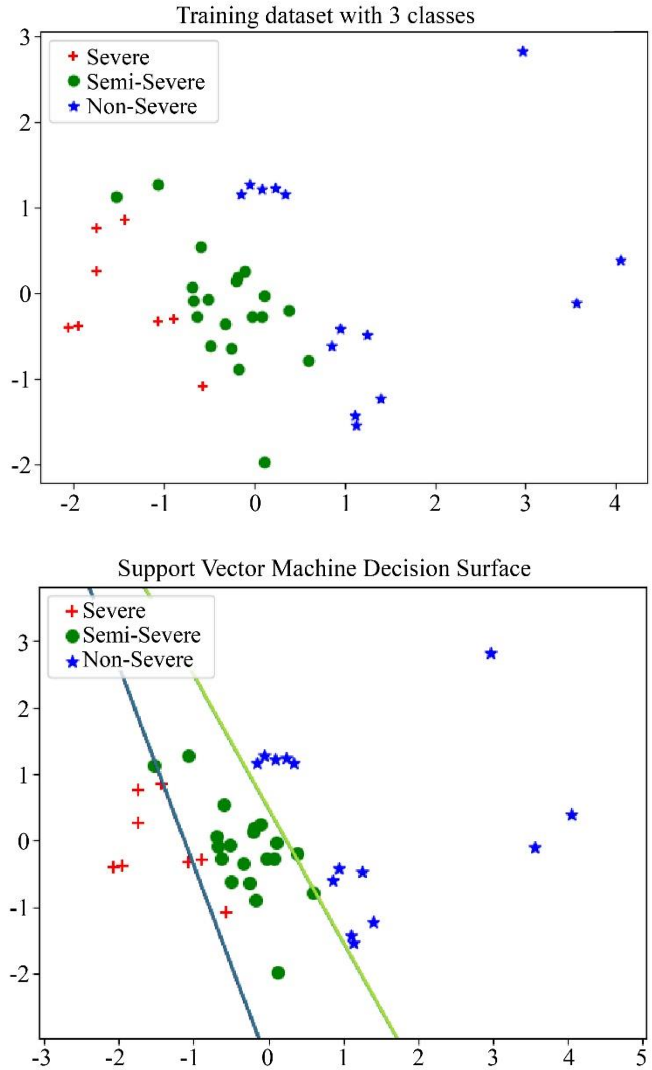

Fig. 7 Scatter plot and the hyperplanes generated for Qd loading trained data

Figure 7 presents the classification output of the SVM model trained on Qd (reactive load) data, with clearly defined hyperplanes demarcating the decision boundaries. The scatter plot illustrates the spatial distribution of training samples in the feature space, colored by severity class. The hyperplanes effectively separate high-risk scenarios from more stable ones, indicating the reliability of the model. The figure supports the premise that Qd loading significantly influences system response and that severity classification can be accurately performed based on reactive power conditions. This enhances the robustness of contingency prediction for voltage stability analysis.

5.3.3. Single Line Outage with both Pd & Qd Load Variation

In this case, a single line outage by varying both the Pd and Qd load in terms of loading conditions was done. The SVM classifier model has been trained with 60% of the dataset, and the remaining data has been used for testing the model's performance, that is, for prediction. Figure 8 visualizes the combined Pd and Qd loading impact on contingency severity classification using an SVM model. The scatter plot illustrates the distribution of data points across the combined loading condition, and the hyperplanes represent the model's decision boundaries. This dual-load scenario provides a realistic and complex representation of operating conditions.

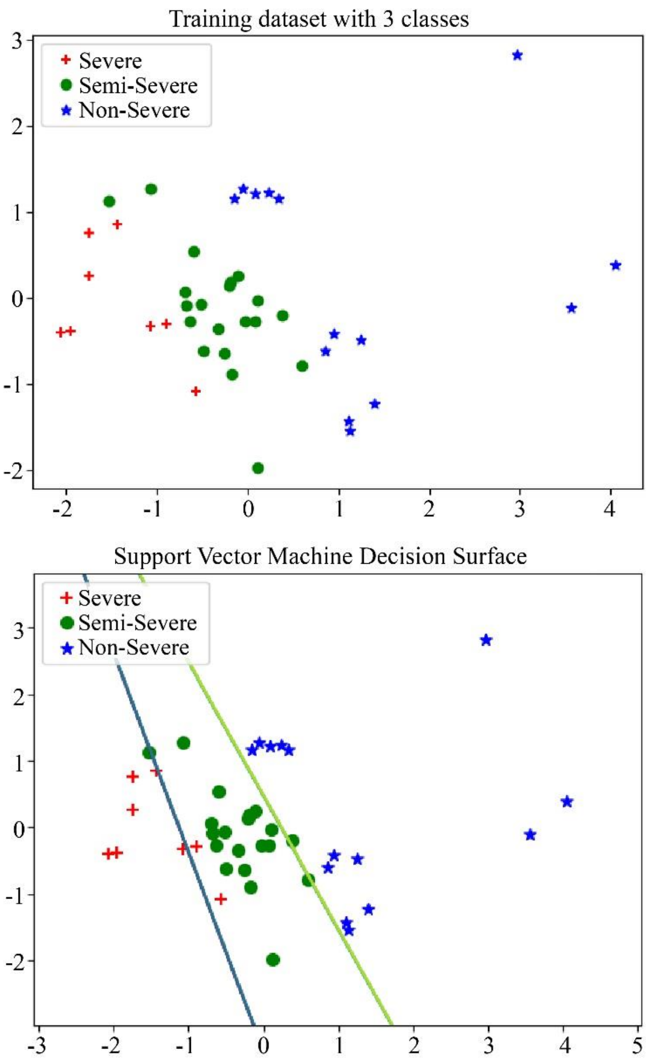

Fig. 8 Scatter plot and the hyperplanes generated for 100% both Pd & Qd loading trained data

Figure 9 gives a clear understanding of the data. The trained data and the test data are shown in the confusion matrix. The true label and the predicted label give the number that the data mapped accurately.

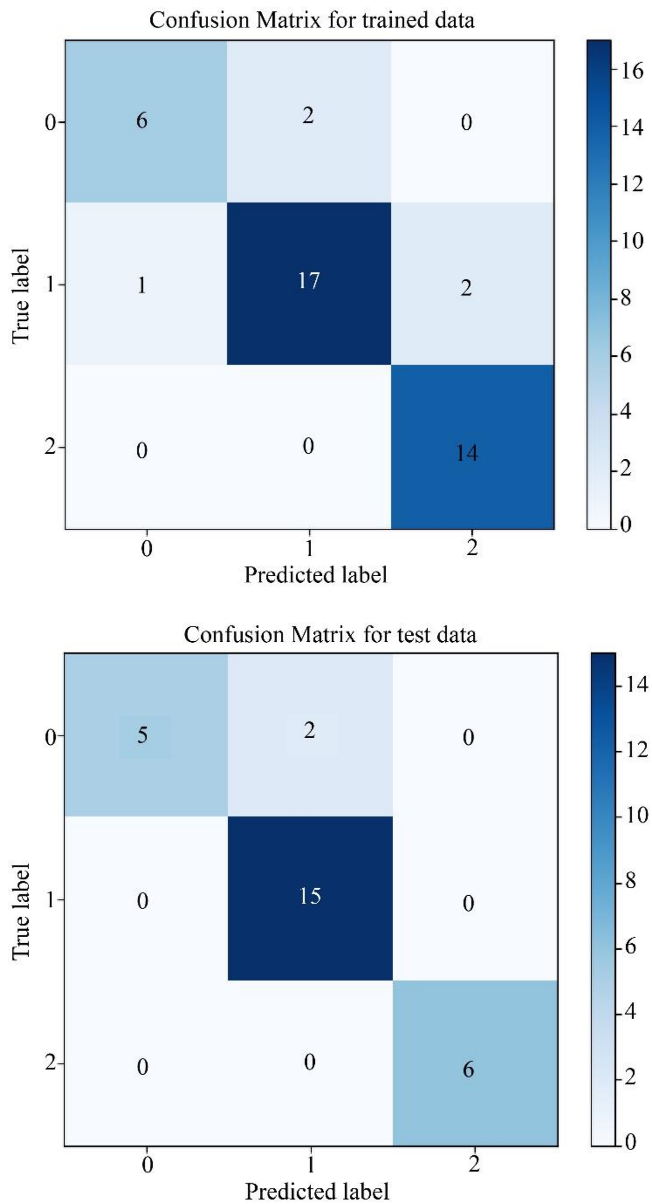

Fig. 9 Confusion matrix for trained and test data

Table 3. Accuracy of the class classification for SVM

Case	Trained Data	Predicted Accuracy	% error
Case I	92.85%	89.59%	3.638799
Case II	92.85%	90.15%	2.995008
Case III	92.85%	91.11%	1.909779

The accuracy of the SVMC for the trained and the predicted value is given in Table 3. For the various loading conditions, the accuracy varies accordingly. The effectiveness of SVMC can be observed for case I, case II, and case III, respectively. The percentage error for case I is higher and is reducing till case III. The comparison of the trained data and the predicted accuracy for SVMC is given in the pictorial representation as in Figure 10.

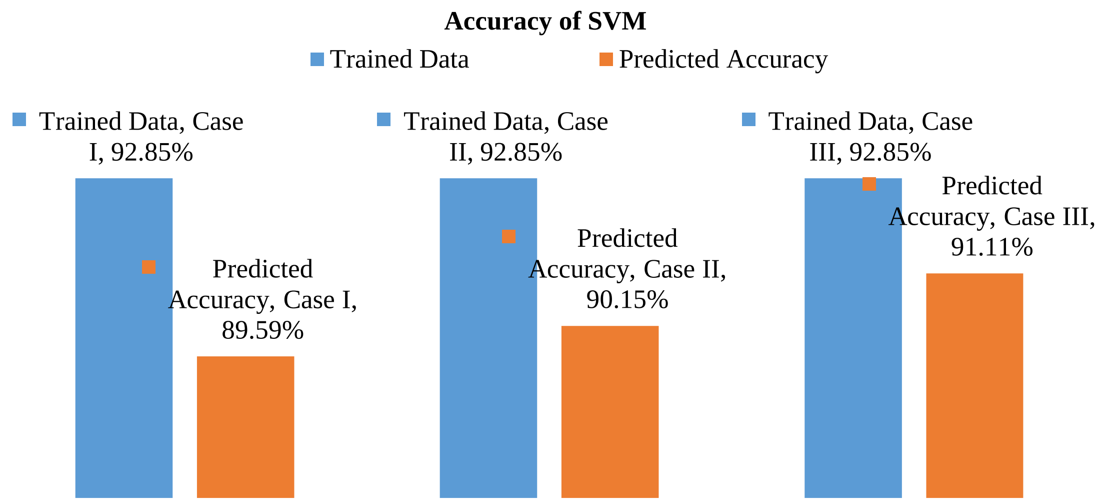

Fig. 10 Accuracy of the class classification for SVM

Table 4. Comparison of SVM with other techniques

Model	Training Data Requirement	Computational Demand	Accuracy
ANN [9]	Very High	High – iterative training	88–91%
DT [10]	Low	Low – fast and simple	82–86%
ANFIS [14]	High	Medium – rule-based	84–87%
FL [15]	Medium	Very High – rule explosion	90–93%
SVM (Proposed)	Low–Medium	Medium – convex optimization	94–97%

The comparative analysis of different machine learning models for contingency ranking for various bus systems is summarized in Table 4. As observed, the ANN model requires a very high amount of training data and involves iterative training, achieving an expected accuracy of 88–91%. Decision Trees (DT), while computationally simple and fast, achieve lower accuracy (82–86%) due to their limited ability to model complex nonlinear patterns. ANFIS offers moderate computational demand with high training requirements and achieves 84–87% accuracy, combining the learning capability of neural networks with fuzzy inference. Fuzzy Logic (FL) shows a very high computational demand due to rule explosion, but provides an accuracy of 90–93%. The proposed SVM-based model, in contrast, achieves the highest accuracy (94–97%) with low-to-medium training data requirements and moderate computational complexity. This is attributed to its margin-maximization principle and strong generalization ability, making SVM the most suitable approach for robust contingency ranking in large-scale power systems.

6. Conclusion

This research uses the Indian Utility 75-Bus System to offer a contingency analysis for single-line failures under different loading circumstances. Based on the Active Power Performance Index (APPI) severity ranking, the study determines which transmission lines are crucial. Severe, Semi-Severe, and Non-Severe lines are classified according to how they affect system stability. Using data produced from various loading circumstances, a Support Vector Machine (SVM) classifier was used to automate this categorisation. 30% of the dataset was utilised for validation, while seventy percent was used to train the SVM model. With an accuracy range of 82% to 100%, the model proved to be successful in determining the severity of outages. System operators can take prompt, preventive measures, such as load modifications or power rerouting, thanks to this categorization, which facilitates real-time operational decisions. By enabling predictive and data-driven outage management, the suggested method helps to improve the power system's security and dependability. Additional machine learning techniques can be used for further conditions to understand the complexity of the larger scale of power systems.

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