Power system contingency classification using machine learning technique

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ABSTRACT

One of the most effective ways for estimating the impact and severity of line failures on the static security of the power system is contingency analysis. The contingency categorization approach uses the overall performance index to measure the system's severity (OPI). The newton raphson (NR) load flow technique is used to extract network variables in a contingency situation for each transmission line failure. Static security is categorised into five categories in this paper: secure (S), critically secure (CS), insecure (IS), highly insecure (HIS), and most insecure (MIS). The K closest neighbor machine learning strategy is presented to categorize these patterns. The proposed machine learning classifiers are trained on the IEEE 30 bus system before being evaluated on the IEEE 14, IEEE 57, and IEEE 118 bus systems. The suggested k-nearest neighbor (KNN) classifier increases the accuracy of power system security assessments categorization. A fuzzy logic approach was also investigated and implemented for the IEEE 14 bus test system to forecast the aforementioned five classifications.

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1. INTRODUCTION

The primary goal of any electric power system is to provide sufficient electrical power supply to customer premises without violating frequency limitations or voltage levels. So that any huge interconnected power system needs a high level of security. Overloading of transmission equipment and insufficient voltage levels at system buses are the two most common operational difficulties in power systems. Therefore, determining whether the system is secure (normal) or insecure (emergency) is essential.

Contingency analysis is one of the most important methods to know the security status of the power system. The main methods for selecting and ranking contingencies are ranking and screening methods based on an approximate order of the overall performance index (OPI) determined from load flow solutions. It is infeasible for real-time applications due to its computational complexity. Artificial intelligence approaches and machine learning algorithms can be utilised to solve this challenge.

Support vector machine-based pattern classification (SVMBPC) was proposed by Kalyani and Swarup [1] as a method of categorizing the security status of power systems as secure, critically secure, unsecure, and severely insecure. Patidar and Sharma [2] developed a hybrid decision tree-based technique for online voltage contingency screening and ranking in energy management systems. Malbasa *et al.* [3] reported an active learning solution for improving existing machine learning applications by enhancing the offline training and online prediction processes. Nandanwar *et al.* [4] developed probabilistic fuzzy decision tree

(PFDT) technique for voltage security assessment which consider load management. Zheng *et al.* [5] forecasted power system stability margins using a regression tree-based technique. Thamizhelvan and Ganapathy [6] discussed core vector machine (CVM) as a data classifier for assessment of static security of power system. Authors in [7] and [8] presented a support vector machine-based binary classification for static and transient security evaluation.

Machine learning and other related automatic learning approaches, such as decision tree induction, multilayer perceptrons, and nearest neighbour classifiers, are being developed by Wehenkel [9] in a framework that is tailored to the specific needs of power system security assessment. Saeh and Mustafa [10] investigated the use of a data mining approach for static security evaluation. Authors in [11] and [12] created LV-SVM for contingency classification and ranking in a large power system, as well as probabilistic neural networks and the least square support vector machine for transient stability assessment (LV-SVM). For static security assessment of power systems, decision tree, random forest, and ensemble classification approaches were reported [13]-[15]. For contingency analysis, a fuzzy logic technique and artificial neural networks are used [16]-[21].

Labed and Labed [22] attempted to reduce the overload and monitor power flow in transmission lines. To solve this problem, a unified power flow controller device was used, and then an extreme learning machine technique was used because of its exceptionally quick training and good generalization performance. The transmission line alleviation is the main point. Ray *et al.* [23] used independent component analysis and support vector machines for power quality analysis in a solar PV integrated microgrid. Sahani *et al.* [24] reported an online sequential extreme learning machine for real-time power quality event recognition. Turovic *et al.* [25] applied machine learning methods to power quality applications in distribution networks. Liao *et al.* [26] discussed the use of deep learning to estimate voltage sag in power systems with sparse monitoring. Vantuch *et al.* [27] applied a multi-objective optimization forecasting model for off-grid systems. Power system voltage stability and transient stability analysis are addressed [28]-[34].

With the advancement of artificial intelligence in recent years, classification-type machine learning algorithms such as k-nearest neighbor (KNN), SVM, and DT ensemble approaches and deep learning algorithms have been increasingly popular for power system security assessment. In this paper, the KNN machine algorithm is proposed for the classification of static security assessments. For each line outage, the suggested KNN classifier is employed for multi-classification based on the calculation of the OPI. Secure, critically secure, insecure, very insecure, and most insecure are the five stages of continuous OPI values. With this evaluation, the operator can figure out the state of the system's stressed lines in case a line goes down. The classification approach is tested on IEEE 14 bus, IEEE 30 bus, IEEE 57 bus and IEEE 118 bus systems and results are validated with a fuzzy logic-based assessment technique.

2. CONTINGENCY ANALYSIS

The effect of line outages, transformer breakdowns, and other contingencies on the Power System model is determined through contingency analysis. It is one of the most effective approaches for determining the severity of line outages and their impact on power system security. To quantify the severity of the system, the contingency classification technique uses the OPI. Newton raphson load flow method (NRLF) is used to obtain the network variables under contingency case.

To determine the severity of the contingency, the following performance indices are used: real power flow performance index (PIp): this PIp equation determines the over loading status of transmission lines.

$$\mathrm{PI_P} = \sum_{l=0}^{NL}\left(\frac{w}{2n}\right)\left(\frac{Pl}{Plmax}\right)^{2n} \tag{1}$$

Voltage performance index (PIv): This PIv equation determines the extent of bus voltage limit violations

$$\mathrm{PI_V} = \sum_{i=1}^{Nb}\left(\frac{W}{2n}\right)\{(|V_i| - |V_{isp}|)\ /\ \Delta V_{i_{Lim}}\}^{2n} \tag{2}$$

Here, the minimum voltage limit is taken Vmin=0.95 pu and the maximum voltage limit is Vmax=1.05 pu. The OPI is calculated by adding the PIp and PIv. Based on the value OPI, the system security is identified. If the value of OPI is more, the insecurity of the system is higher. So that, in contingency ranking first priority is given to the line for which the OPI is high. By performing NRLF solution the system parameters are obtained for each N-1 line outage contingency.

3. MACHINE LEARNING BASED CONTINGENCY ANALYSIS

Traditional contingency analysis is difficult to utilise for real-time applications due to its computational complexity. To solve this problem, a combination of traditional methodologies based on security indices and machine learning algorithms is used to come up with a viable solution.

The KNN machine learning approach is developed in this research for online security assessment classification based on the calculation of OPI for each line outage. The OPI values are classified into five levels. From this online assessment the operator knows the status of security of the system and can take immediate corrective actions. The classification approach is tested on IEEE 14 bus, IEEE 57 and IEEE 118 bus test system and IEEE 14 bus system results are compared with fuzzy logic.

3.1. KNN algorithm

The KNN is a supervised learning-based machine learning algorithm. KNN algorithm stores the available data and classifies the data into different categories based on the similarities. When new data is given, KNN algorithm identifies the category of the new input according to the similarities. K value gives the number of neighbors to be considered to classify the category of the new input. K neighbors are selected based on the Eucledian distance from the new input. Among KNN, the algorithm identifies the most common class or category of the new input to perform the classification. The KNN algorithm can be adjusted by changing the number of neighbors. In this paper, to find thenearest neighbors the Eucledian distances are evaluated by considering the value of K is 1.

3.2. Mathematical model of KNN

In this subsection, KNN algorithm mathematical model was presented, where KNN uses local prior probabilities for classification. For a given value of xt, KNN algorithm predicts the class as:

$$y_t = \underset{c \in \{c_1, c_2, \dots, c_m\}}{\arg\max} \sum_{x_i \in N(x_t,K)} E(y_i, c) \tag{3}$$

Where xt is the new input to be tested and yi is the predicted class for the given new input, m is the number of presented classes in the training data.

$$E(a,b) = \begin{cases} 1 & \text{if } a = b \\ 0 & \text{else} \end{cases} \tag{4}$$

$$N(x,k) = \text{Set of k nearest neighbor of x}$$

In (3) can also be written as

$$y_t = \arg\max \left\{ \begin{matrix} \sum_{x_i \in N(x_t,k)} E(y_i, c_1), \sum_{x_i \in N(x_t,k)} E(y_i, c_2), \dots \\ , \sum_{x_i \in N(x_t,k)} E(y_i, c_m) \end{matrix} \right\} \tag{5}$$

$$y_t = \arg\max \left\{ \begin{matrix} \sum_{x_i \in N(x_t,k)} \frac{E(y_i,c_1)}{k}, \sum_{x_i \in N(x_t,k)} \frac{E(y_i,c_2)}{k}, \dots \\ , \sum_{x_i \in N(x_t,k)} \frac{E(y_i,c_m)}{k} \end{matrix} \right\} \tag{6}$$

And it is familiar that

$$p(c_j)_{(x_t,k)} = \sum_{x_i \in N(x_t,k)} \frac{E(y_i,c_j)}{k} \tag{7}$$

Where $p(c_j)_{(x_t,k)}$ is the probability of occurrence of jth class in the neighbourhood of xt. Hence (4) turns to be

$$y_t = \arg\max \{ p(c_1)_{(x_t,k)}, p(c_2)_{(x_t,k)}, \dots, p(c_m)_{(x_t,k)} \} \tag{8}$$

From (7), it is cleared that, to identify the class of the new input, prior probabilities are used by the KNN algorithm. It doesn't take into account the distribution of classes in the area surrounding the new input point.

4. GENERATION OF DATA FOR CONTINGENCY ANALYSIS IN ORDER TO TRAIN THE KNN MODEL

For the IEEE 30 bus system, data is generated to train the KNN model by executing Newton Raphson load flow for each line outage. PI_V and PI_P are calculated for each line outages. Then OPI is determined by adding PI_V and PI_P and it is normalized between 0.1 to 0.9 for each case of line outage. As seen in Table 1, the normalised data is separated into five classes. The OPI range of categorization is fixed according to international literatures, but the following classification is much more acceptable when compared to performance.

Table 1. Overall performance index classification

Class	Secure	Critically secure	Insecure	Highly insecure	Most insecure
OPI range	0.1-0.3	0.3-0.4	0.4-0.5	0.5-0.6	0.6-0.9

4.1. Normalization of OPI data

OPI data is normalized as shown in (9). The input and output of training data set and testing data set is scaled in the range of 0.1-0.9. Before implementing the KNN classifier, each value of the input and output parameter P is normalised as Pn.

$$Pn=(0.8 \times (P-Pmin)/(Pmax-Pmin)+0.1) \tag{9}$$

The maximum and minimum values of the data parameter are Pmax and Pmin, respectively.

Based on the classification as stated in Table 1, the normalised OPI is classified into five classes: secure, critically secure, insecure, highly insecure, and most insecure. By using the normalised OPI as input and Class(X) as output, this IEEE 30 bus data is used to train the KNN model. At base load and 10% of base load the performance indices PIp and PIv are calculated for IEEE 30 bus system to train the KNN model.

5. FUZZY BASED FORMULATION

Lotfi Zadeh is the father of fuzzy logic and the rules are set in natural language. Fuzzy logic is the study of reasoning systems that consider both true and false statements, whereas classical mathematics exclusively considers absolutely true statements.

5.1. Choosing the input

To validate the results with the suggested KNN classifier, a fuzzy logic technique is used for the identical IEEE 14 test systems. Figure 1 shows the normalised values of PIp, PIv, and OPI provided to the fuzzy logic.

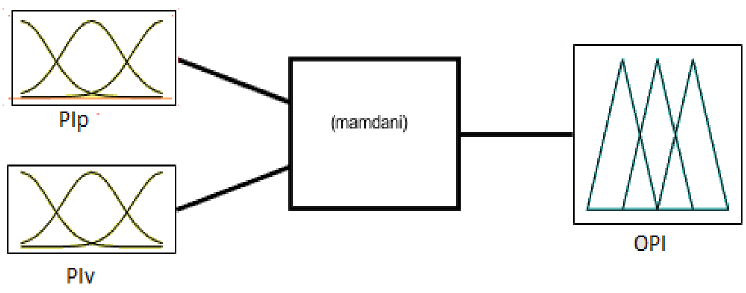

Figure 1. Fuzzy toolbox input and output

5.2. The shape of the membership function

The shape of the membership function is significant in categorization. As shown in Figure 2, Figure 3, and Figure 4, trapezoidal type membership functions, namely trapmf, are employed for both input and output.

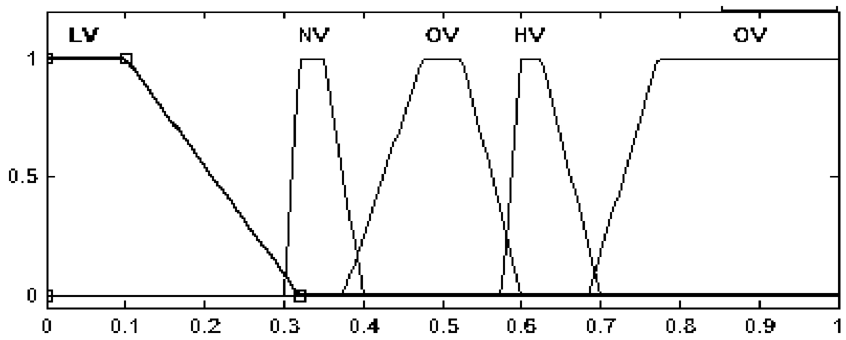

Figure 2. Membership function for the input Piv

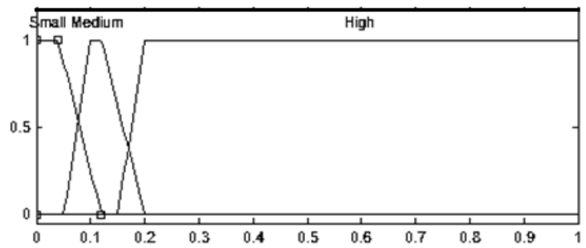

Figure 3. Membership function for the input Pip

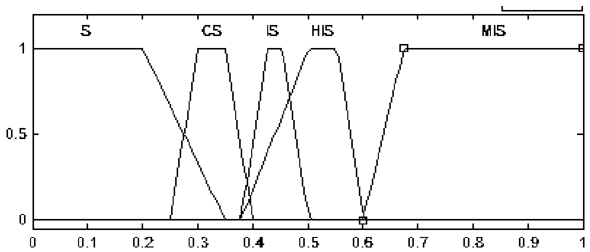

Figure 4. The output OPI of the fuzzy logic system

5.3. Fuzzy rules

For fuzzy classification, with all possible combinations 15 rules are framed as shown below in Table 2. One input PIp is having 3 MFs (small, medium, high), and another input PIv having 5 MFs (LV, NV, HV, VHV and OV).

Table 2. Fuzzy classification rules

PIp\PIv Active power index (Pip)	Voltage performance index (PIv) Low voltage (LV)	Normal voltage (NV)	High voltage (HV)	Very high voltage (VHV)	Over voltage (OV)
Small	S	CS	IS	HIS	MIS
Medium	S	CS	IS	HIS	MIS
High	S	CS	IS	HIS	MIS

Voltage performance index (PIv) assessed as: S: secure; CS: critically secure; IS: insecure; HIS: highly insecure; MS: most insecure

6. RESULTS AND DISCUSSION

Static security assessments are simulated and tested for the IEEE-14 bus using the KNN and fuzzy algorithms. Table 3 summarizes the simulation findings of an IEEE 14 bus system utilizing the KNN method with newton raphson load flow. According to the results, the KNN classifier accurately predicts all classes except for the line outage 4-9. It predicts very insecure rather than most insecure. It has an accuracy of 92.86%. Table 4 displays the mismatched findings of the IEEE 57 and IEEE 118 bus systems. Except for line outages 28-29 and 15-45 on the IEEE 57 bus system, the KNN classifier accurately predicts all classes. It predicts very insecure rather than most insecure. It has a 97.67% accuracy rating. Except for line failures 27-115, the KNN classifier accurately predicts all classes for the IEEE 118 bus system. It predicts critically secure rather than secure. It has a 99.46% accuracy rate.

Table 5 displays the findings of the fuzzy logic system. The KNN method's indexes and line outage categorization are compared to the fuzzy algorithm. The categorisation of line outages is clearly consistent in both techniques.

Table 3. Test results of IEEE 14 bus system for contingency classification

S. No	Line outage	PIp	PIv	OPI	Normalized OPI (Pn)	Predicted class by KNN classifier	Classification by load flow
1	1-2	0.3486	1.2447	1.5933	0.1	Secure	Secure
2	1-5	0.1055	1.9081	2.0136	0.456791	Insecure	Insecure
3	2-3	0.141	1.8201	1.9611	0.412224	Insecure	Insecure
4	2-4	0.1116	1.965	2.0766	0.510272	Highly insecure	Highly insecure
5	2-5	0.1085	2.0482	2.1567	0.578268	Highly insecure	Highly insecure
6	3-4	0.0978	2.2117	2.3095	0.70798	Most insecure	Most insecure
7	4-5	0.1048	1.9515	2.0563	0.493039	Insecure	Insecure
8	4-7	0.1199	2.1429	2.2628	0.668336	Most insecure	Most insecure
9	4-9	0.0917	2.1337	2.2254	0.636587	Highly insecure	Most insecure
10	5-6	0.133	2.4027	2.5357	0.9	Most insecure	Most insecure
11	6-11	0.0934	1.9517	2.0451	0.483531	Insecure	Insecure
12	6-12	0.0932	1.9553	2.0485	0.486418	Insecure	Insecure
13	6-13	0.0977	1.5524	1.6501	0.148217	Secure	Secure
14	7-8	0.0925	1.9143	2.0068	0.451019	Insecure	Insecure
15	7-9	0.1182	1.6585	1.7767	0.255688	Secure	Secure
16	9-10	0.093	2.0502	2.1432	0.566808	Highly insecure	Highly insecure
17	9-14	0.0953	2.005	2.1003	0.53039	Highly insecure	Highly insecure
18	10-11	0.0927	2.1482	2.2409	0.649745	Most insecure	Most insecure
19	12-13	0.0924	2.1694	2.2618	0.667487	Most insecure	Most insecure
20	13-14	0.0935	2.0782	2.1717	0.591002	Highly insecure	Highly insecure

Table 4. Mismatched results of IEEE 57 and IEEE 118 for contingency classification

S. No	Bus system	Line outage	PIp	PIv	OPI	Normalized OPI (Pn)	Predicted class by KNN classifier	Classification by load flow
1	IEEE 57	28-29	0.1795	38.3895	38.569	0.613825	Highly insecure	Most insecure
2	IEEE 57	15-45	0.1837	38.3713	38.555	0.612756	Highly insecure	Most insecure
3	IEEE118	27-115	1.7699	9.1996	10.9695	0.298616	Critically secure	Secure

Table 5. Result of IEEE 14 bus system static security assessments of KNN and fuzzy algorithms

	Secure	Critically insecure	Insecure	Highly insecure	Most insecure
KNN	1,13,15	-	2,3,7,11,12,14	4,5,9,16,17,20	6,8,10,18,19
Fuzzy	1,13	15	2,3,7,11,12,14	4,5,16,17,20	6,8,9,10,18,19

The suggested KNN method appears to be suitable for power system contingency categorization on a real-time scale. The KNN classifier is trained with the data of higher bus systems to classify the security status of a power system. Then, the trained classifier is used to classify the security status of any power system, which has a lower number of buses than the trained bus system. In this work, the IEEE 30 bus system is used to train the classifier and the security status of the IEEE 14, IEEE 57 and IEEE 118 bus systems are tested. The accuracy of the fine KNN algorithm is good and is giving better results even though the training data is less. It is quite a convenient algorithm to find the security status of the power system without complexity.

7. CONCLUSION

The KNN classifier is used to determine the online security status of power system contingencies. The proposed classifier was trained using a dataset generated using the Newton-Raphael load flow technique for power system contingency analysis. Following that, the trained KNN classifier is tested on the IEEE 14, IEEE 57, and IEEE 118 bus systems. The correctness of the KNN algorithm is determined by comparing its findings to the results of the existing Newton-Raphson load flow technique. In addition, the classification accuracy for the IEEE 14 bus system is evaluated by contrasting the KNN method with the fuzzy logic technique. This is done to demonstrate that the results are accurate. Finally, the simulation results reveal that the KNN model is successful in identifying the power system's security situation. The KNN approach may be utilized for live classification of power system contingencies based on simulation findings.

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