Power System Contingency Classification Using KNN Algorithm

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***Abstract:*Contingency analysis is an efficient technique in a large interconnected power system to identify the effect of post contingencies for its security. In this paper, Fast decoupled load flow method is used for each transmission line outage. The overall performance index(OPI) is calculated with the help of active power performance index(PIp) and Voltage performance index(PIv) for the static security classification of the power system. The static security is classified into five classes secure, critically secure, insecure, highly insecure and most insecure. The K nearest neighbour machine learning algorithm is proposed to classify these patterns. The proposed machine learning classifiers are applied on IEEE 14 and IEEE 30 bus test systems.Proposed KNN classifier is giving better accuracy for the classification of security assessment of the power system. Fuzzy logic approach has also been studied and implemented for the same test systems for the prediction of theabove five classes.**

Keywords: Contingency analysis, Active Power Performance Index (PIp), Voltage Performance Index (PIv), Overall PerformanceIndex (OPI), Fast decoupled load flow, KNN classifier.

I INTRODUCTION

The predominant aim of any electric power system is to provide sufficient uninterrupted supply of electrical power to the customer premises without exceeding the set limits of frequency and voltage levels, because high degree of security is essential due to growth of large interconnected power system demands. Powersystem security is defined as the ability of the power system to remain secure without serious consequences to any pre-selected list of credible contingencies. Usually frequent operational problems like transmission equipment overloads and inadequate voltage levels at system buses are quiet common. Therefore, the process for detecting, whether the system remains in secure (normal) or insecure (emergency) state at a given state is critical in its operation.

In power system planning and operation, the most important activity is contingency analysis of a power system. Three main stages in contingency analysis are contingency definition, selection and evaluation. Mainly, ranking and screening methods are used for contingency selection ranking of contingencies are based on approximate order of overall performance index(OPI) obtained from solving load flow solutions. Because of its computation complexity, it is infeasible for real time applications. In order to avoid this problem a combination of traditional approaches on the basis of security indices and machine learning algorithms is the effective method to get solution.

Security index is used as a reference to classifying the security status of power system in classes like secure, critically secure, insecure and highly insecure by a Support Vector Machine-Based Pattern Classification (SVMBPC)[1]. A hybrid decision tree-based approach for fast voltage contingency screening and ranking for online applications in energy management systems is discussed in [2]. In [3] author reported an active learning solution to enhance existing machine learning applications by actively increasing with the offline training and online prediction process. The load management considering voltage security assessment using probabilistic fuzzy decision tree (PFDT) technique is studied in details [4]. In PFDT technique load management is calculated in optimal manner in real time and insecure operating conditions are identified. A regression tree-based approach to predict power system stability margin and detecting impeding system event is projected in [5].CoreVector Machine (CVM) is utilized as a data classifier to evaluate of power system static security assessment [6]. For static and transient security assessment was presented in [7-8] by a support vector machine based binary classification. In [9] series of research and development of machine learning and other complementary automatic learning techniques in a frame work, such as decision tree induction, multilayer perceptrons and nearest neighbour classifiers adapted to the specific needs of power system security assessment. The application of data mining approach static security evaluation was detailed in [10]. Contingency classification and ranking in a large power system using LV-SVM, Transient stability assessment using probabilistic neural networks and least square support vector machine(LV-SVM) was investigated in [11-12]. Assessment of Power system static security was identified by Decision tree, random forest, and Ensemble methods of classification reported in [13-16].

Artificial neural networks Fuzzy logic approach and [17-20] have been used for contingency analysis. But input features are so many for a large power system, because this application of artificial intelligence for contingency selection and ranking of a large power system is limited. Hence ANN architecture becomes complex and training becomes extremely slow. With the development of artificial intelligence in recent years, classification type machine learning algorithms KNN, SVM, DT Ensemble methods are popularly used for security assessment of power system.

The proposed KNN classifier is used for multi classification based on the calculation of overall performance index (OPI) for each line outage. The continuous values of overall performance index values are divided into five classes, secure, critically secure, insecure, highly insecure and most insecure. An operator likes to know exactly the severity level of disturbances for a given system operating condition. On line security assessment allows the operator to know the security status and helps to determine the corrective actions. The classification approach is implemented in IEEE 14 bus and IEEE 30 bus test system and results are compared with fuzzy logic.

II CONTINGENCY ANALYSIS

Contingency analysis involves the simulation of the individual N1 line outage contingency for the power system model. In order to make the analysis easier, it consists of three basic steps:

Contingency creation: This comprises of a set of possible contingencies that might occur in a power system. The process consists of creating the contingencies list.

Contingency selection: This is the process of selecting severe contingencies from the list that leads to the bus voltage and the power limit violations. Therefore, this process minimizes the contingency list by eliminating least severe contingencies. It uses the index calculation to find out the severity of the contingencies.

Contingency evaluation: This involves the necessary security actions needed to be taken or necessary control action in order to mitigate the effect of the contingency.

Thus, one of the major tasks of the power system planning and the operational engineers is to study the effect of the outages in terms of their severity for security assessment. The contingency ranking/classification approach utilizes the overall performance indices (OPI) to quantify the severity. In order to obtain the system parameters under contingency case, Fast decoupled load flow method is used. The FDLF method is also used for contingency analysis and to generate security patterns.

The performance indices which are used to obtain the contingency severity are:

Active Power performance index (PIp): This is the index which determines the extent of line over loading which is given by equation

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

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

$$\mathrm{PIv} = \sum_{i=1}^{Nb} \left(\frac{W}{2n}\right)\{(|Vi| - |Visp|)\ /\ \Delta Vilim\}^{2n} \qquad (2)$$

Here, the minimum and maximum voltage limits are taken as, V_{min}=0.95 pu and V_{max}=1.05 pu. Greater the value of the indices, higher the system insecure. Thus, when assessing security, higher value of index is given first priority in contingency ranking. The system parameters are obtained by performing load flow solution under N-1 line outage contingency.

Classification

In this subsection, the problem of classification and notation used to model the dataset described. The problem of classification is to estimate the value of the class variable based on the values of one or more independent variables (known as feature variables). The Classifier modelled as {x, y} where x is an ordered set of attribute values like $\{x_1, x_2, . . . ,x_d\}$ and y is the class variable to be predicted. Here x_i is the value of the i^{th} attribute and there are d attributes overall corresponding to a d-dimensional space.

Formally, the problem has the following inputs:

• A set of n tuples called the training dataset, $D = \{(x_1, y_1), (x_2, y_2), . . . , (x_n, y_n)\}$.

• A query tuple x_t .

The output is an estimated value of the class variable for the given query x_t , mathematically it can be expressed as:

y_t= f(x_t , D, parameters),

Where parameters are the arguments that the function f() takes. These are generally set by the user or are learned by some method.

III. KNN ALGORITHM

In KNN algorithm, theNearest Neighbour (NN) is a simple nonparametric and highly efficient technique that has been used in several areas, such as pattern recognition, ranking models or text categorization and classification for big data, just to name a few. One of the most used algorithms in machine learning applications is the KNN, also known as k-nearest neighbour. This algorithm works by using an input vector with the k closest training samples in the feature space. To perform the classification, the algorithm identifies the most common class among the k nearest neighbour. The algorithm requires a training to define the neighbour based on the distance from the test sample and a testing step to determine the class to which this test sample belongs. The number of neighbour can be changed to adjust the KNN algorithm.

The Eucledian distances are evaluated to find the nearest neighbours and the number of nearest neighbours is chosen as 1.

Mathematical Model of KNN:

In this subsection, a mathematical model for KNN algorithm was presented and showed that KNN only makes use of local prior probabilities for classification.

For a given query instance x_t,KNN algorithm works as follows:

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

Where y_i is the predicted class for the query instance x_t and m is the number of classes present in the data. Also

$$E(a,b) = \begin{cases} 1 & if\ a = b \\ 0 & else \end{cases} \quad (3.1)$$

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

Equation 3 can also be written as

$$y_t = \arg max \{\sum_{x_i \in N(x_t,k)} E(y_i, c_1), \sum_{x_i \in N(x_t,k)} E(y_i, c_2), \dots, \sum_{x_i \in N(x_t,k)} E(y_i, c_m)\} \quad (3.2)$$

$$y_t = \arg max \left\{\sum_{x_i \in N(x_t,k)} \frac{E(y_i,c_1)}{k}, \sum_{x_i \in N(x_t,k)} \frac{E(y_i,c_2)}{k}, \dots, \sum_{x_i \in N(x_t,k)} \frac{E(y_i,c_m)}{k}\right\} \quad (3.3)$$

And it is familiar that

$$p(c_j)_{(x_t,k)} = \sum_{x_i \in N(x_t,k)} \frac{E(y_i,c_j)}{k} \quad (3.4)$$

Where $p(c_j)_{(x_t,k)}$is the probability of occurrence of j^{th} class in the neighbourhood of x_t. Hence Eq.3.1 turns to be

$$y_t = \arg max\{p(c_1)_{(x_t,k)}, p(c_2)_{(x_t,k)}, \dots, p(c_m)_{(x_t,k)}\} \quad (3.5)$$

It is clear from Eq. 3.4, that KNN algorithm uses only prior probabilities to calculate the class of the query instance. It ignores the class distribution around the neighbourhood of query point. The mathematical calculation of KNN flow chart is shown in fig 1.

Data generation for contingency analysis:

Database for contingency analysis, generated by performing AC load flow (Fast Decoupled load flow) under each line outage for IEEE 30 bus test system. Voltage performance Index (PIv) and Active power Index (PIp) are calculated for each line outages. Then the Overall performance Index (OPI) is calculated and normalized between 0.1 to 0.9 for each contingent case. Overall performance Index (OPI) is the summation of two performance index (PIv) and (PIp). The whole data is suitably divided into 5 classes as given in table -1. The OPI range classification is fixed by observing many published literature, however the following classification is much acceptable by comparing with performance.

Table 1. Overall performance Index classification

Class	**Secure**	**Critically secure**	**Insecure**	**Highly insecure**	**Most insecure**
OPI range	0 - 0.3	0.3 - 0.4	0.4 - 0.5	0.5 - 0.6	0.6 - 0.9

*Data Normalization***:**

Normalization of a vector means dividing by a norm of the vector to make the Euclidean length of the vector equal to one. The input/output training and testing set data is scaled in 0.1-0.9 range. In this work, each input or output parameter X is normalized as Xn before being applied to the classifier according [2,19].

$$X_n=(0.8\times(X-X_{min})/(X_{max}-X_{min})+0.1) \qquad (4)$$

Where X_{max} and X_{min} are the maximum and minimum values of data parameter X.

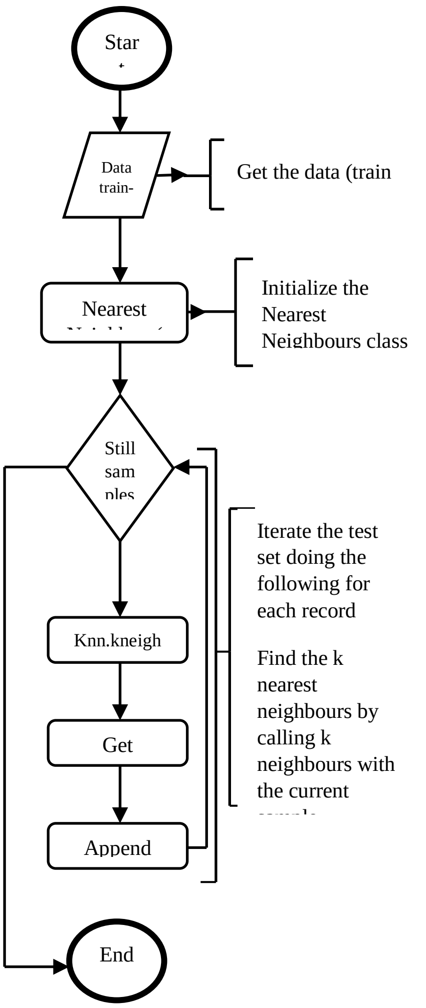


Fig.1 Flow chart of KNN mathematical calculations

The normalized data of 30 bus test system is used to train the classifier is given in table 2. The trained classifier is tested for its performance on IEEE 14 bus system as shown in table 3.

Table 2.Training of IEEE 30 bus system static security assessments using KNN algorithm

Line Outage	**Pi_p**	**Pi_v**	**OPI**	**Xn**	**Class**
1	0.3622	3.7694	4.1316	0.702545	Most insecure
2	0.1347	2.2812	2.4159	0.269219	Secure
3	0.1257	2.6296	2.7553	0.354939	Critically secure
4	0.1329	2.513	2.6459	0.327309	Critically secure
5	0.1545	2.3827	2.5372	0.299855	Secure
6	0.1301	2.4656	2.5957	0.31463	Critically secure
7	0.1322	2.7589	2.8911	0.389238	Critically secure
8	0.1132	3.023	3.1362	0.451141	Insecure
9	0.1271	3.4564	3.5835	0.564114	Highly insecure
10	0.1141	3.2057	3.3198	0.497512	Insecure
11	0.1335	3.0523	3.1858	0.463669	Insecure
12	0.1095	3.0177	3.1272	0.448868	Insecure
13	0.1096	2.0504	2.16	0.204587	Secure
14	0.1328	1.9605	2.0933	0.187741	Secure
15	0.1407	1.6052	1.7459	0.1	Secure
16	0.1094	1.9892	2.0986	0.18908	Secure
17	0.1101	2.8488	2.9589	0.406361	Insecure
18	0.1133	2.187	2.3003	0.240022	Secure
19	0.1099	2.8595	2.9694	0.409013	Insecure
20	0.1093	3.1338	3.2431	0.47814	Insecure
21	0.1094	3.1044	3.2138	0.47074	Insecure
22	0.1101	2.8988	3.0089	0.41899	Insecure
23	0.1095	3.125	3.2345	0.475968	Insecure
24	0.1104	2.9708	3.0812	0.43725	Insecure
25	0.1112	2.8196	2.9308	0.399264	Critically secure
26	0.1101	3.0241	3.1342	0.450636	Insecure
27	0.1107	2.7939	2.9046	0.392647	Critically secure
28	0.1095	3.048	3.1575	0.456521	Insecure
29	0.1093	3.1742	3.2835	0.488344	Insecure
30	0.1098	2.9293	3.0391	0.426617	Insecure
31	0.1102	3.0405	3.1507	0.454803	Insecure
32	0.1094	3.1484	3.2578	0.481853	Insecure
33	0.1094	3.1903	3.2997	0.492436	Insecure
34	0.1051	3.4067	3.5118	0.546005	Highly insecure
35	0.1104	3.0331	3.1435	0.452985	Insecure
36	0.125	4.7884	4.9134	0.9	Most insecure
37	0.1139	3.503	3.6169	0.572549	Highly insecure
38	0.1128	3.4509	3.5637	0.559113	Highly insecure
39	0.1112	3.2696	3.3808	0.512919	Highly insecure
40	0.1094	3.1025	3.2119	0.47026	Insecure
41	0.1111	2.7403	2.8514	0.379211	Critically secure

Table 3. Test results of IEEE 14 bus system Static Security Assessments using KNN algorithm

Line Outage	**Pi_p**	**Pi_v**	**OPI**	**Xn**	**Class**
1	0.3486	1.2447	1.5933	0.1	Secure

2	0.1055	1.9081	2.0136	0.456791	Insecure
3	0.141	1.8201	1.9611	0.412224	Insecure
4	0.1116	1.965	2.0766	0.510272	Highly insecure
5	0.1085	2.0482	2.1567	0.578268	Highly insecure
6	0.0978	2.2117	2.3095	0.70798	Most insecure
7	0.1048	1.9515	2.0563	0.493039	Insecure
8	0.1199	2.1429	2.2628	0.668336	Most insecure
9	0.0917	2.1337	2.2254	0.636587	Highly insecure
10	0.133	2.4027	2.5357	0.9	Most insecure
11	0.0934	1.9517	2.0451	0.483541	Insecure
12	0.0932	1.9553	2.0485	0.486418	Insecure
13	0.0977	1.5524	1.6501	0.148217	Secure
14	0.0925	1.9143	2.0068	0.451019	Insecure
15	0.1182	1.6585	1.7767	0.255688	Secure
16	0.093	2.0502	2.1432	0.566808	Highly insecure
17	0.0953	2.005	2.1003	0.53039	Highly insecure
18	0.0927	2.1482	2.2409	0.649745	Most insecure
19	0.0924	2.1694	2.2618	0.667487	Most insecure
20	0.0935	2.0782	2.1717	0.591002	Highly insecure

Fuzzy based formulation:

Fuzzy set theory was introduced by Zadeh. It achieves machine intelligence by offering a way for representing and reasoning about human knowledge that is imprecise in nature.

1. Choosing the input

Fuzzy logic approach has also been used for the same test systems for validation of the five classes with proposed KNN algorithm. Fuzzyinputs namely PIp, PIv for the output severity index (Overall performance index) of the line in the scale of 0 to 1.The normalized values of PIp, PIv and OPI are given to the fuzzy logic is shown in fig 2.

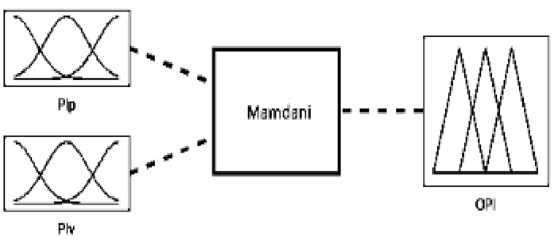
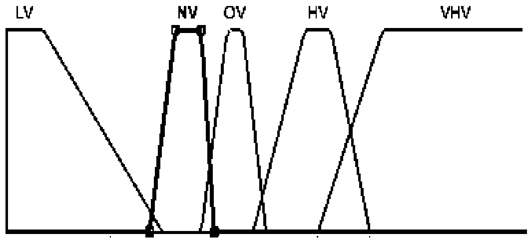


Fig.2. Input and Output to the Fuzzy toolbox

2. Shape of the membership function

In the classification shape of the membership function plays an important role. In this case Trapezoidal type membership functions namely trapmf is used for both input and output as given in fig 3 and fig 4.



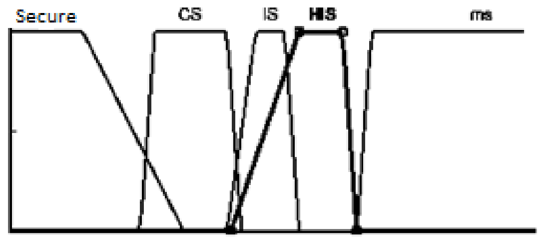


Fig.3.Membership function for the input
Fig.4. Membership function for the output

3. Fuzzy Rule

Fuzzy 15 rules are framed with all possible combination for fuzzy classification. Appropriate Weightage is given to each rule.PIv is X and PIp is Y then severity is Z. out of 15 rules few rules are listed below in table 4. Test results with fuzzy logic approach is for IEEE 14 bus reported in table 5. Results obtained for IEEE 14 bus with KNN and fuzzy approach is compared and reported in fig 5. The summary results are mentioned in table 6.

Table 4. Fuzzy classification rules

Piv	Pip	OPI
Low voltage	Small	Secure
Normal voltage	Medium	Critically secure
High voltage	Small	Insecure
Very High Voltage	High	Mostly insecure
Over voltage	Small	Highly insecure

Table 5. IEEE 14 bus system Static Security Assessments using Fuzzy algorithm

Line Outage	Pip	Piv	OPI	Class
1	0.1	0.9	0.096	Secure
2	0.558307	0.142974	0.475	Insecure
3	0.497513	0.253523	0.46	Insecure
4	0.597617	0.16197	0.5049	Highly insecure

5	0.655095	0.152316	0.564	Highly insecure
6	0.768048	0.118996	0.644	Most insecure
7	0.58829	0.140794	0.475	Insecure
8	0.720518	0.187816	0.644	Most insecure
9	0.714162	0.1	0.644	Most insecure
10	0.9	0.22861	0.644	Most insecure
11	0.588428	0.105294	0.496	Insecure
12	0.590915	0.104671	0.496	Insecure
13	0.312573	0.118684	0.28	Secure
14	0.562591	0.102491	0.496	Insecure
15	0.385872	0.182522	0.32	Critically secure
16	0.656477	0.104048	0.56	Highly insecure
17	0.62525	0.111211	0.515	Highly insecure
18	0.72418	0.103114	0.644	Most insecure
19	0.738826	0.10218	0.644	Most insecure
20	0.67582	0.105605	0.588	Highly insecure

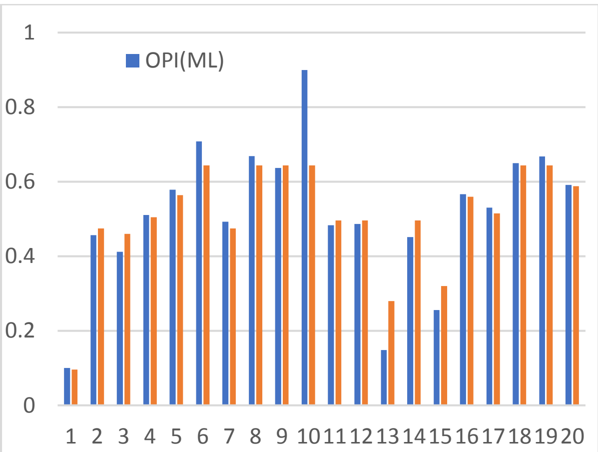


Fig.5. Comparison of OPI of KNN and Fuzzy algorithms for IEEE 14 bus system

Table 6. 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 classificationsresultsof the KNN algorithm are compared with known Fuzzy logic approach and validated the results. Form the table 6, it is evident that proposed KNN algorithm is suitable for power systems contingency classification on real time scale. It is quite convenient and algorithm without complexity.

Conclusion:

Contingency analysis is carried out using the fast-decoupled load flow method to generate the dataset to train the classifier. The trained classifier is tested on IEEE 14 bus system. Further, the classification accuracy of the KNN algorithm results are compared with validated Fuzzy logicapproach. The simulation results finally indicate the fine KNN model is efficient in classifying the security status and outperform over the other types of algorithms. The proposed KNN algorithm can be effectively used for online application to power system contingency classification.

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