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Classification of VSA by Probalistic Fuzzy Decision Tree Approach

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ABSTRACT

This paper addresses the ongoing work of decision tree on static security assessment of power systems. In this paper efforts are made to accommodate a new approach Probabilistic Fuzzy Decision Tree (PFDT) with the Decision Tree (DT). Here security assessment classification is discussed and the results compared with the conventional method with different operating point are presented. PFDT examines and classify the power system whether the system is secure or insecure. The input variables to the network are loadings parameters of the lines and the voltage magnitude of the load busses. The algorithms are tested on IEEE-30 bus systems. The results obtained and indicate that PFDT method is more accurate and computational time is less than conventional method.

Keywords: Probabilistic fuzzy decision tree, static security assessment, decision tree.

1. INTRODUCTION

All around the world, power system security has undergone very important changes which have the strong impact on the electric power sector. Due to this reason there is a trend in modern power systems towards greater utilization of generation and transmission capacity, which means that the systems are required to operate much closer to their security limits.

In operational planning decision makers establishes some operating rules that uses the threshold value of critical attributes for the conditions of power system, whether the post contingency system is secure or not [18]. So for such a decision, we need supportive tool which realize contingency simulation for numbers of operating conditions. A new case has been prepared keeping in view the past knowledge which is extracted from the data base. Their operating limits and rules are used which is taken from database. PFDT tree is an extension of DT algorithm and also an effective tool for knowledge acquisition from uncertain classification problems [20]. PFDT is a method for approximating linguistic as well as the numeric data in precision and it is also capable of handling imprecise data. The learning methods are among the most popular of inductive inference algorithm. [19] PFDT is basically a machine learning or artificial intelligence technique method.

The main part of PFDT based studies is generating the data base. The quality of generated data base gives the better accuracy. Following are the steps to generate data base.

1. Data base is generated considering contingency and different operating conditions. Data base is generated from well defined sample space by accounting fuzzy and probability. These training patterns are generated offline for well defined sample space from projected historical data or forecasted 24 hours data.
2. To obtain initial system state, run optimal power flow [18].
3. Perform the contingency analysis. The operating conditions and contingency conditions are obtained using CPF method [17].

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2. SECURITY MARGIN

For ensuring voltage security of power system, it is essential to know how much system operate steady state after some perturbation has been occurred within the specified limits of safety and supply quality constraints.[10, 11, 12, and 14]. After certain disturbances, power system reaches steady state operating conditions without violating system constraints, which include bus voltage limits and thermal bounds of the line [17, 19]. For this purpose, a static voltage stability index or maximum Loadability margin (MLM) is required which in some respect, quantifies how close a particular point to the point of voltage collapse i.e. to estimate the steady state voltage stability limits of the power system. Voltage stability margin is defined as distance with respect to the bifurcation parameter of the current operating point to the voltage collapse point [7]. The system is said to be voltage secure if this margin is reasonably high. In this work this voltage stability margin is referred to as MLM. Fig 1. depicts the voltage Vs real loading variation of power system bus. In case of contingency the Loadability margin is reduced to a lower value [3, 4, 5, 6, 8, 9, 21] margin is available from the voltage collapse point [1, 2]. Security is defined as the ability of the system to remain in secure equilibrium state even after contingency

3. PROBABILISTIC FUZZY SYSTEM

Fuzzy theory is a result of the insufficiency of Boolean algebra to many problems of the real world. As most of the information in the real world is imprecise, and one of human greatest abilities is to effectively process imprecise and fuzzy information. Today in intelligent systems era the computers are trained to tackle the real world problems. The fuzzy system is incorporation with the machine learning algorithm so

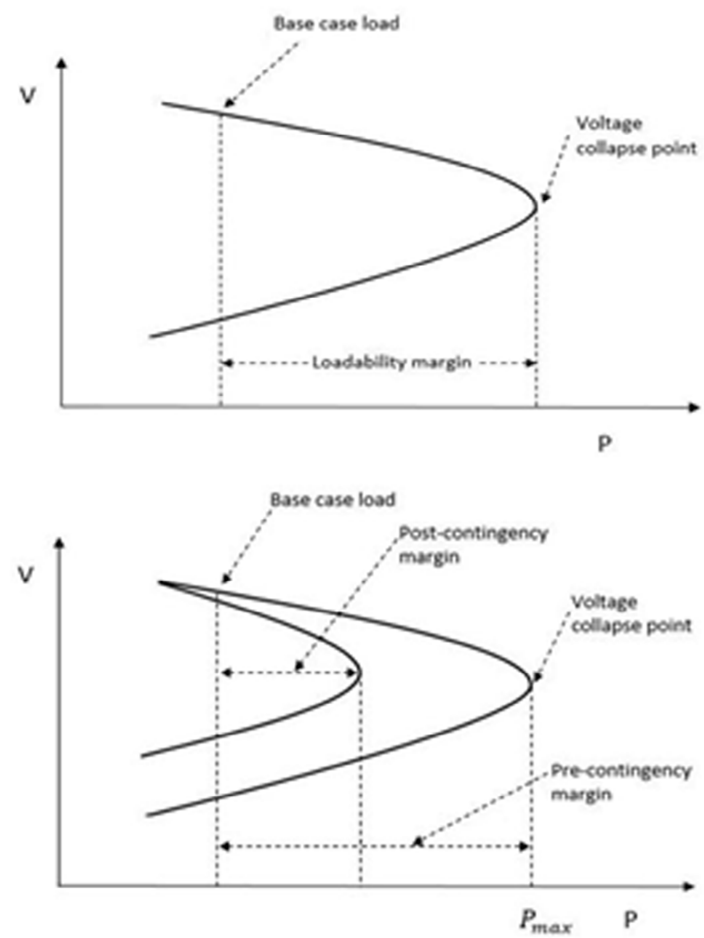

Figure 1: P-V Curve

that it can be capable of taking precise decisions. This paper deals with application of probabilistic fuzzy decision for power system security assessment [13, 15, 16 and 22]

3.1. Probabilistic Fuzzification

Here the continuous and discrete sampling data of power system is fuzzyfied. Basic property of probability is sum of probabilities of N events over a sample space is 1. This means, all attributes have equal weight 1. Thus the fuzzyfied sample space followed by this probabilistic property is known as well defined sample space.

$$P_r(A) = \int_{-\infty}^{\infty} \mu_A(x) f(x)\, dx = E(\mu_A(x)) \tag{1}$$

Basic property of probability is sum of probabilities of N events over a sample space is 1.

3.2. Trapezoidal membership function

In this work trapezoidal membership function is found to be most appropriate fuzzification technique which fulfills probability [27].

$$f(x;a,b,c,d) = \begin{pmatrix} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{pmatrix} \tag{2}$$

Where, the parameters a and d locate the 'feet' of the trapezoid and the parameters b and c locate the 'shoulders'.

3.3. Statistical Fuzzy Entropy

The statistical quantity entropy is used to define the information gain, to choose the most appropriate attribute from different attributes. Statistical fuzzy entropy for a well defined sample space is given as follows [25, 26].

$$H_{sf} = -\sum_{c=1}^{c} E(\mu_{AC}(x)) \log_2 \mu_{AC}(x) \tag{3}$$

where

$$E(\mu_{AC}(x)) = \frac{\sum \mu_{AC}}{\sum \mu_A}$$

H_{sf} represents the entropy of set S of training examples in the node.

μ_{AC} is the membership value of A^{th} pattern to the c^{th} class

μ_A is the membership value of A^{th} pattern

3.4. Statistical Fuzzy information Gain

An information gain of an attribute is the final information contents which is result of the reduction of the ample set entropy after using this attribute to divide the sample set. The information gain of an attribute A relates to sample set S is [26].

$$G(S,A) = H_{sf}(S) - \sum_i \frac{|S_i|}{S} H_{sf}(S_i) \tag{4}$$

Where,

Hsf (S) is the entropy of set S

|Si| is the size of subset S

|S| presents the size of set S

3.5. Stopping criteria

If the learning of probabilistic fuzzy decision tree stops when all the sample data belonging to a node having single class. That node has been considered as node with poor accuracy. In order to improve accuracy, learning of DT should be stopped early which is termed as pruning. The stopping criterion has been classified by following two methods:

a) *Fuzziness control threshold (èr):* If percentage of a class (Ck) at any node is greater than or equal to fuzziness control threshold (èr), stop expanding the tree and make that node as leaf node with corresponding class proportions.

b) *Leaf decision threshold (èn):* If the number of data remaining at any node is less than leaf decision threshold (èn), stop expanding the tree and make that node as a leaf node with corresponding class proportions [24].

4. CASE STUDY

4.1. Study Results on IEEE-30 Bus system

In order to evaluate the applicability of the proposed method, IEEE-30 Bus system has been selected for the online security assessment. This system consists of 24 load buses and 6 generators. The total 300 instances were generated by varying the real and reactive loads under each line outage, with the load variations in the range of 50% to 150% of their case based load. Calculate the maximum loadability margin (MLM) for each of the 300 load patterns and under each line outage. After calculating MLM, secure and insecure operating conditions are to be identified.

MLM classified into two classes namely secure and insecure with respect to threshold or critical value (λcr = 0.3 P.U.) In this work, out of 300 instances for each of the line outages, 250 were used for training pattern and 50 were used for testing pattern. Here the classification of this pattern is done in terms of their accuracy.

$$\%\ \text{Accuracy} = \frac{\text{Total number of Test cases - Incorrect classified cases}}{\text{Total number of Test cases}}$$

Classification is given in Table 1 of insecure operating conditions for line outages-II. Results and analysis of line outage-II is given the description of training set and testing set in Table 2 and Table 3.

Training set consists 250 OC’s and 46 power system parameters along with their security status.

50 different and unseen OC’s has been taken for testing set.

Prediction accuracy

Table 1
Classification of Operating conditions for Line outage-II

Test case number	*Class Estimated by CPF*	*Class predicted by CART*	*Class predicted by PFDT*
1	S	S	S
2	S	S	S
3	S	S	S
4	S	S	S
5	I	S	S
6	I	I	S
7	S	S	S
8	S	S	S
9	S	S	S
10	S	S	S
11	S	S	S
12	S	S	I
13	I	I	S
14	S	S	S
15	S	S	S
16	S	S	S
17	S	S	I
18	I	I	I
19	S	S	S
20	S	S	S
21	S	S	S
22	S	S	S
23	S	S	S
24	I	S	S
25	S	S	S
26	S	S	S
27	S	S	S
28	S	S	S
29	S	S	S
30	S	S	S
31	S	S	S
32	S	S	S
33	S	S	S
34	S	S	S
35	S	S	S
36	S	S	S
37	I	S	S
38	S	S	S
39	S	S	S
40	S	S	S
41	S	S	S
42	S	S	S
43	S	S	S
44	S	S	S
45	S	S	S
46	S	S	S
47	S	S	S
48	S	S	S
49	S	S	S
50	S	S	S

Table 2
Training set

Class	*No. Of OC's*	*Percentage*
Class 1 (Insecure)	227	91%
Class 2 (Secure)	23	9%

Table 3
Testing set

Class	*No. Of OC's*	*Percentage*
Class 1 (Insecure)	44	88%
Class 2 (Secure)	6	12%

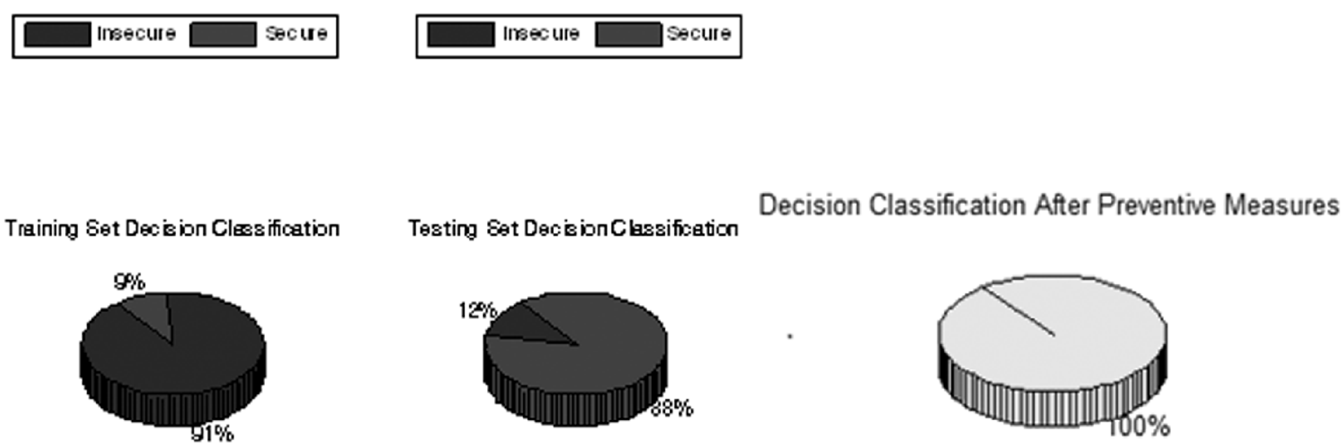

Figure 2: Prediction accuracy

4.2. Comparison of PFDT with conventional method

In decision tree (DT) induction classification and regression Tree (CART) is the basic algorithm which is capable of producing binary classification and decision only [23,24]. The function returns a binary tree, where each branching node is splits the attribute values. This seems to be insufficient for better security prediction. As a result of literature survey on various decision tree induction methods, it is observed that voltage security prediction can be done more precisely by incorporating fuzzy logic and probabilistic reasoning in decision tree induction.

The result and analysis justified the precision of proposed tool over conventional learning algorithm. Both proposed method PFDT and CART DT's trained with five different database generated for different contingency conditions. All databases were identical i.e. 250 OC's for training set and 50 OC's for testing set .After each run it was found that PFDT has performed well and shown high prediction accuracy , however the variation of tree size was not constant. Size of tree may vary with data set and stopping criteria.

These results can be concluded as PFDT has better capability to classify the power system security problems more precisely. The comparative results shown in Table 4.

5. CONCLUSION

Due to the growing size and complexity of power systems, real time decision making becomes extremely difficult. Related to that, the security function is computationally so demanding that it alone decide the size

Table 4
Comparison of CART and PFDT

Line outage number	*From Bus to Bus*	*CART Method*		*PFDT Method*	
		No. of nodes	*% Accuracy*	*No. of nodes*	*%Accuracy*
1	1-2	3	96	5	100
2	1-3	3	94	6	96
4	3-4	6	91	6	95
5	2-5	2	90	7	96
36	27-28	13	84	7	89

and speed of computers in EMS. In order to overcome the above challenges, proposed tool is generic and more efficient. It can capture full system behavior, and effectively characterize the weakness of the current OC's. It is also fast enough to take control actions as soon as a vulnerable event has occurs.

This technology meets the above capabilities using decision tree learning and fuzzy logic with accountability of probabilistic reasoning for efficient and stable tree building. It will be most suitable for implementation in power systems voltage security assessment, since it can handle numeric as well as linguistic data with precision and it is also capable of handling imprecise data.

The results and performance analysis clearly shows that "PFDT is more efficient intelligent system based security assessment technique in comparison of conventional "CART" based technique. Better the database better will be the learning.

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