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**Application of Probabilistic Fuzzy Decision Tree for Voltage Security Assessment Classification in Power System**

***Abstract*—**  ***This chapter presents the application 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). The security assessment classification is obtained using PFDT and the results are compared with the conventional DT (CART algorithm) on test cases. PFDT examines and classify the power system whether the system is secure or insecure. The input variables to the network were loadings and the voltage magnitude of the load buses. The algorithms are tested on IEEE-30 bus systems. The results obtained, indicate that PFDT method is more accurate and computational time is less than conventional method. .***

**Keywords***: Voltage security assessment, Probabilistic decision tree, static security assessment*

1. **I**NTRODUCTION

**I**

n power system security all around the world 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 number of wide operating conditions, for that purpose probabilistic fuzzy decision of the power system is taken into account. 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 that is taken from database. PFDT 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. PFDT is basically a machine learning or artificial intelligence technique method [19]. The main part of PFDT based studies is generating the database.

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 continuation power flow.

3. Perform the contingency analysis. The operating conditions and contingency conditions are obtained using CPF method [17].

II. **S**ECURITY **M**ARGIN

For ensuring voltage security of power corresponding tos essential to know how much to operate steady state after some perturbation has been occurred within the specified limits of safety and supply quality constraints corresponding the contingencies [10, 11, 12, 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 from 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.





***Fig.1. P-V Curve***

III. **P**ROBABLISTIC **F**UZZY **S**YSTEM

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

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.

………………..(1)

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

2. Trapezoidal membership function: in this work trapezoidal membership function is found to be most appropriate fuzzification technique which fulfills probability.

Trapezoidal shaped membership function is used for fuzzification of each attribute

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

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].

Where
Where

*H*sf represents the entropy of set S of training examples in the node.

*µ*AC is the membership value of Ath pattern to the cth class

*µ*A is the membership value of Ath pattern

4. Statistical Fuzzy information Gain: A statistical quantity information gain is defined to determine the cost of attribute. An information gain of an attribute is the final information contents which is result of the reduction of the sample 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].

………………..(2)

Where,

Hsf (S) is the entropy of set S

|Si| is the size of subset S

|S| presents the size of set S

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

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

IV. **C**ASE **S**TUDY

*A. Study Results on IEEE-30 Bus system:*

In order to evaluate the applicability of the proposed method, IEEE-30 Bus system is 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. Maximum loadability margin (MLM) for each of the 300 load patterns and under each line outage are calculated. After calculating MLM, secure and insecure operating conditions are defined by limiting value of MLM.

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 these patterns are done in terms of their accuracy.



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

**TABLE –I**

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

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

**TABLE – II**

|  |  |  |
| --- | --- | --- |
| **Class** | **No. Of OC’s** | **Percentage** |
| Class 1 (Insecure) | 213 | 85% |
| Class 2 (Secure) | 37 | 15% |

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

**TABLE- III**

|  |  |  |
| --- | --- | --- |
| Class | No. Of OC’s | Percentage |
| Class 1 (Insecure) | 43 | 86% |
| Class 2 (Secure) | 7 | 14% |

*B. Comparison of PFDT with conventional method:*

In decision tree (DT) induction classification and regression Tree (CART) is the basic algorithm which is

**Prediction accuracy**

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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.

PFDT tree is an extension of DT algorithm and also an effective tool for knowledge acquisition from uncertain classification problems. By using PFDT, the result and analysis have 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 are shown in Table IV.

|  |
| --- |
| **TABLE- IV** |
| **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  | 92  | 6  | 94  |
| 4  | 3-4  | 6  | 90  | 6  | 98  |
| 5  | 2-5  | 2  | 88  |  7  | 96  |
| 36  | 27-28  | 13  | 84  |  7  | 88  |

V. **C**ONCLUSION

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 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 proposed tool has better capability to classify power system security problems more precisely. The results and

Performance analysis clearly shows that "PFDT is the far more efficient intelligent system based security assessment technique in comparison of conventional "CART" based technique. Accuracy also depends on richness of database.

VI**. R**EFERENCES

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