

APPLICATION OF PROBABILISTIC FUZZY DECISION TREE FOR VOLTAGE SECURITY ASSESSMENT CLASSIFICATION IN POWER SYSTEM

Abstract

This chapter explores the utilization of decision trees for conducting static security assessments in power systems. Within this research, we introduce an innovative technique known as the Probabilistic Fuzzy Decision Tree (PFDT) in conjunction with the traditional Decision Tree (DT). The classification of security assessment is accomplished using the PFDT, and its outcomes are compared to those of the conventional DT, specifically employing the CART algorithm, across various test cases. The PFDT is employed to assess and categorize the power system as either secure or insecure. The input variables considered for the network include loadings and the voltage magnitude of the load buses. These algorithms are put to the test using IEEE-30 bus systems. The results demonstrate that the PFDT method provides superior accuracy while demanding less computational time compared to the conventional approach.

Keywords: Voltage stability evaluation, Utilization of Probabilistic decision trees, Static security analysis

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I. INTRODUCTION

1. The global power system security landscape has experienced substantial changes, leading to profound effects on the electric power industry. As a result, contemporary power systems are showing a growing trend toward optimizing the utilization of generation and transmission capacity, which requires operating much nearer to their security limits.
2. During operational planning, those in charge of making decisions establish operating guidelines that depend on critical attribute threshold values for assessing the post-contingency security of the power system [18]. To aid in making such decisions, it is crucial to have a robust tool capable of simulating contingencies under various operating conditions. This is where the importance of the power system's probabilistic fuzzy decision comes into play.
3. A unique method has been devised utilizing historical data extracted from a database, integrating operating constraints and guidelines also derived from the same database. PFDT, which extends the capabilities of the DT algorithm, serves as an efficient tool for gaining insights from uncertain classification challenges [20]. PFDT excels in approximating both linguistic and numeric data with precision, making it adept at handling imprecise data. Learning methods, including PFDT, are highly favored in inductive inference algorithms. PFDT, essentially a machine learning and artificial intelligence technique [19], plays a central role in power system studies, particularly in the generation of databases.

The accuracy of the generated database significantly impacts the quality of the results. Below are the steps involved in creating this database:

4. The database is formulated with considerations for a range of contingencies and diverse operating scenarios. This is accomplished by generating data from a meticulously defined sample space, which integrates elements of fuzzy logic and probability. These training patterns are established in an offline manner, relying on a precisely defined sample space that utilizes historical data or forecasts for the upcoming 24 hours.
5. To establish the initial system state, a continuation power flow analysis is conducted.
6. Contingency analysis is executed to assess both the operational and contingency conditions, utilizing the CPF method described in reference [17].

II. SECURITY MARGIN

To ensure the voltage security of the power system, it is essential to assess its capability to operate under steady-state conditions following disturbances, all while adhering to specified safety limits and supply quality constraints related to contingencies [10, 11, 12, 14]. Following specific disturbances, the power system attains a stable operational state without violating system constraints, which include bus voltage limits and line thermal limits [17, 19]. To accomplish this, it is necessary to utilize a static voltage stability index known as Maximum Loadability Margin (MLM). MLM serves as a measure to estimate how close a

specific point is to the voltage collapse threshold, essentially defining the steady-state voltage stability boundaries of the power system to some extent. The system is considered to have voltage security when this margin is reasonably high. In this study, we use the term MLM to refer to this voltage stability margin. Figure 1 illustrates the voltage variation versus real loading at a power system bus. In contingency scenarios, the load ability margin decreases to a lower value [3, 4, 5, 6, 8, 9, 21], but it remains crucial to maintain a margin from the voltage collapse threshold [1, 2]. In this context, security denotes the power system's ability to maintain a stable equilibrium state even after a contingency event.

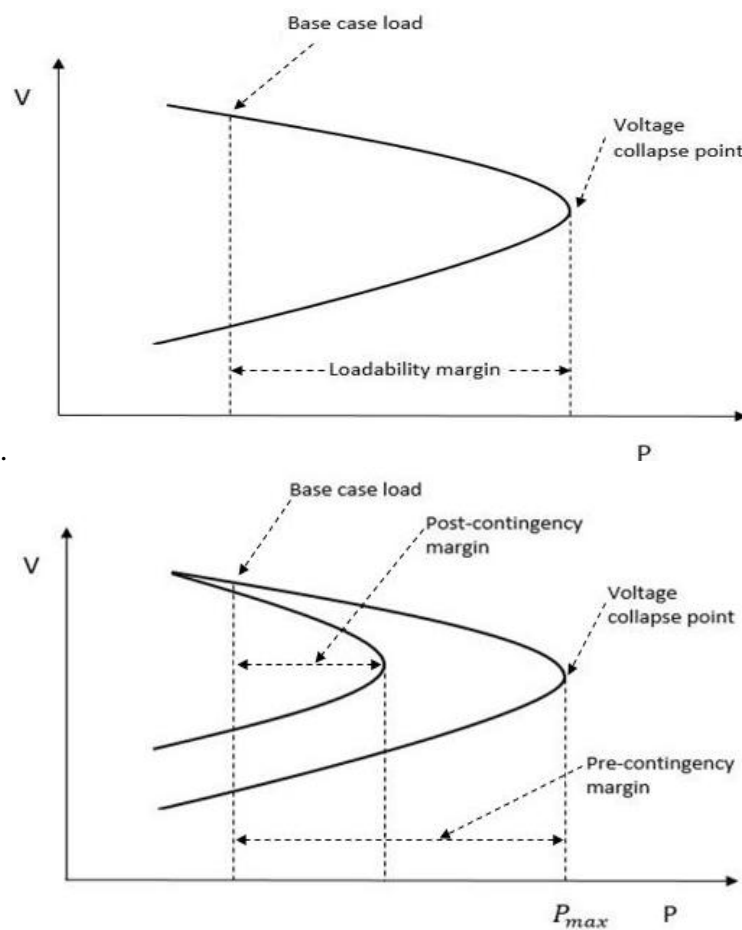


Figure 1: P-V Curve

III. PROBABILISTIC FUZZY SYSTEM

Fuzzy theory emerged due to the limitations of Boolean algebra in addressing numerous real-world problems. Due to the inherent imprecision of a significant portion of real-world information, humans demonstrate a high degree of proficiency in effectively handling such imprecise and fuzzy data. In the current era of intelligent systems, computers are trained to handle real-world challenges. Fuzzy systems are integrated with machine learning algorithms to enable them to make precise decisions. This Chapter focuses on the utilization of probabilistic fuzzy decision-making in the assessment of power system security [13, 15, 16, 22].

- 1. Probabilistic Fuzzification:** In this scenario, both continuous and discrete sampled data from the power system undergo a transformation into fuzzy representations. A fundamental feature of probability theory is that the sum of probabilities for N events within a sample space equals 1. Consequently, all attributes are uniformly assigned a weight of 1. Hence, the fuzzified sample space that conforms to this probabilistic principle is denoted as a clearly defined sample space.

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

A fundamental principle of probability states that the total probabilities of N events within a sample space always equal 1.

- 2.** In this research, the trapezoidal membership function is recognized as the optimal fuzzification technique that fulfills the criteria of probability. A trapezoidal-shaped membership function is applied to fuzzify each attribute.

$$f(x; a, b, c, d) = \begin{pmatrix} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{d-x}{d-c}, & c \leq x \leq d \\ 0, & d \leq x \end{pmatrix}$$

In this context, the values of 'a' and 'd' are responsible for establishing the location of the 'feet' of the trapezoid, whereas 'b' and 'c' are used to define the placement of the 'shoulders.'

- 3. Statistical Fuzzy Entropy:** Fuzzy entropy, which serves as a statistical metric, is utilized to measure information gain and aid in the choice of the most appropriate attribute from multiple options. The formula for calculating statistical fuzzy entropy within a clearly defined sample space is presented as follows [25, 26].

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

Where

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

Where

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

- 4. Statistical Fuzzy Information Gain:** In the context of attribute analysis, a statistical metric known as information gain is employed to assess the attribute's utility. The information gain of an attribute represents the net reduction in sample set entropy achieved by partitioning the sample set based on that attribute. The formula expressing the information gain of an attribute A with respect to sample set S is provided as follows [26].

$$G(S, A) = H_{sf}(S) - \sum_i \frac{|S_i|}{|S|} H_{sf}(S_i) \dots \dots \dots (2)$$

Where,

$H_{sf}(S)$ is the entropy of set S

$|S_i|$ is the size of subset S

$|S|$ presents the size of set S

5. Termination Conditions: The training process of the probabilistic fuzzy decision tree concludes when all the data samples within a node are assigned to a single class, indicating poor accuracy for that node. To improve accuracy, the decision tree learning process can be halted prematurely through a practice called pruning. There are two categories of stopping criteria:

- Fuzziness Control Threshold (θ_r): The expansion of the tree is halted, and a node is converted into a leaf node with the respective class proportions when the percentage of a class (C_k) within the node equals or exceeds the fuzziness control threshold (θ_r). This threshold acts as a control point to manage the degree of fuzziness in the decision tree.
- Leaf Decision Threshold (θ_n): When the count of remaining data points within a node drops below the leaf decision threshold (θ_n), the expansion of the tree is ceased, and the node is converted into a leaf node while preserving the associated class proportions [24].

IV. CASE STUDY

1. Results on IEEE-30 Bus System: To evaluate the effectiveness of the proposed method, the IEEE-30 Bus system has been selected for online security assessment. This system comprises 24 load buses and 6 generators. A total of 300 instances were created by altering the real and reactive loads during each line outage event. These load variations spanned from 50% to 150% of their base case values. For each of the 300 load patterns under different line outage conditions, the Maximum Loadability Margin (MLM) was computed. Following the MLM calculations, secure and insecure operational states were defined based on a specified MLM threshold ($\lambda_{cr} = 0.3$ P.U.).

MLM was divided into two groups, denoted as secure and insecure, with respect to the critical threshold value ($\lambda_{cr} = 0.3$ P.U.). In this investigation, out of the 300 instances for each line outage scenario, 250 were allocated for training patterns, while the remaining 50 were designated as testing patterns. The categorization of these patterns was determined

$$\% \text{ Accuracy} = \frac{\text{Total number of Test cases} - \text{Incorrect classified cases}}{\text{Total number of Test cases}} \times 100$$

by their accuracy.

The classification of insecure operating conditions for line outages-I is presented in Table-I. The results and analysis of line outage-I include descriptions of the training set and testing set in Table-II and Table-III, respectively.

APPLICATION OF PROBABILISTIC FUZZY DECISION TREE FOR
VOLTAGE SECURITY ASSESSMENT CLASSIFICATION IN POWER SYSTEM**Table 1**

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

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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

The training set comprises 250 Operating Conditions (OCs) and 46 power system parameters, each associated with its respective security status.

Table 2

Class	No. of OC's	Percentage
Class 1 (Insecure)	213	85%
Class 2 (Secure)	37	15%

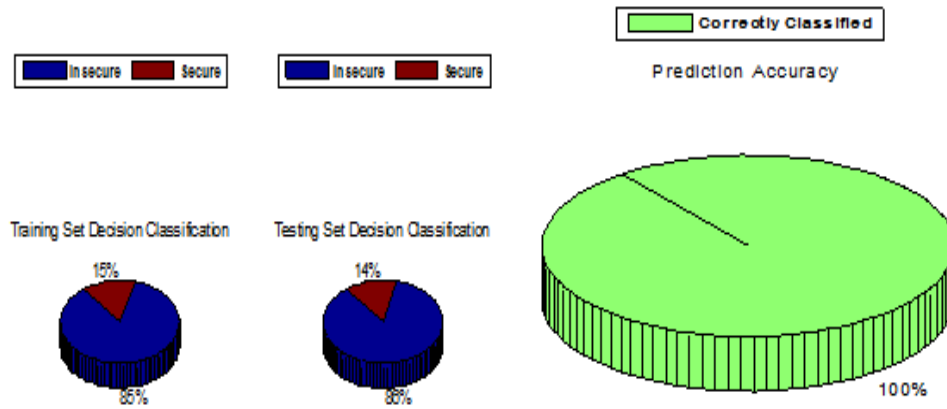
50 different and unseen OC's has been taken for testing set.

Table 3

Class	No. of OC's	Percentage
Class 1 (Insecure)	43	86%
Class 2 (Secure)	7	14%

2. Comparison between PFDT and conventional methods: In the context of decision tree (DT) induction, the basic algorithm includes Classification and Regression Trees (CART), which is commonly used for comparison.

Prediction accuracy



The traditional approach is proficient at providing binary classification and decisions exclusively [23,24]. It generates a binary tree structure in which each branching node partitions attribute values. Nevertheless, this appears to be inadequate for enhancing security prediction. Upon examining various decision tree induction methods in existing literature, it has been noted that the integration of fuzzy logic and probabilistic reasoning into decision tree induction can substantially enhance voltage security prediction.

PFDT (Probabilistic Fuzzy Decision Tree) represents an extension of the DT algorithm and serves as a potent tool for extracting knowledge from uncertain classification problems. Through the results and analysis conducted using PFDT, its superior precision in comparison to conventional learning algorithms has been consistently demonstrated. Both the proposed PFDT method and the CART DT were trained using five distinct databases generated for various contingency scenarios. All databases remained consistent, with 250 operating conditions (OCs) in the training set and 50 OCs in the testing set. It was evident, following each iteration, that PFDT consistently delivered exceptional performance and achieved a high level of prediction accuracy, albeit the tree size exhibited variability. The tree's size may fluctuate depending on the dataset and the specified stopping criteria.

To summarize, these results highlight the superior capacity of PFDT in accurately categorizing power system security concerns. Comparative outcomes can be found in Table 4.

Table 4

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. CONCLUSION

1. As power systems continue to expand in size and complexity, real-time decision-making becomes increasingly challenging. The security function, in particular, places significant computational demands, influencing the choice of computer size and speed for Energy Management Systems (EMS). To address these challenges, the proposed tool is both versatile and efficient. It can comprehensively capture the entire system behavior and effectively identify weaknesses in the current Operating Conditions (OCs). Moreover, it operates swiftly, allowing for prompt control actions when vulnerable events occur.
2. This technology achieves these capabilities through a combination of decision tree learning, fuzzy logic, and the incorporation of probabilistic reasoning to construct trees efficiently and reliably. It is particularly well-suited for application in voltage security assessment within power systems. Notably, it can handle both numeric and linguistic data with precision, making it adept at managing imprecise data.
3. The proposed tool excels in classifying power system security issues with greater precision. Results and performance analysis clearly demonstrate that "PFDT" outperforms the conventional "CART" technique, with accuracy influenced by the richness of the database.

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