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CART for Online Security Evaluation and Preventive Control of Power Systems

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Abstract: - This paper presents an application of CART algorithms for online security evaluation and preventive control of power system. The CART algorithm generates a security classifier in the form of a decision tree. The effect of various design parameters on the performance of the classifier has also been investigated. The method has been applied on an IEEE test systems and the results have been reported.

Key-words: - Power system security, Decision tree (DT), CART, Preventive control, Entropy, Gini index, Class probability

1 Introduction

The competitive business environment has forced modern electric power industries to operate their systems closer to their transient security limits. Under such conditions even a small disturbance, if not taken care of, could endanger system security. Therefore there is a pressing need to develop fast on line security monitoring methods, which could analyze the level of security and suggest possible control strategy.

A complete answer about power system security requires evaluation of transient stability of power systems following some plausible contingencies. Several method for fast transient stability evaluation have been proposed in the past by adopting namely direct methods, pattern recognition (PR) technique, Decision Tree (DT) method and Artificial Neural Network (ANN) approach[1]. The direct methods & PR Methods are not suitable for on line transient security evaluation of power system [2]. Neural Networks have shown great promise as a means of predicting security of large power systems [3, 4]. But because of their black box type nature, neural network based security classifiers are not able to provide information about preventive control. Though, some efforts have been made to infer this information from the hidden layer of the neural network but under very simplified modeling assumption [5]. The Decision Tree based classifiers, on the other hand, are known for their interpretability and therefore can be used to infer preventive control strategy.

The DT method for on line transient security assessment was first proposed by L. Wehenkel et. al [6]. Since then extensive research affords [7-17] have been made in this direction in which different aspect of power system security were investigated. Almost all the research efforts exploited Inductive Inference Method except S. Rovnyak et. al. [15]. They have used CART algorithm [18] to generate DT classifier. However the classifier generated by Rovnyak et. al. can not be used for preventive control purposes due to the nature of attribute set chosen.

This paper presents a DT method for on-line security evaluation and preventive control of power system. In this method, CART algorithm [18-20] has been used to generate DT classifier which takes only a few system parameters to predict system security and to provide necessary preventive control strategy. The proposed method attempts to generate a classifier which is independent of minor changes in power system topology. A comparison of different node splitting criteria have also been explored and reported. The method has been applied and tested for its applicability and effectiveness on IEEE 57 bus system.

2 The DT methodology

The proposed method uses DT as a classifier which classifies an operating state of a power system into ‘secure’ or ‘insecure’ class under a predefined contingency set. The DT classifier is generated using an off-line data set, which is generated by the most accurate power system solution methodology. The complete description of DT methodology is beyond the scope of this paper and can be referred [18-20]. Nevertheless, it is important to discuss the basic design procedure, which involves the following steps:

1. Attribute selection 2. Data set generation 3. DT building algorithm 4. Performance evaluation.

The attribute selection is an important step. The guiding principal for the choice of attribute set is to select those system variables which are monitorable, controllable and which adequately characterized an operating state of a power system from security classification point of view. C.M. Arora and Surana [21, 22] have derived that the real and reactive power generations of generators carry sufficient information about the class of system security (secure or insecure system security. This fact is also supported by the outcome of the research paper [3]. Therefore, the proposed initial feature set consists of pre-disturbance real and reactive power generation of each generator.

The second step in the design of DT classifier is data set generation for the classifier training. The primary objective of data set generation is to obtain a sufficiently rich data base containing plausible operating states of power system. To generate a data set, initially a large numbers of load samples are randomly generated in the typical range of 50 to 150 percent of their base case values. For each load sample (load combination) optimal power flow (OPF) study is performed to obtain steady operating state. A disturbance (fault), from a predefined set of contingency, is simulated for a specified duration of time. Using dynamic stability studies, load angle trajectories of all generators is computed and plotted over a period long enough to ascertain system stability under the specified disturbance. Similarly for each of the disturbances from the contingency set dynamic simulation is performed to ascertain system stability under the corresponding disturbance. For carrying out dynamic simulation, numerical integration techniques is used as it has the flexibility to include all kind of modeling sophistication and thus is able to provide desired degree of accuracy. If a steady state operating point is found to be stable, for all disturbances of the contingency set, the operating state is assigned “secure (0)” class label else it is assigned “insecure (1)” class label. During data set generation some operating states are also generated in the neighborhood of optimal dispatch to ensure inclusion of all realistic operating states. Some frequent topological changes may also be considered during data generation.

To generate the DT classifier commercially available CART software has been used [23]. The aim of CART is to construct an efficient piece-wise constant estimator of a classifier from a learning set. This classifier is in a form of a tree. The tree is structured in top-down fashion consisting of various test and terminal nodes. Each test node is associated with an optimal splitting rule and a subset of the Learning set (LS). A terminal node is a class pure node. A built tree is, thus, a hierarchical organization of the LS into a collection of subsets. The most general subset is the LS itself and corresponds to the top (root) node of the DT. Starting from the root node, at each level of the DT, the corresponding subsets are partitioned on the basis of some optimal splitting rules. These rules are in the form of "if- then-else" rules. The lower is the level, the more refined is the corresponding partition. Therefore, generating successors of a given non-terminal (test) node amounts to reducing the uncertainty about the classification. To split a given node (subset), the CART algorithm makes use of impurity functions such as Gini-Index, Entropy and Class-probability based impurity functions. The particular choice of the splitting criteria depends on the problem in hand.

3 Simulation and results

To investigate the effectiveness of the proposed method a study was performed on IEEE - 57 bus system. The system consists of 7 generators, 57 buses, 67 transmission lines, 18 transformers and 42 loads. The diagram of the system is given in [24] and the data were taken from [24, 25]. It is assumed that contingency set contains only one disturbance, which is a 3-phase fault on the 400kV transmission line connecting buses 8 and 9, near bus 9. Duration of the disturbance is assumed to be 210 ms, which is cleared by opening the line at both the ends. By varying the loads randomly from 50% to 150% of their base case values two sets of data have been generated. The first data set consists of 1000 operating states with fixed system topology. Second data set consisting of 2200 operating states is generated under 12 different topological conditions. The changes in topology are spread through out the system and include removal of single 400kV transmission lines 2, 5, 14, 15, 19 and 28 one at a time, simultaneous removal of a set of three transmission lines at a time such as (2, 5, 14), (15, 19, 28) etc. The second data set is then shuffled several times to thoroughly mix the data of different topology.

Since the there are 7 generators in the system therefore attribute set consists of the 14 attributes (features) namely PG_1, PG_2, PG_3, PG_4, PG_5, PG_6, PG_7, QG_1, QG_2, QG_3, QG_4, QG_5, QG_6 and QG_7. However, during data generation it has been found that generators 2, 3, 4 and 6 are always operating at their upper active power generation limits and so corresponding features carry no discriminating information about system security. Therefore these features can be ignored. Thus the attribute set consists of following 10 features:

A = [PG_1, PG_5, PG_7, QG_1, QG_2, QG_3, QG_4, QG_5, QG_6, QG_7]

By applying CART algorithm on the learning set of 500 load samples of fixed system topology 3 different DT classifiers have been generated as shown in the Fig. 1, Fig. 2 & Fig. 3. Each block of the non terminal nodes defines an optimal splitting rule in the form of

A(i) <= threshold value?

Here A(i) is the i^{th} feature.

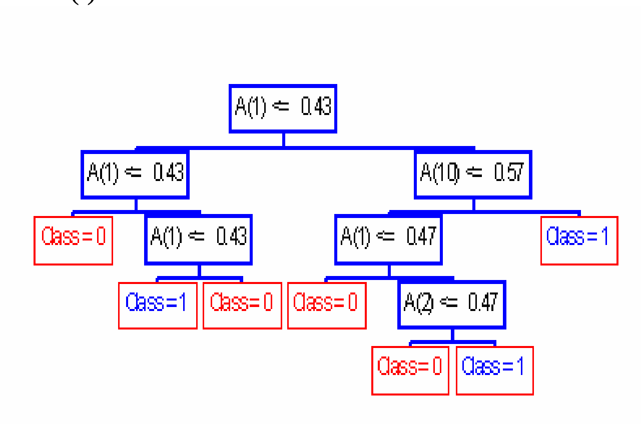

Fig. 1: Tree generated using CART (Gini-Index)

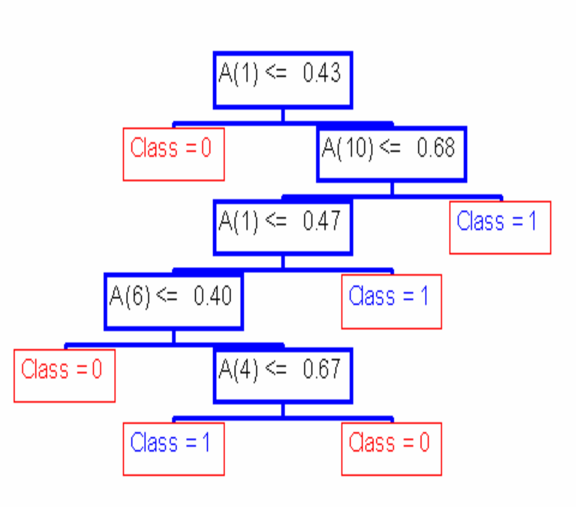

Fig. 2: Tree generated using CART (Entropy)

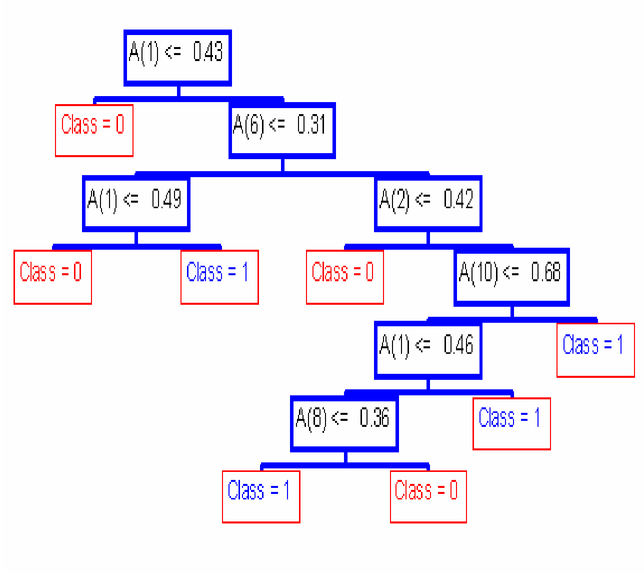

Fig. 3: Tree generated using CART (Class Probability)

The test results of the classifiers on a test set of 300 load samples are summarized in Table 1. The result shows that entropy based classifier gives better accuracy.

Table 1

Percentage test set Error		
Gini-Index	Entropy	Class Prob.
3.91675	3.666	4.16675

To investigate the effect of the size of training set on performance of DT classifier 5 different set of DT classifiers have been generated using 5 different training set and the corresponding test results are summarized in Table 2. The error versus size of training set curve is shown in figure 4.

From the results it can be observed that for smaller training set size the entropy based splitting criteria gives poor accuracy rate as compared to the gini-index based and class-probability based criteria. However when the size of available training set is large the entropy based classifier gives better accuracy rate as compared to the others.

Table 2: Fixed Topology

Training Set Size	Percentage test set Error		
	Gini-Index	Entropy	Class Prob.
300	5.7335	6.23225	5.698
400	4.85875	5.27375	4.85875
500	4.68125	4.73075	4.731
600	4.1875	3.6875	4.25
700	3.91675	3.666	4.16675

Fig. 4: Percentage Error versus Training Set Size curve

Moreover it can also be observed that as the size of training set increases there is appreciable increase in the accuracy of the classifier and when the size of training set is large enough no appreciable change in accuracy is observed.

Modern power systems are prone to frequent changes in system topology due to many factors such as maintenance, repair etc. Therefore, special care needs to he taken to minimize the effect of topology changes on the performance of the neural network. One approach to deal with this problem is to build different DT classifier for each possible system topology and to use the specific classifier that reflects the current topology of the system. This approach is only practical when there are a few possible changes in system topology. Another approach is to build a DT classifier which is independent of changes in system topology. This allows a single DT classifier to tackle security assessment problem of the power system under varying system topology. This also allows the single network to predict security of the power system under unexpected topological changes.

In order to investigate the effect of topology on the performance of DT classifier 8 set of DT classifiers have been generated with different training sets taken from varying topology data set. The corresponding results are summarized in Table 3 and figure-5.

Table 3: Varying Topology

Training Set Size	Gini	Entropy	Class Prob.
400	6.2168	7.1674	5.2908
800	4.6308	3.6958	4.1922
900	3.9632	3.6518	4.1094
1000	4.1592	3.8938	3.8276
1100	3.641	3.2882	3.2878
1200	2.88	2.6	2.54
1300	2.4666	2.0664	2.4442
1400	2.75	1.975	2.575

From the test results it can be observed that if the DT classifier is generated using a varying topology data set the accuracy of the classifiers is not affected. In other words the classifier becomes independent minor changes of power system topology. Therefore a single classifier can be used to predict security of power system even under changing topology. It may also be observed that for smaller training set size the entropy based splitting criteria gives poor accuracy rate as compared to the gini-index based and class-probability based criteria. However when the size of training set is large the entropy based classifier gives better accuracy rate as compared to the others. Moreover it can also be observed that as the size of training set increases there is appreciable increase in the accuracy of the classifier. When the size of training set is large enough no appreciable change in accuracy is observed. In fact the accuracy of the classifier slightly decreases.

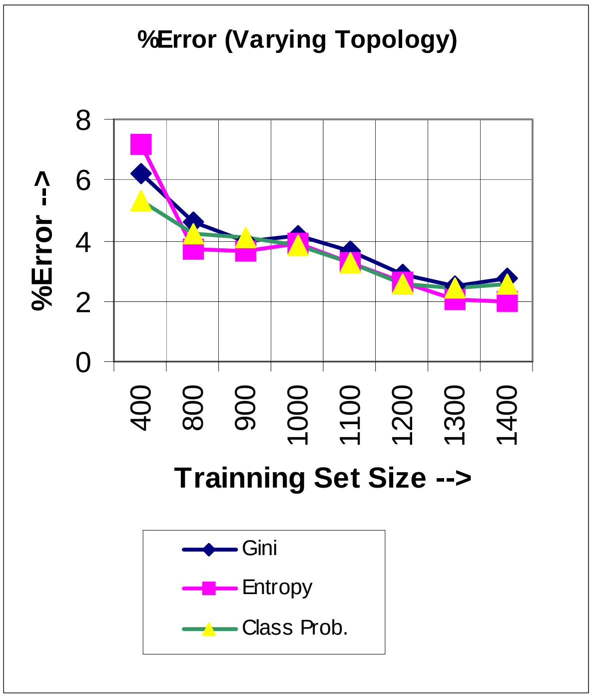

Fig. 5: Percentage Error versus Training Set Size curve for varying topology

One of the important properties of the proposed DTC is that it provides security classification rules in the form of constraints on the system attributes i.e., active and / or reactive power generation of some or all generators. That is for secure operation

$$PGi <= PGi^{s} \qquad (1)$$

$$QGi <= QGi^{s} \qquad (2)$$

Where PGi^{s} and QGi^{s} are the upper limits of active and reactive generation of i^{th} generating unit, imposed by DTC for secure operation. Therefore, when the operating state of the power system is insecure, it violates some or all of the above constraints. To bring the system back into secure operating state, the generators are re-dispatched optimally in a manner to satisfy the security constraints (1) and (2). The DT provides several re-dispatch alternatives. The choice of an appropriate re-dispatch alternative would depend upon the feasibility of the solution and nearness to secure terminal node.

4 Conclusion

The transient security evaluation of modern power system is becoming a major concern for on line operation. This paper investigates the potential of CART algorithms for on-line security evaluation and preventive control of power system. The results obtained on IEEE 57-bus system show that the CART based DT classifier are able to predict system security with a high degree of accuracy. The effects of various CART design parameters have also been investigated. It is found that in general a DT classifier requires a large training set and entropy base splitting criteria is the most suitable criteria for security evaluation using DT classifier. It has been found that DT classifier can also tackle security assessment problem of the power system under varying system topology. The DT approach provides preventive control strategy in term generation re-dispatch alternatives. The choice of appropriate preventive control action would depend upon the feasibility and economic aspect of the preventive control solutions provided by the DT classifier. The approach can be generalized to handle multi-contingency security assessment under varying topological conditions.

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