A DECISION TREE METHOD FOR REAL-TIME TRANSIENT STABILITY PREDICTION

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ABSTRACT

This paper presents a decision tree (DT) method for predicting transient stability in real-time operation. Based on artificial intelligence, it successively makes use of inductive inference method to automatically build decision rules and a deductive inference method to apply them on-line. On the other hand, the method provides an effective feature selection tool. It identifies the significant system parameters, their correlation to the system stability, and hence it provides a clear picture of the phenomena to guide decision making in real-time operation. The method could be considered in principle to aid corrective control actions for the stability enhancement of a power system. The proposed method has been successfully demonstrated using the 4-machine, 6-busbars system. The validity of the approach has been tested under different system topologies, and fault clearing policies.

KEYWORDS: On-line transient stability assessment, artificial intelligence, decision trees, pattern recognition, real-time corrective control.

1. INTRODUCTION

‘Transient Stability’ problems are due to large power imbalances between generators mechanical input power and the available electrical load. Under these conditions, the synchronous generators either accelerate or decelerate, upsetting the synchronous operation. Their rotors then start swinging with respect to each other, until the controls in the excitation and speed governing loops act to restore synchronous operation in the post-disturbance period and lead the system to a new or earlier steady-state condition. The most generally used methods are:

(i) Numerical integration method performs a solution to the differential equations that describe the system dynamics during the fault and post-fault period. The
most widely used methods are Runge-Kutta and predictor-corrector methods. Considerable progress has been made in speeding up these methods; however, they currently remain too slow for on-line environments.

(ii) Energy function method uses a stability criterion based on the construction of a Lyapunov function in order to determine the stability of the post-contingency operating point of the system. This method is less computationally demanding than the numerical integration approach; however, it does not achieve the same level of accuracy due to the use of reduced order modeling [1].

(iii) Pattern recognition method relies on reducing the on-line computational overhead to a minimum at the expense of intensive off-line studies. By performing off-line training of a pattern classifier, using results obtained from a time domain simulator, an accuracy close to that of a numerical integration method may be achieved within the computational and time constraints of on-line operation [2].

(iv) Expert system method provides the user guidance in conducting stability studies with the formation of conclusions. The expert system can cover a broad spectrum of the activities, which includes qualitative and quantitative evaluation of system transient performance, suggestions for further processing, and contributions to study organization [3].

(v) Neural Network method provides very accurate and continuous on-line stability assessment in terms of margins or critical clearing times CCTs. This new emerging AI technology appears to be capable of carrying out complex mappings and their transparent nature allows one to have an insight on what combination of features lead to particular decision [4].

(vi) Decision Tree method provides an inductive learning technique for solving classification problems that have a small number of categories (e.g. stable vs. unstable). The method provides decision rules in the form of DTs built off-line from a preclassified learning set consisting of a large number of simulation results. The DTs can then be utilized on-line to correctly classify unseen states in real-time [5].
2. PROCEDURE STEPS OF APPLYING DECISION TREE METHODOLOGY

The description of the proposed methodology will systematically be illustrated through the application described below. The way of compressing, organizing and extracting the off-line information relies on information theory [6]. Fig. 1 illustrates the overall algorithmic organization of this methodology.

![Decision Tree Diagram]

Fig. 1. The overall algorithmic organization of the DT methodology
2.1 Test System

The 4-machine power system shown in Fig. 2 is selected for this study. Network parameters, machine data and nominal operating points are provided in reference [7]. The generator at bus 1 is considered to be the reference unit and the fault clearing time is 0.4 seconds.

![Fig. 2. One-line diagram of the 4-machine power system.]

2.2 Selection of Candidate Attributes

The main parameters used to draw randomized pre-fault operating states are as outlined below:

**Item 1** Topological variations, such as line switching ($TP_{25}$).

**Item 2** Load level ($PL_2$, $QL_2$, $PL_5$, $QL_5$, $PL_6$, $QL_6$).

**Item 3** Active power generation ($PG_1$, $PG_2$, $PG_3$, $PG_4$).

**Item 4** Reactive power generation ($QG_1$, $QG_2$, $QG_3$, $QG_4$).

**Item 5** Accelerating power squared for each machine immediately following the application of a fault. This item is scaled by dividing by the machine inertia and is claimed to give information of individual machine accelerating energy

\[
(En_1 = \frac{P_{a1}^2}{M_1}, \quad En_2 = \frac{P_{a2}^2}{M_2}, \quad En_3 = \frac{P_{a3}^2}{M_3}, \quad En_4 = \frac{P_{a4}^2}{M_4}).
\]
Item 6 Rotor angles for each machine, prior to the fault ($\delta^0_1, \delta^0_2, \delta^0_3, \delta^0_4$).

Item 7 Power flows on important lines (\(PF_{12}, PF_{23}, PF_{34}, PF_{45}, PF_{56}, PF_{61}, PF_{23}\)).

Item 8 Busbar voltages (\(V_1, V_2, V_3, V_4, V_5, V_6\)).

Item 9 Fault attributes (\(F_{30}, F_{34}, F_{32}\)).

2.3 Random Generation of States

The primary objective is to obtain a sufficiently rich database, which at the same time contains secure operating states of the region and covers as much as possible weakened situations. The database has 54% stable and 46% unstable learning states. Fig. 3 illustrates the statistical distributions of important variables of the study system.

2.4 Construction of the Decision Tree

Fig. 4 illustrates the 2-class tree built for a 3-phase to ground fault at busbar 3. The fault clearing policy is to restore the pre-fault system topology. The fault-clearing time is 0.4 sec. It can be observed that out of the 35 candidate attributes the method has selected only 7. The following information measures are provided [6]:

(i) The entropy of the node ($H_c$): it measures the impurity of the subset $S$ in the node. Let $S^+$ be the subset of the stable class (resp. $S^-$

$$H_c(S) = -\left[\frac{S^+}{S} \log_2 \frac{S^+}{S} + \frac{S^-}{S} \log_2 \frac{S^-}{S}\right]$$

$H_c$ ranges in between 0 and 1: $H_c = 0$ corresponds to a perfect pure subset, while $H_c = 1$ corresponds to a perfectly impure subset.

(ii) The mean conditional entropy ($H_m$): it measures the residual impurity of $S$ given the outcome of a test $T$. Let test $T$ splits $S$ into $S_{Yes}$ and $S_{No}$

$$H_m(S) = \frac{S_{Yes}}{S} \times H_c(S_{Yes}) + \frac{S_{No}}{S} \times H_c(S_{No})$$
If $H_m$ is less than a threshold value then the node is declared to be a leaf. The threshold value affects directly the reliability of the DT, as it is responsible for terminating the splitting process.

(iii) The information gain ($I_c$): it measures the information provided by a test

$$I_c(S) = H_c(S) - H_{c^*}(S)$$  \hspace{1cm} (3)
(iv) The information quantity ($I_q$): it measures the contribution of the test attribute to the classification ability of the overall tree

$$I_q(S) = \text{Num}(S) \times I_c(S)$$  \hspace{1cm} (4)

where Num(S) denotes the number of learning states contained in S.

(v) The entropy of the outcome of the test ($H_T$):

$$H_T(S) = \frac{S_{\text{Yes}}}{S} \times \log_2 \frac{S_{\text{Yes}}}{S} + \frac{S_{\text{No}}}{S} \times \log_2 \frac{S_{\text{No}}}{S}$$  \hspace{1cm} (5)
(vi) The test score \( G \): it measures the normalized correlation between the test and the goal partition in \( S \).

\[
G(S) = \frac{2 I_c(S)}{H_r(S) + H_f(S)}
\]  

(6)

This quantity vanishes if there is no gain of information is provided by the test, and it equals 1 if the test provides the maximum of information and yields perfectly pure subsets. The criterion is being that at each node the selection of the test attribute along with its threshold value relies on the highest score. Fig. 5 shows the variation of test score at node N1 (in the DT of Fig. 4) with different thresholds of PG3.

![Score vs Threshold of PG3](image)

**Fig. 5. Test score at node N1 with different thresholds of PG3**

### 2.5 The Multilayer Perceptron Structure (MLP)

The MLP structure reformulates a DT as an equivalent neural network. The structure is suitable for real-time implementation. It is composed of three layers of neurons, connected in a feed-forward unidirectional manner. The *TEST layer* is constructed from the DT test nodes, the *ANDing layer* is constructed from the DT terminal nodes, and the *ORing layer* is constructed from the DT stability classes. The weight is considered +1 if the terminal node is located in the left-hand successor, and –1 if it is located in the right-hand successor. Terminal nodes are connected to class nodes always by +1 weights. The output of the *TEST* layer neuron is high (+1) if the attribute value is larger than the threshold, otherwise it is low (-1). The output of the
ANDing layer neuron is high only if the activations of its weighted inputs are all high. The output of the ORing layer neuron is high if at least one of the activations is high.

Fig. 6 illustrates the resulting MLP structure of the DT described in Fig. 4.
Fig. 6. the MLP structure equivalent to the DT of Fig. 4.

2.6 Effects of Topology

The method can handle in an effective and transparent way the effect of topological variations on system stability. The topological attribute TP25 could be defined to simulate the switching of transmission line 2-5. This will generate another set of learning states added to the database. Fig. 7 illustrates, using swing curves, one of the cases in which the stability is affected by this topological variation. The decision tree obtained is shown in Fig. 8.

![Fig. 7. Effect of topological variations on system stability.](image)

Fig. 9 shows the contribution of the various test attributes to the classification ability of the overall tree of Fig. 8; in particular this may be assessed in terms of the amount of information provided by each one of them.

![Fig. 9. Contribution of test attributes to the classification ability.](image)
Fig. 9 Contribution of various test attributes to the classification ability of DT of Fig. 8
Fig. 8. A 2-class tree for fault at bus 3 considering the topological effect of line 2-5

2.7 Testing the Decision Tree

The reliability of the method is measured by its ability to properly classify seen and unseen cases. To assess this or equivalently the misclassification rate, various test samples, not considered during the learning stage, have been selected. Topological effect is also considered. The obtained ratio of misclassified states is 4.08%. A close examination shows that the misclassified states are concentrated on the nodes N11222 and N1122112 in the structure of Fig. 8. Thus, the states misclassified by these leaf nodes are assessed as unstable whereas they are stable. Fig. 10 shows the swing curves of the misclassified states.

Fig. 10. Swing curves for the misclassified states in the test set

3. DETERMINING THE CORRECTIVE ACTION

The DT obtained off-line can be considered to provide on-line aid to the system operator in carrying out corrective control actions. This would consist in the transition of the system from an unstable leaf to a stable one, by acting on the control variables in order to modify accordingly the attribute values.
Based on the DT of Fig. 8, the operating state characterized by \((PG_3 = 40, V_3 = 0.95)\) is located in the unstable leaf \(N_{111}\) and is classified as unstable state. Machine 3 accelerates away from the other three machines and loses synchronism with the rest of the system. In order for the operating state to be declared stable, it has to be directed to a stable leaf, e.g., leaf \(N_{11212}\). In other words it has to obey the constraints relative to leaf \(N_{11212}\): \([OP \in N_{11212}] \iff [V_3 > 1.095] \cap [32.5 < PG_3 \leq 36.5]\). These constraints define a hypercube in the attribute space. Thus two corrective actions are suggested: The first correction is for the test attribute \(PG_3\) to be decreased less than or equal to 36.5 and the second correction is for \(V_3\) to be increased greater than 1.095. Fig. 11 shows the resulting rotor angles after correcting the operating state parameters to \((V_3 = 1.1\) and \(PG_3 = 35)\). It can be noticed that the swing curves are quite stable, with generator 3 nicely damped.

![Swing curves before correction](image1)

![Swing curves after correction](image2)

Fig. 11. Effect of corrective action on system stability.

4. EFFECT OF FAULT CLEARING POLICY
The method has been extended to deal with the fault at busbar 3 with different clearing policies. A new type of test could be defined for splitting the nodes of the DT based on the fault attributes. The following tests have been considered:

(I) Fault=30, for a 3-phase to ground fault at bus 3. The fault is cleared by itself;

(II) Fault=34, for a 3-phase to ground fault on the line between buses 3 and 4, near bus 3. The fault is cleared by the opening of the circuit breakers at both ends of the line between buses 3 and 4;

(III) Fault=32, for a 3-phase to ground fault on the line between buses 3 and 2, near bus 3. This is the worst possible location for the fault in the transmission system. The fault is cleared by the opening of the circuit breakers at both ends of the line between buses 3 and 2.

Each “stability case” is specified by a pre-fault operating state and a fault, identified by a discrete attribute; it is accordingly classified as (un)stable if its operating state is (un)stable with respect to its fault. Fig. 12 portrays the resulting DT structure built for a 3-phase to ground fault at busbar 3, taking into consideration different clearing policies.

5 CONCLUSION

In this paper the application of a Decision Tree method to on-line transient stability assessment of a power system is proposed. The method can automate the process of transforming off-line simulation into on-line decision rules. The method replaces the “black box” type approaches traditionally used in transient stability studies, by a “transparent box”, which relates explicitly the characteristics of the power system and its stability. The on-line computer usage is drastically reduced, since on-line processing of the DTs requires the application of just a few IF.THEN.ELSE numerical tests equal to the number of the DT’s hierarchical levels. The method offers
interesting prospects as a supplementary aid for on-line corrective control. Thus, the method proves to be an efficient tool for on-line stability prediction.
Fig. 12. A DT for 3-phase fault on bus 3 considering different clearing policies
REFERENCES