A Fast Stability Assessment Scheme based on Classification and Regression Tree

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***Abstract*--Traditional power system stability analysis based on full model computation shows its drawbacks in real-time applications where fast variations are present at both demand side and supply side. This paper presents the use of Decision Trees (DT) for fast evaluation of power system oscillatory stability and voltage stability based on voltage and current phasor measurements. An operating point is grouped into one of several stability categories based on the value of corresponding stability indicator. A new methodology for knowledge base creation has been elaborated to assure practical and sufficient training datasets. Encouraging results are obtained through the performance examination using the generated knowledge base. The impact of DT growing method and node setting on the classification accuracy has been explored. Finally, the differences in performance between regression tree and several other data mining tools have been compared.**

***Index Terms*--Classification and regression tree, knowledge base, oscillatory stability, voltage stability**

I. INTRODUCTION

FROM the control center operators point of view, the fast assessment of power system oscillatory stability and voltage stability is of great importance for real-time operation. It is desirable that the impending system events can be immediately detected and that operators are provided with the updated information on whether or not a power system can maintain synchronism and acceptable voltage levels when subject to disturbances.

Traditionally, the method of time-domain simulation is used to analyze system stability status [1]. However two obstacles prevent the traditional method's application in real-time monitoring and control. Firstly, the need of full system model computation makes the simulation method time-consuming. Considering the fast onset of an instability event, the traditional method may not be able to provide immediate event detection. Using a simplified system model could accelerate the simulations, but this brings concern over approximate analysis results leading to inaccurate decisions. Secondly, the data used for the stability analysis in electrical utilities are obtained from the Supervisory Control and Data Acquisition (SCADA) system or state estimation functions, which are refreshed on a time scale from several seconds to several minutes. In some cases the forecasted load pattern and unit commitment dispatch are used instead of actual data to analyze system performance. When a disturbance occurs and immediate controls need to be initiated, traditional stability analysis using slowly updated or forecasted data can only provide limited decision making support.

To make the situation worse, in power system planning and on-line applications a complete model may not be readily available. This model is necessary for obtaining the linearized system description required by traditional oscillatory stability analysis. Similar problems exist in the voltage stability assessment process [2-3]. Under such circumstances, the Decision Tree (DT) approach, benefiting from accurate generalization ability without detailed knowledge of all system parameters, becomes an attractive alternative.

The DT method, developed by Breiman et al. [4], was first introduced to the field of power systems to assess the transient stability [5-6]. In [7-10], DTs were successively applied to assess system operational security by applying a pre-defined set of credible contingencies and enforcing an acceptable threshold criterion on system variables based on standard operating practices. Later, in [11], the system post-disturbance stability has been analyzed by DT using its fast evaluation capability. In [12], a genetic algorithm was applied in feature selection to search for the best inputs to DT for oscillatory stability region prediction. In [13], Kamwa et al. showed that there is a trade-off between a data mining model's accuracy and its transparency. A review of literature reveals that the problem of using DT for stability margin monitoring from substation field measurements has not yet been fully explored. It is also imperative to develop a systematic approach to generating a sufficient and realistic knowledge base for off-line training of DT.

The motivation of this paper is to explore the above mentioned problems and gain a deeper understanding of the performance of classification and regression trees. It is organized as follows: the proposed assessment scheme is formulated first. A new methodology for knowledge base generation is presented next. The DT node setting and growing method have been varied to explore their impact on the tree performance. At the end the prediction accuracy of stability margins between DT and other data mining tools have been compared.

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II. PROPOSED METHODOLOGY

A. Oscillatory Stability Assessment (OSA)

Modern power systems have evolved into systems of very large size. Due to the deregulation and the difficulty of transmission expansion, operators are often forced to operate the system close to its stability limits, which leads to occurrence of small-signal oscillation problem. As a consequence, the inter-area oscillatory stability becomes increasingly important.

The oscillatory stability is usually evaluated through modal analysis. This is carried out by a linearization of power system differential algebraic equations (DAE) around a certain system equilibrium point:

$$\begin{cases} \Delta \dot{x} = A\,\Delta x + B\,\Delta u \\ \Delta y = C\,\Delta x + D\,\Delta u \end{cases} \tag{1}$$

where x is the state vector, y is the output vector, and u is the control vector. Each pair of complex conjugate eigenvalues of matrix A corresponds to an oscillation mode of the system. The matrix A can be further decomposed as:

$$A = \Phi \Lambda \Psi \tag{2}$$

where Λ represents the diagonal eigenvalue matrix, Φ and Ψ are the left and right eigenvector matrices. For the i^{th} oscillation mode with the following conjugate pair:

$$\lambda_i = \sigma_i \pm j\omega_i \tag{3}$$

The mode damping ratio (DR) can be calculated by:

$$DR_i = \frac{\sigma_i}{\sqrt{\sigma_i^{\,2} + \omega_i^{\,2}}} \tag{4}$$

The critical oscillation mode that is insufficiently damped should be closely monitored. Assume DR_{crit} is the damping ratio of the critical mode, the scheme shown in Fig. 1 is proposed for OSA:

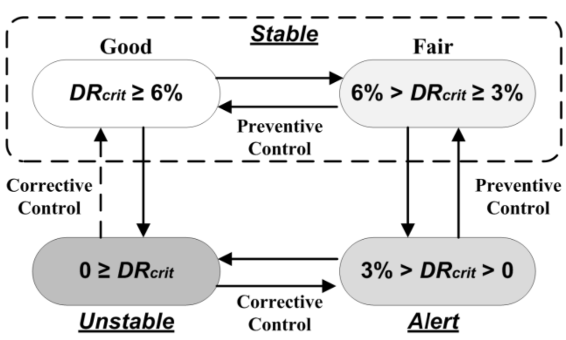


Fig. 1. Oscillatory stability assessment scheme

Three oscillatory stability states, namely *Stable* (including Good and Fair), *Alert* and *Unstable*, are defined according to the value of DR_{crit}. A classification tree (CT) is used to assign a system operating point (OP) into one of the above stability states, and a regression tree (RT) is used to predict the numerical value of DR_{crit}.

B. Voltage Stability Assessment (VSA)

Voltage instability occurs when the load attempts to step beyond the capability of the combined transmission and generation system, i.e. crosses the maximum deliverable power [2]. Various methodologies for voltage stability analysis have been proposed. Among them the Continuation Power Flow (CPF) method [14] is able to provide a reliable measure of how far the system can move away from its current OP and still remain secure.

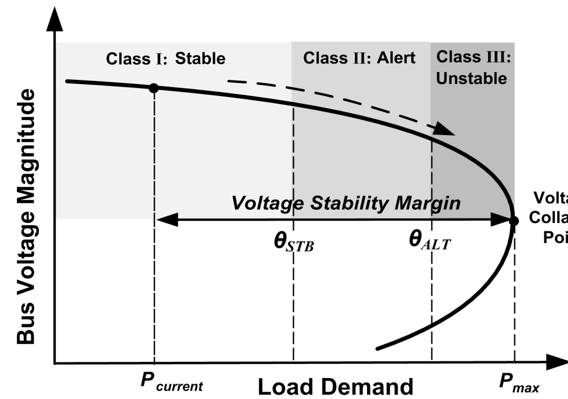


Fig. 2. Voltage stability assessment scheme

Assuming a constant load power factor, the variation of the voltage magnitude with the increase of load demand is plotted in Fig. 2. In this work the idea of CPF algorithm is explored, and the MW-distance from current OP to the critical voltage collapse point is used as the voltage stability indicator:

$$MW_{distance} = P_{max} - P_{current} \tag{5}$$

$$VS^{\,i}_{margin} = \frac{MW^{\,i}_{distance}}{P^{\,i}_{\max}} \times 100\,\% \tag{6}$$

where P_{max} is the maximum deliverable power, and $P_{current}$ is the active load demand of current OP. VS^{i}_{margin} represents the voltage stability margin of the i^{th} OP.

For the given voltage stability thresholds $\boldsymbol{\theta}_{\mathbf{STB}}$ and $\boldsymbol{\theta}_{\mathbf{ALT}}$ ($\boldsymbol{\theta}_{\mathbf{STB}} > \boldsymbol{\theta}_{\mathbf{ALT}}$), OPs will be labeled as 'Stable' as long as they satisfy $VS^{i}_{margin} \geq \boldsymbol{\theta}_{\mathbf{STB}}$; and 'Unstable' when $\boldsymbol{\theta}_{\mathbf{ALT}} \geq VS^{i}_{margin}$. The remaining OPs are labeled as 'Alert'.

C. Proposed DT-based Predictive Model

The relationship and difference between the conventional time-domain simulation approach and the DT method is shown in Fig. 3. Compared with the traditional method, the advantage of DT method lies in its capability of fast analysis facilitated by fewer required inputs and straightforward model structure. By learning the system behavior from a known set of OPs, the DT model can predict system responses without detailed model computations. In addition, the DT method is appealing because it uses a white-box model, which makes the results easy to interpret. Based on the combination of splitting rules along a path of the tree, preventive and corrective control strategies could be formulated.

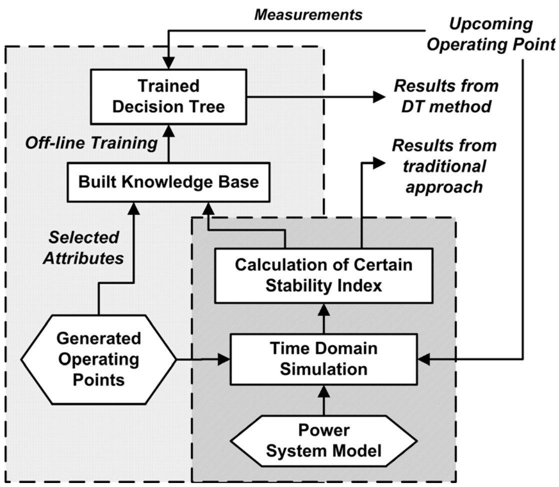


Fig. 3. Comparison between conventional approach and the DT method

III. Knowledge Base Generation

The knowledge base is a database used for off-line training of the DT-based predictive model. It is composed of a number of instances, and each instance represents a system operating point and is labeled with corresponding stability status. The larger the system is, the more attributes are needed to characterize the OP. These attributes comprise voltage and current phasors, active/reactive power flow, and some composite attributes.

Typically, the DT-based predictive model will gain more generalization power if a larger number of instances are included in the knowledge base. However the database generation process should be correctly designed, otherwise it will not capture sufficient information from the entire problem space.

It has been reported that both the oscillatory stability and voltage stability are closely related to the load/generation composition at a certain system snapshot, and their increase/decrease trends. Each load/generation combination corresponds with a different stability status. The change in the load demands and generation outputs can be described as:

$$P_G = P_G^0 + \Delta P_G \qquad Q_G = Q_G^0 + \Delta Q_G$$
$$P_L = P_L^0 + \Delta P_L \qquad Q_L = Q_L^0 + \Delta P_L \times Q_L^0 / P_L^0 \tag{7}$$

where P_G and Q_G are active/reactive power outputs of all non-slack bus generators, P_L and Q_L are vectors of active/reactive power delivered to the loads. The vectors ΔP_G, ΔQ_G, ΔP_L and ΔQ_L stand for the changes in power of system components. Superscript 0 represents the base case.

The power system analysis software PSS/E is used to solve load flow and derive system linearization at each specific OP. Python [15] and MATLAB are used to automate the PSS/E analysis process and label the OPs with stability status. The procedures for building the knowledge base are illustrated in Table I.

Step 6 of Table I is to check if the database is adequate. The following two stopping criteria need to be satisfied:

(a) Each generator/load/shunt should be varied at least 4 times ($u \geq 4$) and the total variation should be at least 30% of the base value ($u \times C_{G/L/S} \geq 30$). The goal is to capture the most system behavior from the problem space;

(b) The DT training and testing accuracy converges. Or an accuracy of at least 0.95 in training and 0.90 in testing is reached. Note that the accuracy of a classification tree is measured differently from that of a regression tree.

TABLE I
Procedures for Knowledge Base Generation

Steps	Description
1	Import system model data (*.raw).
2	Let u ($u \in N$) be the iteration index. Step change is $C_{G/L/S}$ %. Systematically vary the generation/load/shunt: a) Scale the generation at Bus i to: $P_{Gi} = P_{Gi}^0 (1 + u_i \times C_{Gi} \%)$ b) Scale the load at Bus j to: $P_{Lj} = P_{Lj}^0 (1 + u_j \times C_{Lj} \%)$ c) Scale the output of shunt capacitors at Bus k to: $Q_{Sk} = Q_{Sk}^0 (1 + u_k \times C_{Sk} \%)$
3	Solve the load flow at the new OP: $\{P_{G2}, ..., P_{Gi}, P_{L1}, ..., P_{Lj}, Q_{S1}, ..., Q_{Sk}\}$ If this OP is unsolvable, eliminate it from knowledge base.
4	Oscillatory Stability Assessment: Import model dynamic data (.dyr). Derive the *A* matrix and DR_{crit}. Classify the OP into one of the four stability states.
5	Voltage Stability Assessment: Python programming to derive the voltage collapse point via CPF-based method.
6	Check if sufficient OPs are generated. If not, back to Step 2.
7	Stop the generation. Export the computed attributes and stability label of each OP to the knowledge base.

The commercial software CART [16] is used to develop DTs for evaluation of oscillatory and voltage stability.

IV. Performance Examination of Classification Tree

Two test systems, namely the IEEE 3-machine 9-bus system [17] and IEEE 10-machine 39-bus system [18], are used to implement the proposed scheme. The knowledge base generated for these two systems are summarized in Table II.

TABLE II
Procedures for Knowledge Base Generation

System	Instances included in OSA Knowledge Base			Total
	Stable	Alert	Unstable	
9-Bus	**663 (61.90%)**	**358 (33.43%)**	**50 (4.67%)**	**1071**
39-Bus	**2549 (71.30%)**	**962 (26.91%)**	**64 (1.79%)**	**3575**
	Instances included in VSA Knowledge Base			
9-Bus	**707 (51.68%)**	**495 (36.18%)**	**166 (12.13%)**	**1368**
39-Bus	**2206 (60.21%)**	**1175 (32.07%)**	**283 (7.72%)**	**3664**

A. Adjustment of Priors and Selection of Attributes

From Table II the number of instances included in each class is highly unbalanced. Compared with some other data mining tools that do not perform well when dealing with unbalanced data, the classification tree integrated in CART has the strength to assure that every class will be treated equally regardless of its size. This is achieved by specifying the *Priors* for each class. In this work the *Prior* for the "Unstable" class has been adjusted to be slightly higher than that of other classes. The objective is to put more emphasis on the detection of unstable instances.

With respect to the input attributes of a decision tree, it is reported that different attribute combinations may result in different data mining accuracies [12]. In order to accelerate the prediction process, it is desirable to use the least number of attributes as DT inputs while keeping an acceptable level of overall prediction accuracy. Typically the input attributes are selected using engineering insight and empirical evidence.

In this work we consider the basic measurements from a Phasor Measurement Unit (PMU). The involved DT input attributes are as follows:

- VM_i and VA_i: positive sequence voltage magnitude and phase angle at Bus i;
- IM_i_j and IA_i_j: positive sequence current magnitude and phase angle from Bus i to Bus j.

B. Performance of Classification Tree

The theoretical background of developing a CT in CART can be found in [4]. Each of the above generated knowledge bases has been randomly split into two data sets: 80% of the instances are used as training set; the remaining 20% serve the purpose of independent testing. Due to the stochastic nature of the splitting process, slight differences may occur between the derived CTs and their performance. Therefore in this work, the process of knowledge base splitting, tree training and testing has been replicated at least 10 times until the mean value and standard deviation of new case testing accuracy become stable.

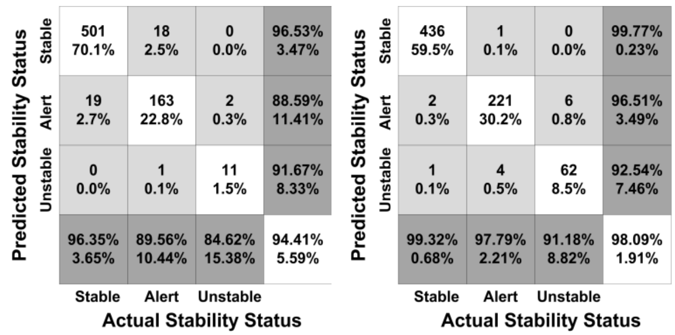
The *Entropy* method is adopted to grow the CTs in CART. The performance of CTs in new case testing is summarized in Table III.

TABLE III
PERFORMANCE OF THE CLASSIFICATION TREE

System	Method	Accuracy of New Case Testing	
		OSA	VSA
9-Bus	***Entropy***	**98.63%**	**99.56%**
39-Bus	***Entropy***	**94.38%**	**97.95%**

The CT new case testing results of one replication for the 39-bus system are shown in Fig. 4. An interesting observation from Table III and Fig. 4 is that the CT performance for OSA is less accurate than that of VSA. This is because the system oscillatory stability behavior is highly non-linear. In order to reach certain prediction accuracy, a larger training dataset is needed by OSA-CT compared with VSA-CT. In this work, more instances could be generated if we set the *Stopping Criterion (b)* with a higher accuracy requirement.

The classification tree can be developed using different methodologies, e.g. *Gini*, *Twoing*, and *Entropy* [16]. Another important setting is the minimum cases a parent node should have, which may impact the size of resulted CT. In this work the tree settings are varied to explore their impact on the assessment accuracy. The results are shown in Fig. 5.



a) Testing results of 39-bus OSA b) Testing results for 39-bus VSA

Fig. 4. CT stability assessment for the 39-bus system in one replication

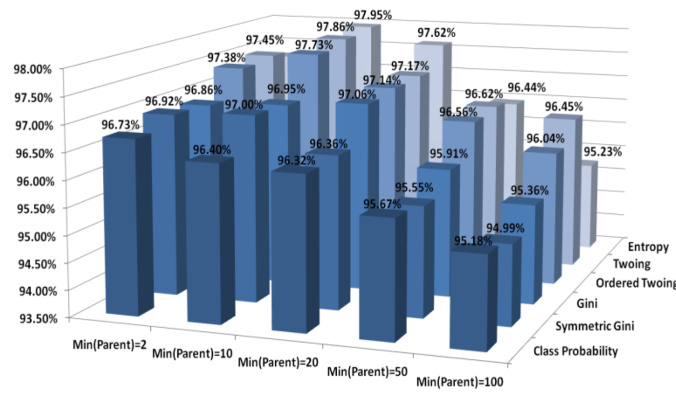


Fig. 5. Classification tree performance using different tree growing methods

Two conclusions could be made from Fig. 5: 1) the CT performance for the stability assessment problem is related to how the tree is developed. In this case the *Entropy* method achieved the best classification accuracy; 2) the setting for minimum parent node cases can alter the shape of the resulted tree as well as its performance. In general, the more cases a parent node is required to have, the less terminal nodes the derived CT may possess. This experiment demonstrated that there is a trade-off between tree complexity and accuracy. A large-sized tree may encounter the over-fitting problem, whereas a small-sized tree that is not adequately developed may produce less accurate classification results. A trial and comparison process is needed to find the best CT, and this can typically be accomplished by nested cross-validation.

V. PERFORMANCE EXAMINATION OF REGRESSION TREE

Compared with the CT-based classification model which groups an OP into one of several pre-defined stability categories, the RT-based predictive model provides operators with a quantification of how far the system is away from a possible instability event. This section examines the use of RT for fast prediction of stability margins (OSM and VSM), and compares its performance with other data mining tools.

A. Measures of Accuracy

In contrast with a CT for which the accuracy could be directly computed from the misclassification rate, the performance of a RT is measured through a statistical index, termed *Residuals Squared Error* (R^2). The accuracy of a RT model is reported as follows:

$$R^2 = 1 - \frac{\sum_{(x_i, y_i) \in TS} [y_i - d(x_i)]^2}{\sum_{TS} (y_i - \bar{y}_{root})^2} \quad (8)$$

where TS is the set of training samples, x_i is input, y_i is the actual stability margin, $d(x_i)$ is the RT predicted value, and $\bar{y}_{root}$ is the mean of y_i in the tree root node. The closer the R^2 is to 1, the better the RT prediction accuracy is.

If the typical difference between values predicted by RT and the actual stability margins is required, another measure, the *Root-Mean-Square* (RMS), is utilized:

$$RMS = \sqrt{\frac{\sum_{i=1}^{n} [y_i - d(x_i)]^2}{n}} \quad (9)$$

where n is the number of test instances. The value of RMS error depends on the base magnitude of the target stability margin to be predicted. In our proposed metric, a typical value of OSM is in the range of -1% to 10%, and the VSM is usually ranging from 0.05 to 1.0. Hence the RMS errors of VSM-RT are usually several times larger than that of the OSM-RTs.

B. Performance of Regression Tree

The previously generated instances are labeled with the numerical value of DR_{crit} or VS_{margin}. The way to develop a RT is slightly different from that of a CT. The RT growing, node splitting, tree pruning and optimal tree selection algorithms are detailed in [4] and [16].

Once the training is complete, the derived RTs were tested using the unseen instances. Much more emphasis should be put on the accuracy of unseen instance testing because, for real-time applications, a predictive model which cannot fit the unseen system behavior well is unacceptable. The training and testing accuracy is summarized in Table IV.

TABLE IV
PERFORMANCE OF THE REGRESSION TREES

System	OSM-RT			VSM-RT		
	Train R^2	Unseen OPs		Train R^2	Unseen OPs	
		R^2	RMS		R^2	RMS
9-bus	**0.9984**	**0.9858**	**0.0023**	**0.9928**	**0.9791**	**0.0184**
39-bus	**0.9617**	**0.9520**	**0.0034**	**0.9941**	**0.9694**	**0.0211**

The performances of differently sized OSM-RTs are summarized in the relative error curve shown in Fig. 6. Among these trees, a 13-node subtree pruned from the 45-node "optimal" tree is shown in Fig. 7(a), and the "Largest" tree with 465 nodes is shown in Fig. 7(b).

Compared with the optimal tree, numerical results show that although the 465-node tree has boosted the training accuracy from 0.9617 to 0.9872 R^2, its accuracy in new case testing actually dropped from 0.9520 to 0.9407 R^2. This is because an over-developed tree may perform well in training, but it will lose the generalization power in predicting unseen instances. The optimal tree with the lowest relative cost has the best generalization power and should be selected.

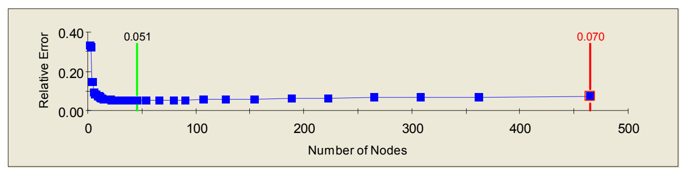
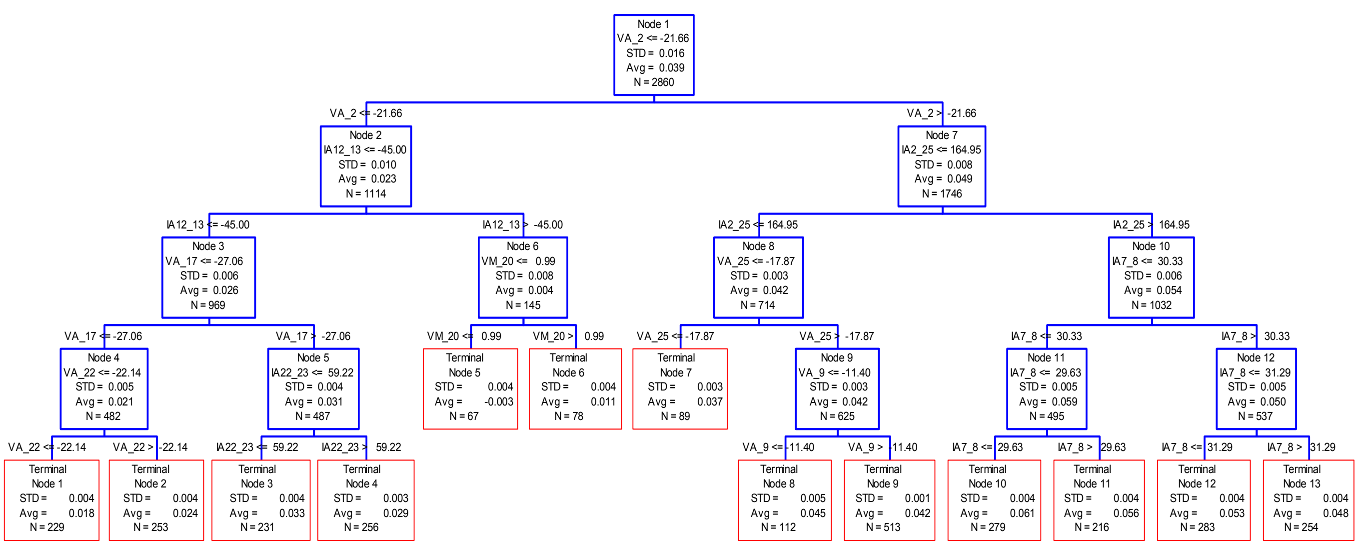


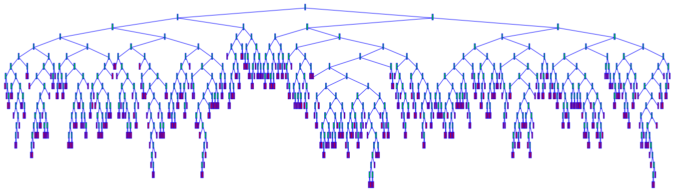
Fig. 6. Relative cost of a series of differently sized RTs

C. Comparison with Other Data Mining Tools

In this work the performance of RT has been compared with two widely used data mining tools: Support Vector Machine (SVM) [19] and Neural Network (NN) [20]. The R^2 accuracy of different data mining tools for the 39-bus system is summarized in Table V.



(a. 13-node tree pruned from the optimal OSM-RT)



(b. Largest RT with 465 terminal nodes)

Fig. 7. Regression trees for oscillatory stability margin prediction

TABLE V
NEW CASE TESTING ACCURACY USING DIFFERENT DATA MINING TOOLS FOR THE 39-BUS SYSTEM

Tools	Testing R^2 of OSM	Testing R^2 of VSM
RT	**0.9519**	**0.9694**
SVM	**0.9591**	**0.9811**
NN	**0.9579**	**0.9572**

According to the results, the RT-based model achieved almost identical prediction accuracy as other data mining tools. Compared with some "black-box" tools, the DT piece-wise structure as shown in Fig. 7(a) provides system operators with a clearer cause-effect relationship of how the system variables lead to the onset of an instability event. It is possible to identify the critical variables and thresholds that need to be analyzed to gain insight into the stability margin of a system.

VI. CONCLUSIONS

This paper explores the use of classification and regression trees for fast evaluation of oscillatory and voltage stability. The following conclusions were reached:

- Two reliable stability metrics have been deployed and several stability states were defined. They provide an accurate assessment of the stability status of each OP;
- A systematic methodology for knowledge base generation has been proposed. Stopping criteria were elaborated to assure a sufficient dataset for DT training. Encouraging results were obtained through performance examination using the generated knowledge base;
- The DT classification accuracy is related to how the tree is developed, and the setting for minimum parent node cases can alter the shape of the resulted tree as well as its performance;
- The optimal tree with the lowest relative cost has the best generalization power and should be selected. Compared with SVM and NN, almost identical prediction accuracy was achieved by using RT.

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