Online Estimation of Oscillatory Stability Using a Measurement-based Approach

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***Abstract*—Evaluation of oscillatory stability in power systems traditionally relies on model-based analysis. Recent interest has shifted towards the measurement-based techniques such as ringdown analyzers and mode meters. These approaches have limitations when noise is present in measurements or short windows of time-series data are analyzed, respectively. In this paper we show how to overcome these disadvantages by using decision trees to directly map synchrophasor measurements to one of four predefined stability states. The proposed approach is illustrated using synthetic data from simulations on an IEEE test system, and PMU measurements collected from field substations. Decision tree performance is compared to that of artificial neural networks and support vector machines. Results indicate that the proposed measurement-based approach complements the traditional model-based approach, enhancing situational awareness of control center operators in real time stability monitoring and control.**

***Index Terms*--Decision tree, electromechanical oscillation, PMU, power system stability, synchrophasor measurement**

I. Introduction

Power system oscillatory stability assessment is the task of monitoring the rotor angle synchronism of generators at different locations [1-2]. The recent trend in the electric power industry is to interconnect transmission lines linking small autonomous systems into large integrated systems, some of which span the entire continent. For example, in the United States and Canada generators which are located thousands of miles apart are operated simultaneously and synchronously. As a consequence inter-area electromechanical oscillations are becoming a more common occurrence. Since modern systems are optimally run near their stability threshold, the estimation of the distance of an operating point from instability region is critical for stable operation.

Traditional oscillatory stability assessment methods may not satisfy the online monitoring requirements because: 1) they are based on time-domain model simulations which are computationally intensive and time-consuming; 2) they use data collected from Supervisory Control and Data Acquisition (SCADA) systems, or state estimation functions, both of which are updated relatively infrequently.

With improved data acquisition technology, such as temporal synchronization of measurements at different locations, it may be possible to detect the onset of instability more accurately. The ability of synchrophasors to capture system-wide dynamics shows their potential in real-time system stability monitoring applications [3].

The advantages of a measurement-based approach include lower computational complexity, reduced knowledge requirements about system model parameters, and the potential to provide system stability assessment in real time. Most measurement-based approaches use appropriate signal processing or spectral analysis techniques to extract information from periodically collected power systems data. One such method is Prony analysis, which has been investigated by Kumaresan et al. in exponentially damped signal analysis [4-5], and later applied to power systems by Hauer et al. in oscillatory stability assessment [6-7]. Prony analysis is a powerful tool for mode parameter identification of electromechanical oscillations. However, if noise is present in measurements it performs poorly [5]. Another shortcoming of Prony's method is that it is only suitable for transient, or ringdown, data analysis, and cannot be applied to ambient data such that the system is excited by random load variations [8]. Therefore it is termed a ringdown analyzer that operates specifically on transient portion of a measured signal.

Alternatively, several mode meters, such as the Yule-Walker method [8], autoregressive moving average (AR/ARMA) model [9], and subspace estimation method [10-11], have been extensively studied in the past two decades in order to estimate mode parameters from both ambient data and transient data. While in previous efforts accurate estimation has been achieved for oscillation mode frequency, the problem of identifying mode damping, a more important task in terms of stability assessment, has not been satisfactorily resolved, although encouraging results were reported under certain test scenarios [6-12].

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In this paper, a data mining approach is used to estimate oscillatory stability in real time. The decision tree (DT) method proposed by Breiman et al. [13] is deployed to map system operating point at each moment to one of several pre-defined stability states. Compared to previous research [3] [14], the proposed approach casts the task as a multi-class classification problem, as detailed in Section III. In Section IV we show the results of the proposed method using the IEEE 39-bus test system. Finally, the data mining approach is evaluated on field PMU measurements from Salt River Project (SRP), a public electrical utility in Phoenix, Arizona, U.S.A.

II. Theoretical Background

A. Oscillatory Stability Assessment

Oscillatory stability is related to Hopf Bifurcation [1]. An instability event occurs when, following a small disturbance, the damping torques are insufficient to bring the system back to a steady-state operating condition, identical or close to the pre-disturbance condition.

Power system oscillations may be classified into four categories in terms of frequency: 1) speed governor band, from 0.01 to 0.15 Hz; 2) inter-area electromechanical band, from 0.15 to 1.2 Hz; 3) local electromechanical band, from 1.2 to 5 Hz; and 4) torsional dynamics band, from 5 to 15 Hz. This work focuses on the second category: the low-frequency inter-area oscillations.

B. Model-based Analysis

Traditionally, the stability of inter-area oscillations is evaluated through modal analysis of the system's non-linear differential algebraic equations (DAE) using detailed system model parameters [15],

$$\begin{cases} \dot{x} = f(x, y, u) \\ 0 = g(x, y, u) \end{cases}, \tag{1}$$

where x is the state vector, y is the output vector, and u is the control vector. A linearization of (1) will result in

$$\begin{cases} \Delta\dot{x} = A\Delta x + B\Delta u \\ \Delta y = C\Delta x + D\Delta u \end{cases}. \tag{2}$$

From modal analysis theory, each pair of complex conjugate eigenvalues of matrix A stands for an oscillation mode. For the i^{th} oscillation mode the following conjugate pair may be termed,

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

Then the mode's damping ratio (DR) is calculated as

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

The inter-area oscillation modes that carry significant amount of energy but with insufficient DR are critical among all modes and need to be closely monitored.

C. Mode Identification without System Model

In contrast to the model-based approach, the measurement-based approach does not require detailed system model information. Recent efforts take measurements from different locations during the same period of time, and identify oscillation mode parameters through signal processing techniques. The mode parameters that can be estimated include frequency, *f*, damping, σ, amplitude, *A*, and phase, θ, as shown in Fig. 1.

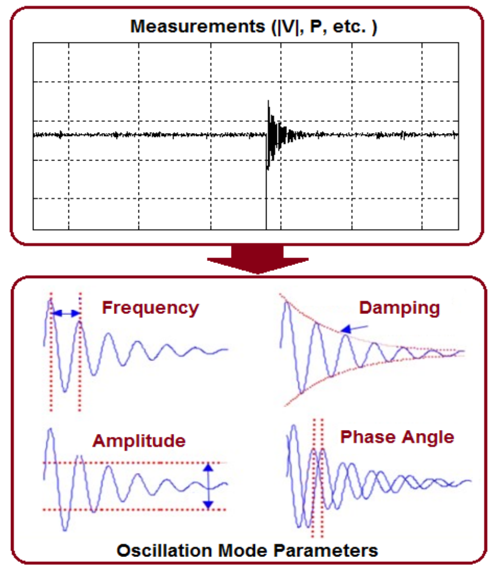

Figure 1. Mode parameters identified from power system measurements

There are three types of relevant power system measurements: ambient data, transient (ringdown) data, and probing data. Fig. 2 shows the ambient and ringdown measurements. The probing data is beyond the scope of this work and will not be discussed further. For ambient data an AR/ARMA model is used to derive mode parameters while Prony analysis is used for ringdown data.

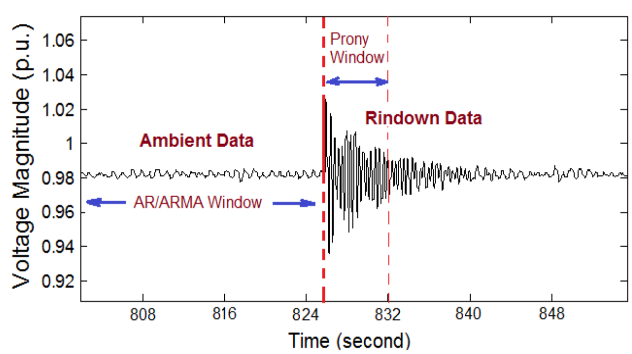

Figure 2. Model-based and measurement-based methods

D. Data Mining Approach

The DT algorithm has been used as a classification tool for online oscillatory stability estimation. The DT is created by sequentially splitting the training data set at each tree node, starting from the root. The node splitting rule is determined by searching all candidate attributes, and finding the split which gives the largest decrease in class impurity. A terminal node is reached when maximum purity has been achieved.

In the experimental section we compared results obtained using DTs with those obtained using artificial neural networks (ANNs) and support vector machines (SVMs). An ANN may be characterized by the number of neurons and the weights of connections between them. The SVM and its variants can make accurate predictions for non-linear problems in kernel space, and is resilient to the presence of noise in data.

Compared to ANNs and SVMs, the advantage of the DT method lies in the relatively simple model structure and fast analysis. The method is particularly appealing because the DT uses a more transparent model which makes the results easy to interpret and replicate. The OP is related to its stability state through a unique top-down path. The splitting rule at each node that belongs to a given path represents an operational threshold. Based on the combination of splitting rules along the path, preventive and corrective control strategies could be formulated and initiated.

In this work the commercial data mining software CART [16] is used to train the DTs. MATLAB [17] is used to implement the neural networks and support vector machines. Synchrophasors collected from Phasor Measurement Units (PMUs) are used as the input attributes to data mining tools.

III. Proposed Approach

A. Framework

A framework of the proposed measurement-based scheme is shown in Fig. 3. The model-based approach, which was investigated by the authors in [3] and [18], is also shown in the figure for comparison purposes.

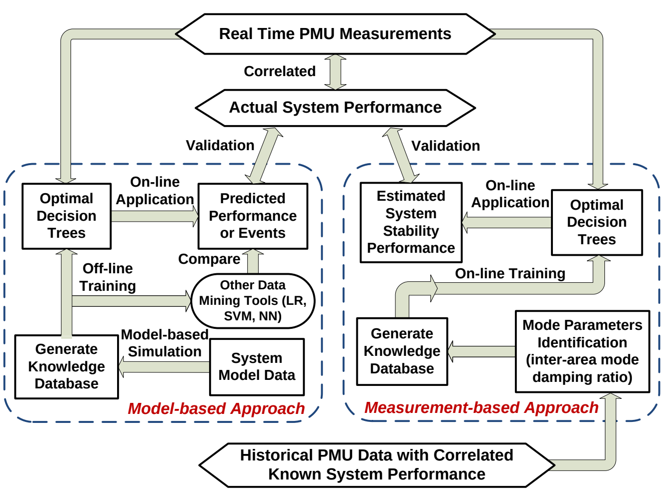

Figure 3. Model-based (left) and measurement-based (right) methods

For each power system, several stability thresholds are specified with respect to the typical damping ratio of the critical oscillation mode (DR_{crit}), and a set of stability states is defined accordingly. As shown in Fig. 4, for the given oscillatory stability thresholds θ_{STB} and θ_{ALT} ($\theta_{STB} > \theta_{ALT}$), operating points (OPs) will be labeled as ‘Good’ if they satisfy $DR_{crit} \geq \theta_{STB}$; “Fair” if they satisfy $\theta_{STB} > DR_{crit} \geq \theta_{ALT}$; “Alert” if they satisfy $\theta_{ALT} > DR_{crit} \geq 0$; and ‘Unstable’ when $0 > DR_{crit}$. In practice, the values of θ_{STB} and θ_{ALT} are usually around 10% and 5% respectively.

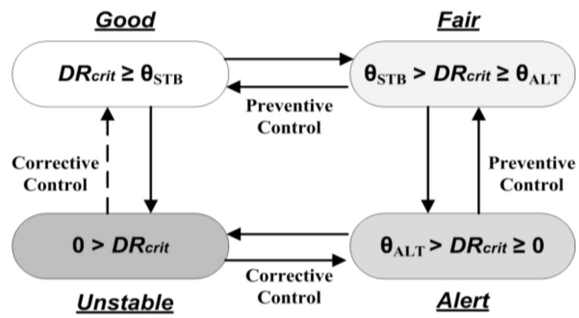

Figure 4. Classification of oscillatory stability states

B. Mode Parameter Identification

Fig. 5 illustrates the online application procedures of the proposed scheme. As the first step, a knowledge base needs to be created in order to train the classification tree. Included in the knowledge base are the input PMU measurements at each system operating point (OP), as well as the oscillatory stability state corresponding to each OP.

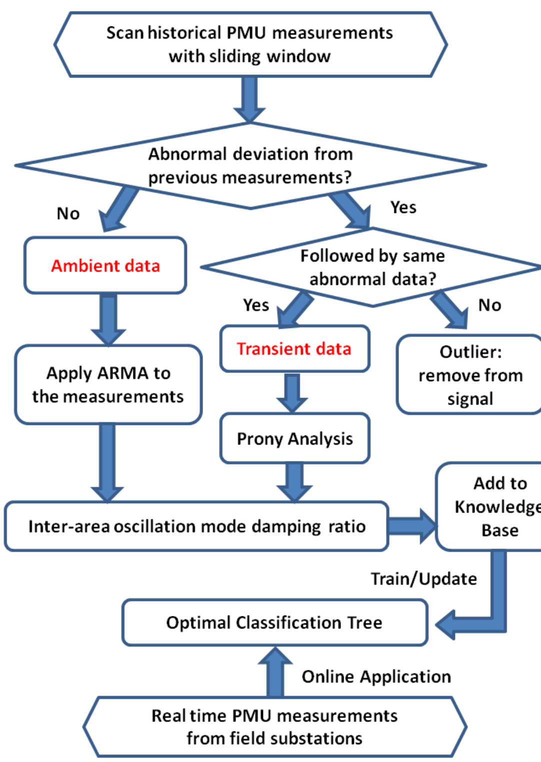

Figure 5. Online application of the proposed scheme

The procedure is initialized with a window scanning of the historical PMU measurements. An Oscillation Detector (OD) is designed to detect whether a transient event occurs by monitoring the presence of a sudden deviation in recorded measurements. If there are no abnormal changes, the OD suggests that the system is operated under a steady state, and an AR/ARMA model is employed to estimate the mode parameters in a sliding window manner. The required window length for ambient data analysis varies from 5 minutes to half an hour, depending on the variation level of system loads. If a sudden deviation is detected, but only limited to fewer than 5 data points, the corresponding measurements are considered outliers caused by sensor or communication error, and are discarded from consideration. If a continued deviation has been observed, the OD will report that a transient process is potentially occurring, and Prony analysis is applied to scan the transient data using a sliding window with a length of 5 to 10 seconds, depending on the critical mode frequency of the inter-area electromechanical oscillation.

C. *Classification Tree for Stability Assessment*

In order to overcome the limitations of Prony and ARMA methods, the ringdown data is pre-processed using a low-pass filter, and the window length of AR/ARMA model is sufficiently large to assure accurate estimation. Once a sufficient number of cases have been accumulated, the knowledge base is used to train the classification trees. The derived optimal DT is then applied online. As shown in Fig. 5, new PMU measurements are dropped down through the tree to predict the oscillatory stability status of each OP in real time.

One of the key challenges of embedding DTs in online applications is the problem of evolving system operating conditions. Due to variations in system generation and loading patterns, and changes in system topology, the DR_{crit} of inter-area electromechanical oscillations may also change. To deal with this eventuality, the classification tree derived in CART needs to be periodically refreshed in order to reflect the most current system operating conditions. This is done by updating the knowledge base using the most recent PMU measurements, and re-training the DT.

IV. CASE STUDY

The IEEE 10-machine 39-bus test system (New England system) [19] is used to implement the proposed scheme. Its one-line diagram is shown in Fig. 6. Firstly the oscillation mode parameters are estimated through model-based eigenvalue analysis. They will be used later to validate the results of the measurement-based approach.

The 39-bus system is modeled in MATLAB/SIMULINK. As shown in Fig. 7, the Network Solution Module initializes the time-domain simulation, calculates power flow, and provides real time network solutions using dynamic model parameters.

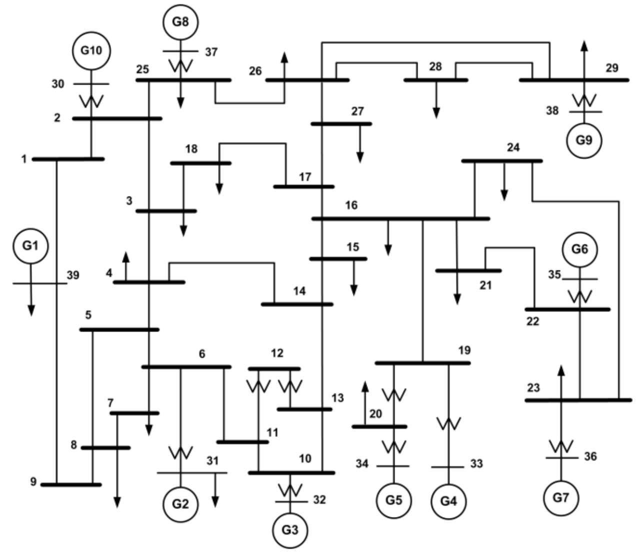

Figure 6. One-line diagram of IEEE 39-bus test system

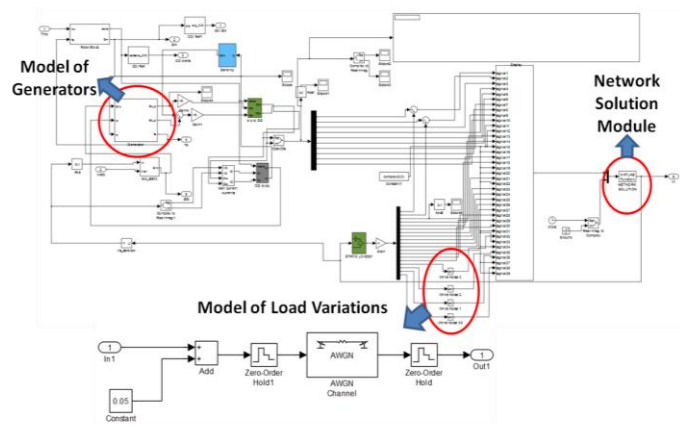

Figure 7. Simulink model of the IEEE 39-bus test system

The low-frequency oscillation modes with insufficient DRs are listed in Table I. They are obtained from model-based eigenvalue analysis of the IEEE 39-bus system. Also listed in this table are the dominant generators that participate in the correlated oscillation modes.

TABLE I. LOW-FREQUENCY OSCILLATION MODES OBTAINED FROM MODEL INITIALIZATION OF THE IEEE 39-BUS SYSTEM

	Mode #1	Mode #2	Mode #3	Mode #4	Mode #5
Frequency (Hz)	**1.21**	**1.13**	**1.03**	**0.96**	**0.58**
Damping Ratio (%)	**1.06**	**4.62**	**1.87**	**8.81**	**6.35**
Dominant Generator	**G1, G3**	**G4, G6**	**G3**	**G10**	**G2**

In this work the Mode #5 with a frequency of 0.58 Hz is targeted for monitoring. To simulate the load variations, Gaussian noise with Mean = 0.05 and Signal to Noise Ratio (SNR) = 20 dB has been introduced to four system loads. The time-domain simulation has been performed for 15 minutes. To create transient signal, a fault that caused the line between

Bus 26 and Bus 28 to trip has been simulated. The fault occurred at t = 700s, and lasted for 0.02s. The resulting measurements from all system buses are recorded. In particular, the voltage magnitudes and phase angles at Bus 7 and Bus 39 are shown in Fig. 8 and Fig. 9.

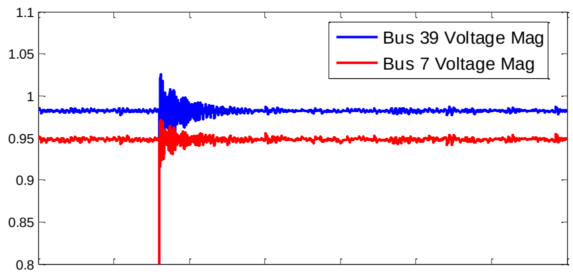

Figure 8. Voltage magnitude signals

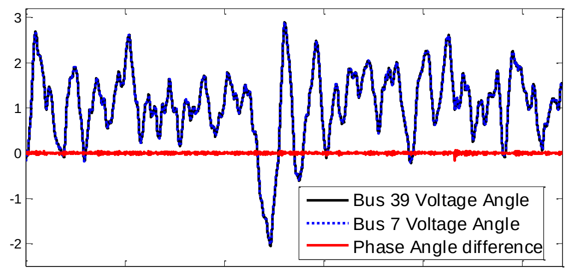

Figure 9. Phase angles and their difference

Prony analysis has been applied to the Bus 39 voltage magnitude signal during the transient process. The sliding window has a length of 5 seconds and the Prony model order is set to be N=30.

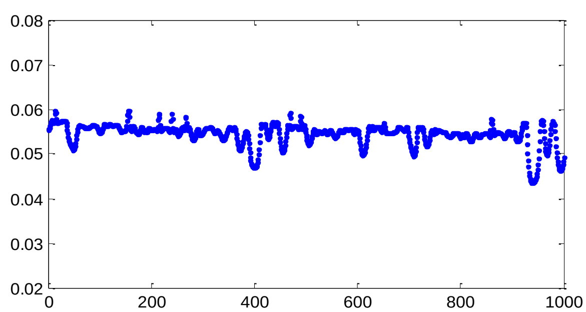

Figure 10. Damping ratios estimated from ambient measurements

TABLE II. ESTIMATE MODE #5 BY APPLYING AR TO AMBIENT DATA

	Order	Frequency (Hz)	Damping Ratio (%)
AR	***N*=30**	**0.5622**	**4.391**
	***N*=60**	**0.5819**	**5.637**
	***N*=90**	**0.5753**	**6.224**
Prony	***N*=30**	**0.5787**	**5.185**

The AR model has been applied to the phase angle difference between Bus 7 and Bus 39, which is shown in Fig. 9. The ambient data before the fault are treated using a sliding window with a length of 10 minutes. Different model orders have been deployed to compare the results. The mode damping ratios estimated by AR of order N=60 are drawn in Fig. 10. The Mean of the damping ratios estimated with different model orders have been summarized in Table II. Table II shows that the mode frequency estimated from AR and Prony are very close to the eigen-analysis results in Table I. The damping ratio estimated by AR is approaching the actual value when increasing the model order. The DR estimated by Prony analysis is different due to the change in system topology.

By varying the load disturbance level and fault scenario, the time-domain simulations have been replicated and a total of 4938 OPs with their corresponding stability states are included in the knowledge base. A classification tree has been developed in CART using 80% of the cases, and the rest 20% has been used in new case testing. The classification accuracy is evaluated as follows,

$$Accuracy = \frac{Number\ of\ Correct\ Prediction}{Total\ Number\ of\ Prediction}. \tag{5}$$

The DT accuracy is summarized in Table III. It is observed that an overall prediction accuracy as high as 98.38% has been achieved.

TABLE III. CLASSIFICATION TREE PERFORMANCE

	Good	Fair	Alert	Accuracy
Good	**610**	**8**	**2**	**0.9839**
Fair	**3**	**349**	**1**	**0.9887**
Alert	**0**	**2**	**13**	**0.8667**
Accuracy	**0.9951**	**0.9721**	**0.8125**	**0.9838**

V. APPLICATION TO FIELD PMU MEASUREMENTS

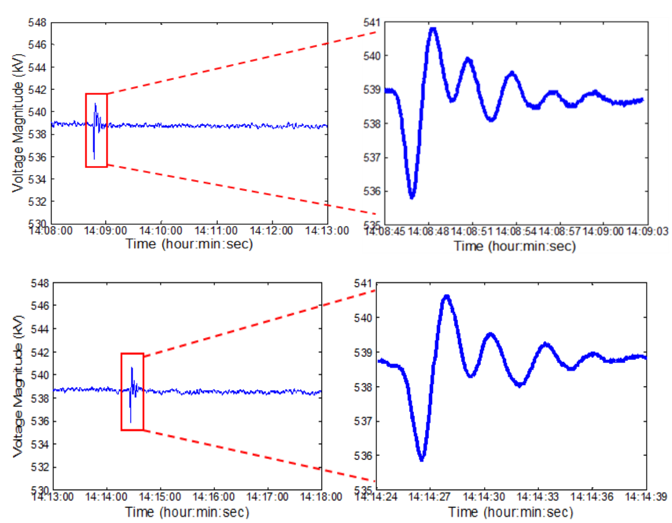

Figure 11. Field voltage magnitude measurements from PMUs

The field PMU measurements received from a public electrical utility in Phoenix, Arizona, U.S.A., the Salt River Project (SRP), have been used to evaluate the proposed scheme. The data include synchronized voltage and current phasor measurements, under both ambient and transient conditions. The transient data recorded two consecutive brake insertion applications at a major transmission substation. The voltage magnitude measured at another substation has been divided into two 5-minute signals as shown in Fig. 11. Each of the signals includes one transient process.

A knowledge base has been created by applying the same procedure introduced in Section IV to the field measurements from PMUs. The resulting DT performance has been summarized in Table IV. Two other data mining tools, the ANN and SVM, have also been used to compare the results.

From Table IV, the DT-based prediction model achieved similar accuracy to other data mining tools. Compared to black-box models, the DT provides a more transparent structure with a clearer cause-effect relationship. Its piece-wise structure and node splitting rules enable the identification of the critical variables and thresholds that should be analyzed to gain insight into the oscillatory stability of a system.

TABLE IV. RESULTS COMPARISON

Data Mining Tools	Misclassification Rate			Overall Accuracy
	Good	Fair	Alert	
DT	**0.0219**	**0.0667**	**0.0737**	**0.9739**
ANN	**0.0034**	**0.0902**	**0.1852**	**0.9873**
SVM	**0.0008**	**0.0738**	**0.0602**	**0.9940**

VI. CONCLUSIONS

The use of Decision Trees for online stability assessment without the knowledge of system model parameters has been investigated in this paper. Several conclusions have been reached:

- The proposed scheme is a measurement-based method that complements the traditional model-based approach. It is particularly useful when system model parameters are not readily available;
- The proposed approach is able to provide control center operators with real time support by making use of the quickly updated PMU measurements;
- Once trained using the knowledge base, the DT-based predictor can achieve high accuracy in online oscillatory stability estimation;
- The data mining tools are capable of reflecting the evolving system operating conditions when the most recent PMU measurements and corresponding knowledge base are used;
- With almost identical prediction accuracy, compared to ANNs and SVMs, the DT approach enables a more transparent model and provides engineering insight in support of the decision-making process.

ACKNOWLEDGMENTS

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