

Online Stability Assessment Scheme with Decision Tree for Power Systems with Renewable Generation

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Abstract: The fluctuation of renewable energy resources has significant impact on the stability of the power system with renewable generations and results in change in stability. Therefore, it is necessary to track the changing stability of the power system with renewable generations, a task that can be performed online. This paper details the use of decision trees to predict multi-mode damping of power system integrating renewable generations. Power systems with renewable source generation are complex with vast amounts of data being collected. Decision trees (DTs) are employed as a means to handle vast quantities of wide-area information, which involves the mode damping information indicating the stability. A 5-generator, 14-bus system with photovoltaic power generation and wind power generation is used as the test system. Remote signals obtained from phasor measurement units (PMUs) are employed as the input variables of DTs for predicting purposes. The simulation results demonstrate that the proposed predicting scheme is able to suggest the optimal course of action to remedy any near instability or unstable electromechanical oscillations even without prior knowledge of the varying output of the renewable source power.

Keywords: Decision trees (DTs), static VAr Compensator (SVC), thyristor controlled series capacitor (TCSC) and thyristor control phase shifter (TCPS).

I. INTRODUCTION

The power flow analysis also known as load-flow study is an importance tool involving numerical analysis applied to a power system. Unlike traditional circuit analysis, a power flow study usually uses simplified notation such as a one-line diagram and per-unit system, and focuses on various form of AC power (i.e: reactive, real and apparent) rather than voltage and current. The advantage in studying power flow analysis is in planning the future expansion of power systems as well as in determining the best operation of existing systems. Power flow analysis is being used for solving power flow problem by Newton-Raphson method. Load flow studies are used to ensure that electrical power transfer from generators to consumers through the grid system is stable, reliable and economic. Conventional techniques for solving the load flow problem are iterative, using the Newton-Raphson or the.

Load flow analysis forms an essential prerequisite for power system studies. Considerable research has already been carried out in the development of computer programs for load flow analysis of large power systems. However, these general purpose programs may encounter convergence difficulties when a radial distribution system with a large number of buses is to be solved and, hence, development of a special program for radial distribution studies becomes necessary. There are many solution techniques for load flow analysis. The solution procedures and formulations can be precise or approximate, with values adjusted or unadjusted, intended for either on-line or off-line application, and designed for either single-case or multiple-case applications. Since an engineer is always concerned with the cost of products and services, the

efficient optimum economic operation and planning of electric power generation system have always occupied an important position in the electric power industry. With large interconnection of the electric networks, the energy crisis in the world and continuous rise in prices, it is very essential to reduce the running charges of the electric energy. A saving in the operation of the system of a small percent represents a significant reduction in operating cost as well as in the quantities of fuel consumed. The classic problem is the economic load dispatch of generating systems to achieve minimum operating cost.

II. POWER SYSTEM STABILITY

A dynamic phenomenon in a power system is, as said above, initiated by a disturbance in the system. Such a disturbance could as an example be that a line impedance is changed due to an external cause. The behavior of the system after this disturbance depends of course on a how “large” this disturbance is. A small disturbance results usually in small transients in the system that is quickly damped out, while a larger disturbance will excite larger oscillations. We all have an intuitive feeling for what is meant with stability in this context.

Stability is associated with that the system oscillations decay and that the operation of the power systems can continue without any major impacts for any of the consumers. But, and this is very important, as the power system is a nonlinear system (this will be elaborated on later) system stability depends on the kind and magnitude of the disturbance. This distinguishes nonlinear systems

from linear systems that can be classified as stable or unstable independent of the disturbance, i.e. stability is a property of the linear system as such. As will be shown later, stability of a power system is strongly coupled to both the magnitude and character of the disturbance as well as to the initial operating point. Over the years many different definitions of power system stability have been proposed. The most recent one, which will be adopted in these lecture notes, was the result of a joint IEEE/CIGRE working group activity. The following definition is given: Definition: Power system stability is the ability of an electric power system, for a given initial operating condition, to regain a state of operating equilibrium after being subjected to a physical disturbance, with most system variables bounded so that practically the entire system remains intact.

III. CLASSIFICATION OF POWER SYSTEM STABILITY

(A) Rotor Angular or Synchronous Stability:

The total active electrical power fed into the power system by the generators is always equal to the active power consumed by the loads including the losses in the system. On the other hand, there is not always a similar balance between the loads and the power fed into the generators by the prime movers, e.g. the hydro and steam turbines. If such an imbalance develops, the rotating parts of the generators and other rotating machines will act as energy buffer, and the kinetic energy stored in these will decrease or increase as a result of the imbalance. Rotor angle stability refers to the ability of synchronous machines of a power system to remain in synchronism after a disturbance. If the disturbance is local and substantial, e.g. an earth fault close to a generator, the generator can fall out of step since it has been accelerated during the fault. As quite big currents will flow in the generator windings in such a case, it must be disconnected to avoid that it is damaged. Typical time scale for such instability to develop is a second to a couple of seconds.

This kind of instability is called transient instability and instability appears usually in form of aperiodic angular separation due to lack of synchronizing torque. This form of instability is also referred to as large-disturbance rotorangle instability. Small-disturbance (or small-signal) rotor angle stability is concerned with the ability of the power system to maintain synchronism under small disturbances. These disturbances are considered to be sufficiently small that linearization of the system equations is permissible for purposes of analysis. Usually small-disturbance rotor angle stability is associated with insufficient damping of oscillations.

(B) Frequency Stability:

A third variety of active power imbalance, which is different from the ones above, is when the imbalance is not local but global. In the preceding cases, the sum of active power in feed was enough but there was an imbalance locally. But if the total power fed into the system by the prime movers is less than what is consumed by the loads, including losses, this imbalance will

influence the frequency of the whole system. As explained above the kinetic energy stored in rotating parts of the synchronous machines, and other rotating electrical machines, will compensate for the imbalance resulting in a frequency deviation. If the imbalance is not too large the generators participating in the frequency control will regulate the active power input from their prime movers, and bring back the frequency deviation to acceptable values. If the imbalance is too large, the frequency deviation will be significant with possible serious consequences. Particularly thermal power plants are sensitive to large frequency drops of long durations, since detrimental oscillations could be excited in the turbines. As a last resort the generators are disconnected, making the situation even more serious. This type of instability is called frequency instability and the time scale could be from a few seconds up to several minutes. Since the involved mechanisms could be quite different, one often distinguishes between short-term and long-term frequency instability. In the latter, the control and protections characteristics of turbines, boilers, and reactors play important roles.

(C) Voltage Stability:

When it comes to reactive power balance the situation is not as clear and simple as concerning active power. There is always a balance between "produced" and "consumed" reactive power in every node of a network. This is in fact a direct consequence of Kirchhoff's first current law. When one talks about imbalance in this context we mean that the injected reactive power is such, normally too small, that the voltage in the node cannot be kept to acceptable values. (At low load the injected reactive power could be high resulting in a too high voltage, possibly higher than the equipment might be designed for. This is of course not desirable but it could usually be controlled in such a way that no instabilities develop.) When we talk about imbalance in this case we thus mean that the injected reactive power differs from the desired injected reactive power, needed to keep the desired voltage. If this imbalance gets too high, the voltages exceed the acceptable range. Reactive power is a more local quantity than active power since it cannot be transported as easily in power system where normally $X \gg R$. This explains why voltage problems often are local, and often only occur in part of the system.

When the imbalances (voltage problems) develop into instabilities these are called voltage instabilities or voltage collapses. In the latter case the instability develops into very low voltages in the system. In principle too high voltages can also occur at voltage instability. Low voltages arise at high load conditions, while high voltages are associated with low load conditions. Depending on the time scale the voltage instabilities are classified as short-term, a couple of seconds, or long-term, tens of seconds to minutes. The short-term voltage instability involves dynamics of fast acting components such as induction motors, electronically controlled loads, and HVDC converters, while the long-term voltage instability involves slower acting equipment such as tap-changing transformers, thermostatically controlled loads, and

generator current limiters. As for rotor angle stability one distinguishes between large-disturbance and small-disturbance voltage stability Connection between Instabilities and System Components.

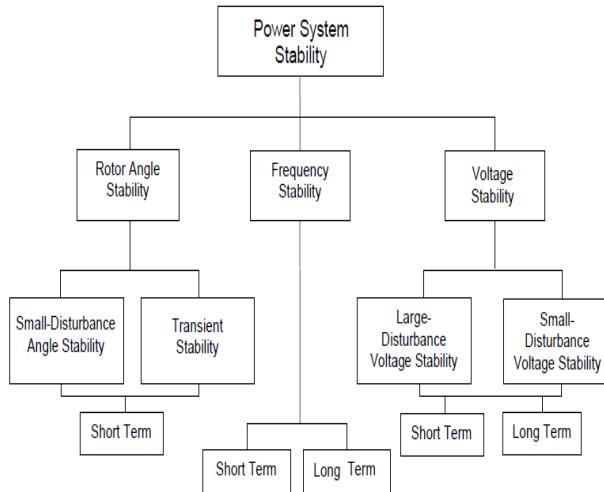


Figure 1.1 Classification of power system stability.

As explained above the generators, i.e. the synchronous machines, are very important in angular instabilities, and it is sometimes said that these are the driving force in this instability. A more detailed analysis shows that the loads are very often the driving force when it comes to voltage instability, which consequently sometimes is called load instability.

The classification above is based on simplified and ideal conditions in the system. In a real system these assumptions might not be valid. In real systems it is not seldom a combination of active and reactive power imbalances that trigger an instability. However, in many cases it is possible to identify which is the dominating process in the beginning of the instability.

During the course of the dynamics new consequential imbalances might occur, resulting in a combined angular and voltage instability in the final phase. There are examples of black outs in power systems that have started as slow voltage instabilities, which through low voltages have reduced the power transfer capability resulting in rotor angular instabilities causing the final collapse of the system.

On the other hand, rotor angular instabilities can cause generators to trip, which most systems are designed to cope with, but it can effect the reactive power balance in such a way that voltage instabilities can develop. The purpose of a classification is to define a structure for a complicated problem and thereby better understanding it. Furthermore it often helps to identify important and critical quantities, processes and components in the system.

Classifications of this kind should not be driven too far. Most important is always that useful and adequate results are obtained from realistic models of the power system.

IV. DECISION TREE BASED PREDICTION SCHEME

A. Decision Tree

A decision tree is a flowchart-like structure in which each internal node represents a “test” on an attribute (e.g., whether a coin flip comes up heads or tails); each branch represents the outcome of the test and each terminal node represents a class label (decision taken after computing all attributes). The paths from root to terminal node represent classification rules. Classification and regression tree [3] are non-parametric decision tree learning from a data set that produces either classification or regression trees. The classification tree is trained off-line and the regression tree is utilized online with real-time data. The branches of a decision tree end in a terminal node that denotes the different classes in which the data can be separated, with each observation getting mapped to its corresponding class. In this paper, each class represents the stability level, such as the mode damping of the power system. The basic design procedure involves five steps: 1) attribute selection, 2) data set generation, 3) tree growing, 4) tree pruning, and 5) performance evaluation.

B. Selection of Variables for Decision Tree

The guiding principle for the choice of variables is to select those system variables that are monitorable, controllable, and that adequately characterize an operating state of a power system from a classification point of view. C. M. Arora and Surana [4], [5] have shown that the real and reactive power generations of generators carry sufficient information about the class of system security.

Meanwhile, since the oscillations manifest the active power oscillation between coherencies Groups, the tie-line flows between groups are considered as options. When multiple modes exist in the power system, only one tie-line flow is not adequate for classification. Thus, multiple tie-line flows between groups are considered as options. In this paper, the tie-line flows are chosen according to observability with respect to the oscillation modes. Moreover, tie-line flows in this paper are calculated using the angle shift δ_{ik} and the voltages provided by PMUs in real time, as shown in (8)

$$P_{ik} = U_i U_k$$

$$P_{ik} = \frac{U_i U_k}{X_{ik}} \sin(\delta_i - \delta_k) = \frac{U_i U_k}{X_{ik}} \sin \delta_{ik}.$$

In (8), δ_i and U_i are the angle and voltage magnitude of bus, while δ_k and U_k are the angle and voltage magnitude of bus, respectively.

C. Damping Classes

It is beneficial to qualify what constitutes a major deterioration in damping. Table I provides an assessment of damping performance as provided by the National Electricity Marketing Management Company Australia [6]. Based on the criteria in Table I, a change in damping will be considered unacceptable and detrimental if

damping moves into the inadequate region (i.e., damping is worse than 0.07). The damping classes are used as the terminal nodes of a decision tree of each oscillation mode.

Table no. 1 qualitative reference to damping performance

Damping Ratio	Qualitative Description	Class
$\xi < 0$	Unstable	1
$0 < \xi < 0.05$	Very Inadequate	2
$0.05 < \xi < 0.07$	Inadequate	3
$0.07 < \xi < 0.139$	Marginally Inadequate	4
$0.139 < \xi < 0.2$	Acceptable	5
$\xi > 0.2$	Highly Acceptable	6

D. Tree Growing

The trajectory followed by the real power measurements corresponding to changes in the system parameters is used to predict the mode damping for stability assessment. Since a decision is being made based on a combination of the trajectories of different measurements, the Fisher's Linear Discriminant technique developed in [7] becomes a suitable choice for decision making. The distance from an optimally selected hyper-plane that is used for splitting two classes is given by

$$d = \left[h - \frac{(\mu_\alpha + \mu_\beta)}{2} \right] (\Sigma_\alpha + \Sigma_\beta)^{-1} (\mu_\alpha - \mu_\beta)^T.$$

In (9), d is the one-dimensional variable representing the distance to the hyper-plane that is sent to the classification tree for splitting purposes, h is the current operating point, α and β are the two classes, respectively. Σ_α and Σ_β are the covariance of the measurements of two classes α and β , respectively. μ_α and μ_β are the means of the measurements of two classes α and β , respectively. According to the sign of the distance d , h is identified to be in class α or β . For example, if d is positive, the current operating point is identified to be in damping class α , and if d is negative, the current operating point is identified to be in damping class β . In this paper, the negative distance makes sense. Then, the regression tree is performed to learn where the current operating power system is and the class in which the current mode damping is. A new distance variable d_0 from the current operating point h_0 is dropped down to the decision tree, and the decision suggesting the current operating point is made upon reaching a terminal node, representing the damping ratio class. Finally, the damping class is adaptively determined by the terminal node.

On doing so, the distances from each point to the hyperplane are then employed as the one-dimension input data for DT. For multiple measurements of multiple sampling points, the technique needs to be extended. Assume there exists damping classes, measurements for each damping class, and sampling points per second. Then, the original learning data set will be in an r dimensional space. Diverse disturbances around each sample are generated through a combination of output power of wind and PV

generation scaling. This idea of performing diverse disturbance is to model the disturbances for guaranteeing the reliability of the identification method. Simulations with subsequently increasing and decreasing output power of wind and PV generation are carried out.

If available, historical information of daily output power of wind and PV generation can further enhance the original data set. By extending the idea into two dimension space developed to higher dimensions, the original data set into k subspaces can be separated such that each subspace contains the measurements belonging to one damping class.

The hyper-planes that optimally partition the k damping class can then be expressed as $\pi_{12}; \pi_{13}; \dots; \pi_{ij}; \dots; \pi_{(k-1)k}$. The subscript of π_{ij} represent the i th and j th damping classes that partitioned optimally by the chosen hyper-plane. Due to Fisher's Linear Discriminant, the normal vector to the hyper-plane that maximizes separation of classes i and j is given by

$$m_{ij} = \frac{(\Sigma_i + \Sigma_j)^{-1}(\mu_i - \mu_j)^T}{\sqrt{(\mu_i - \mu_j)(\Sigma_i + \Sigma_j)^{-T}(\Sigma_i + \Sigma_j)^{-1}(\mu_i - \mu_j)^T}}, \quad (10)$$

where m_{ij} is $n \times 1$ unit normal vector of the hyper-plane. The distance between a point $h(h_1, h_2, \dots, h_i, \dots, h_{n \times r})$ and the hyper-plane can be calculated by the projection, which the vector $h - 1/2(\mu_i + \mu_j)$ projects on the unit normal vector m_{ij} given by (11).

$$d_{ij} = \left[h - \frac{1}{2}(\mu_i + \mu_j) \right] m_{ij}, \quad (11)$$

$$d = [d_{11} \dots d_{1r} \dots d_{r1} d_{21} \dots d_{2r} \dots \\ d_{ij} \dots d_{nj} \dots d_{nr}], (0 \leq i \leq n, 0 \leq j \leq r). \quad (12)$$

In this manner, the distance vector from one damping class to each hyper-plane is then calculated by (11) and (12).

The original set of data in higher dimension space is reduced to the distance vector to the hyper-planes, which is one dimension. With prior knowledge of the distances of the data points from a previously computed hyper-plane, a decision tree is built.

Then, regression is performed to learn where the current damping class is in the parameter space. A new distance vector d_0 from current damping class h_0 to the hyperplane α is dropped down the tree, and the decision to alter the current damping class is made upon reaching a terminal node. In this way, based on the PMU information trajectory in real time, DT is able to adaptively identify the current damping class.

It then can suggest the optimal course of action to remedy any near instability or unstable electromechanical oscillations without prior knowledge of varying output of the renewable source power.

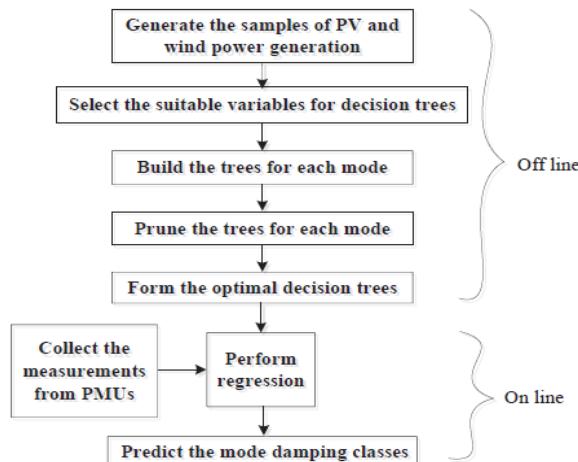


Fig. 1. Flowchart for DTs based on prediction scheme design procedure.

E. Tree Pruning

Pruning is the process of reducing a tree by turning some branch nodes into leaf nodes, and removing the leaf nodes under the original branch. Actually, pruning is basically an estimation problem. Since less reliable branches are removed, the pruned decision tree often gives better results over the whole instance space. Different pruning approaches use the testing data for pruning. However, pruning is necessary to improve the tree capability and reduce the error cost [3]. First, accuracy is computed by counting the misclassification at all tree nodes. Then, the tree is pruned by computing the estimates following the bottom-up approach (post-pruning). The cross validation estimation is computed next. The cross-validation estimate provides an estimate of the pruning level needed to achieve the best tree size. Finally, the best tree is the one that has a residual variance that is no more than one standard error above the minimum values along the cross-validation line.

F. DT Based Prediction Scheme Design Procedure

Fig. 1 gives a flowchart of DT based prediction scheme design procedure. It is explained as follows.

Step 1: Generate the samples according to the PDF of PV and wind power generation. The samples are used to generate the trajectories as training data to train a tree.

Step 2: Select the suitable variables for DTs based on the highest observability of each oscillation mode.

Step 3: Grow DTs for each mode using the class and regression tree as the algorithm

Step 4: Prune DTs by cross-validation estimation

Step 5: Form the optimum DTs for each mode.

Step 6: Collect the relative angles and calculate the real flowing in the tie-lines. Send these wide-area signals to the optimal trees to perform regression

signals to the optimal trees to perform regression.

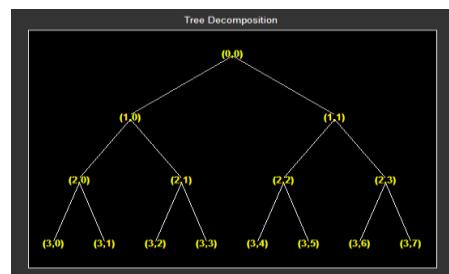
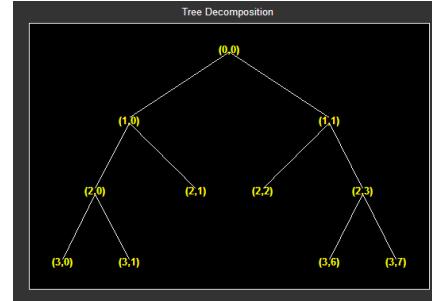
Step 7: Predict the corresponding damping classes of each mode, and suggest to system operators the optimal course of action to remedy any near instability or unstable oscillations

In this paper, the proposed method includes two stages, the off-line stage and the online stage. In the process of building the trees for each mode, Eigen analysis is used

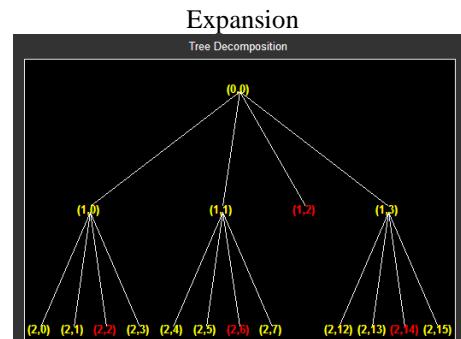
off-line, and the damping ratios with different samples of output power of wind and PV generation are classified to different damping classes in the first stage. In the second stage, the identification process, i.e., the regression is performed using wide area information to predict the mode damping classes online.

IV. DECISION TREE OUTPUTS

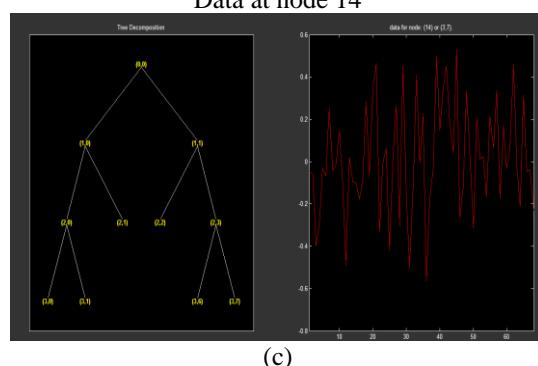
Tree decomposition



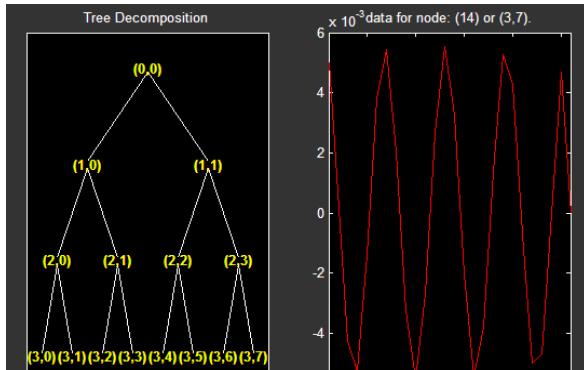
(a)



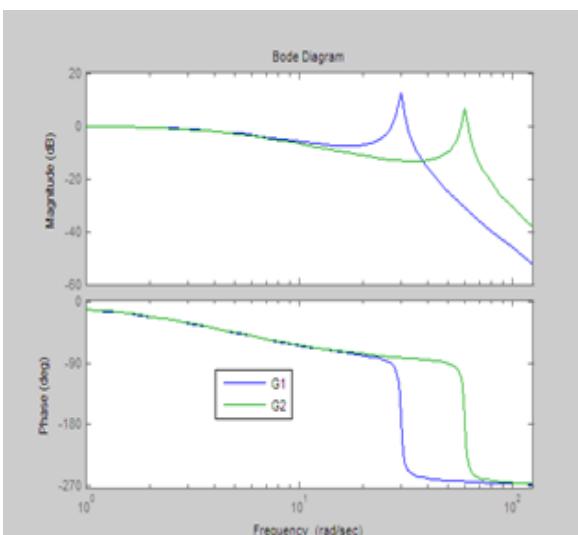
Fault detection from node Data at node 14



Node action result at node 14



(d)



(e) BODE result for generators 1 and 2 with frequency analysis

Fig 3 Decision Tree Output

- | | |
|-----------------------------------|----------------------------------------------------------------|
| (a) Tree Decomposition | (b) Expansion |
| (c) fault detection at node 14 | |
| (d) Node action result at node 14 | (e) BODE result for generators 1 and 2 with frequency analysis |

V. CONCLUSION

load flow analysis of Transmission Network has been consists of 17 total buses in which 3 buses are of 220kV and 14 buses are of 132kV. From 17 buses, 4 buses are generation buses and 13 are load buses. From the 4 generation buses, bus number 4 is considered as a slack bus. With the availability of fast and powerful digital computers all kinds of power system studies including load flow can now be carried out conveniently. For solving non-linear power flow equations for 17 buses Newton-Raphson iterative method by polar coordinates is used. Load flow solution using admittance method is obtained by programming in MATLAB. In this program we can change the parameters of the system active and reactive power outputs are displayed on computer screen. The results of the test system are studied. The load flow analysis is performed for normal load and the

corresponding voltage profiles are noted. The results of normal operation without contingency have compared with actual system data. The computer program provides information of the parameters such as line data, bus data, active and reactive power, generation limit, number of iterations of load flow, magnitude of voltage in per unit and its angle in degrees. Also, line flows in both the directions and real losses in the system are obtained. The maximum percentage error for active power shown in table I is observed at line 11-12 is 12.29%. It seems that this error is due to commercial losses. The maximum percentage error in reactive power (Q) observed at line 2-4 is 10.57%. It seems that it is due to low power factor. This can be minimized by adding static VAR compensator or synchronous condenser. The use of decision trees to predict multi-mode damping of a power system incorporating renewable energy sources generation with the help of WAMS has been proposed in this paper. Decision trees are employed as a means to handle vast quantities of wide-area information, which involves the mode damping information indicating the stability. DT is built off-line using the learning data and is regressed online for prediction purposes. The simulation results of 16-generator, 68-bus system added with PV and wind power generation demonstrate that the proposed stability prediction method can predict the damping class correctly using the wide-area information from PMUs, and also can suggest optimal course of action for operators to remedy any near instability or unstable electromechanical oscillations even without prior knowledge of varying output of the renewable energy source power.

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BIOGRAPHIES



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