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Effective Appraisal of Transient Stabiliy in a Multiple DG System Using Hybrid SVMDT

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Abstract

Power system is the major part in the energy and electrical engineering that comprises of electrical devices which performs the operation such as generation, transmission and consumption of electric power. In this methodology, the stability of the system is evaluated by using transient stability assessment (TSA). In most cases, disturbance occurs in the system which may leads to the unstable system condition and blackouts. The TSA feature is used here is to make the system back to its stable condition. The drawbacks of blackouts are avoided by introducing distributed generators which supplies power to the system, this process is known as islanding. The islanding feature are also comprises of certain drawbacks. These islanding drawbacks are overcome by using hybrid Support vector machine with Decision Tree (SVMDT) classifier with less detection time. The proposed method is implemented in MATLAB platform and the experiment result determines the performance and feasibility of the system

Keywords: - Transient Stability Assessment (TSA), Islanding, Distributed Generator (DG), Support vector machine with Decision Tree, Neural Network (NN).

INTRODUCTION

Nowadays generators contend to vend more power and customers endeavour to acquire the most economical energy. However, the transmission network contains only fixed capacity [1]. The major factors of power systems include: Load flow, Short circuit, Transient stability, optimal dispatch of generating units and optimal power flow [2]. Transient instability generally emerges as aperiodic angular separation owing to deficient synchronizing torque. If there is any riot, then fast recognition of the potentially hazardous conditions is very pivotal [3, 4]. Power system transient stability control is normally surrounded by a twofold problem. One is the assessment of severity of an instability and choice of an action capable to preserve it [5]**.**

To deal with the issue of transient stability assessment (TSA) there are some general methods like time-domain simulations, transient energy function (TEF) method, the extended equal area criterion (EEAC), artificial neural networks (ANNs) [6]. BCU method is proposed for direct analysis of power system transient stability [7]. To achieve highly prosperous prediction rate in actual-time, a novel class of fuzzy hyper rectangular composite neural networks is presented [8]. A faster Implicitly Decoupled PQ Integration technique is discussed to diminish the computing time. Two piecewise dynamic equivalents is utilized here [9]. Based on a Jacobian-free Newton-GMRES (m) method, this algorithm requires only exchanges of states of boundary buses among different regions [10].

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To draw away the high-speed of power system, a piecewise constant-current load equivalent (PCCLE) strategy is presented which makes use of synchronised phasor measurements [11]. The realistic-precision post-fault phasor measurements are used to develop a single tree based on short window employment strategy [12]. Here support vector machine (SVM) is applied to expose the suitability for TSA (Transient Stability Analysis) [13]. A multi-agent approach is proposed by two parts. The first is the prediction agent forecast the instability of power systems. The remaining multi-agent approach forecast system instability and establishes system stability [14]. This newly implemented system is actualized for calculating the transient stability margin in a normalized power system [15]. To augur online transient stability, a classical method does not sound better. So here the hybrid SVMDT approach is introduced to forecast the status of power system.

RELATED WORK

Francisco R. Gomez et.al [16] implemented a new algorithm for analyzing the status of transient stability condition by introducing large disturbance (fault) in the system. The sampled values from rotor angles, generator voltages or frequencies are collected by phasor measurement units (PMU) after fault clearance. Finally these values are used as inputs to a support vector machines (SVM) classifier in order to estimate the status of stability present in the system. The transient stability analysis algorithm along with the voltage magnitude measurement is used to test the robustness and accuracy of the system. The proposed algorithm is tested using 39-bus test system which predicts the stability of the system only when the transient instability approaches over 95% of success rate [16].

Meiyan Li et.al [17] developed a technique to forecast the transient stability of power systems because traditional methods for predicting do not work well for real-time stability predictions. Hence the Phasor Measurement Units (PMUs) is utilized to reduce the problem by providing information in real-time for transient stability analysis and improvement. However, these methods often require more than 300ms after the transient event begin to make consistent predictions. The phasor measurement unit is scheduled in certain locations in order to rapidly detect the transient stability status using trajectory of apparent impedance. From the simulations results, it was recognized that the stability of the system can be predicted in approximately 200ms [17].

Istemihan Genc et.al [18] proposed decision tree (DT)-based preventive and corrective control methods were proposed to enhance the dynamic security of power systems against the credible contingencies causing transient instabilities. The preventive control is achieved by using generator re-scheduling scheme where as the corrective control is carried out by load shedding method. These schemes are developed to calculate the space of approximate decision variables based on security regions and boundaries. The rules of DTs in generated databases are used to determine the boundaries and security regions. This work also involves improving the accuracy of security boundaries as well as the optimal solutions [18].

PROPOSED METHOD

Transient stability is referred as an essential subset of power system stability and plays a major role in planning and operation of power system. In order to prevent the problem of collaboration during severe disturbances like short circuits in the transmission line, the transient stability of the power system is evaluated by relating its values to the ability of the power system. Transient stability relies on both the initial operating state of the system and the severity of the disturbance. Predicting the status of the power system is based on the operating modes. If the status of system is unstable then islanding scheme is used. Consider if the system is unstable so in this case islanding must be detected to make the system stable. To estimate islanding accurately, three principle stages are performed which consolidate feature extraction, feature selection and classification. In this paper another strategy is introduced for effective assessment of islanding in classification phase known as hybrid SVMDT to abuse the benefits of both the classifiers.

The current and voltage signals are measured from the specific location of DG and taken as input to the processing unit for further processing such as feature extraction and classification. Feature selection is preferred in our work to reduce the computation or detection time during the prediction of islanding condition. And finally a classification is done by means of a novel effective classifier which results the output as islanding or non-islanding state based on the selected features.

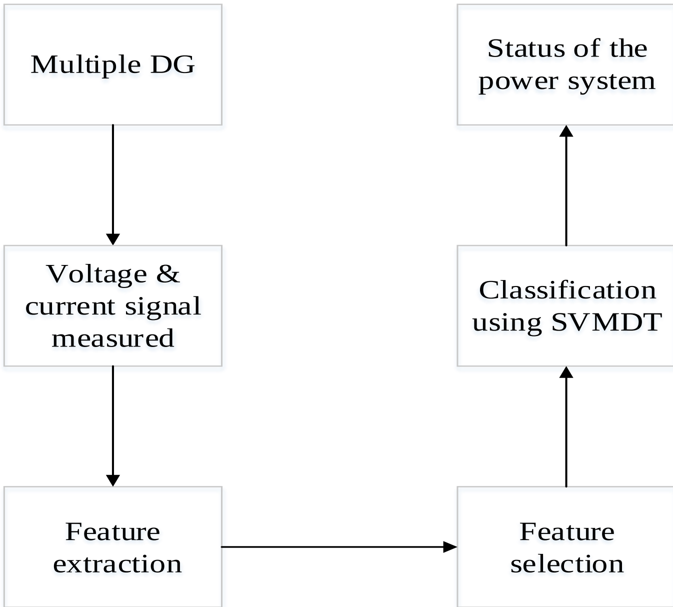

Figure 1: Process Flow Diagram for Transient Stability Assessment

Feature selection

Islanding detection in power system based on neural networks can be treated as a problem separating the stable class from the unstable class. In such a classification problem, the feature extraction and selection is the major task to be carried out. The separability-index of the input spaces is estimated while finding the ‘inconsistent cases. Here the separability-index is considered as a principle. The minimal and optimal subsets of initial feature sets are calculated using breadth-first searching methodology. In our proposed scheme this feature selection and reduction is done by the employment of neural networks.

Neural network

The assignment of feature selection of islanding detection is to select an "insignificant" or "ideal" subset of an underlying feature set given. The distinguishableness record is utilized as the criterion of feature selection. The feature space created by the at long last acquired ideal feature subset must have a detachability record esteem not littler than the first one. For an underlying feature set acquired, there might be atleast one insignificant subsets fulfilling the distinguishableness requirement. As we realize that, the BFS strategy finds the solution practically by investigating all nodes. If a state tree has restricted branches and layers, and a solution exists, the expansiveness first searching strategy can guarantee the solution. So the BFS strategy with minor modification of the searching process is a fitting apparatus for the feature selection undertaking. For the issue of feature selection of islanding detection, each node of the state-tree speaks to a feature subset of the underlying feature set. The root-node ND_0 communicates to the underlying feature set. A node ND_i on the tree is reached out by on the other hand. The successor is legitimate just if the detachability record created by the feature subset is more noteworthy than its parent mode; else, the successor is not lawful. The searching process is carried out until the Open List is an empty list. The general searching process of feature selection in islanding detection is the process of developing any node ND_i is shown in [19].

Classification using hybrid SVMDT

Classification is one of the main step in transient stability assessment because the overall accuracy relies on the output of the process. The classifier may result in misclassification due to training dataset, learning dataset and independent and dependent variables. This misclassification leads to increase the expense of the system as well as degrade the overall performance of the system. So a productive classifier should be utilized for the classification procedure. In existing strategies there are distinctive kinds of classifiers utilized for classification to furnish high precision just with more number of components. At the point when the quantities of components are decreased, the exactness gets dropped. So that, for productive and quick classification another strategy called hybrid SVMDT is proposed, which orders the sign as islanding or non-islanding. Figure 1 represents the overall process flow diagram of a proposed method

SVM

In certain large sized power system implementation, the representative sample sets must be generated in order to inbuilt the TSA and SVM into the system. The SVM classifier can learn to predict the transient stability status of the system using these training samples with required operating conditions for recognizing the existance of islanding condition. Inorder to calculate the accuracy of the of SVM classifier, these representative sample sets are very essential

(i) Generation of training and testing data

For the purpose of validating the proposed SVM for islanding detection, the IEEE 39-bus system has been considered in fig. 2. The IEEE 39 bus system is characterized by large block of generators as shown in [21]. The disturbances considered are three-phase to ground faults on three locations on each transmission line. The fault application time for each disturbances is ta= 0.1 s and four different types of fault clearing time t_{cla}/t_{clb} were taken as 0.15 s/0.2 s,0.17 s/0.22 s,0.35 s/0.4 s and 0.45 s/0.5 s. The calculation of transient stability index in terms of generator rotor angle is defined as,

$$\eta = 360^{\circ} - |\Delta\delta|_{\max} \tag{1}$$

Where $|\Delta\delta|_{\max}$ is the absolute value of the maximum angle of separation between any two generators during the period of post-disturbance.

Each simulation case in transient stability index calculation class label is assigned, for $\eta > 0$ the system is stable and the class label is assigned to "-1" otherwise the class label is assigned to "1"and the system is unstable

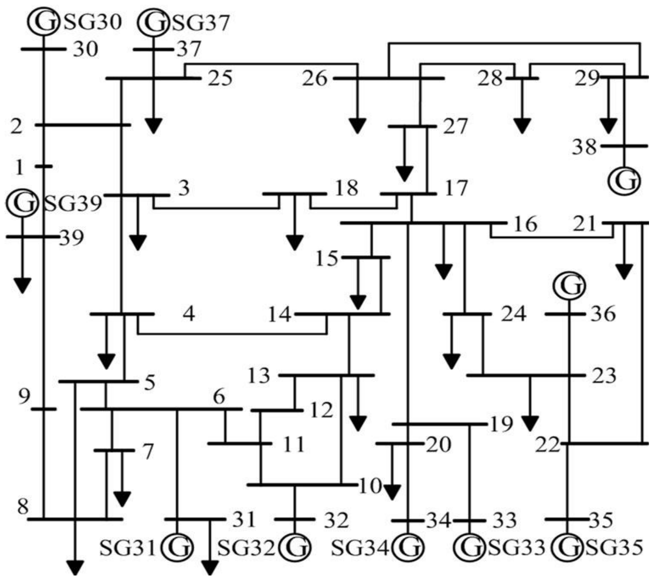

Figure 2: IEEE-39 bus system

(ii) Input/output variables

The input to the SVM classifiers are the variables of trajectories or combinatorial trajectories such as speed, magnitude of voltage, imbalance power, rotor angle, electromagnetic power etc. The status of the transient stability is obtained at the output of the SVM. Two schemes are developed in order to calculate the efficiency of the transient status with different inputs. The number of inputs N_{input} of schemes -1 and -2 can be calculated by Eq. (2) using the number of variables N_{var} and the time $T_{last}(ms)$ that the trajectories last post-disturbance.

$$N_{input} = N_{var} \times \left(T_{last} + 10\right) \quad (2)$$

Where $N_{var} = 1$ in scheme -1 and $N_{var} = 2 or 3$ in scheme -2, $T_{last} = 20 – 300$.

(iii) Transient stability status prediction scheme based on SVM

In this article the islanding condition is predicted by using SVM based binary classifiers, flow for these scheme [23]. The inputs of the classifier $x_i(k)$, are the sampled values of the predictor variable are sampled simultaneously using PMUs, while the output is the presence or absence of islanding condition. Trajectories of electromagnetic power and imbalance power can be calculated by Eqns. (3) & (4).

$$Pe_i = \mathrm{Im}\left(U_i * \dot{I}_i\right) \quad (3)$$

$$P_{imbi} = d\omega_i / dt \quad (4)$$

Where Pe_i is the electromagnetic power of generator *i* and P_{imbi} is the imbalance power of generator *i*.

(iv) Cross validation

The process of partitioning the database into learning set and training set is known as cross validation. Here k-number of data are partitioned with equal size hence called k-fold cross validation. For every different partition of data training and testing process is repeated. Finally, the expected prediction error is calculated from the overall average of errors. For various inputs, a fivefold cross validation was preferred.

Decision tree

In order to build the CART model, denote the target variable for case i by y_i, which takes the value of either 0 or 1. The objective is to construct a decision tree model from the training set. This decision tree comprises of three stages: (i) Tree growing, (ii) tree pruning, and (iii) optimal tree selection. The detailed explanation of these stages is stated as follows.

(i) Tree growing

Beginning from a root node, a feature, called the "splitting feature", is selected and a value for that feature, called the "splitting value", is selected to partition the training node into two subset child node, either internal or terminal will be the result of two child nodes. The internal child node becomes the parent node only on further splitting feature and the related splitting values are selected. This sequential splitting procedure eventually leads to terminal nodes called "leaf nodes". In this manner, the CART model is simple and transparent to interpret. Node impurity functions in (5) and (6) are defined in such a way to be maximized if the cases belonging to a node include an equal number of stable and unstable cases, making it difficult to classify the node as "stable" or "unstable" with any confidence. Based on the intuition above, two possibilities for the node impurity function are described, one of which is based on the Gini diversity index and the other on the Entropy function. In the context of this work, there are only two possible classes:

Stable (1) and unstable (0). Thus, denote the probability of stable cases corresponding to node z as $p(z) = \Pr(1/z)$. Based on the Gini diversity index at node z, the impurity function of the system is expressed as follows.

$$i(z) = 2p(z)\left(1 - p(z)\right) \quad (5)$$

Based on the entropy function for two classes, impurity function for node z, is expressed as follows.

$$i(z) = -p(z)\log p(z) - \left(1 - p(z)\right)\log\left(1 - p(z)\right) \quad (6)$$

(ii) Tree pruning

Let Z represent the classification tree obtained from the tree-growing process a node z' is a descendant of node z. A branch z_z of Z consists of the node z and all descendants of z, and branch z_z has z as its root node. Reducing a branch z_z from a tree Z consists of deleting, from Z, all descendants of z, while retaining node z, which becomes a leaf node of the pruned tree. Suppose z' is obtained from Z by successively pruning off branches, then $z'z$ is a pruned sub-tree of Z. The misclassification rate is to be estimated by "resubstituting estimate" denoted by $\rho(z)$, for a two-class data set, is expressed as

$$p(z) = \min\left(p(z), 1 - p(z)\right) \quad (7)$$

Where $p(z) = \Pr(1/z)$. Based on (7), the resubstituting estimate of the misclassification rate for Z is expressed as

$$\varsigma(Z) = \sum_{l=1}^{L(Z)} \rho\left(z_l\right)\pi\left(z_l\right) \quad (8)$$

(iii) Optimal tree selection

From the set of sub trees generated in the pruning procedure, namely $z * \left(\alpha_0\right), \ldots\ldots Z * \left(\alpha_M\right)$, the sub tree with the minimum misclassification rate is selected as the final CART model shown in [20].

HYBRID SVMDT FOR THE PREDICTION OF TRANSIENT STABILITY

Hybridization of SVM with DT classifier (SVMDT)

Speeding up SVMs in testing stage was finished by hybridize SVM with DT. So hybridization of SVM with DT gives better results with accuracy and speed and is called SVM based DT (SVMDT).Similarly hybridization of SVM with DT have few difficulties. As testing a data point in DT just incorporates course of action of sensible operations when appeared differently in relation to complex number juggling operations required by SVM. Testing an information point with SVM requires $O(MN_{svm})$ operations, where N_{svm} speaks to the quantity of support vectors and M speaks to the quantity of operations required in assessing the portion. In light of this hybridizing DT and SVM is done to get advantages of both learning methods.

In SVMDT a solitary twofold SVM is prepared once and is situated in a portion of the leaves of the DT. Given the way that accelerating SVM is conceivable by diminishing any of accompanying parameters: l_{test} or n or N_{svm}. The methodology we propose in this paper is an endeavour to lessen l_{test} with the assistance of choice trees. It could be seen that SVM identification limit is near the genuine choice limit while DT's limit is a rough one. A SVM decision function is expressed as follows.

$$f(x) = \sum_{i=1}^{N_{SVM}} \alpha_i \beta_{ii} k(x, X_i) + a \qquad (9)$$

Where $X_i \in R^n$ is a support vector, β_{ii} is a target of support vector, α_i represents Lagrangian multiplier, $a \in R$ is bias, N_{SVM} represents the number of support vectors, K represents the kernel function and $x \in R^n$ is the new data point to be tested.

CONCLUDING REMARKS

Performance Evaluation

Initially set the values for selected number of features *s* = 10 and k. the reliability, security and accuracy of the SVMDT-based ensemble classifier is calculated by selecting various SVMs. Figure 2 represents performance evaluation of the SVMDT-based ensemble classifiers using different numbers of features.

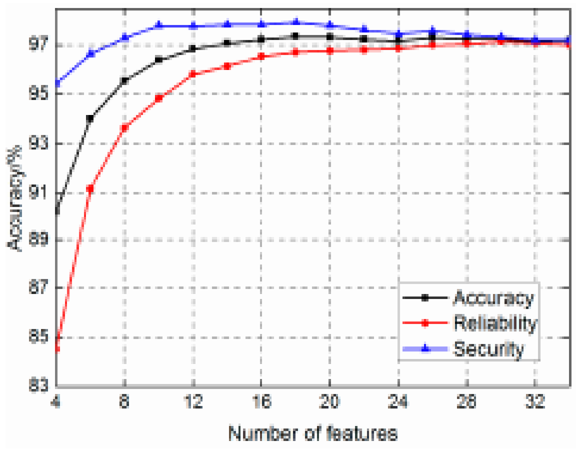

Figure 2. Prediction results of SVMDT-based ensemble classifiers using different numbers of features.

Confidence Evaluation

The "Confidence-Accuracy" graphs are used to calculate the confidence level of individual SVM and SVM-based ensemble classifiers. In figure 3, accuracy is plotted along vertical axis and the confidence level is plotted in horizontal axis. The below graph represents that the confidence-accuracy level of SVM based ensemble classifier is better when compared to individual SVM classifier.

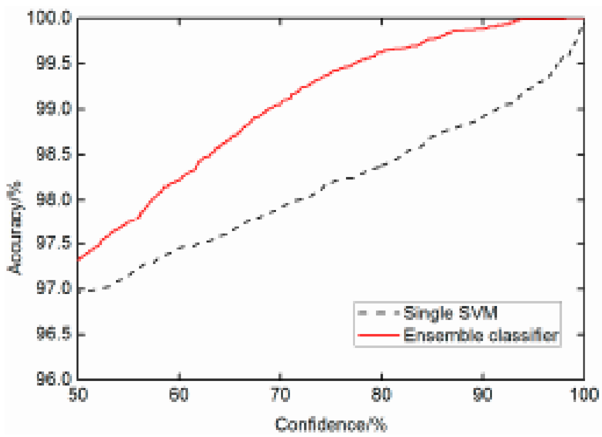

Figure 3: Prediction Results with Higher Confidence

In Figure 3, the horizontal axis is the confidence, e.g., CI = x. The vertical axis is the accuracy of the instances with CI _ x.

CONCLUSION

This paper presents a new TSA approach in distribution network inked with various DGs. Predicting the status of the transient stability is an essential feature in distributed systems.

So in this paper we have introduced a hybrid SVMDT for the prediction of status of power system. Hybrid approach is proposed here to vanquish the burdens of both SVM and DT classifier and to acquire exact classification result. Our proposed technique is employed to speedup SVMs in its testing stage for twofold classification undertakings by lessening the quantity of components by the employment of neural networks. By the utilization of these neural networks the ideal features are chosen from the quantity of separated elements. This makes the design simple and rate up the classification procedure. Likewise this hybrid approach prompts high accuracy with a predetermined number of components.

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