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Transient Stability Assessment in the Presence of STATCOM Using Combined Neural Network

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Abstract. In this paper we have tried to introduce a model for transient stability prediction of a power system with a Static Compensator (STATCOM) to add a contribution to the subject. For this reason we applied so called, Committee Neural Networks (CNNs) methods as tools for Transient Stability Assessment (TSA) of power system. Transient stability of a power system is first determined based on the generator relative rotor angles procured from time domain simulation outputs. Simulations were carried out on the IEEE 9-bus test system with STATCOM considering three phase faults on the system. The data collected from the time domain simulations are then used as inputs to the CNN in which CNN is used as a classifier to determine whether the power system is stable or unstable.

Keywords: Transient Stability Assessment (TSA), Committee Neural Networks (CNN), STATCOM.

1 Introduction

Recent development of power electronics introduces the use of FACTS devices in power systems. FACTS devices are capable of controlling the network condition in a very fast manner and this unique feature of FACTS devices can be exploited to improve the transient stability of a system. Reactive power compensation is an important issue in electrical power systems and shunt FACTS devices play an important role in controlling the reactive power flow to the power network and hence the system voltage fluctuations and transient stability [1]. STATCOM is member of FACTS family that is connected in shunt with the system. Even though the primary purpose of shunt FACTS devices is to support bus voltage by injecting (or absorbing) reactive power, they are also capable of improving the transient stability by increasing (decreasing) the power transfer capability when the machine angle increases (decreases), which is achieved by operating the shunt FACTS devices in capacitive (inductive) mode [2].

Methods normally employed to assess TSA are by using time domain simulation, direct and artificial intelligence methods. Time domain simulation method and direct method are considered most accurate but are time consuming and need heavy computational effort. In addition, the emergence of FACTS devices in power systems makes transient stability study more complex than before [3].

Presently, the use of artificial neural network (ANN) in TSA has gained a lot of interest among researchers due to its ability to do parallel data processing, high accuracy and fast response [9]. Transient stability evaluation usually focuses on the Critical Clearing Time (CCT) of the power system in response to a fault, defined as the maximum time after occurrence of disturbance, during which if the fault is cleared, the power system can save its transient stability [4–8]. The CCT is the maximum time duration that a fault may occur in power systems without failure in the system so as to recover to a steady state operation [4]. Some works have been carried out using the feed forward Multilayer Perceptrons (MLP) with back propagation learning algorithm to determine the CCT of power systems [10], the use of radial basis function networks to estimate the CCT [11]. Another method to assess power system transient stability using ANN is by means of classifying the system into either stable or unstable states for several contingencies applied to the system [10], [12]. A combined supervised and unsupervised learning for evaluating dynamic security of a power system based on the concept of stability margin [14] used ANN to map the

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operating condition of a power system based on a transient stability index which provides a measure of stability in power systems [15].

In this paper, a method for transient stability assessment power system in the Presence of STATCOM is proposed using committee neural network (CNN). The actions of transient stability assessment using CNN are explained and the performance of the CNN is compared with the PNN, RBF and the MLP so as to verify the effectiveness of the proposed method.

2. STATCOM

The STATCOM is based on a solid state synchronous voltage source which generates a balanced set of three sinusoidal voltages at the fundamental frequency with rapidly controllable amplitude and phase angle. The configuration of a STATCOM is shown in Fig. 1. Basically it consists of a voltage source converter (VSC), a coupling transformer and a dc capacitor. Control of reactive current and hence the susceptance presented to power system is possible by variation of the magnitude of output voltage (V_{VSC}) with respect to bus voltage (V_B) and thus operating the STATCOM in inductive region or capacitive region[3].

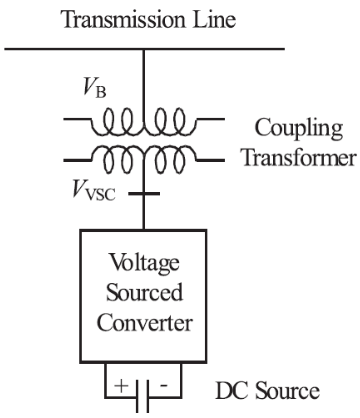

Fig. 1: configuration of a STATCOM

3. Mathematical Model of Multi-Machine Power System

The differential equations to be solved in power system stability analysis using the time domain simulation method are the nonlinear ordinary equations with known initial values. Using the classical model of machines, the dynamic behavior of an n-generator power system can be described by the following equations [3]:

$$M_i \frac{d^2\delta_i}{dt^2} = P_{mi} - P_{ei} \tag{1}$$

It is known that,

$$\frac{d\delta_i}{dt} = \omega_i \tag{2}$$

By substituting (2) in (1), therefore (1) becomes

$$M_i \frac{d\omega_i}{dt} = P_{mi} - P_{ei} \tag{3}$$

Where:

. M_i= moment of inertia of machine i

. P_{ei} = electrical power of machine i

. P_{mi} = mechanical power of machine i

. ω_i = rotor speed of machine i

. δ_i = rotor angle of machine i

A time domain simulation program can solve these equations through step-by-step integration by producing time response of all state variables.

4. Committee Neural Network:

A complex computational task is solved by dividing it into a number of computationally simple tasks and then combining the solutions to those tasks. In supervised learning, computational simplicity is achieved by distributing the learning task among a number of experts, which in turn divides the input space into a set of subspaces. The combination of experts is said to constitute a committee machine. Basically, it fuses knowledge acquired by experts to arrive at an overall decision that is supposedly superior to that attainable by any one of them acting alone. The idea of a committee machine may be traced back to Nilsson (1965); the network structure considered therein consisted of a layer of elementary perceptrons followed by a vote taking perceptron in the second layer. Committee machines are universal approximators. They may be classified into two major categories [18]:

4.1. Static structures

In this class of committee machines, the responses of several predictors (experts) are combined by means of a mechanism that does not involve the input signal, hence the designation "static." This category includes the following Methods: Ensemble averaging, where the outputs of different predictors are linearly combined to produce an overall output. Boosting where a weak learning algorithm is converted into one that achieves arbitrarily high accuracy.

4.2. Dynamic structures

In this second class of committee machines, the input signal is directly involved in actuating the mechanism that integrates the outputs of the individual experts into over all outputs, hence designation “dynamic”. [18] In this paper, we used from the Stacked Generalization that stood in type Static combiners trainable. Stacked generalization is a recursive form of learning ensemble which uses the predictions of a set of neural network and/or other traditional models to combine and feed into another set of models [19]. This process can be repeated many times and finally a prediction is produced for an unseen instance that is the result of a multi-level model combination process [20]. In stacked generalization, the output pattern of an ensemble of trained experts serves as an input to a second level expert.

5. Study Power System:

The implementation of ANN for TSA is illustrated through the Power Stability Test The IEEE 9-bus system with STATCOM [3,14,15]. The single line diagram of the test system is shown in Fig. 2. The system consists of three Type-2 synchronous generators with AVR Type-1, six transmission lines, three transformers and five loads. Also for compensation, a 100 MVA STATCOM is connected to bus 5. STATCOM as a parallel compensator is added to improve the system transient stability of the system.

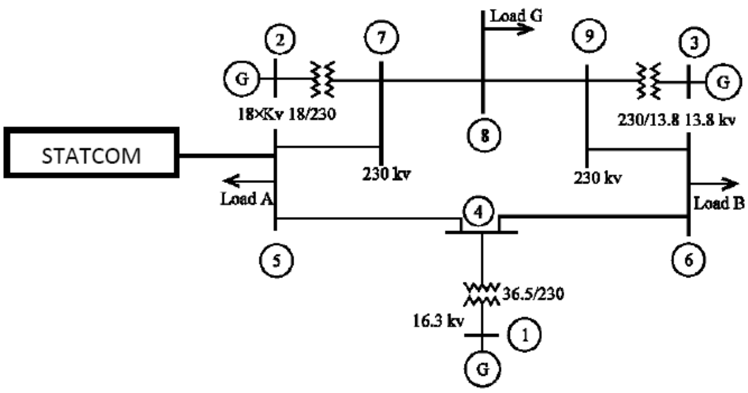

Figure 2.IEEE 9-bus system with STATCOM

Figure 3 schematically shows the effect of reactive power compensation using STATCON in power system transient stability when system encountered a three phase fault on bus 5.

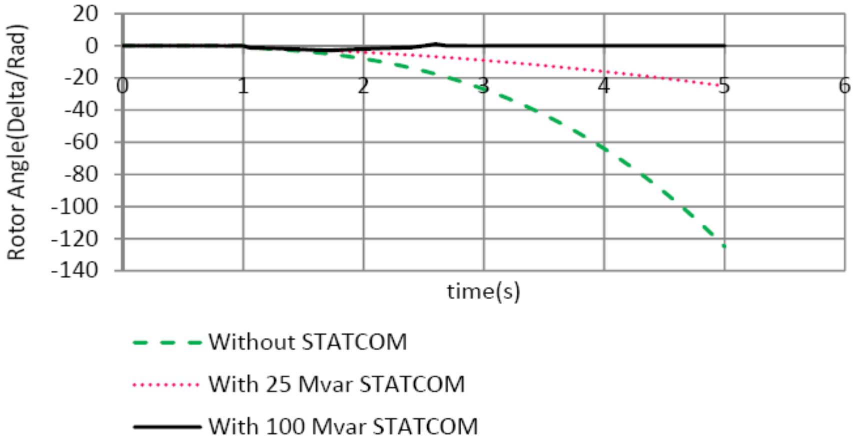

Figure3. Effect of reactive power compensation using STATCON in power system transient stability

6. Neural Network Model Development:

In this paper, we used from the Stacked Generalization that stood in type Static combiners trainable. Figure 4-the CNN (stacked generalization)- shows that first layer experts inputs are data training sets and outputs of first layer experts are inputs of second layer expert. Finally, output of the second layer expert of the CNN is a binary neuron that produces the classification decision. As for this work, the classification is either class 1 for stable cases or class 0 for unstable cases.

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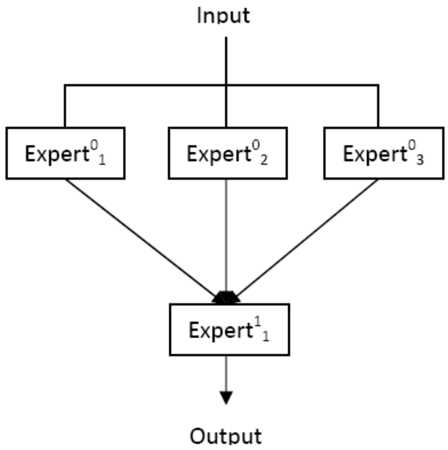

Fig. 4: The scheme of stacked generalization model

In first layer experts were used from 3 weakly networks that were 3 multi layer persreptrons (MLP) and in second layer the expert was used from one weakly network that is a MLP. Table 1 shows characteristics of the networks.

Table 1: Characteristics of the networks in first and second layers of the

Expert	Type	Number of neurons in hidden layer	Epochs
Expert 0-1	MLP	4	20
Expert 0-2	MLP	9	25
Expert0-3	MLP	8	20
Expert1-1	MLP	8	20

Performance of the developed CNN can be gauged by calculating the error of the actual and desired test data. Firstly, error is defined as,

$$E_n = |\,(\text{Desired output})_n - (\text{Actual output})_n\,| \qquad (5)$$

Where, n is the test data number. The desired output is the known output data used for testing the neural networks. Meanwhile, the actual output is the output obtained from testing on the trained networks. From equation (5), the percentage mean error, ME (%), can be obtained as:

$$ME(\%) = \sum_{n=1}^{N} \frac{E_n}{N} \times 100 \quad (6)$$

Where N is the total number of test data. The percentage classification error, CE (%), is given by,

$$CE(\%) = \frac{No.\ of\ Misclassified\ of\ the\ test\ data}{N} \times 100 \quad (7)$$

7. Data Preparation and Features Selection:

The IEEE 9-bus system with STATCOM topology is considered during preparing Input/output pattern. Time domain simulations considering several contingencies were carried out for the purpose of gathering the training data sets. Simulations were done by using the MATLAB-based PSAT software [16]. Time domain simulation method is chosen to assess the transient stability of a power system because it is the most accurate method compared to the direct method. In PSAT, power flow is used to initialize the states variable before commencing time domain simulation. The differential equations to be solved in transient stability analysis are nonlinear ordinary equations with known initial values. To solve these equations, the techniques available in PSAT are the Euler and trapezoidal rule techniques. In this work, the trapezoidal technique is used considering the fact that it is widely used for solving electro-mechanical differential algebraic equations [16]. A large number of input/output patterns are generated either from historical stored data or by perturbing both real and reactive loads randomly in a wide range of loading states. In this paper, input/output pattern is generated by randomly varying active and reactive loads at all load buses in the range from 50% to 125% of their base case operating point. The type of contingency considered is the three-phase balanced faults created at various locations in the system at any one time.

When a three phase fault occur at any line in the system, a breaker will operate and the respective line will be disconnected at the Fault Clearing Time (FCT) which is set by a user. The FCT is set randomly by considering whether the system is stable or unstable after a fault is cleared. According to [21], if the relative rotor angles with respect to the slack generator remain stable after a fault is cleared, it implies that FCT < CCT and the power system is said to be stable but if the relative angles go out of step after a fault is cleared, it means FCT >CCT and the system is unstable[5].

Twenty contingencies distributed in all system areas were selected based on CCT less than 400 milliseconds are considered as critical contingency set. For each operating point, PSAT software is used to get all the required data during simulation and calculate the corresponding CCT for the predefined set of critical contingencies. One hundred and thirty different operating points for each contingency are used in data preparation. There are 20 contingencies simulated on the IEEE 9-bus system with STATCOM and this gives a size of 20×130 or 2600 data sets collected.

Feature set is selected based on the knowledge of power system and the required target to be estimated. These features should be adequately characterizing all operating state of a power system from transient stability point of view and system topology changes. The proposed initial selected features in this paper are listed as follows in Table 2.

Table 2: Selected Feature Set

Name of Input Features	No. of Features
Relative rotor angle(δ_i-1)	2
Generator speed(ω_i)	3
Pgen & Qgen	6
Pline & Qline	12
Ptrans & Qtrans	6
$Q_{STATCOM}$	1
Total number of feature	30

9. Experimental Result:

The training input/output pattern is normalized, shuffled and divided with different random splits into training, testing and validation samples (60% for training, 20% for testing and 20% for validation). The performance of the TSA using the developed ANN is evaluated by calculating percentage mean error, ME(%), and percentage classification error, CE (%). Performance of the methods is compared in table 3.

Table 3: Performance comparison of methods

ANN Model	Number of Input Features	Mean Error (%) (ME (%))	Misclassification (%) (CE (%))
MLP	30	6.1	8.12
RBF	30	7.8	9.4
PNN	30	1.71	2.11
CNN	30	0.85	0.91

Table 3 shows for CNN testing results using the 30 input features, the total error of misclassification and the mean error are less than 1%. It shows very suitable performance of the proposed method over other reported methods. The error rate of the proposed method reached to 1%, which is a very demand improvement compared with other methods and can be used in TSA.

10. Conclusion:

The CNN developed in this work is used for classifying power system transient stability states in which the CNN classifies '1' for stable cases and '0' for unstable cases.

The use of CNN proposed for transient stability assessment of the 9-bus power system into either stable or unstable states for several three phase faults applied to the system. Time domain simulations were first carried out to generate training data for both neural networks and to visualizing the generator relative rotor angles. The

CNN was organized 3 weakly MLP networks in first layer experts and one weakly MLP network in second layer expert. Accordingly to table 3, the CNN network is then compared with the PNN,RBF and MLP so as to evaluate its effectiveness in transient stability assessment. The performance of CNN compared to PNN,RBF and MLP are better in terms of mean and misclassification errors.

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