An Improved Method in Transient Stability Assessment of a Power System Using Committee Neural Networks

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Summary

In this paper**,** a Committee Neural Networks (CNN) is proposed for transient stability prediction**.** 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 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. To verify the effectiveness of the proposed CNN method, it is compared with the Probabilistic Neural Networks (PNN) and the Multi Layer Perceptrons Neural Networks (MLP). Results show that the CNN gives more accurate transient stability assessment compared to the probabilistic neural network and multi layer perceptrons neural networks in terms of classification results.

Key words:
Transient Stability Assessment (TSA). Committee Neural Networks (CNN). Time domain simulation method. Artificial Neural Networks (ANN).

Introduction

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 [1-2]. Due to the complexity and vastness of this problem, it has been divided to smaller areas including rotor angle, frequency, and voltage stabilities. Rotor angle stability refers to the ability of synchronous machines of an interconnected power system to remain in synchronism after being subjected to a disturbance [1-2]. Rotor angle stability is divided to two subcategories: small signal and transient stabilities [2-4]. These valuations aim to assess the dynamic behavior of a power system in a fast and accurate way. Methods normally employed to assess TSA are by using time domain simulation, direct and artificial intelligence methods. Time domain simulation method is implemented by solving the state space differential equations of power networks and then determines transient stability. Direct methods such as the transient energy method determine transient stability without solving differential state space equations of power systems [5]. These two methods are considered most accurate but are time consuming and need heavy computational effort. 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 [6–8].

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]. ANN method based on fuzzy ARTMAP architecture is also used to analyze TSA of a power system [13]. 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 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 powerful manner for transient stability assessment of power systems 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 and the MLP so as to verify the effectiveness of the proposed method.

2. 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:

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

It is known that,

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

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

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

Where:

. δ_i = rotor angle of machine i

. ω_i = rotor speed of machine i

. P_{mi} = mechanical power of machine i

. P_{ei} = electrical power of machine i

. M_i = moment of inertia 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.

3. Committee Neural Network Theory:

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]:

3-1. 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.

3-2. 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.

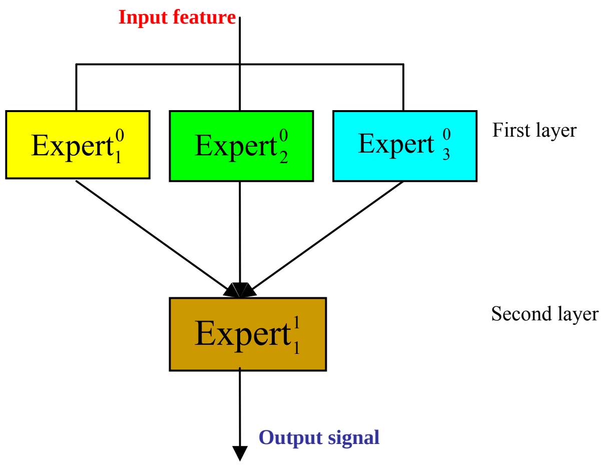


Fig. 1: The scheme of stacked generalization model

In this paper, 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 model

Expert	Type	Number of neurons in hidden layer	Epochs
Expert $_1^0$	MLP	4	20
Expert $_2^0$	MLP	9	25
Expert $_3^0$	MLP	8	20
Expert $_1^1$	MLP	8	20

Figure 1-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.

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

$$\textbf{\textit{Error}}, \textbf{\textit{E}}_n = \left|(\textbf{\textit{Desired}}\ \text{output})_n - (\textbf{\textit{Actual}}\ \text{output})_n\right| \quad (4)$$

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:

$$\text{Percentage of Mean Error, Me}(\%) = \sum_{n=1}^{N} \frac{E_n}{N} \times 100 \quad (5)$$

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

$$\text{CE}(\%) = \frac{\text{No of misclassfi ed of the test data}}{\text{N}} \times 100 \quad (6)$$

4. Methodology:

In the CNN method used for transient stability assessment, the IEEE 9-bus test system is used for verification of the method. Before the PNN implementation, 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]. 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].

Table 2: Input feature selected

Name of input features	No. of features
Relative rotor angles $(\delta_i - 1)$	2
Generator speed (ω_i)	3
Pgen & Qgen	6
Pline & Qline	12
Ptrans & Qtrans	6
Total number of feature	29

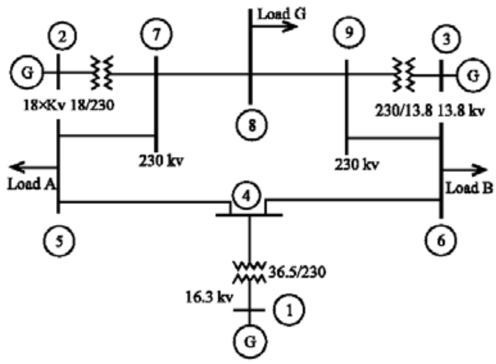


Fig. 2: IEEE 9 bus System

5. Transient Stability Simulation on the Test System:

Figure 2 shows the IEEE 9-bus system in which the data used for this work is obtained from [16]. The system consists of three Type-2 synchronous generators with AVR Type-1, six transmission lines, three transformers and three loads. Figure 4 shows examples of the time domain simulation results illustrating stable and unstable cases.
A three phase fault is said to occur at time t=1 second at bus 7. In Figure 3(a), the FCT is set at 1.083 second while in Figure 3(b) the FCT is set at 1.3 second.
Figure 3(a) shows that the relative rotor angles of the generators oscillates and the system is said to be stable whereas Figure 3(b) shows that the relative rotor angles of the generators go out of step after a fault is cleared and the system becomes unstable. It can be deduced from Figure 3 that the FCT setting is an important factor to determine the

stability of power systems. If FCT is set at a shorter time than the CCT of the line, the system is stable; otherwise the system will be unstable.

6. Data Preprocessing:

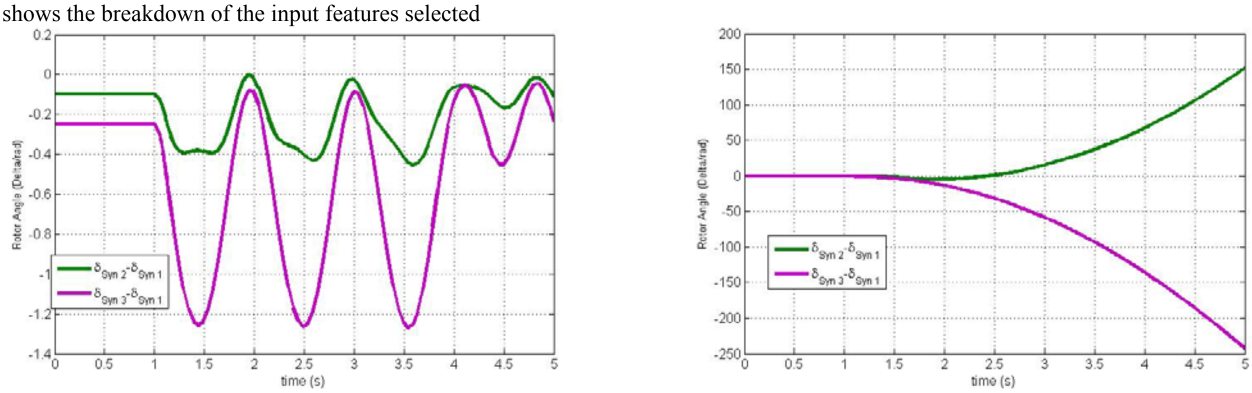
The simulation on the system for a fault at each line runs for five seconds at a time step Δt, set at 0.05sec. The fault is set to occur at one second from the beginning of the simulation. Data for each contingency is recorded in which one steady state data is taken before the fault occurs and 20 sampled data taken for one second duration after the fault occurs. There are 25 contingencies simulated on the system and this gives a size of 25×21 or 525 data collected. The collected data are further analyzed and trimmed down to 468 due to repetitions of data. The one steady state data taken before all faults occur are reduced to one only since the values will be the same for all faults. Next, the repetitions are due to the faults that occur on the same line. The FCT of the same line are set at four different times, two for stable cases and two for unstable cases. At the start of the fault, same values of data are recorded for all the four faults. A few milliseconds after the fault, the recorded data differ from each other due to different FCT settings. For the repetitions of data recorded, one data out of the four different FCT settings are kept. These data are denoted as data for stable cases. The data collected are normalized so that they have zero mean and unity variance.

Table3:The Committee NN Testing Results Using 29 Input Features

Test data	Desired output	C NN output	Test data	Desired output	C NN output	Test data	Desired output	C NN output
1	1	1	40	0	0	79	1	1
2	1	1	41	0	0	80	1	1
3	1	1	42	0	0	81	1	1
4	1	1	43	0	0	82	1	1
5	1	1	44	0	0	83	1	1
6	1	1	45	0	0	84	1	1
7	1	1	46	0	0	85	0	0
8	1	1	47	0	0	86	0	0
9	1	1	48	0	0	87	0	0
10	1	1	49	0	0	88	0	0
11	1	1	50	0	0	89	1	1
12	1	1	51	0	0	90	1	1
13	1	1	52	1	1	91	1	1
14	1	1	53	1	1	92	0	0
15	1	1	54	1	1	93	0	0
16	1	1	55	1	1	94	0	0
17	1	1	56	1	1	95	0	0
18	1	1	57	1	1	96	0	0
19	1	1	58	0	0	97	0	0
20	1	1	59	0	0	98	0	0
21	1	1	60	1	1	99	1	1
22	1	1	61	0	0	100	1	1
23	1	1	62	0	0	101	1	1
24	1	1	63	0	0	102	1	1
25	1	1	64	0	0	103	1	1
26	1	1	65	1	1	104	1	1
27	1	1	66	1	1	105	1	1
28	1	1	67	1	1	106	1	1
29	1	1	68	1	1	107	1	1
30	0	1	69	1	1	108	1	1
31	0	0	70	1	1	109	0	0
32	0	0	71	0	0	110	0	0
33	1	1	72	0	0	111	0	0
34	1	1	73	0	0	112	0	0
35	1	1	74	0	0	113	1	1
36	1	1	75	0	0	114	1	1
37	1	1	76	0	0	115	0	0
38	1	1	77	0	0	116	0	0
39	1	1	78	0	0	117	0	0

6.1 Input Features Selection: The selection of input features is an important factor to be considered in the ANN implementation. The input features selected for this work are relative rotor angles (δ_{i-1}), motor speed (ω_i), generated real and reactive powers (P_{gen}, Q_{gen}), real and reactive power flows on transmission line (P_{line}, Q_{line}) and the transformer powers (P_{trans}, Q_{trans}). Overall there are 29 input features to the ANN. Table

1 shows the breakdown of the input features selected



(a) (b)

Fig 3: Relative rotor angle bents of generators for a) stable and b) unstable cases

Table 4: Comparisons of the presented method with the related

Model	CNN	PNN[4]	MLPNN[4]
Number of input features	29	29	29
Mean error	0.0085	0.0171	0.06
misclassification	1(0.85%)	2 (1.71%)	13 (11.1%)

for the neural network. Out of the (468) data collected from simulations, a quarter of the data which is (117) data are randomly selected for testing and the remaining (351) data are selected for training the neural networks.

7. Test Results:

In this section, the results obtained from the CNN for transient stability assessment are presented. Initially, the CNN results using 29 input features are given and discussed.

Table 5: The expert conditions of the first CNN layer

Expert	**Expert** $^0_1$	**Expert** $^0_2$	**Expert** $^0_3$
Mean error	0.0453	0.0253	0.0251
misclassification	6(5.13 %)	4 (3.42%)	4 (3.42%)

7.1 The Experts Results for Transient Stability Assessment:

The architecture of the expert_i^0 $(i = 1,2,3)$ is such that it has 29 input neurons representing the 29 input features and the architecture of the expert_1^1 is such it has 3 input neurons representing the 3 experts in the first layer CNN. The training algorithm used for these experts are the back propagation algorithm. Each expert is one hidden layer of tangent sigmoid transfer function and a single output neuron of standard log sigmoid transfer function. Learning rate of each expert in all training phases was 0.9.

From the Table 5, the calculated mean error of expert_1^0 is (4.53%), for expert_2^0 is (2.53%) and for expert_3^0 is (2.51%). Some of the expert_i^0 $(i = 1,2,3)$ outputs are not accurate 0 or 1but in the range 0 to 1. If the expert_i^0 is in the range 0.9 to 1, it will indicate that the system is stable whereas if the expert_i^0 output is in the range of 0 to 0.1, it means that the system is unstable. The response of all the expert_i^0 case 30 from table 3 are wrong.

7.2 CNN Results for Transient Stability Assessment:

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. According to [4], the architecture of the PNN is such that it has 29 input neurons, the hidden layer neurons equal the number of training data which is 351 and with a single output neuron. Table 4 shows the CNN testing results using the 29 input features. From the table 3; 68 data from test set is stable and 49 data from test set is unstable. Alone one data is bad response; thus, the total error of misclassification and the mean error are both (0.85%).The PNN and the MLPNN results for Transient Stability Assessment bones [4], [8].

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 wonky MLP network in second layer expert. Accordingly to table 4, the CNN network is then compared with the PNN and MLP so as to evaluate its effectiveness in transient stability assessment. The performance of CNN compared to PNN and MLP are better in term of mean and misclassification errors.

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