Transient Stability Assessment of a Power System by Mixture of Experts

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Abstract

Recent blackouts in different countries have illustrated the very importance and vital need of more frequent and thorough power system stability. Therefore transient stability investigation on power system have became in focus of many researchers in the field. We have tried to introduce a new model for transient stability prediction of a power system 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. We use the "Mixture of Experts" (ME) in which, the problem space is divided into several subspaces for the experts, and then the outputs of experts are combined by a gating network to form the final output. In this paper Mixture of the Experts (ME) is used to assess the transient stability of power system after faults occur on transmission lines. Simulations were carried out on the IEEE 9-bus and IEEE 14-bus tests systems considering three phase faults on the systems. The data collected from the time domain simulations are then used as inputs to the ME in which is used as a classifier to determine whether the power systems are stable or unstable.

Keywords: Transient Stability Assessment, Committee Neural Networks, Mixture of the Experts, Time domain simulation method.

1. INTRODUCTION

This paper presents a novel method of using a neural network to predict transient stability. The security assessment of a power system requires analysis of the dynamic system behavior under a prescribed set of events known as contingencies. Conventionally this is done by simulating the system nonlinear equations. Since the stability limits cannot be determined from a single simulation. More than one simulation is required. The large size of the system adds to the complexity [1-3]. This method consists of simulating during and post-fault behaviors of the system for a given disturbance, observing its electromechanical angular swings during a few seconds. It is usually used to estimate stability status and to provide detailed operation information of the faulted systems as a benchmark. However, the simulation method is infeasible for on-line TSA mainly due to its time-consuming computation [2].

Problem of transient stability prediction has been treated by the flowing methods such as application of numerical routines or state space techniques [4,5], decision trees [6] , fuzzy neural networks [7,8], Multi Layer Perceptrons (MLPs) neural networks [3,9], radial base function neural networks[10-12], Probabilistic Neural Network (PNN) [13]. In a accordance to [2, 3] we proposed use of Committee Neural Networks (CNNs) for TSA.

By predicting transient stability status of power system, proper control actions can be taken. For instance, use can be made of this prediction to initiate important relay operations such as out-of-step blocking and tripping, or other control actions such as fast-valve control of turbines, dynamic braking, superconducting magnetic energy storage system, system switching, modulation of high voltage direct current (HVDC) link power flow and load shedding [6,7]. Moreover, by means of these predictions, the system planners can identify weak points of their power system (from transient stability viewpoint) for future developments [2].

N. Amjadi et al. in [2] uses non-trainable static combiners CNNs. They proposed a new hybrid intelligent system for transient stability of power system. In this method interpreter combine the response of neural networks in a voting procedure to determine the transient stability by status of the power system. The initiative work [3] we use stacked generalization model that it is trainable static combiners in CNNs. In this paper, we return our keen focus to dynamic combiners by the employment of mixture of experts. The result is a powerful and reliable method for transient stability assessment of power systems.

The actions of transient stability assessment using ME are explained and the performance of the CNNs is more efficient comparing with the stacked generalization model and the MLPs.

2. Mathematical Model of Multi-machine Power System

These 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:

It is known that,

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

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

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. Mixture of Experts

Mixture of experts is the most famous method in the category of dynamic structures of classifier combining, in which the input signal is directly involved in actuating the mechanism that integrates the outputs of the individual experts into an overall output [16].

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. Committee machines are universal approximations. They may be classified into two major categories:

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.

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 an overall output, hence the designation “dynamic”. Here we mention two kinds of dynamic structures:

- Mixture of experts, in which the individual responses of the experts are nonlinearly combined by means of a single gating network.
- Hierarchical mixture of experts, in which the individual responses of the experts are nonlinearly combined by means of several gating networks arranged in a hierarchical fashion [14].

In this paper we used mixture of experts by a single gating network that shows in fig 1.The first model’s network architecture is the well-known “mixture of experts” (ME) network.

The ME network contains a population of simple linear classifiers (the “experts”) whose outputs are mixed by a “gating” network [15].

In a revised version of “mixture of experts” model, to improve the performance of the expert networks, we use MLPs instead of linear networks or experts in Fig.1. The application of MLPs in the structure of expert networks calls for a revision in the learning algorithm. In order to match the gating and expert networks, the learning algorithm is corrected by using an estimation of the posterior probability of the generation of the desired output by each expert. Using this new learning method, the MLP expert networks’ weights are updated on the basis of those estimations and this procedure is repeated for the training data set. It should be mentioned that we do not use the notation of [15 & 16] to formulize the learning rules of the modified ME, but we follow the one which is described of [12], since it’s clear explanation of learning rules makes its extension easier for our purpose (the learning algorithm of the mixture structure with linear classifiers as experts is described in [16]).

Each expert is an MLP network with one hidden layer that computes an output O_i as a function of the input stimuli vector, x, and a set of weights of hidden and output layers and a sigmoid activation function. We assume that each expert specializes in a different area of the input space. The gating network assigns a weight g_i to each of the experts’ outputs, O_i. The gating network determines the g_i as a function of the input vector x and a set of parameters such as weights of its hidden and output layers and a sigmoid activation function [16]. The g_i can be interpreted as estimates of the prior probability that expert g_i can generate the desired output y. The gating network is composed of two layers: the first layer is an MLP network, and the second layer is a soft max nonlinear operator. Thus, the gating network computers O_g, which is the output of the MLP layer of the gating network, then applies the soft max function to get:

$$g_i = \frac{\exp(O_{gi})}{\sum_{j=1}^{N}\exp(O_{ji})} \qquad i=1,2,3,\ldots,N \qquad (4)$$

Where N is the number of expert networks. So the g_i is nonnegative and sum to 1. The final mixed output of the entire network is:

$$O_T = \sum_i O_i g_i \qquad i=1,2,3,\ldots,N \qquad (5)$$

The weights of MLPs are learned using the error back-propagation, BP, algorithm. For each expert i and the gating network, the weights are updated according to the following equations:

$$\Delta w_y = \eta_g h_i (y - O_i)(O_i(1 - O_i))O_{hi}^T \qquad (6)$$

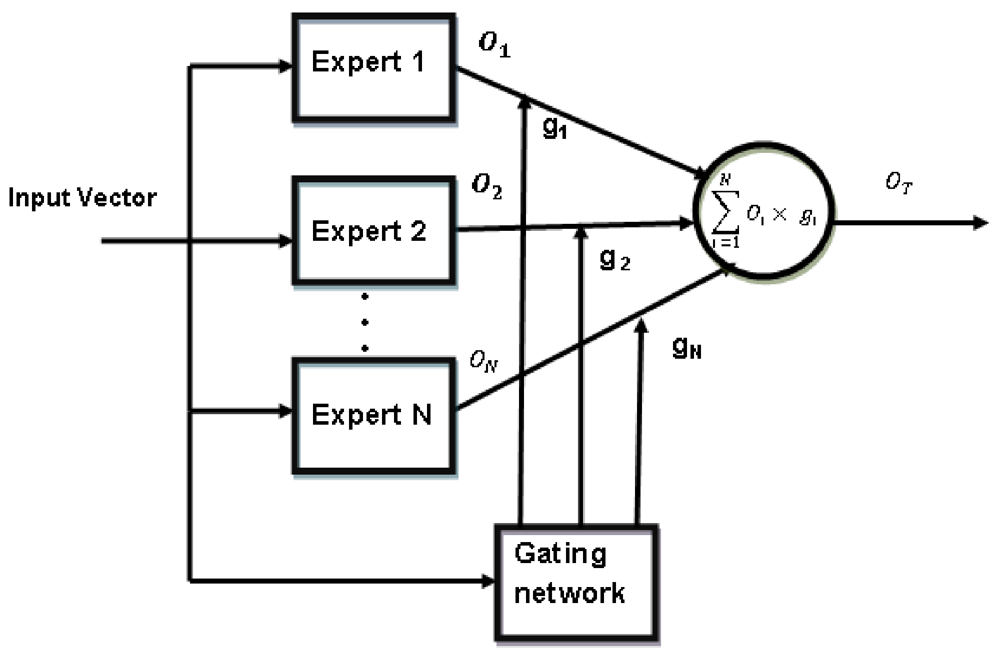


FIGURE 1: Mixture of experts is composed of expert networks and a gating network. Each expert is a feed forward network and all experts receive the same input and have the same number of outputs. The gating network is also feed forward, and typically receives the same input as the expert networks.

$$\Delta w_h = \eta_e h_i w_y^T (y - O_i)(O_i(1 - O_i))O_{hi}(1 - O_{hi})x_i \qquad (7)$$

$$\Delta w_{yg} = \eta_g (h - g)(O_g (1 - O_g))O_{hg}^T , \quad (8)$$

$$\Delta w_{hg} = \eta_e w_{yg}^T (y - O_i)(O_g (1 - O_g))O_{hg} (1 - O_{hg}) x_i \quad (9)$$

Where η_e and η_g are learning rates for the expert and the gating networks, respectively. w_y and w_h are the weights of input to hidden and hidden to output layer, respectively, for experts and w_{hg} and w_{yg} are the weights of input to hidden and hidden to output layer, respectively, for the gating network. O_{hg}^T and O_{hi}^T are the transpose of O_{hi} and O_{hg}, the outputs of the hidden layer of expert and gating networks, respectively. h_i is an estimate of the posterior probability that expert i can generate the desired output y:

$$h_i = \frac{g_i \exp(-\frac{1}{2}(y - O_i)^T (y - O_i))}{\sum_j g_j \exp(-\frac{1}{2}(y - O_i)^T (y - O_i))} \quad (10)$$

As pointed out by Dailey and Cottrell [15], in the network's learning process, "the expert networks 'compete' for each input pattern, while the gate network rewards the winner of each competition with stronger error feedback signals. Thus, over time, the gate partitions the input space in response to the expert's performance".

In this paper, we use 3 experts that experts are MLPs which are 10 neurons in hidden layer and gating network is a MLP which is 4 neurons in hidden layer.

Learning rate for gating network is $\eta_g = 0.01$ and learning rate for experts networks are $\eta_e = 0.28$ and numbers of epoch for training are 100 epochs.

4. **Methodology**

For validation and verification of the ME method in transient stability assessment we use the IEEE 9-bus and IEEE 14-bus power systems. Before the ME 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 [20].

Time domain simulation method is chosen to assess the transient stability of a power system because it is the more 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 [6].

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 occurs 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 the user. The FCT is set randomly by considering whether the system is stable or unstable after a fault is cleared. According to [18], 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].

5. Transient Stability Simulation on the Test Systems:

Figure 2 shows the IEEE 9-bus system in which the data used for this work is obtained from [3, 6, and 20]. The system consists of three Type-2 synchronous generators with AVR Type-1, six transmission lines, three transformers and five loads.

By using data IEEE 9-bus system and applied data to PSAT software step time responses in Fig. 4 are resulted. By observing results stable and unstable cases come be clearly classified. A three phase fault is said to occur at time t=1 second on tree phase lines between bus 7 and 5. In Fig. 4(a), the FCT is set at 1.083 second while in Fig. 4(b) the FCT is set at 1.3 second. Fig. 4(a) shows that the stable relative rotor angles of the second and third generators oscillation compared to the first relative rotor angles generator. Figure 4(b) shows that the relative rotor angles of the generators that go out of step after a fault is cleared and inconsequence system is unstable.

Figure 3 shows the IEEE 14-bus system in which the data used for further investigation in this research work is obtained from [6]. The system consists of five Type-2 synchronous generators with AVR Type-1, 20 transmission lines and eleven loads. Figure 5 shows examples of the time domain simulation results illustrating stable and unstable cases.

A three phase fault is assumed to occur at time t=1 second between bus 4 and 2. In Figure 5(a), the FCT is set at 1.083 second while in Figure 5(b) the FCT is set at 4 second.

Name of input features	No. of features
Relative rotor angles $(\delta_i - 1)$	2
Generator speed (ω_i)	3
P_{gen} & Q_{gen}	6
P_{line} & Q_{line}	12
P_{trans} & Q_{trans}	6
Total number of feature	29

Table 1: Input feature selected for IEEE 9-bus system

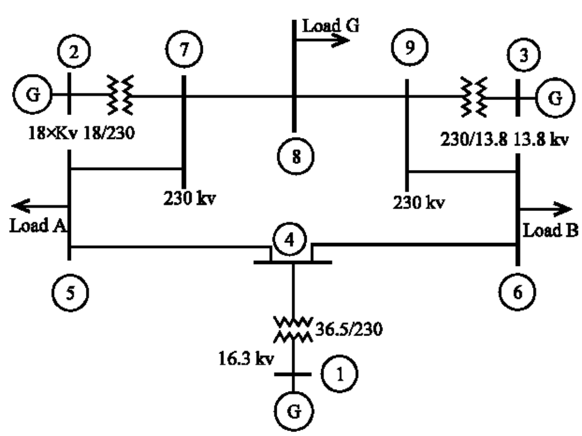


FIGURE 2: IEEE 9 bus System

Name of input features	No. of features
Relative rotor angles $(\delta_i - 1)$	4
Generator speed (ω_i)	5
P_{gen} & Q_{gen}	10
P_{line} & Q_{line}	40
P_{trans} & Q_{trans}	48
Total number of feature	107

Table 2: Input feature selected for IEEE 14-bus system

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 0.05 sec. 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 21 sampled data taken for one second duration after the fault occurs.

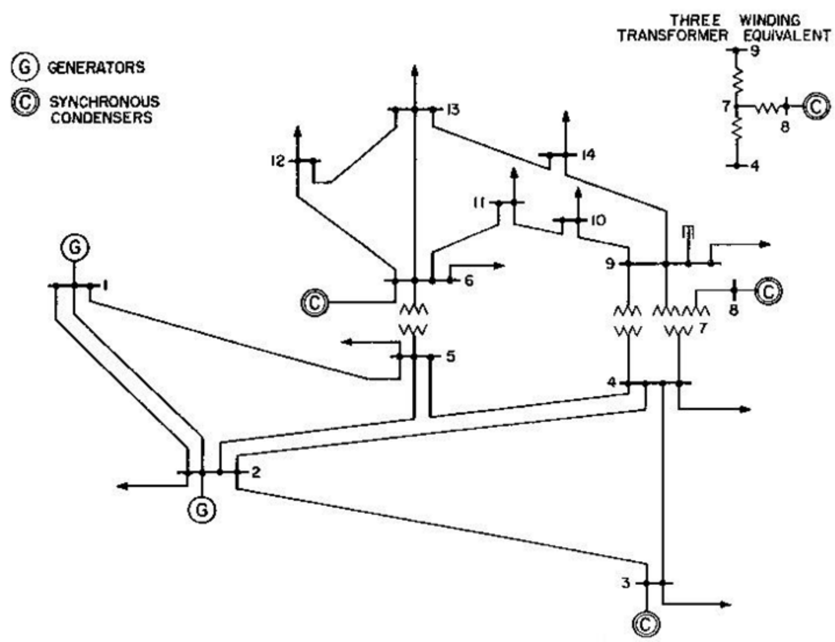
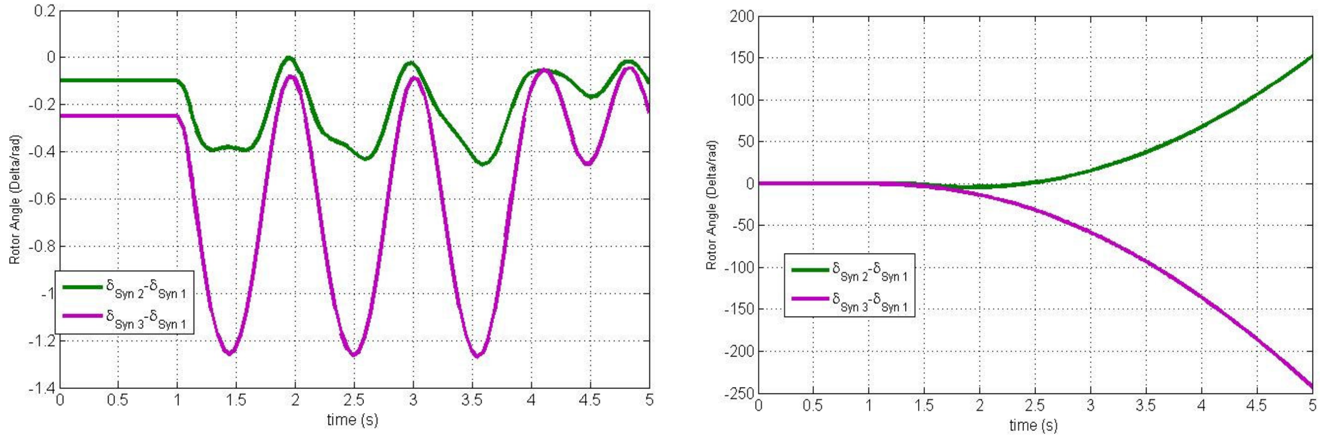


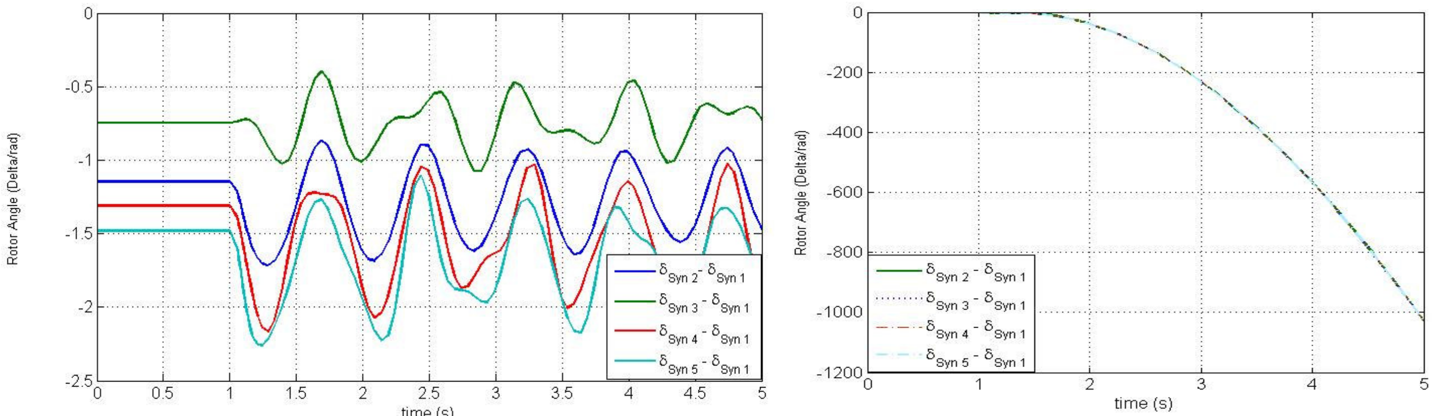
FIGURE 3: IEEE 14 bus System

There are 25 contingencies simulated on the IEEE 9-bus system and this gives a size of 25×21 or 525 data collected. The collected data were reduced to 468 after eliminating of data redundancy. There are 39 contingencies simulated on the IEEE 14-bus system and this gives a size of 39×21 or 819 data collected. Next, the repetitions are due to the faults that occur on the same line. For IEEE 9-bus systems, the FCT of the same line are set at four different times, two for stable cases and two for unstable cases.



(a) **(b)**

FIGURE 4: - Relative rotor angle bents of generators for a) stable and b) unstable cases for the IEEE 9-bus



(a) (b)

FIGURE 5: Relative rotor angle bents of generators for a) stable and b) unstable cases for the IEEE 14-bus system

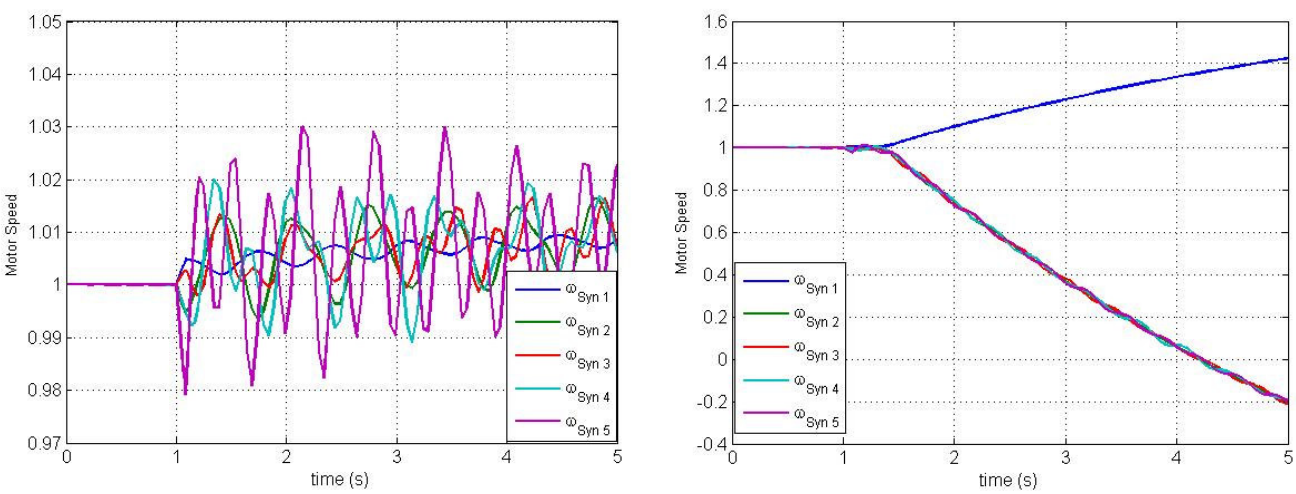


FIGURE 6: Relative angle speed bents of generators for a) stable and b) unstable cases for the IEEE 14-bus system

Model	**Number of input features**	**Mean error**	**Misclassification**(%)
MLP	107	53.2	370 (56.97%)
ME	107	0	0%

Table 3: The result of for IEEE 14-bus system

Model	**Number of input features**	**Mean error**	**Misclassification**(%)
MLP	29	0.0253	4 (3.42%)
CNN	29	0.0085	1(0.85%)
ME	29	0	0%

Table 4: The result of for IEEE 9-bus system

Methods	**Mean error**	**Misclassification**(%)
N.Izzri et al. [13]	1.71	1.71
R.Ebrahimpour et al. [3]	0.85	0.85
S.Kirishna et al. [11]	2.29	1.64
L. S. Moulin et al. [33]	4.8	4.8
N.Amjadi et al. [2]	0. 28	
A.G. Bahbah et al. [12]	0.025	
The proposed method	**0**	**0**

Table 5: Comparisons of the presented method with the related (%)

7. Input Features Selection in IEEE 9-bus system:

The selection of input features is an important factor to be considered in the ME implementation. The input features selected for this work are relative rotor angles (δ_{i-1}),generator angle speed(ω_i), generated real and reactive powers (Pgen , Qgen), 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 ME for IEEE 9-bus systems shown in table 1. 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. For IEEE 14-bus system a new feature namely voltage buses is consider too. In this case, there are 107 input features to the ME shown in table 2. Similarly 150 data out of 800 are randomly selected for testing and remaining data used as training.
ME results using 29 input features for IEEE 9-bus and 107 feature for IEEE 14-bus are given respectively in the tables 3&4.

8. Performance evaluation:

In the proposed method, three experts and one gating network are used which we consider it as MLPs. For MLPs evaluation we used : Learning rate for gating network is $\eta_g = 0.01$ and learning rate for experts networks are $\eta_e = 0.28$ and the number of iteration reaches 100. After training all the neural networks are trained with same input features which are parameters of transient stability assessment.
Performance of the developed ME can be gauged by calculating the error of the actual and desired test data. Firstly, error is defined as,

$$\text{Error, } E_n = \left|(\text{Desired output})_n \text{ -(Actual output)}_n\right| \quad (11)$$

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 (12), the percentage mean error, ME (%), can be obtained as:

$$\text{Percentage of Mean Error, Me}(\%) = \sum_{n=1}^{N} \frac{E_n}{N} \times 100 \qquad (12)$$

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

$$CE(\%) = \frac{\text{No of misclassfied of the test data}}{N} \times 100 \qquad (13)$$

We compare assessment methods in table 3&4 where we showed zero mean error and zero percent miss classification in ME method for both IEEE 9-bus and IEEE 14-bus systems.
Table 3&4 show ME testing results using the 29 & 107 input features the total error of misclassification and the mean error are both (0%).The MLPs result for transient stability assessment according to table 3 with IEEE 14-bus system, the total error of misclassification is 370 (56.97%and the mean error (53.2%) , too, with IEEE 9-bus, total error of misclassification is 4 (3.42%) , the mean error (0.0253) and the CNN result for transient stability assessment according to table 4 with IEEE 9-bus system the total error of misclassification is 1 (0.85%) and the mean error (0.0085).
Table 5 shows very suitable performance of the proposed method over other reported methods. The error rate of the proposed method reached to (0%) , which is a very demand improvement compared with other methods.

9. Conclusion

We should announce that ME proposed method in transient stability assessment has a very high reliability. When we compared with others methods namely MLP and CNN, the proposed ME method shows zero mean error and zero percent miss classification for IEEE 9-bus and IEEE 14-bus power systems, which assures very greats performance.

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