Intelligent Voltage Instability Detector Based on Phasor Measurement Units

Ahmed K. Ali, Noha H. El-Amary, A.M. Ibrahim, Said F.Mekhamer

Abstract— A neural network based voltage instability detector is proposed in this paper utilizing wide area monitoring system and the measured angle of the installed Phasor Measurement Units (PMUs). Voltage instability is considered one of the critical problems that severely affect the electric power quality. The system which suffers from voltage instability can be easily exposed to fast failure due to voltage collapse. A proposed neural network based voltage instability detector is introduces. This detector depends on the bus voltage angle which is measured by the installed PMUs. A developed Feed-Forward Neural Network (FFNN) is designed and trained. It consists of one input layer with five neurons, two hidden layers, and one output layer. The two hidden layers consist of twelve and nine neurons respectively. The output layer consists of one neuron. The main advantage of the smart developed system is that, it can detect the voltage instability of the whole power system buses in the same time. The developed proposed system is tested on 14 bus IEEE system. The 14 bus IEEE system is simulated using MATLAB to get the system load flow results. Furthermore, the effect of different loading conditions is applied to the simulation system to get their corresponding bus angles values. About 1000 different studied cases are held for different loading values with different power factors on different buses. The results of these cases are tabulated, normalized and processed using the ANN. The ANN is trained by the third of these cases. The other values are used to test the performance of the developed system. The results of ANN are analyzed and considered to be satisfactory because of the high accuracy and reliable operation.

Index Terms — Artificial Neural Network (ANN), Phasor Measurement Units (PMUs), Voltage instability detector.

1 Introduction

VOLTAGE instability has been given much attention by power system researchers and planners in recent years because voltage instability problems in power systems have become one of the major concerns in power systems planning and operation [1]-[4]. At any point of time, a power system condition should be stable, meeting various operational criteria, and it should also be secure in the event of any credible contingency. Nowadays, power systems are being operated closer to their stability limits due to economic and environmental constrains. Maintaining a stable and secure operation of power system is therefore a very important and challenging issue [1].

Voltage instability means that the receiving end voltage decreases below its normal value and does not restore its rated value even after using stabilizing devices such as VAR compensators [2]. This voltage continues to oscillate without any ability to maintain stable against the disturbances. The main result of voltage instability is the voltage collapse [2].

It is highly recommended to take care of voltage stability especially in high developed networks as a result of heavier loading. The main factors causing voltage instability are excessive loading of transmission lines, high transmission line losses, lake of reactive power supply, transmitting power over long distances and presence of non-linear loads. Because of that, many techniques have been developed to identify critical power system, buses and lines. The largest concern to the electric utility industry is voltage stability.

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Phasor Measurement Units are now one of the recent measuring devices that attract electrical engineering researchers. In protection and control, it is used in many applications for measuring the synchronized phasor parameters needed for taking a decision or an action from the protection or control device. It can improve the voltage instability detection process

Phasor Measurement Unit (PMU) technology provides phasor information (both magnitude and phase angel) in real time [5]-[8]. Due to the strong correlation between PMUs and the Global Positioning Satellites (GPSs), PMUs began to spread widely after the great improvement in the satellite techniques and communications.

- *Ahmed Kamal Ali is currently pursuing masters degree program in electric power engineering in Arab Academy for Science and Technology (AAST), Egypt, PH-01001345616. E-mail: kamal_307@hotmail.com*
- *Noha H. El-Amary, Assistant Prof in electric power and Control, Arab Academy for Science and Technology (AAST), Cairo, Egypt. E-mail: noha_helamary@hotmail.com*
- *A.M. Ibrahim, Assistant Prof in electric power and Machines Engineering, Ain Shams University, Cairo, Egypt. E-mail:amrmohamedhassan@yahoo.com*
- *Said F. Mekhamer, Associated Prof in electric power and Machines Engineering, Ain Shams University, Cairo, Egypt. E-mail:saidfouadmekhamer@yahoo.com*

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The advantage of referring phase to a global reference time is helpful in capturing the wide area snap shot of power system. Effective utilization of this technology is very useful in mitigating blackouts and learning the real time behavior of the power system.

Many techniques is used in voltage instability detection such as, Particle Swarm Optimization Technique [9]

The Artificial Neural Network (ANN) technique is one of the familiar artificial intelligent techniques which is used in this paper. Artificial Neural Networks (ANNs) are inspired by biological nervous systems and they were first introduced as early as 1960 [10]. It is used in solving many power system problems such as protection problems, stability problems, and control studies. A simulation of new Voltage stability detector is discussed in this paper. This detector utilized the phasor readings of PMUs, which are connected to the terminals of the distribution systems.

2 VOLTAGE INSTABILITY STUDIES

Artificial Neural Networks have been used to solve many problems obtaining outstanding results in various applications such as classification, clustering, pattern recognition, and forecasting among many other applications corresponding to different areas. One of these areas is Power System Stability Detection.

Power system stability is the property of a power system which enables it to remain in a state of equilibrium under normal operating conditions and to regain an acceptable state of equilibrium after a disturbance.

The determination of the state of the system voltage stability is classified by using the relation between active and reactive power each with the voltage (PV,QV) where the transmitted active and reactive power equations is used to drive the relation between the voltage magnitude and the power. The real and reactive power flow from bus-i to bus-j (P_{ij}, Q_{ij}) are calculated by (**1**) and (**2**)**.** Two buses of an electrical network with voltage phasors $V_i \angle \delta_i$ and $V_j \angle \delta_j$ are shown in Fig. 1. The two buses are connected through a transmission line with impedance Z = R + jX.

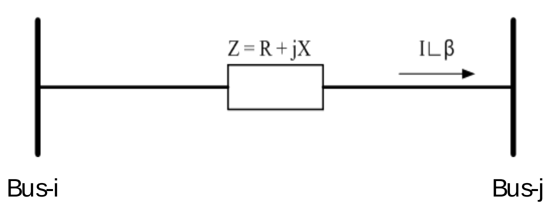

Fig 1 Simplified two-bus network

$$P_{ij} = V_i V_j Y_{ij} \cos(\delta_i - \delta_j + \theta_{ij}) - V_i^2 Y_{ij} \cos(\theta_{ij}) \quad (1)$$
$$Q_{ij} = V_i V_j Y_{ij} \sin(\delta_i - \delta_j + \theta_{ij}) - V_i^2 (Y_{ij} \sin(\theta_{ij}) + B_{capij}) \quad (2)$$

Where:

Y_{ij}	:	is the admittance magnitude of the line connected bus-i and bus-j.
θ_{ij}	:	is the admittance angle of the line connected bus-i and bus-j.
δ_i	:	is the angle of the bus-i voltage.
B_{capij}	:	is the total line charging susceptance.
N	:	is the total number of the network buses.

Since the total power transmitted from bus-i to bus-j is S = P + jQ, so a direct relation between V_j, P and Q for certain V_i, can be expressed in **(3)**

$$V_j^4 + (2P_{ij}R_{ij} + 2Q_{ij}X_{ij} - V_i^2)\,V_j^2 + (R_{ij}^2 + X_{ij}^2)(P_{ij}^2 + Q_{ij}^2) = 0 \qquad \textbf{(3)}$$

The relation between the real power and the voltage magnitude is shown in **Fig 2**

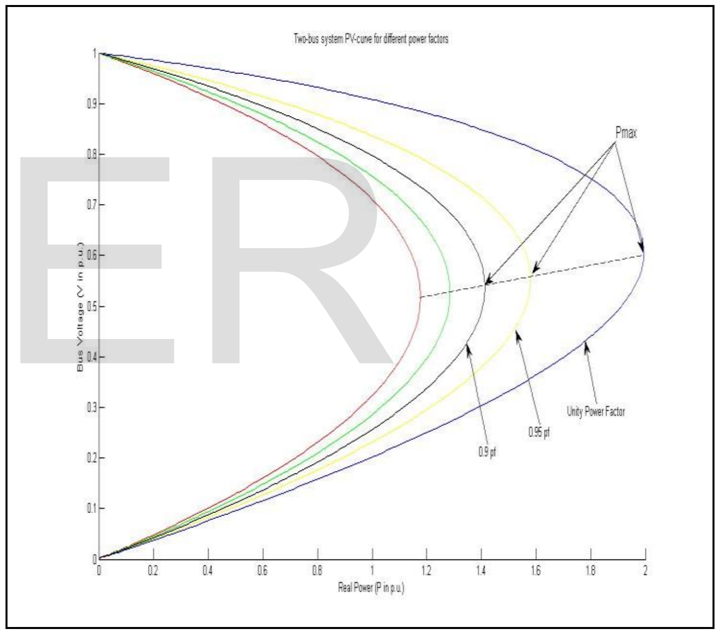

Fig 2 Two-bus system PV-curves for different power factors

Depending on PMUs' readings, a simulation of real-time voltage instability alarming predictor using ANN is discussed. This predictor has been made using MATLAB program, this program is consists off some steps. In the beginning, the system data and parameters are entered to the program. Then, the system PV-curves for different power factors are designed. From PV-curves, the maximum P for V with 10% and 15% is determined. From the entered system data and parameters, different readings of the system load flow are calculated. These readings are converted into a look up table which is used to train the ANN. At the next level, the online data of PMUs' readings are entered to the ANN. The ANN gives an output of 1, 0, and -1 for each system bus which indicates the status of the system bus as stable, alarm and trip. A flow chart of the MATLAB program can be presented as in **Fig 3**

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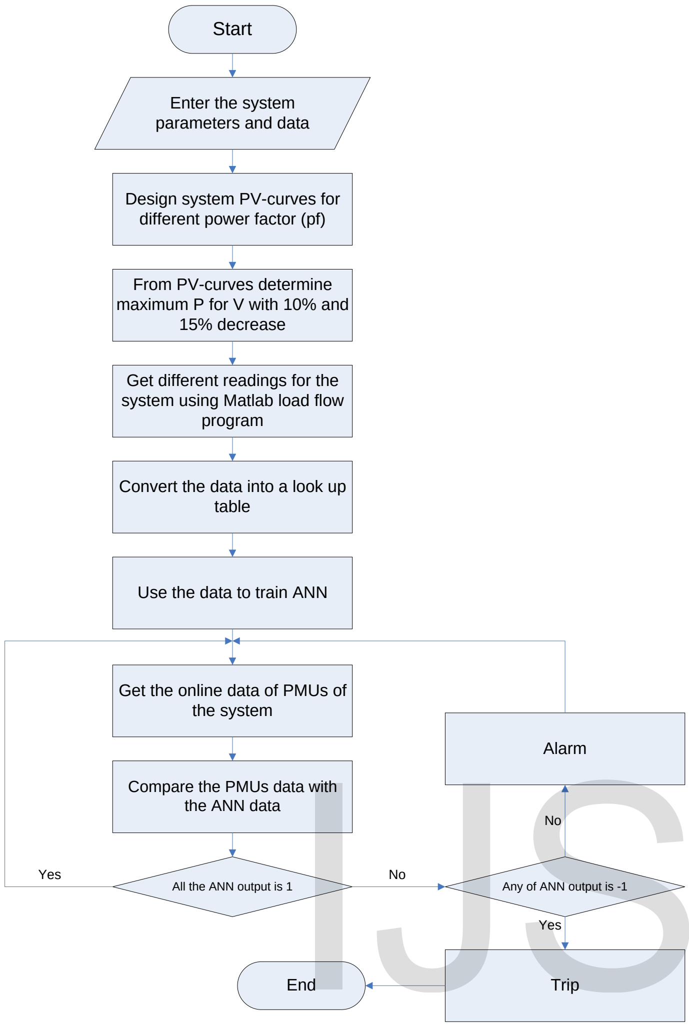

Fig 3 A flow chart of MATLAB program of a simulation of voltage instability alarming predictor

The smart voltage instability detector is developed through three stages. The first stage is the simulation of the power system using MATLAB. Different loading cases at different locations of the system are applied and studied in this stage. The load changing is applied through two strategies. The first strategy is by increasing the load while keeping the same power factor. The second strategy is by varying the power factor while fixing the total consuming apparent power of the load. In the second stage, the normalization of the output data of the first stage takes place. The third stage is the design of a feed-forward neural network, which is the taking decision unit.

3 Artificial Neural Network.

Artificial Neural Networks (ANNs) are inspired by biological nervous systems and they were first introduced as early as 1960 [10]. ANNs can be defined as a set of processing units (neurons) interlinked with each other by means of a big number of interconnections (artificial synapses) as shown in **Fig 5** These synapses are responsible for storing information, i.e., for the learning of the network [11].

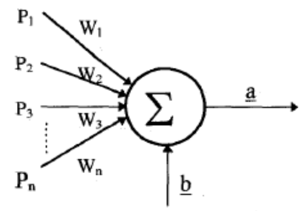

Fig 4 Perceptron representation

Once trained, a network response can be, to a degree, insensitive to minor variations in its input. This ability to see through noise and distortion to the pattern that lies within is vital to pattern recognition a real world environment [10-12]. The neuron is the nervous cell and is represented in the ANN universe as a perceptron. **Fig 4** shows a simple model of a neuron characterized by a number of inputs P, P2, ..., PN, the weights WI, W2, ...Wn, the bias adjust "b" and an output "a". The neuron uses the input, as well as the information on its current activation state to determine the output a, given as in (4).

$$a = \sum_{k=1}^{n} W_k P_k + b \tag{4}$$

The neurons are normally connected to each other in a specified fashion to form the ANNs. These arrangements of interconnections could form a network which is composed of a single layer or several layers. As mentioned before, the ANN models must be trained to work properly. The desired response is a special input signal used to train the neuron. A special algorithm adjusts weights so that the output response to the input patterns will be as close as possible to the respective desired response. In other words, the ANNs must have a mechanism for learning. Learning alters the weights associated with the various interconnections and thus leads to a modification in their strength.

3.1 Feed-forward Neural Network.

Feed-Forward Neural Networks (FFNN) can be classified in a single layer or multilayer feed-forward neural networks. Multilayer FFNN architecture comprises of input-layer(X); hidden-layer (V); and output-layer (Y); as shown in **Fig 5** [13].

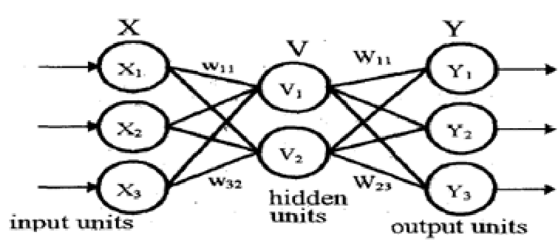

Fig 5 Multilayer Feed-forward neural network architecture

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The algorithm gives a prescription for changing the weights in any feed forward network to learn a training set of input-output pairs. The use of the bias adjustment in the ANNs is optional, but the results may be enhanced by it. A multilayer network with one hidden layer is shown in **Fig. 5** This network consists of a set of N input units (Xi, i = 1 ... N), a set of p output units (Yp, p = 1 ... P) and a set of Jhidden units (Vj, j = 1 ... J). Thus, the hidden unit Vj receives a net input and produces the output [10], [12-13].

$$Vj = F\{ \sum_{k=1}^{n} W_{ik} X_k \} \tag{5}$$

Where j= 1….J

The final output is then produced

$$Yp = F\{ \sum_{m=1}^{J} W_{pm} V_{km} \} \tag{6}$$

Where p= 1…P

The Artificial Neural Network (ANN) which is used in this paper consists of one input layer, two hidden layers, and one output layer. The input layer consists of five input neurons. The two hidden layers consist of twelve and nine hidden neurons respectively, while the output layer consists of one output unit.

4 Studied System

The Voltage instability alarming predictor using ANN technique is applied to 14-bus IEEE standard system [14] which is shown in **Fig 6**

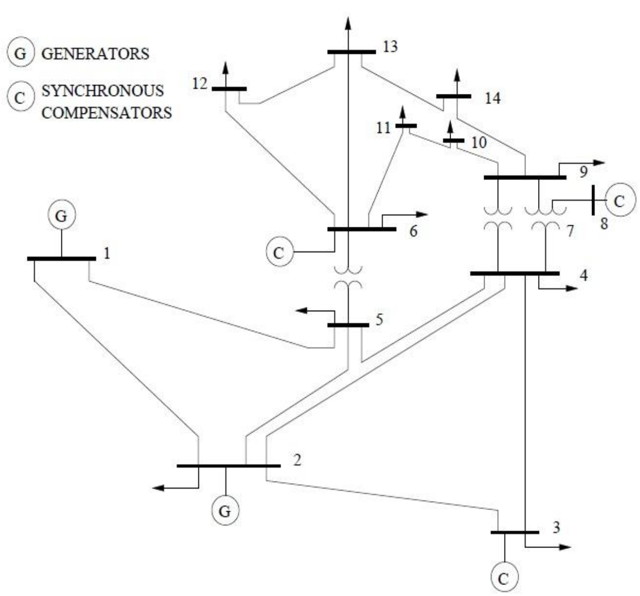

Fig 6 14-Bus IEEE standard system

The simulated data is normalized and used to train the ANN. Two studied cases are normlized and shown in **Table 1.**

Table 1 Sample of training points

	Voltage Angle Degree	Load MW	Load MVAR	Generation MW	Generation MVAR	Target
Case 1	0.4882	0.0593	0.0402	0.5618	0.0015	0
	0.4749	0	0	0.4420	0.0013	1
	0.4301	0.2574	0.0602	0.1390	0.0015	1
	0.4360	0.1306	0.0226	0.1390	0.0013	0
	0.4411	0.0208	0.0051	0.1390	0.0013	0
	0.3703	0.0305	0.0238	0.1390	0.0017	1
	0.4096	0	0	0.1390	0.0013	1
	0.4096	0	0	0.1390	0.0014	1
	0.3955	0.0806	0.0526	0.1390	0.0013	0
	0.3879	0.0246	0.0184	0.1390	0.0013	0
	0.3739	0.0096	0.0057	0.1390	0.0013	0
	0.3590	0.0167	0.0051	0.1390	0.0013	0
	0.3554	0.2823	0.2028	0.1390	0.0013	-1
	0.3857	0.0407	0.0158	0.1390	0.0013	0
Case 2	0.4882	0.0593	0.0402	0.40099	0.0014	0
	0.4810	0	0	0.4420	0.0014	1
	0.4371	0.3400	0.2443	0.1390	0.0016	1
	0.4536	0.1306	0.0226	0.1390	0.0013	1
	0.4599	0.0208	0.0051	0.1390	0.0013	1
	0.4364	0.0305	0.0238	0.1390	0.0013	1
	0.4388	0	0	0.1390	0.0013	1
	0.4389	0	0	0.1390	0.0013	1
	0.4308	0.0806	0.0526	0.1390	0.0013	1
	0.4304	0.0246	0.0184	0.1390	0.0013	1
	0.4330	0.0096	0.0057	0.1390	0.0013	1
	0.4329	0.0167	0.0051	0.1390	0.0013	1
	0.4333	0.0369	0.0184	0.1390	0.0013	1
	0.4220	0.0407	0.0158	0.1390	0.0013	0

The simulated voltage instability detector is applied to IEEE 14-bus system. The simulated detector gives effective results. The detector reacts with the system changes in good and reasonable behavior.

International Journal of Scientific & Engineering Research Volume 5, Issue 4, April-2014
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It is found from the tested cases that the accuracy of ANN is about 90%. Two samples of the tested cases, with their targeted values are shown in **Table 2**

Table 2 Sample of testing points

	Voltage Angel Degree	Load MW	Load MVAR	Generation MW	Generation MVAR	Target	Output
Case 1	0.4882	0.0593	0.0402	0.1390	0.0018	0	0
	0.5227	0	0	0.4420	0.0018	0	0
	0.5207	0.2574	0.0602	0.1390	0.0017	1	1
	0.5788	0.1306	0.0226	0.1390	0.0013	0	1
	0.5462	0.0208	0.0051	0.1390	0.0013	0	0
	0.5106	0.0305	0.0238	0.1390	0.0028	0	-1
	0.7065	0	0	0.1390	0.0013	-1	-1
	0.7521	0	0	0.1390	0.1232	-1	-1
	0.6743	0.0806	0.0526	0.1390	0.0013	-1	-1
	0.6808	0.4681	0.4071	0.1390	0.0013	-1	1
	0.6689	0.0096	0.0057	0.1390	0.0013	-1	-1
	0.4941	0.0167	0.0051	0.1390	0.0013	-1	-1
	0.6057	0.0369	0.0184	0.1390	0.0013	-1	-1
	0.6852	0.0407	0.0158	0.1390	0.0013	-1	-1
Case 2	0.4882	0.0593	0.0402	0.4015	0.0014	0	0
	0.4818	0	0	0.4420	0.0013	1	1
	0.4455	0.2574	0.0602	0.1390	0.0014	1	1
	0.4530	0.1306	0.0226	0.1390	0.0013	1	1
	0.4584	0.0208	0.0051	0.1390	0.0013	1	1
	0.4222	0.0305	0.0238	0.1390	0.0014	1	1
	0.4353	0	0	0.1390	0.0013	1	1
	0.4352	0	0	0.1390	0.0013	1	1
	0.4259	0.0806	0.0526	0.1390	0.0013	1	1
	0.4235	0.0246	0.0184	0.1390	0.0013	1	1
	0.4213	0.0096	0.0057	0.1390	0.0013	1	1
	0.4143	0.0916	0.0797	0.1390	0.0013	0	0
	0.4175	0.0369	0.0184	0.1390	0.0013	1	1
	0.4162	0.0407	0.0158	0.1390	0.0013	0	0

5 Conclusion

As voltage instability is danger for power systems, this paper has proposed an early voltage instability detector based on PMUs readings utilizing ANN. The work done in this paper is developed through three stages. The first stage is the simulation of the power system using MATLAB. In this stage, different loading cases at different locations of the system are applied, analyzed and studied. The load changing is applied through two strategies. The first strategy is by increasing the load while keeping the same power factor. The second strategy is by varying the power factor while fixing the total consuming apparent power of the load. A huge number of different studied cases are produced and tabulated using Excel files.

The second stage is the normalization of the output of the first stage.

In the third stage, a feed-forward neural network is designed and trained utilizing thirty percent of the studied cases. The ANN consists of one input layer with five hidden neurons, two hidden layers with twelve and nine hidden neurons respectively, and one output layer with one output neuron. The network is programmed to give the voltage stability status of the power system buses based on bus voltage angles. The newly developed ANN based voltage detector is designed to study the voltage stability status of the whole system buses as one unit.

The smart developed method is applied to IEEE 14-bus system. The system is simulated and around one thousand studied cases are obtained. Four hundred studied cases of them are used for training the ANN and the rest are used for the testing stage. It is found that the accuracy of ANN is about 90%.

6 Appendix

Table 3 14-Bus Standard IEEE system line data

From Bus	To Bus	Resistance (p.u.)	Reactance (p.u)	Line charging (p.u.)	tap ratio
1	2	0.01938	0.05917	0.0528	1
1	5	0.05403	0.22304	0.0492	1
2	3	0.04699	0.19797	0.0438	1
2	4	0.05811	0.17632	0.0374	1
2	5	0.05695	0.17388	0.034	1
3	4	0.06701	0.17103	0.0346	1
4	5	0.01335	0.04211	0.0128	1
4	7	0	0.20912	0	0.978
4	9	0	0.55618	0	0.969
5	6	0	0.25202	0	0.932
6	11	0.09498	0.1989	0	1
6	12	0.12291	0.25581	0	1
6	13	0.06615	0.13027	0	1
7	8	0	0.17615	0	1
7	9	0	0.11001	0	1
9	10	0.03181	0.0845	0	1
9	14	0.12711	0.27038	0	1
10	11	0.08205	0.19207	0	1
12	13	0.22092	0.19988	0	1
13	14	0.17093	0.34802	0	1

International Journal of Scientific & Engineering Research Volume 5, Issue 4, April-2014
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Table 4 The load flow output for a normal operating condition of 14-Bus IEEE system

Bus No	Angle Degree	Load MW	Load Mvar	Gen MW	Gen Mvar
1	0	30.38	17.78	153.521	46.704
2	-1.251	0	0	232	38.922
3	-13.325	131.88	26.6	0	39.396
4	-9.979	66.92	10	0	0
5	-8.204	10.64	2.24	0	0
6	-16.055	15.64	10.5	0	21.33
7	-15.125	0	0	0	0
8	-15.128	0	0	0	28.164
9	-17.749	41.3	23.24	0	0
10	-17.99	12.6	8.12	0	0
11	-17.169	4.9	2.52	0	0
12	-17.407	8.54	2.24	0	0
13	-17.024	18.9	8.12	0	0
14	-20.699	20.86	7	0	0

Table 5 The load flow output data for 14-Bus IEEE system after normalization

Bus No	Angle Degree	Load MW	Load Mvar	Gen MW	Gen Mvar
1	0.4882	0.0593	0.0402	0.2148	0.0014
2	0.4911	0	0	0.4420	0.0013
3	0.4723	0.0937	0.0815	0.1390	0.0013
4	0.4698	0.1306	0.0226	0.1390	0.0013
5	0.4729	0.0208	0.0051	0.1390	0.0013
6	0.4505	0.0305	0.0238	0.1390	0.0013
7	0.4549	0	0	0.1390	0.0013
8	0.4549	0	0	0.1390	0.0013
9	0.4468	0.0806	0.0526	0.1390	0.0013
10	0.4462	0.0246	0.0184	0.1390	0.0013
11	0.4479	0.0096	0.0057	0.1390	0.0013
12	0.4476	0.0167	0.0051	0.1390	0.0013
13	0.4475	0.0369	0.0184	0.1390	0.0013
14	0.4376	0.0407	0.0158	0.1390	0.0013

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