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Saya yang bertanda tangan dibawah ini:

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Dengan ini menyatakan bahwa karya ilmiah yang saya hasilkan dan digunakan untuk pengurusan kenaikan Jabatan Guru Besar adalah memiliki kebaruan dari sisi konten terhadap disertasi kami yang berjudul : "*Modelling of Load Characteristic, Tap Changer And Current Limiter for Steady State Stability Studi Using Combination Dimo Method with Artificial Intelligence*"

Adapun paper yang menjadi syarat khusus dalam pengajuan Guru Besar adalah:

1. *Forecasting Voltage Collapse when Large-Scale Wind Turbines Penetrated to Power Systems Using Optimally Pruned Extreme Learning Machines (OPELM) - Case Study: Electric Power System South Sulawesi-Indonesia.*

2. *Determination of stability index of electrical power system using REI-Dimo methods*

3. *The Impact of the Injection of Wind Power Plant on the Steady State Condition and the Dynamics of SULSELBAR Power System*

Analisa kebaruan:

1. **Paper-1** ini membahas terkait prediksi *Voltage Collapse* ketika wind turbine skala besar masuk ke sistem tenaga listrik menggunakan metode Optimally Pruned Extreme Learning Machines (OPELM). Ini sangat berbeda dengan konten disertasi kami, walaupun masih dalam satu tema besar yakni mengupas tentang masalah kestabilan sistem tenaga.

2. **Paper-2** ini membahas penentuan batas kestabilan sistem menggunakan REI-Dimo dengan kasus Sistem Sulbagsel dan dengan pendekatan metode simulasi menggunakan Simulink, untuk menampilkan batas kestabilan sistem. Hal ini yang tidak digarap pada disertasi kami, walaupun pada disertasi juga menggunakan metode REI-Dimo.

3. **Paper-3** ini membahas terkait dampak masuknya Wind Turbine dari sisi kestabilan transient, sangat berbeda dengan tema disertasi yang focus pada kestabilan steady state. Walaupun paper

dan disertasi ini sama-sama membahas tema terkait Stability, akan tetapi cabang kajian stability nya berbeda.

Demikianlah surat klarifikasi ini kami buat. Terima kasih atas kerjasamanya.

Makassar, 3 April 2023

Mengetahui,
Wakil Dekan I Fak. Teknik Unhas

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Yang Membuat Pernyataan,

SEPULUH RIBU RUPIAH 10000 METERAI TEMPEL 4DA52AKX146079030

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Steady State Stability Assessment Using Extreme Learning Machine Based on Modal Analysis

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Abstract – *The growth of electricity market led to increase utilization and higher loading of the electric transmission grids worldwide. This situation made power system operate close to steady-state stability limit (SSSL). It could trigger a voltage instability or a voltage collapse phenomenon. An assessment approach on steady state stability analysis was provided using Extreme Learning Machine taking the Modal Analysis as an assessment index. The nonlinear problem between voltage, power flow and participation factor in power system could be solved by Extreme Learning Machine. The method was tested on the IEEE 14 bus and Java-Bali system. The simulation results showed that the proposed method could accurately predict the weakest bus in power system.*

***Keywords**: Voltage Collapse, Steady State Stability, Extreme Learning Machine, Modal Analysis*

Nomenclature :

$\Delta\mathbf{P}$	active power
$\Delta\mathbf{Q}$	reactive power mismatch
$\mathbf{J}$	jacobian matrix
$\mathbf{J_R}$	jacobian reduction matrix
$\Delta\mathbf{V}$	voltage magnitude
$\Delta\boldsymbol{\theta}$	angle correction
$\boldsymbol{\Phi}$	right eigenvector matrix of J_R
$\boldsymbol{\Gamma}$	left eigenvector matrix of J_R
$\boldsymbol{\Lambda}$	diagonal eigenvalue matrix of J_R
$\mathbf{P}_{ki}$	participation of the k^{th} bus in i^{th} mode

I. Introduction

Nowadays, in electric power system, load growth is not accompanied by the rapid development of transmission networks and generation capacity. This condition will cause the electric power system to operate at conditions that are particularly vulnerable to the phenomenon of a voltage instability or a voltage collapse. Nowadays, the voltage collapse has become a very important issue in the operation of electric power systems [1-3].

There are many researchers who have evaluated the technique to predict a voltage collapse in power systems. Morison and Kundur provide a method named Modal Analysis. This method is performed by calculating the eigen value and eigenvector of the Jacobian reduction matrix of system power. Power system stability condition can be determined by observing the results of these eigen values. If all the eigen values are positive, the system is considered to be in a stable condition. On the other hand, if eigen values are negative, the system is considered to be in an unstable voltage.

Furthermore, by applying methods of bus participation factor, the weakest bus or node can be determined - which is the greatest contributing factor for a system to reach a voltage collapse situation-[2].

This paper proposes an artificial intelligent namely a Extreme Learning Machine (ELM) approach for an assessment of steady state stability. The nonlinear characteristic between power flow and voltages on load bus with given load increases mode. However, as the operating conditions of a power system continuously changes, it is difficult to calculate the bus participation factor for each load bus directly by the mathematical analysis on line. As a result, this paper presents ELM method to estimate the participation factor sequentially to assess the system voltage stability rapidly and timely.

II. The Modal Analysis

The modal analysis or eigen value analysis can be used effectively as a powerful analytical tool to verify both proximity and mechanism of a voltage instability. It involves the calculation of a small number of eigen values and related eigenvectors of a reduced Jacobian matrix. However, by using the reduced Jacobian matrix, the focus is on the voltage and the reactive power characteristics. The weak modes (weak buses) of the system can be identified from the system reactive power variation sensitivity to incremental change in bus voltage magnitude. The stability margin or distance to voltage collapse can be estimated by generating the Q-V curves for that particular bus. Load characteristics have been found to have significant effect on power system stability. A simplified voltage dependent real and reactive power load model is used to figure out that effect. Induction machine is one of the important power system loads. It influences the system voltage stability

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especially when large amount of such load is installed in the system[3].

Equation (1) represents the power flow equation in power system at such as an operating system.

$$\begin{bmatrix}\Delta\mathbf{P}\\ \Delta\mathbf{Q}\end{bmatrix}=\begin{bmatrix}\mathbf{J}_{11} & \mathbf{J}_{12}\\ \mathbf{J}_{21} & \mathbf{J}_{22}\end{bmatrix}\begin{bmatrix}\Delta\boldsymbol{\theta}\\ \Delta\mathbf{V}\end{bmatrix} \tag{1}$$

With asumption

$\Delta\mathbf{P}=0$

$$\Delta\mathbf{P}=0=\mathbf{J}_{11}\Delta\boldsymbol{\theta}+\mathbf{J}_{12}\,\Delta\mathbf{V}\,,\;\Delta\boldsymbol{\theta}=-\mathbf{J}_{11}^{-1}\,\mathbf{J}_{12}\,\Delta\mathbf{V} \tag{2}$$

and

$$\Delta\mathbf{Q}=\mathbf{J}_{21}\,\Delta\boldsymbol{\theta}+\mathbf{J}_{22}\,\Delta\mathbf{V} \tag{3}$$

Subtituting equation (2) in equation (3) :

$$\Delta\mathbf{Q}=\mathbf{J_R}\,\Delta\mathbf{V} \tag{4}$$

where :

$$\mathbf{J_R}=\left[\mathbf{J}_{22}-\mathbf{J}_{21}\,\mathbf{J}_{11}^{-1}\,\mathbf{J}_{12}\right]$$

The matrix $\mathbf{J}_R$ represents the linearized relationship between the incremental changes in bus voltage ($\Delta\mathbf{V}$) and bus reactive power injection ($\Delta\mathbf{Q}$).

Voltage instability can be detected by identifying modes of the eigenvalues matrix $\mathbf{J}_R$. Eigenvalue analysis of $\mathbf{J}_R$ results in the following :

$$\mathbf{J_R}=\boldsymbol{\Phi}\,\boldsymbol{\Lambda}\,\boldsymbol{\Gamma} \tag{6}$$

By changing the $\mathbf{J}_R$ to $\mathbf{J}_R^{-1}$:

$$\mathbf{J_R}^{-1}=\boldsymbol{\Phi}\,\boldsymbol{\Lambda}^{-1}\,\boldsymbol{\Gamma}$$

If $\boldsymbol{\Phi}_i$ and $\boldsymbol{\Gamma}_i$ represent the right- and left- hand eigenvectors respectively for the eigenvalue λ_i of the matrix $\mathbf{J}_R$, the participation factor measuring the participation of the k^{th} bus in i^{th} mode is defined as :

$$\mathbf{P}_{ki}=\boldsymbol{\Phi}_{ki}\,\boldsymbol{\Gamma}_{ik} \tag{10}$$

So the eigenvalues of importance are the critical eigenvalues of the reduced Jacobian matrix $\mathbf{J}_R$. Thus, the smallest eigenvalues of $\mathbf{J}_R$ are taken to be the least stable modes of the system. The rest of the eigenvalues are neglected because they are considered to be strong enough modes. Once the minimum eigenvalues and the corresponding left and right eigenvectors have been calculated, the participation factor can be used to identify the weakest node or bus in the system[2-3].

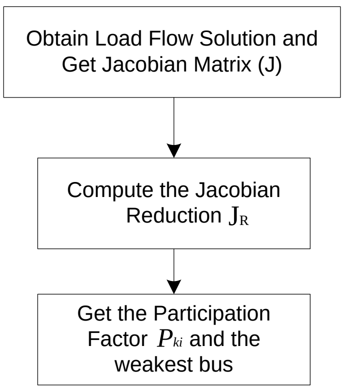

Fig. 1. Algorithm of Modal Analysis

III. Extreme Learning Machine

Conventional methods such as back-propagation (BP) and the method of Levenberg-Marquardt (LM) have been used extensively in training neural networks although this algorithm is relatively slow in learning. A new learning method for single-hidden-layer feed forward neural-networks (SLFNs) is the so-called extreme learning machine (ELM). In ELM, the input weights and hidden biases are randomly chosen. The output weights obtained using the Moore-Penrose (MP) generalize inverse. ELM has the capability in terms of speed and it is easier than traditional methods of gradient-based learning algorithms [8-9].

In ELM, the input weights and hidden biases are generated randomly. Furthermore, the nonlinear system has been transformed into a linear system:

$$\mathbf{H}\boldsymbol{\beta}=\mathbf{T}$$

Whereas named in Huang et al. [15], $\mathbf{H}=\{\mathbf{h}_{ij}\}$ (i=1,…,N and j=1,…,K) is hidden-layer output matrix, $\boldsymbol{\beta}=[\boldsymbol{\beta}_1,\boldsymbol{\beta}_2,...,\boldsymbol{\beta}_K]^T$ is matrix of output weights and $\mathbf{T}=[\mathbf{t}_1,\mathbf{t}_2,...,\mathbf{t}_N]^T$ is matrix of targets.

In this paper, ELM is utilized to map the highly non-linear relationship between network voltage profile, power generation of power system and the corresponding bus participation factor of power system. First, the simulation starts with running the power flow program for IEEE 14 bus and Java-Bali system. Then, by using Modal Analysis, the weakest bus of each cases will be obtained. The data from modal analysis will be training in ELM.

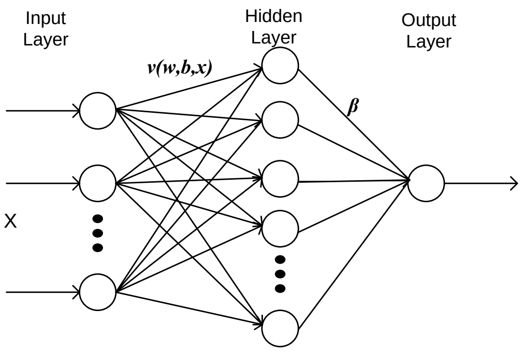

Fig. 2. Structure of an SLF-NN

IV. Application of Extreme Learning Machine

Bus participation factor values were obtained from the Modal Analysis method and then trained at Extreme Learning Machine. Data input was the generator bus voltage, active power and reactive generator, four of the largest values of participation factor, the change of power at the load bus.

In this simulation, the input data used was as many as 150 data in which 30 data were used as testing data. Algorithm of this study can be seen in fig. 4.

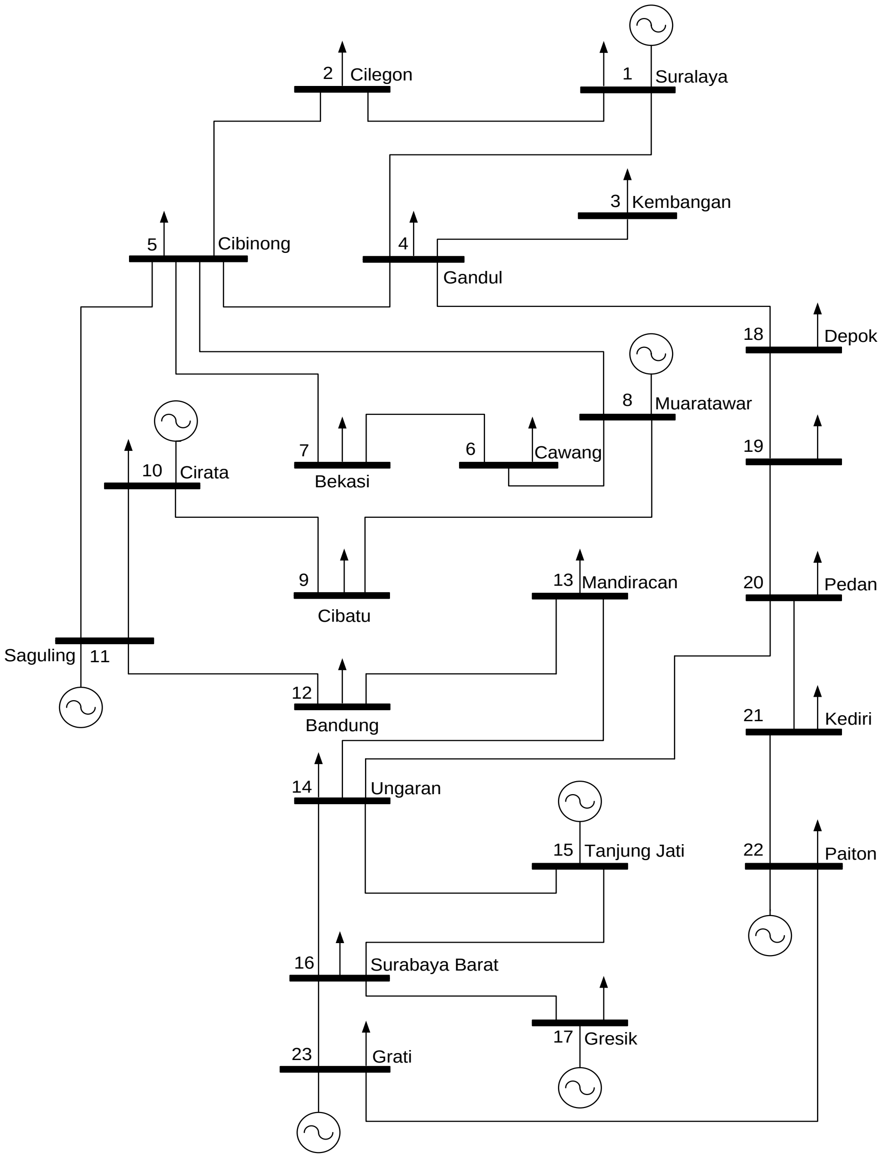

Fig. 3. Single Line Diagram of 500 kV Java-Bali Power System

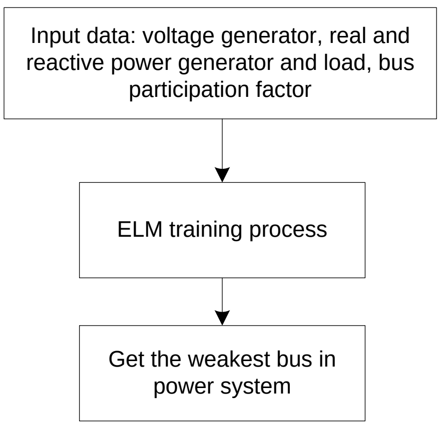

Fig. 4. Simulation process of ELM Method

Application of Modal Analysis method for IEEE-14 bus and Java-Bali system would obtain the bus participation factor values as shown in Fig. 5 and Fig. 6.

In this simulation, the relationship between changes in bus loads to the bus participation factor would be obtained.

The load on bus number 4 has been changed, so for any changes in this value, the new participation factor for all load buses would be obtained. The value of participation factor was taken as the input data. This data were limited to 4 ELM greatest value of participation factor, namely: Bus 9, Bus 10, Bus 11 and Bus 14.

Active and reactive power data for generator, the voltage at any bus generator, the voltage at the load bus, and load change at bus 4 were used as input data and the fourth largest participation values were used as data output for the ELM method, as shown in table 1.

Activation function in this simulation was the sigmoid method. After the simulation, the results obtained were:
Average Testing Accuracy = 2.6383e-004
Average Training Accuracy = 3.1689e-024
Average Training Time = 0.1477
Average Testing Time = 0.0233

The process of training indicated that: time was short and error was small. So we could conclude that the ELM could be used to estimate the modal analysis and improve the stability of steady state conditions.

For Java-Bali case, the load changes were given in bus 12. With the simulation steps as in IEEE-14 bus system, participation factor values obtained with the max error was 0.0764.
Average Testing Accuracy = 0.0019
Average Training Time = 0.0324
Average Testing Time = 0.0030
Testing Accuracy = 7.0417e-004
Training Time = 0.0313
Training Accuracy = 1.1445e-016

TABLE I
SAMPLE OF DATA INPUT FOR EXTREME LEARNING MACHINE FOR IEEE 14 BUS`SYSTEM

P1	Q1	V1	…	V2	V3	V6	V8	PL4	QL4	PF9	PF10	PF11	PF14
Real Power G1	Reactive Power G1	Bus Voltage	…	Bus Voltage	Bus Voltage	Bus Voltage	Bus Voltage	Real Power Bus Load	Reactive Power Bus Load	Part. factor bus 9	Part. factor bus 10	Part. Factor bus 11	Part. factor bus 14
1.517	0.308	1.06	…	1.04	1.01	1.07	1.08	0.967	0.3383	0.1912	0.2319	0.1095	0.327
1.528	0.306	1.06	…	1.04	1.01	1.07	1.08	0.977	0.338	0.1912	0.2319	0.1095	0.327
1.551	0.314	1.06	…	1.04	1.01	1.07	1.08	0.997	0.438	0.1914	0.232	0.1094	0.3266
1.564	0.324	1.06	…	1.04	1.01	1.07	1.08	1.007	0.538	0.1914	0.2321	0.1094	0.3262
1.679	0.331	1.06	…	1.04	1.01	1.07	1.08	1.107	0.738	0.1921	0.2323	0.109	0.3254
1.794	0.326	1.06	…	1.04	1.01	1.07	1.08	1.207	0.8383	0.1924	0.2325	0.1089	0.3249
1.91	0.322	1.06	…	1.04	1.01	1.07	1.08	1.307	0.9383	0.1927	0.2326	0.1087	0.3243
2.027	0.319	1.06	…	1.04	1.01	1.07	1.08	1.407	1.038	0.193	0.2327	0.1085	0.3237
2.145	0.317	1.06	…	1.04	1.01	1.07	1.08	1.507	1.138	0.1933	0.2328	0.1083	0.3231
2.265	0.315	1.06	…	1.04	1.01	1.07	1.08	1.607	1.238	0.1936	0.233	0.1081	0.3225

TABLE II
SAMPLE OF DATA INPUT FOR EXTREME LEARNING MACHINE FOR JAVA-BALI`SYSTEM

P1	Q1	V1	…	PL12	QL12	PF14	PF19	PF20	PF21
Real Power G1	Reactive Power G1	Bus Voltage G1	..	Real Power Bus Load 12	Reactive Power Bus Load 12	Part. factor bus 14	Part. factor bus 19	Part. Factor bus 20	Part. factor bus 21
3.323	0.957	1.02	…	0.59	0.351	0.0867	0.3688	0.281	0.1657
3.426	0.963	1.02	…	0.69	0.451	0.0868	0.3686	0.281	0.1656
3.529	0.97	1.02	…	0.79	0.551	0.0869	0.3683	0.281	0.1655
3.633	0.978	1.02	…	0.89	0.651	0.087	0.3681	0.2809	0.1654
3.737	0.986	1.02	…	0.99	0.751	0.0871	0.3679	0.2809	0.1653
3.84	0.996	1.02	…	1.09	0.851	0.0873	0.3676	0.2808	0.1652
3.945	1.006	1.02	…	1.19	0.951	0.0874	0.3674	0.2808	0.1651
4.049	1.017	1.02	…	1.29	1.051	0.0875	0.3671	0.2807	0.165
4.154	1.029	1.02	…	1.39	1.151	0.0876	0.3669	0.2807	0.1648
4.259	1.042	1.02	…	1.49	1.251	0.0877	0.3667	0.2806	0.1647
4.364	1.055	1.02	…	1.59	1.351	0.0878	0.3665	0.2805	0.1646
4.47	1.07	1.02	…	1.69	1.451	0.0879	0.3662	0.2804	0.1644
4.576	1.085	1.02	…	1.79	1.551	0.088	0.366	0.2803	0.1643

After going through the training process, ELM was tested using test data. This data were not included in the training process. In the picture, look 4 the ratio of the highest bus participation factor in the IEEE-14 bus system.

The weakest bus is bus 14, followed by bus 10, bus 9 and bus 11 respectively. This value of participation factor will change the value of any change in the load bus.

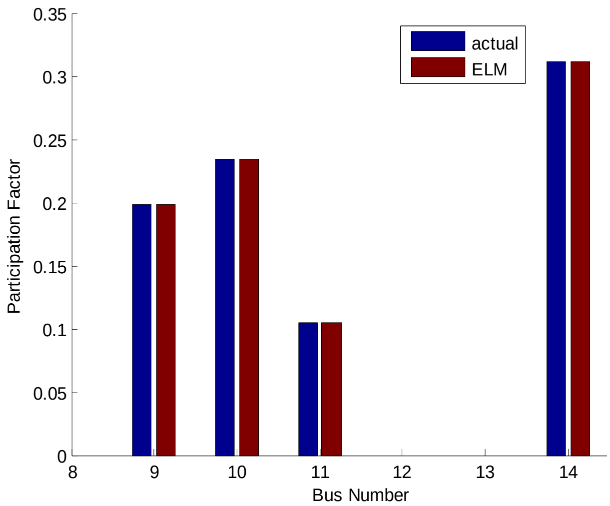

Fig. 5. Comparison of Modal Analysis and ELM Result for IEEE 14 Bus

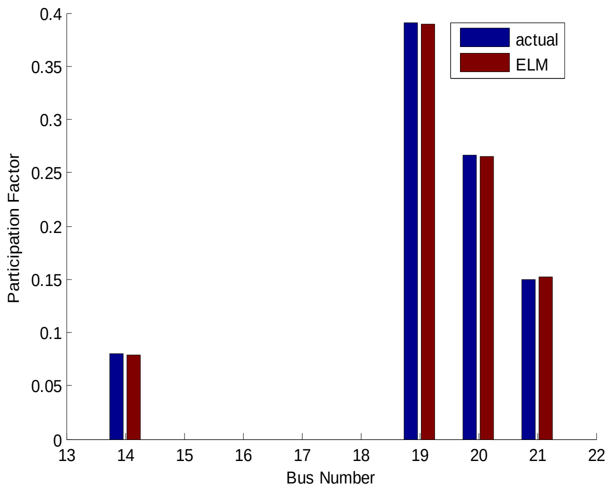

Fig. 6. Comparison of Modal Analysis and ELM Result for Java-Bali

In the Java-Bali system, buses having the largest participation for instability is bus 19 in a row followed by the bus 20, bus 21 and bus 14. Bus 12 (Bandung Selatan) was used as bus load changes. Any change in the load on this bus will affect the change in the value of power generation, the generator terminal voltage, load bus voltage and the bus participation factor. All of these change the value in teaching the ELM.

TABLE III

THE COMPARATION OF DATA TESTING AND ELM RESULTS FOR IEEE 14 BUS`SYSTEM

Testing Data PF	Learning PF	Errors
0.1049	0.105	0.003
0.1045	0.1048	0.0101
0.1039	0.1046	0.0244
0.1034	0.1043	0.0495
0.3114	0.3119	0.0007
0.3098	0.3115	0.0025
0.3079	0.3117	0.0052
0.3058	0.3127	0.0105

Actual data values and learning PF data were obtained from the ELM comparison and the error value was obtained as shown in table III and table IV. Of the error, it could be seen that the ELM was very accurate and fast in determining the voltage stability assessment.

TABLE IV
THE COMPARATION OF DATA TESTING AND ELM RESULTS FOR JAVA-BALI`SYSTEM

Testing Data PF	Learning PF	Errors
0.361	0.3621	0.0006
0.3608	0.3651	0.001
0.3605	0.3771	0.0102
0.3603	0.3878	0.0049
0.3601	0.4471	0.0518
0.2764	0.2749	0.0031
0.2761	0.2717	0.0118
0.2758	0.2619	0.0461
0.2755	0.2433	0.0764

V. Conclusion

In this paper, the estimated result obtained from ELM method showed that this approach was able to predict the voltage stability condition in power system. The result showed that Modal Analysis and ELM had overall error in output values was less 0.07 which would be acceptable and it meant that the ELM method had strong potential to be a useful tool for a voltage stability assessment and suitable for on line steady state stability assessment of power system.

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Ontoseno Penangsang was born in Indonesia in 1949. He received the Ph.D degree in electrical engineering from University of Wisconsin, USA, in 1983. He is currently a Professor of Department of Electrical Engineering, Sepuluh Nopember Institute of Technology (ITS). His research interest include power system analysis and power quality.

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