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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

***Abstract**. The problem of voltage collapse is a major issue in the operation of the current power system, especially when the penetration of wind turbines into the system continues to increase. The intermittency of the wind turbine has an impact on the stability of the system voltage. Fast Voltage Stability Index (FVSI) is used as a parameter for the condition of the system with the phenomenon of voltage collapse. This study aims to observe and predict the value of the Line stability index using Optimally Pruned Extreme Learning Machine (OP-ELM). The test case in this study is the South Sulawesi-Indonesia Electric Power System, with a total wind turbine penetration of 142 MW. From the simulation, it can be seen that OP-ELM can do forecasting very well with an error rate of 0.0886%.*

***Streszczenie.** Problem załamania napięcia jest poważnym problemem w funkcjonowaniu obecnego systemu elektroenergetycznego, zwłaszcza gdy penetracja turbin wiatrowych do systemu nadal wzrasta. Przerywalność turbiny wiatrowej ma wpływ na stabilność napięcia systemu. Wskaźnik stabilności szybkiego napięcia (FVSI) jest używany jako parametr stanu systemu ze zjawiskiem załamania napięcia. Niniejsze badanie ma na celu obserwowanie i przewidywanie wartości wskaźnika stabilności linii przy użyciu maszyny OP-ELM (ang. Optimally Pruned Extreme Learning Machine). Przykładem testowym w tym badaniu jest system elektroenergetyczny South Sulawesi-Indonesia, z całkowitą penetracją turbin wiatrowych 142 MW. Z symulacji widać, że OP-ELM może bardzo dobrze wykonywać prognozy ze wskaźnikiem błędu 0,0886%. (**Prognozowanie zapadu napięcia, gdy wielkoskalowe turbiny wiatrowe przenikną do systemów energetycznych przy użyciu optymalnie przyciętych maszyn do nauki ekstremalnych (OPELM) — studium przypadku: system elektroenergetyczny South Sulawesi-Indonesi**a)*

Keywords: Voltage Collapse, Extreme Learning Machine, Wind Turbine, Intermittency.
Słowa kluczowe: Zapade napięcia, maszyna do ekstremalnego uczenia się, turbina wiatrowa, przerywanie.

Introduction

The voltage stability problem is highly correlated with the limited distribution of reactive power in the power system [1-2]. Development of load and generation, not the development of transmission network construction. Coupled with the development of renewable energy, which continues to increase rapidly, it has a significant impact on the stability of the electric power system [3].

There are many methods that researchers in the field of stability have developed to determine the stability limit of electric power systems. These methods include Modal Analysis, L-index, Voltage Stability Index (VSI), Fast Voltage Stability Index (FVSI), and others [4]. This method is based on deterministic calculations developed using mathematical equations. The application of Artificial Intelligence within the limits of stability has also been developed.

This research was conducted by applying Optimally Pruned Extreme Learning Machine (OP-ELM) to determine system voltage stability limits by training data derived from FVSI computational results. Using OP-ELM in this research aims to create a real-time voltage stability monitoring model in an electric power system.

Artificial Intelligence methods have been widely applied in determining system stability, including the application of Artificial Neural Networks in determining voltage stability in power systems [5].

The electrical system used as a case study is the South Sulawesi-Indonesia Electric Power System. This system is the first electricity system in Indonesia that has been integrated with a large-scale Wind Turbine. There are two wind turbines integrated into the South Sulawesi system, namely the Sidrap Wind Turbine Plant (WTP) with a power capacity of 70 MW and the Tolo Wind Turbine Plant with a power capacity of 72 MW [6].

The integration of Sidrap WTP and Tolo WTP in the South Sulawesi interconnection system has had an impact in terms of system stability. It can be seen from the system frequency deviation data at the time before the two WTPs enter the system, the standard deviation of the system frequency is 0.078, while when the Sidrap WTP with a power capacity of 70 MW enters the system, the standard deviation is 0.095, and then when the two WTPs enter the system, the standard deviation is 0.095. to the system, obtained a standard deviation of 0.109. This shows that the intermittency of WTPs has a negative impact on foreign exchange frequencies in the Southern Sulawesi system [7].

This study aims to forecast the stability condition of the South Sulawesi system due to the intermittency of the Wind Turbine Plant using the OP-ELM method. Forecasting the condition of the voltage collapse is needed in the operation of the power system. It is hoped that the OP-ELM method developed can be applied to real time monitoring systems.

South Sulawesi-Indonesia electricity system

The South Sulawesi Electrical System consists of 77 buses with voltage levels of 77 kV, 150 kV and 270 kV with a total power at load of 1202.16 MW and 262 MVar. Figure 1 shows a single line diagram of the South Sulawesi – Indonesia interconnection system. There are 2 units of WTP, namely Sidrap WTP and Tolo WTP [6-7].

The South Sulawesi-Indonesia electricity system consists of 22 generator buses dominated by coal thermal generators with a total power percentage of 43.66%, followed by Hydro generators at 18.79%, Fuel at 16.44%, gas at 14.95% and Wind Turbine at 6.7%.[7]

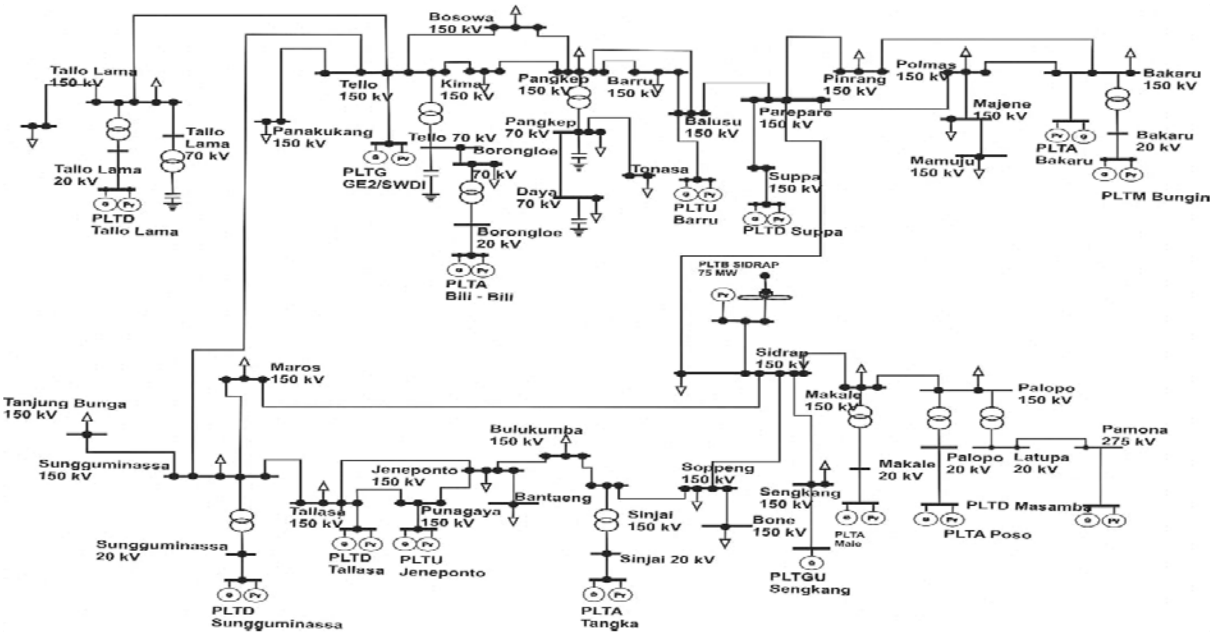

Fig. 1 South Sulawesi - Indonesia Interconnection System

Voltage Stability

In the electric power system there are various methods for assessing a system from a stable voltage or not and how close the system is to instability [8-10]. To be able to keep the voltage at the permissible value at the time after the disturbance is closely related to the stability of the voltage and the behavior of the load. This tool is often called the stress stability index. This index helps power system planners and operators to find out the stability voltage conditions in a power system that is operating in real terms. They can show how close the system is to voltage changes or instability caused by dynamic behavior. To find out the index must be simple, easy to implement and computational. In carrying out index detection, exposing critical buses or buses with low voltage from the power system and the level of stability of the transmission line that connects the buses in the system [11-12]. Figure 1 shows 5 state conditions of the system, starting during normal conditions and during disturbances. The voltage stability method has the following provisions:

1. Establish the proximity of the system to the collapse.
2. Determine when voltage instability can occur.
3. Determine the unstable bus in the system
4. Determine the affected area

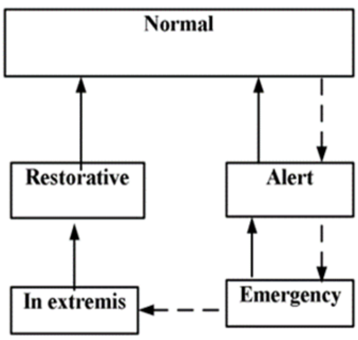

Fig.1. Various Conditions in the Power System (Lamine, 2011)

Artificial Neural Network (ANN)

Neural Networks can be called Artificial Neural Networks (ANN); this can be defined as simplifying the structure of the human brain model built on thousands of neural nets. To convey information signals from one point to another that the performance of the neural network structure is interconnected, these points are often referred to as neurons. Neurons are the smallest information signal processing unit in brain performance. The system of the human brain network is composed of more than 1013 neurons, with 10-15 dendrites connecting them [13]. With such a large number, the brain can receive several input signals, recognize a pattern with a large memory capacity, perform calculations, and provide a response to the body's organs at a very high speed. Neurons consist of essential components such as dendrites, soma, and axon. Dendrites connect one neuron to another, where dendrites receive input signals from other neurons. Then the signal enters the soma to add up the incoming calls and then activates it. The summation has a threshold that will be controlled by synapses that act as signal amplifiers or attenuators. If the sum of the signals is strong enough, then the call is transmitted to other neurons through the axon. The simple structure of a neuron can be represented in figure 2.

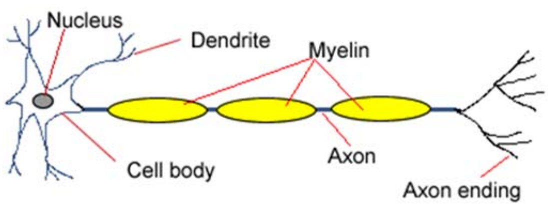

Fig.2. The structure of the neural network

Optimally Pruned Extreme Learning Machine (OPELM)

One of the reasons why feedforward neural networks tend not to be widely used in industrial data mining systems is almost certainly due to the prolonged training process.

This is because some parameters are set with a slow algorithm. Furthermore, the training stage must be repeated to display the selection of the model structure, for example, the selection of the number of hidden layers or the choice of several regularization parameters [13]. Guang-Bin Huang [14] proposed an algorithm for determining hidden nodes and selecting weights called ELM. The advantage of this method is that it divides the computational time into hundreds and makes the learning process of neural networks simple. Based on the ELM method, OPELM is intended to overcome the weaknesses that exist in ELM when there are irrelevant or uncorrelated variables. For this reason, the OPELM method was introduced to trim unrelated variables by pruning non-essential neurons from SLFNs constructed by ELM.

The OPELM model was built in three stages [14]. The first step of the OPELM method is to construct the SLFN structure using the ELM algorithm. Then the ranking of neurons in the hidden layer is carried out with the MRSR (Multiresponse Spare Regression) algorithm. Finally, the number of pruned neurons is determined based on the Leave-One-Out (LOO) error estimation method. The OPELM algorithm uses a combination of three kernel types, linear, sigmoid, and gaussian. While in ELM, only one kernel is used, for example, sigmoid.

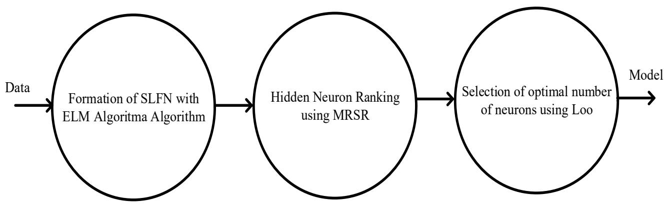

Fig.3. Fig. The three main steps of the ELM Method

Transmission Line Stability Index

The level of stability in the transmission connecting the two buses in the power system can be determined using various mathematical approaches. There are several methods that have been developed by researchers in determining the value of transmission line stability indexes, including: Lmn, LQP, VCPI and FVSI [15].

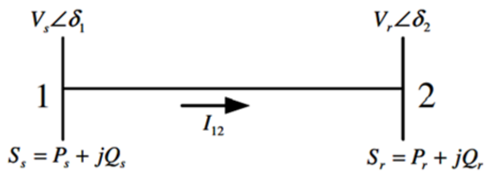

Fig.4. The three main steps of the ELM Method

The FVSI value can be obtained using the following equation:

(1) $$FVSI = \frac{4Z^2Q_r}{V_s^2X}$$

Forecasting Voltage Collapse Index

Forecasting the value of the Voltage Stability Index is carried out by conducting a training process of data obtained from FVSI. Every change in power in the load will affect the difference in the FVSI value.The data changes in load and changes in FVSI as much as 1500 data changes. As much as 80% of the FVSI change data is used as OP-ELM training data; the remaining 20% is used as testing data on OP-ELM. Fig.5 shows the structure of the data parameters used as training and testing data for determining the stress stability index when the Wind Turbine is integrated with the South Sulawesi system.

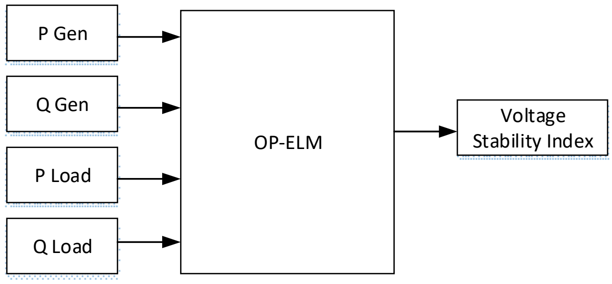

Fig.5. Parameter Structure Data on Voltage Stability Index OP-ELM

Changes in the active power load (P) and reactive power load (Q) are carried out at each shipment then the FVSI value will also change. The maximum loading limit on each bus can be obtained by looking at the convergence of the load flow program created. The accuracy of the OP-ELM Voltage Stability Index (OP-ELM VSI) can be seen from the errors that appear during training and testing.

This study was validated using the error value of MAPE (Mean Absolute Percentage Error). MAPE is the absolute average error percentage (complete). MAPE means statistical measurement of the accuracy of the forecast (prediction) in the forecasting method. The broader community can use calculations because it is easy to understand and apply in predicting forecasting accuracy. The MAPE calculation method provides information on how much the forecast error is compared to the actual value of an experiment. The smaller the percentage error in MAPE, the more accurate the forecasting results using Matlab will be. The Mean Absolute Percentage Error (MAPE) value is analyzed as written in table 1.

Table 1. MAPE Value Range

MAPE Range	Value meaning
<10%	Forecasting model is very good
10%-20%	Good forecasting model ability
20%-50%	The ability of the forecasting model is feasible
>50%	Poor forecasting model ability

The formula used to find the MAPE value is:

(2) $$MAPE = \frac{\sum_{t=1}^{n} |(\frac{A_t - F_t}{A_t})100|}{n}$$

where : A_t = Actual data to t; F_t = Forecasting data to t; n = the amount of forecasting data

Result and Discussion

Determination of the value of the stress stability index in the South Sulawesi system is carried out by several methods including the Lmn index, FVSI index and LQP Index. The value of the voltage stability index on each transmission branch line in the South Sulawesi system can be seen in the Fig. 6, Line Branch No. 48 has the highest stress stability index value of 0.1222, followed by branch numbers 43, 15, 63 and so on.

The value of the FVSI transmission line stability index for the 10 largest transmission line branches in the South Sulawesi system is sorted and seen in the table 2.

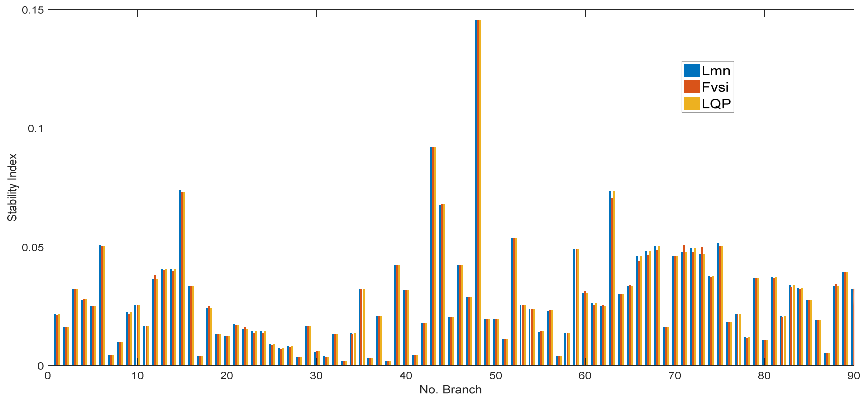

Fig. 6 Comparison of Voltage Stability Index Values in the South Sulawesi Electrical System

Table 2. The largest FSVI index value for 10 branches

Ranking.	Branch No.	FVSI Index
1	48	0.1222
2	43	0.0901
3	15	0.0732
4	63	0.0706
5	44	0.0618
6	52	0.0527
7	71	0.0508
8	6	0.0505
9	75	0.0504
10	73	0.0498

Determination of the value of the FSVI index is done by increasing the load on a certain bus until the maximum loading limit is obtained on the bus. Table 3 shows the change in load and the load limit on bus 41 (Pangkep 70 kV). From table 3, it can be seen that the maximum load limit on the 70 kV Pangkep bus is 155 Mvar.

Table 3. Maximum Loading Limit on Pangkep Bus

No.	Reactive Load Q (MVAR)	FVSI index
1	0	0.1208
2	1	0.1209
3	5	0.1213
4	10	0.1219
5	15	0.1225
6	30	0.126
7	50	0.1287
8	70	0.1318
9	90	0.1358
10	100	0.1379
11	120	0.143
12	140	0.154
13	150	0.1618
14	155	Not Convergen

Furthermore, by carrying out the data training process and data testing on the OP-ELM, the OP-ELM index value is obtained for various changes in load power. The following is an example of the results of changes in power and the value of OP-ELM VSI along with the MAPE value.

Table 4. MAPE values for the OP-ELM VSI Training process

Load Q (MVAR)	FSVI	OPELM_Index	Absolute Error
0	0.1208	0.1208	0
1	0.1209	0.1209	0
5	0.1213	0.1213	0
10	0.1219	0.1219	0
15	0.1225	0.1225	0
30	0.126	0.126	0
50	0.1287	0.1287	0
70	0.1318	0.1318	0
90	0.1358	0.1358	0
100	0.1379	0.1379	0
120	0.143	0.143	0
140	0.154	0.154	0
150	0.1618	0.1618	0
		MAPE	0

Table 4. shows the MAPE error value that occurs in the training process for the case of an increase in load on the 70 kV Pangkep bus. Table 5. shows the MAPE error value that occurs in the training process for the case of an increase in load on the Mandai bus.

Table 5. OP-ELM index value on bus 36 (Mandai)

Load Q (MVAR)	Lmn	OPELM_Index	Absolute Error
30.1	0.1301	0.1301	0
40.1	0.1336	0.1336	0
50.1	0.1373	0.1373	0
60.1	0.1413	0.1413	0
70.1	0.1456	0.1456	0
80.1	0.1503	0.1503	0
90.1	0.1554	0.1554	0
100.1	0.1611	0.161	0.062073246
110.1	0.1673	0.1676	0.179318589
120.1	0.1742	0.1737	0.287026406
130.1	0.182	0.1827	0.384615385
140.1	0.1951	0.1945	0.307534598
150.1	0.2059	0.2063	0.194269063
160.1	0.2188	0.2186	0.091407678
170.1	0.2344	0.2344	0
180.1	0.2543	0.2543	0
190.1	0.2815	0.2815	0
		MAPE	0.088602645

By using the method proposed in this paper, OP-ELM VSI is able to predict voltage collapse prediction on the electricity system of South Sulawesi. In Figure 7, Figure 8 and Figure 9, the limit of voltage stability on the Mandai, Pangkep and Bulukumba buses can be obtained with a very low error rate.

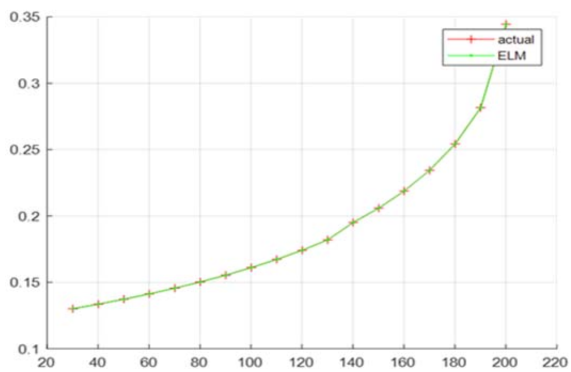

Fig.7 Voltage Collapse Prediction Using ELM for Bus 36 (Bus Mandai)

On the Mandai bus, the maximum power value is 200 MVar with the OP-ELM VSI index value of 0.35. While on the Pangkep bus, the maximum power value that can be consumed on the bus is 150 Mvar, with the OP-ELM VSI index value of 0.162

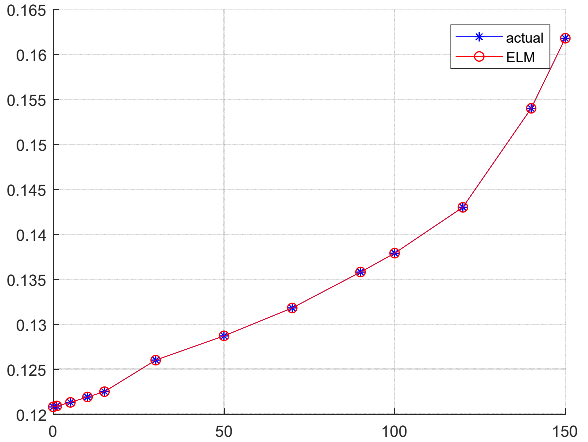

Fig. 8 Voltage Collapse Prediction Using ELM for Bus 41 (Bus Pangkep)

While on the Bulukumba bus, the maximum reactive power loading limit is 450 Mvar with an OP-ELM VSI index value of 0.094. These results show that the bus capability in the South Sulawesi electricity system is largely determined by the network configuration and loading.

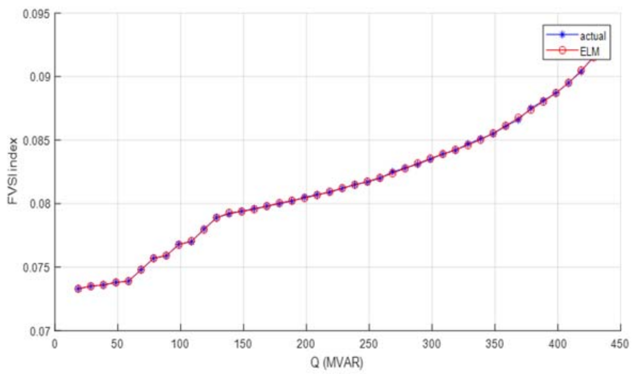

Fig. 9 Voltage Collapse Prediction Using ELM for Bus 11 (Bus Bulukumba)

Conclusion

From the simulation results, it can be seen that the application of OP-ELM in determining the forecasting value of voltage stability in the power system shows very good results. It is evident from the largest MAPE error value obtained at 0.0886%. This shows that OP-ELM is very appropriate to be applied in determining and forecasting voltage collapse in power systems, especially for online monitoring purposes which require fast computing time and with increasing power system dynamics due to the integration of large-scale wind turbines in the power system

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