Stability Margin When Wind Turbine Large Scale Penetrated to South Sulawesi-Indonesia Power System Using Optimally Pruned Extreme Learning Machine (OPELM)

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Abstract. The objective of this study is to determine the distance to the point of power system instability that occurs when wind turbine power output suddenly changes. The introduction of large-scale wind turbines affects the stability of the power system, and the intermittency factor has a significant influence on this distance to the instability condition. The South Sulawesi—Indonesia interconnection system is used as a test case in Indonesia. The OPELM method yields an average testing accuracy of 1.537%, which is derived from the training and testing results of the REI net system value.

Keywords: Wind Turbine, Stability Margin, Intermittent, REI-net, OPELM

1 Introduction

The current power system is running under extremely stressed conditions, which raises additional challenges. In such a circumstance, voltage instability is a relatively regular occurrence that impairs the operation of the power system. The power system needs to be examined in light of voltage stability for a variety of system circumstances in order to prevent system outages. The fundamental purpose of voltage stability study is to discover the maximum load ability limit of the system and the causes of voltage instability [1] and [2], which are centered on the stability and control of the power system. He described how to evaluate the stability of a power system, how to

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increase system stability through various analyses, and how to keep the power system from becoming unstable.

On the other hand, the dampening of the inter-area mode is marginally improved by increasing the penetration level of wind turbines with permanent magnet generators. With the increase in the penetration level of renewable energy and different power generating portfolios, [3], [4] emphasized on voltage and small signal stability of a power system. They recommended 20% to 30% renewable energy (in MW) penetration in the test system as a preferred penetration, which gives appropriate load ability and optimal grid loss.

The paper examined the advantages of energy storage in power networks with high levels of intermittent generation, and it provided a methodology to estimate how much energy would have to be restricted and how much electrical demand would have to go unmet [5].

Power transmission capacity has historically been constrained by the thermal loading capacity of transmission lines and equipment or by synchronous (or rotor angle) stability. To prevent voltage collapse and the resulting partial or complete system blackout, voltage stability is a key issue that must be taken into account while building and running electrical power systems. System operators must understand not only the severity of their system but also the mechanisms causing voltage instability, according to the examination of various approaches and strategies used to increase the voltage stability of electrical power systems [6-9].

Load bus proximity is shown by two metrics: load power margin (LPM) and voltage stability margin (VSM). The indicators that indicate how close a load bus is to experiencing voltage instability are the voltage stability margin (VSM) and load power margin (LPM). The load bus in question is more prone to voltage instability the lower its VSM or LPM values. The use of probabilistic neural networks (PNNs) for VSM and LPM value classification is presented in this paper [10]. The penetration of Renewable Energy with Large Scale in the past few decades has had an impact on the power system, particularly on stability. In the South Sulawesi-Indonesia system, the penetration of Wind Turbines has achieved a very large magnitude. With a total power output of 142 MW from Wind Turbines located in two places, Sidrap and Tolo, Jeneponto, South Sulawesi, Indonesia [11-12].

A lot of artificial intelligence techniques have been used to assess system stability, such as the use of artificial neural networks to assess voltage stability in power systems [13-15]. The electrical system employed in the case study was the South Sulawesi-Indonesia Electric Power System. It is the first time an enormous wind turbine has been integrated into an electricity system in Indonesia. The two wind turbines incorporated into the South Sulawesi system are the 70 MW Sidrap Wind Turbine Plant (WTP) and the 72 MW Tolo Wind Turbine Plant [16].

The goal of this study is to forecast the South Sulawesi system's steady state stability margin using the OP-ELM method in light of the intermittent nature of the wind turbine plant. Predicting the state stability condition is necessary for the power system to operate. The application of the OP-ELM technique to real-time monitoring systems is looked for.

2 Stability in Power System

2.1 Voltage Stability

The power system's ability to restore a state of operational balance after a physical disturbance, while ensuring that most system variables are within limits and the system remains largely intact, is referred to as power system stability. On the other hand, instability is a state that signifies a lack of synchronization or a deviation from the intended rhythm. Furthermore, stability in the context of a power system pertains to its ability to generate counteracting forces that are equal or greater in strength than the forces causing disruption, with the aim of maintaining a state of balance. Disturbances, as defined by the given definition, encompass a range of events including faults, load variations, generator failures, line outages, voltage collapse, and other similar occurrences. The user's text is already straightforward and precise.

Voltage stability refers to the system's capacity to withstand disturbances and sustain a consistent voltage level at each system bus. Voltage stability for significant disturbances is correlated with significant disturbances, while voltage stability for minor disturbances is correlated with minor disturbances. Voltage instability in power systems occurs when there are highly loaded, defective, or underpowered reactive power transmission lines. The ability of the power system to maintain or restore the balance between supply and demand for loads is crucial. The gradual fluctuation of voltages in certain buses can result in voltage collapse, which may lead to system instability. Through the examination of the production, one can analyze the inherent characteristics of voltage stability [18].

2.2 Load Margin

The probability of voltage instability in a load bus can be assessed using two indicators: the load power margin (LPM) and the voltage stability margin (VSM). The closer a load bus's Voltage Stability Margin (VSM) or Load Power Margin (LPM) is to zero, the closer it is to experiencing voltage instability. Conversely, the further away the VSM or LPM is from zero, the further away the load bus is from voltage instability. The acronyms "VSM" and "LPM" denote the distinction between the critical/collapse point of voltage/load power and the beginning operating point of voltage/load power. The closeness to voltage breakdown can be determined using many indicators. The loading margin, a commonly employed indicator, is determined by the load ability limit. The load ability limit refers to the maximum loading point when the operating point ceases to exist under a specific operating condition [19].

2.3 South Sulawesi-Indonesia Grid

The voltage levels of the 77 buses in the South Sulawesi Electrical System are 77 kV, 150 kV, and 270 kV. The system's total power at load is 1202.16 MW and 262 MVar. The connectivity infrastructure between South Sulawesi and Indonesia is illustrated in a single line diagram shown in Fig. 1. The Sidrap Water Treatment Plant (WTP) and the Tolo Water Treatment Plant (WTP) are two units of water treatment plants.

The South S`ulawesi-Indonesia electricity system consists of 22 generator buses, primarily coal thermal generators, with a total power percentage of 43.66%. The subsequent sources of energy were as follows: fuel accounted for 16.44%, gas for 14.95%, hydro generators for 18.79%, wind turbines for 6.7%, and fuel for 16.44%. The schematic diagram of South Sulawesi's electrical system in Indonesia is shown in Fig. 1. Following the incorporation of the wind turbine into the southern Sulawesi system, there was an alteration in the system's frequency deviation, causing the system frequency to depart from the 50 Hz position.

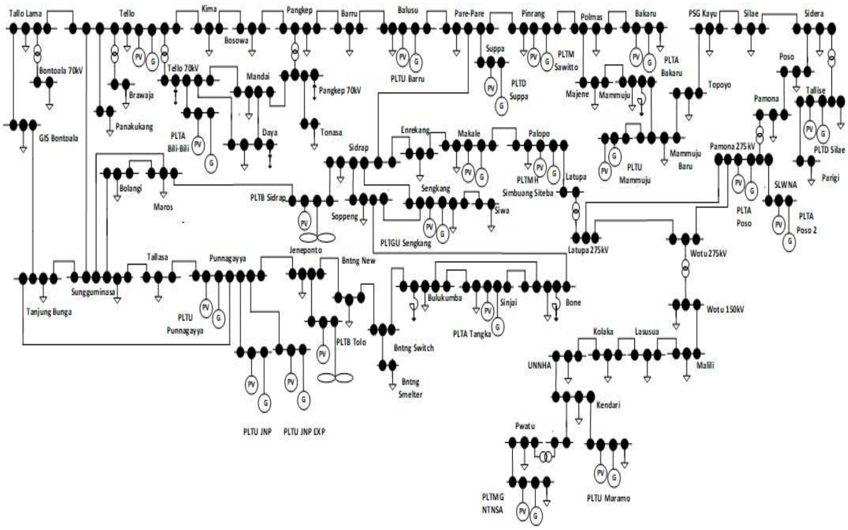

Fig. 1. Interconnection system of South Sulawesi-Indonesia.

3 Methodology

3.1 P-V and Q-V curves

PV curve analysis is utilized to ascertain the voltage stability of both a radial system and a huge meshed network. V represents the measurement of voltage, which is detected at specific load buses that are important. P represents the measurement of power at a particular point, which is gradually increased. Subsequently, a static analysis method will be employed to generate curves representing the voltage stability of the system for the specified buses. Monitoring of buses is necessary as PV curves are specifically plotted for each individual bus.

A QV study investigates the correlation between changes in reactive power injection (Q) at a certain bus and changes in voltage (V) at the same bus. Furthermore, it is feasible to observe and trace supplementary system parameters while the reactive power injection fluctuates. The voltage stability margin (VSM) can be derived from the PV and QV curves, as depicted in Fig. 2. Voltage instability is more likely to occur at the power system's bus when the VSM value is lower, and vice versa.

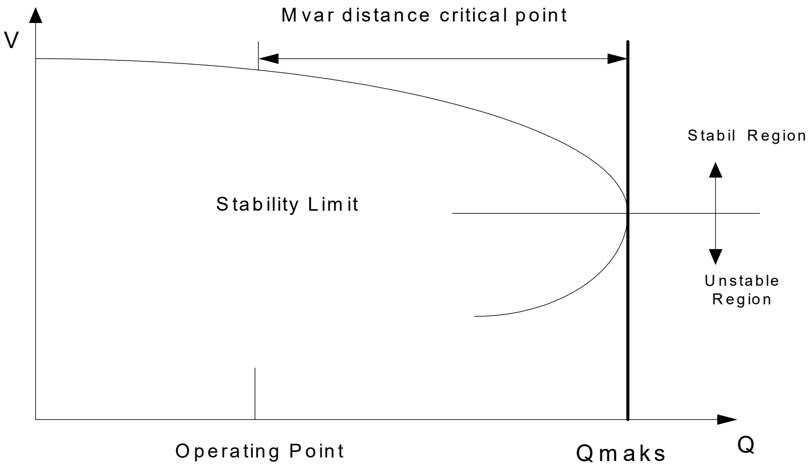

Fig. 2. PV and QV curve.

3.2 Optimally Pruned Extreme Learning Machine (OPELM)

The term "Optimally Pruned Extreme Learning Machine (OPELM)" is used to denote a certain machine learning technique or method. The Extreme Learning Machine (ELM) is a well-recognized type of artificial neural network that is renowned for its user-friendly nature and high efficacy in training. OPELM, short for Optimally Pruned Extreme Learning Machine, appears to be a modified version of the ELM algorithm. Its objective is to enhance performance by selecting and refining the network architecture.

The network design of OPELM can be enhanced or streamlined to improve accuracy or efficiency for a specific task. In order to maintain optimal performance, it may be imperative to eliminate unnecessary neurons or connections from the network. The specifications and approaches for pruning or optimization in OPELM may vary depending on the application and circumstance [20].

The creation of the OPELM model involved three distinct phases. The initial step of the OPELM approach involves constructing the SLFN structure using the ELM algorithm. The Multi response Spare Regression (MRSR) technique is subsequently employed to prioritize the neurons in the buried layer. The Leave-One-Out (LOO) error estimate technique is ultimately employed to determine the overall count of pruned neurons. The OPELM method utilizes three distinct kernel types: gaussian, sigmoid, and linear. In ELM, a solitary kernel, such as the sigmoid function, is employed. Fig. 3 displays the schematic diagram of the OP-ELM.

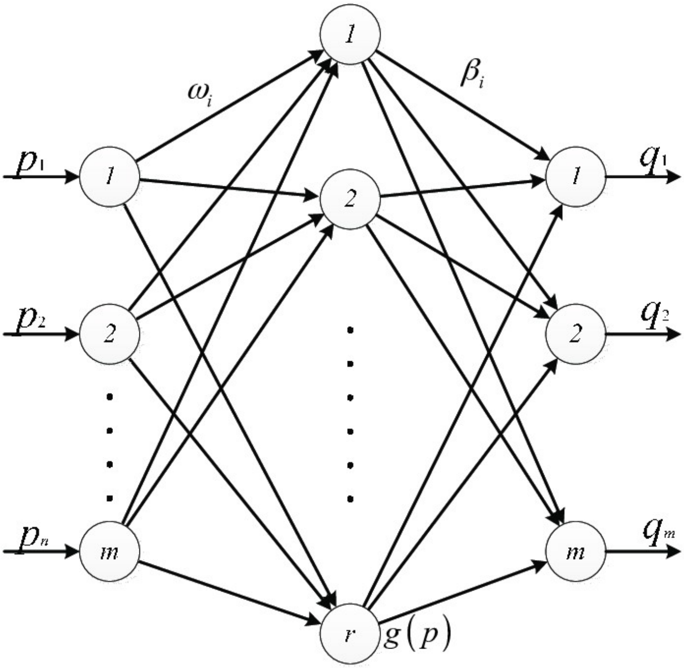

Fig. 3. The ELM schematic diagram.

3.3 Radial Equivalent Independent (REI)

By incorporating a consistent admittance into a hypothetical bus, the transmission network is substituted in the REI-Dimo methodology. The network is referred to as a "zero power balance network" and represents the fundamental concept of the REI-Dimo approach. Fig. 4 depicts the REI-Net model designed for power systems.

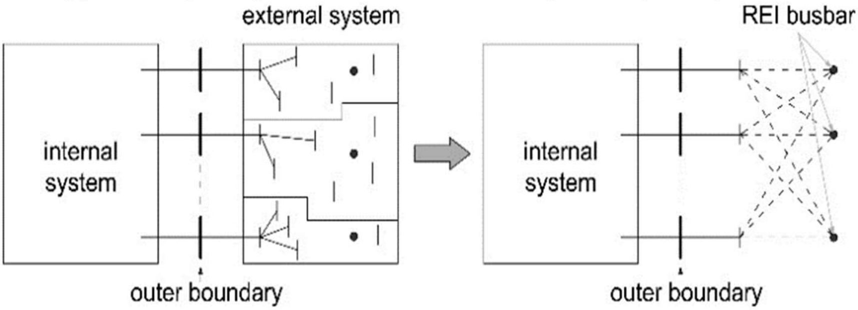

Fig. 4. Lower model in the REI technique.

The reactive power load is computed at each step, taking into account a constant load structure with a fixed power factor (cos θ). The requirements for this have been formulated using mathematical equations:

$$\frac{d\Delta Q}{dV} = \sum_m \frac{Y_m E_m}{\cos(\delta_m + Y_m)} - 2\left(\sum_m Y_m \cos Y_m + Y_{load} + Y^Y\right)V \quad (1)$$

3.4 Forecasting of Steady State Stability Margin

The technique employed to predict the value of the Steady State Stability Margin is training with data obtained from REI-Net. The Margin Stability (MS) rating is subject to change with every fluctuation in power within the load center. The load and MS data contain a maximum of 3000 data changes 85% of the FVSI change data is utilized for training the OP-ELM, while the remaining 15% is allocated for testing the OP-ELM.

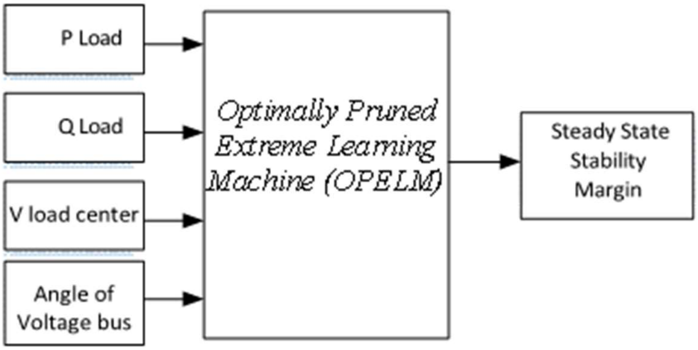

Fig. 5. Parameter organization margin stability data (OP-ELM).

Table 1. Example data for training and testing.

Total Real Power of Load Center (MW)	Total Reactive Power of Load Center (MVAR)	Voltage on Load Center (pu)	Angle of Voltage Bus (Degree)	Stability Index
785.41	136.35	0.94	-0.0012	-31.2755
790	140	0.939	-0.0015	-31.2133
795.41	146.35	0.938	-0.0018	-31.1202
800.41	151.35	0.936	-12.655	-31.0422
805.41	156.35	0.935	-12.806	-30.964
810.41	161.35	0.934	-12.957	-30.8855
820.41	171.35	0.932	-13.261	-30.7277
830.41	181.35	0.93	-13.566	-30.569
840.41	191.35	0.928	-13.873	-30.4092

850.41	201.35	0.926	-14.181	-30.2483
860.41	211.35	0.924	-14.491	-30.0865
870.41	221.35	0.922	-14.802	-29.9235
880.41	231.35	0.92	-15.115	-29.7594
900.41	251.35	0.916	-15.746	-29.4279
920.41	271.35	0.912	-16.383	-29.0918
940.41	291.35	0.906	-15.0149	-28.7701
960.41	311.35	0.903	-17.514	-28.4464
980.41	980.41	0.899	-18.079	-28.121
1000.41	351.35	0.894	-18.641	-27.7945
1020.41	371.35	0.89	-19.201	-27.4675
1040.41	391.35	0.886	-19.755	-27.1667
1060.41	411.35	0.881	-20.308	-26.8833

4 Result and Discussion

The initial phase of this simulation involves doing the training and testing procedures on a dataset consisting of 3000 test samples. By utilizing four input parameters, namely bus center voltage, bus center angle, active power, and reactive power of the bus center. The utilized output data is the value of the system stability margin. Fig. 6 illustrates the training process for achieving steady state stability margin in the OP(ELM) system.

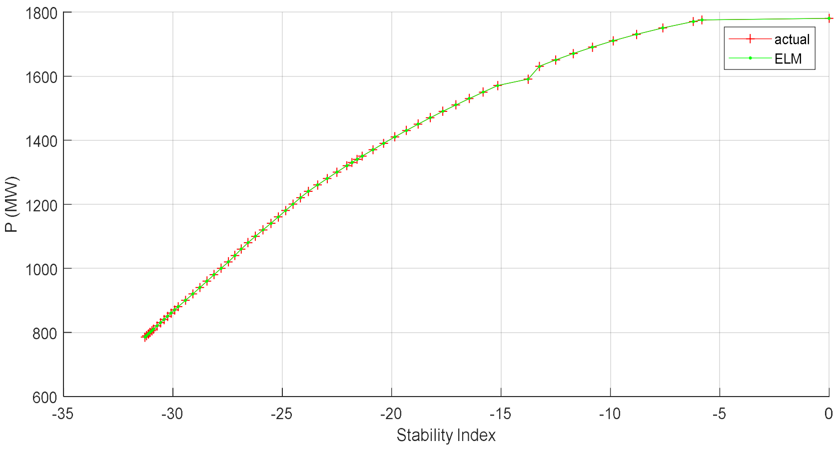

Fig. 6. Process of training for steady state stability margin OP(ELM).

The stability boundary of the Sulawesi system is determined by incrementally applying load and calculating the stability index using the REI indicator. A load increase of 785.41 MW results in a stability index value of -31.2755. At the load center, the voltage value is 0.94 per unit (p.u), the voltage angle is -0.0012 degrees, and the reactive power value is 136.35 MVar. Power adjustments are implemented in increments of 5 MW, leading to modifications in voltage, voltage angle, reactive power Q, and the stability index. The steady state stability margin value for the South Sulawesi-Indonesia system is 1800 MW, as indicated in Fig. 7.

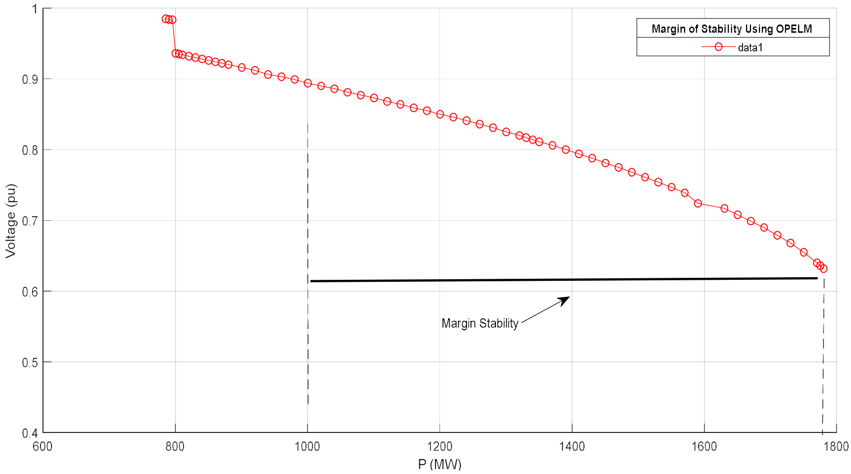

Fig. 7. Steady state stability margin for the South Sulawesi-Indonesia using OP-ELM.

The MAPE approach is utilized to demonstrate the precision of OP-ELM. The simulation results indicate that the MAPE value produced is 1.537%. These results demonstrate that OP-ELM is capable of precisely determining the limit value of steady state stability margin.

5 Conclusion

The simulation findings demonstrate that employing OP-ELM for calculating the steady state stability margin value in the electric power system yields exceptional outcomes. This is evidenced by the highest MAPE error value, which was 1.537%. The increasing complexity of the electric power system, caused by the integration of large-scale wind turbine energy systems, highlights the effectiveness of OP-ELM as a tool for predicting and assessing stability margins in electric power systems. This is particularly useful for online monitoring applications that require fast computation.

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References

1. C. M. Reddy, “Power System Voltage Stability Analysis,” no. June, 2011
2. M. H. Nguyen, T. K. Saha, and M. Eghbal, “Impact of High Level of Renewable Energy Penetration on Inter-area Oscillation.”
3. T. Aziz and N. Ketjoy, “PV Penetration Limits in Low Voltage Networks and Voltage Variations,” vol. 5, 2017.
4. I. Stadler and S. T. Sma, “Power Grid Balancing Of Energy Systems With High Renewable Energy Penetration By Demand Response,” no. March, pp. 17–19, 2009.
5. P. Europe, A. Schmelter, and D. Morton, “Challenges in Integrating Distributed Energy Storage Systems into Future Smart Grid,” no. August, 2008.
6. D. Verma, S. Rajakaruna, and T. Johnson, “Stability Assessment of a Small Islanded Power Network with High Penetration of Renewable.
7. S. B. Bhaladhare and P. D. Scholar, “P-V , Q-V Curve – A Novel Approach for Voltage Stability Analysis,” pp. 31–35, 2013.
8. A. Fateh, M. Nor, M. Sulaiman, A. Fazliana, A. Kadir, and R. Omar, “CLASSIFICATIONS OF VOLTAGE STABILITY MARGIN (VSM) AND LOAD POWER MARGIN (LPM) USING PROBABILISTIC NEURAL NETWORK (PNN),” vol. 12, no. 19, pp. 5591–5596, 2017.
9. Javad Modarresi, et.al, " A comprehensive review of the voltage stability indices," Renewable and Sustainable Energy Reviews 63 (2016) 1–12
10. M. Sulaiman, A. Fateh, M. Nor, and N. R. Bujal, “Voltage Instability Analysis on PV and QV Curves for Radial-Type and Mesh- Type Electrical Power Networks Voltage Instability Analysis on PV and QV Curves for Radial-Type and Mesh-Type Electrical Power Networks,” no. February, 2015.
11. Gunadin I.C, et. al, The Impact of the Injection of Wind Power Plant on the Steady State Condition and the Dynamics of SULSELBAR Power System, International Journal of Electrical and Electronic Engineering & Telecommunications Vol. 8, No. 6, November 2019
12. Suroso, Experience and Role Intermittent Generating Operation in the Sulawesi Electrical System, CIGRE Webinar, 26 June 2020
13. A. Fateh, M. Nor, M. Sulaiman, A. Fazliana, A. Kadir, and R. Omar, “CLASSIFICATIONS OF VOLTAGE STABILITY MARGIN (VSM) AND LOAD POWER MARGIN (LPM) USING PROBABILISTIC NEURAL NETWORK (PNN),” vol. 12, no. 19, pp. 5591–5596, 2017.
14. I. Musirin, et. al, "Novel fast voltage stability index (Fvsi) for voltage stability analysis in power transmission system," in Research and Development, Student Conference on SCOReD 2002, pp. 265-268, 2002.
15. [9]. G. K. Morison, B. Gao, and P. Kundur, "Voltage stability analysis using static and dynamic Approaches," IEEE Transactions on Power Systems, vol. 8, pp. 1159-1171, 1993.

16. Siswanto, A., Steady State Stability Limit Assessment when Wind Turbine Penetrated to the Systems using REI Approach. Vol. 1. 2019. 53-57.
17. Goh, H.H., et al. Validation of steady-state stability evaluation exerting with Dimo's approximation. in 4th IET Clean Energy and Technology Conference (CEAT 2016). 2016.
18. Isaac A. et. al., "Prediction of Voltage Collapse in Electrical Power System Networks using a New Voltage Stability Index." International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 2 (2017) pp. 190-199
19. R. Balasubramania et.al, Power System Voltage Stability Analysis Using ANN and Continuation Power Flow Methods, International Conference on Intelligent System Applications to Power Systems, 2011
20. Yoan Miche, et.al, " OP-ELM: Optimally Pruned Extreme Learning Machine," IEEE transactions on neural networks, Vol. 21, No. 1, January 2010