Planning for Battery Energy Storage Systems Control to Enhance Stability of the Microgrid using Power Forecasting

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Abstract— *A microgrid system which uses renewable energy has to enhance the system stability because the fluctuation of renewable energy source in the microgrid system may damage the system. Therefore, this paper proposes a method to strengthen the stability of a microgrid system by using planning to control the Battery Energy Storage System (BESS). The proposed method aims (i) to forecast power of the system based on the previous information by using Artificial Neural Network (ANN), (ii) to analyze the stability and to select the operation mode for BESS by using load flow analysis, and (iii) to control the BESS according to the appropriate process from part (i) and part (ii) for enhancing the system stability. The IEEE 13 node standard test system has been used to evaluate the proposed method, and the system has been modified to the off-grid system which uses hybrid renewable energy resources including wind and solar energy sources. The simulation was performed using MATLAB. By using the proposed method, the simulation results show that the system stability obtaining from the proposed method is better than the conventional controlling method because the proposed method can maintain the voltage in the range belong to the IEEE 1547 standard. The study results also showed that an accurate power forecast could manage microgrid effectively.*

Keywords— **Power forecasting, BESS, battery control, steady-state stability.**

1. INTRODUCTION

The microgrid system which uses Renewable Energy Resource (RER) to provide energy has to install BESS for supplying load when load demand over generated power from RER. This system requires voltage control and frequency control for prevented power system instability by the power fluctuation. Power system instability can be classified into three types, i.e., (i) steady-state instability, (ii) transient instability and (iii) dynamic instability. For the off-grid system, the steady-state instability has been the most interesting because such an event can easily occur by load and generated power from RER slow change.

For a decade, researchers have been focused on BESS control to improve the stability of a microgrid system which was fluctuated by RER and load demand using BESS. Optimal BESS control for the microgrid system which uses RER has many methods such as voltage stability were improved by optimal active power and reactive power output control of storage battery system, microgrid with RER was controlled by Optimal BESS control [1]-[3].

The objective of BESS control is mainly focused to supply enough power to the system all the time. However, a BESS cannot always provide enough power to the system due to the fluctuation of renewable energy generation sources and leads to instability of a microgrid system. Recently, system stability improvement is widely considered.

Forecasting technique is interesting to use to solve many problems in a power system. Such as forecasting the wind power curve from inconsistent data and forecasting the photovoltaic power using the artificial neural network. The PV distributed generation is forecasted in consideration of its effects on load forecasting [4]-[6]. Therefore, power forecasting is an attractive technique to manage the microgrid system.

The planning to control an insufficient power from BESS to maintain the stability of a microgrid system using the power forecast is proposed in this paper. The rest of the research work structured as follows: In section 2 details about the theory of power forecasting. A comparison of a learning method for power forecasting shown in section 3. Section 4 presents the voltage standard and BESS control modes. A case study and the simulation results along with discussion presented in section 5. Finally, the conclusion of the paper shown in section 6.

2. POWER FORECASTING

Many techniques can be applied to power forecasting such as a short-term load forecasting based on wavelet theory, and a load power forecasting based on feedforward Artificial Neural Network (ANN) [7], [8]. This paper, power forecasting based on ANN has been used to forecast wind power generation, PV power generation, and load demand. The accuracy of power forecasting depends on using into account all essential factors from the system to forecast.

Power Forecasting from Wind Turbine

A wind turbine which use to convert the kinetic energy of the airflow to mechanical energy. After that, the

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mechanical energy is converted into electrical energy by the generator in a wind turbine. The influential factors of generated power from the wind turbine are wind speed and the air density which depends on temperature [9]. Electrical power generated from wind power can be expressed as equation (1).

$$P_{wind} = f(\mathrm{w}_s \mathrm{V} + \mathrm{w}_a \mathrm{A}) \tag{1}$$

where P_{wind} = generated power from a wind turbine (W)
w_s = weight of wind speed
V = wind speed (m/s)
w_a = weight of air density
A = air density (kg/m^3)

Power Forecasting from PV

A solar cell is used to generate electrical power from sunlight. Nowadays, many types of solar cell panel have been available for electrical power generation. However, power generation from solar cell depends on the two influential factors, i.e., sunlight irradiation and temperature. [10]. Electrical power generated from the solar cell can be expressed as equation (2).

$$P_{solar} = f(W_t T + W_i I) \tag{2}$$

where P_{solar} = generated power from the solar panel (W)
w_t = weight of the temperature
T = temperature ($^\circ C$)
w_i = weight of irradiance
I = irradiance (W/m^2)

Load Forecasting

In this work, load forecasting has been focused into two factors, i.e., dry bulb and dew point, because of one-day forecasting. Although, some researchers have focused on longtime forecasting [11]. However, short time forecasting is concentrated in this study. The relation can be expressed as equation (3)

$$P_{load} = f(\mathrm{w}_{dry} D_r + \mathrm{w}_{dew} \mathrm{D}_e) \tag{3}$$

where P_{load} = load demand (W)
w_{dry} = weight of the dry bulb
D_r = dry bulb ($^\circ C$)
w_{dew} = weight of dew point
D_e = dew point ($^\circ C$)

Artificial Neural Network

ANN is a mathematic model or a computer model for Processing Information by connectionist calculation. The basic concept of this technique is derived from the bioelectric networks study inside the brain which has neural cells and synapse. Each neural cell has bias and between cell is connected by weight. Bias and weight can change according to the learning system of ANN. The infrastructure of ANN has three layers as following.

1. Input layer, information is modified into a specified range and put to the input layer.

2. Hiden layer, the number of layers and node in the hidden layer depends on the complexity of the problem. If the hidden layer has many layer and node, this procedure will also use a long time for calculating.

3. Output layer, The results are showed in this layer following Fig.1 [12], [13].

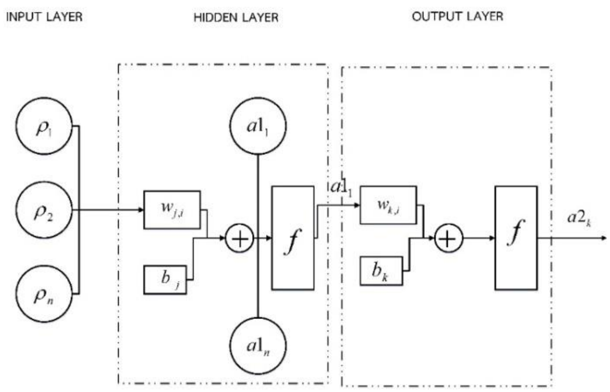


Fig.1. The procedure of the neural network.

Moreover, $a1_l$ and $a2_k$ are depending on the complexity of the problem as shown in equation (4) and (5).

$$a1_l = f\left(\sum_{t=1}^{m}(w_{f,t}) + b_j\right) \tag{4}$$

$$a2_k = f\left(\sum_{t=1}^{m}(w_{k,j}) + b_k\right) \tag{5}$$

where ρ_i = input
$a1_l$ = results from the calculation in the hidden layer
$a2_k$ = results from output layer
w = weight
b = bias
$f(c)$ = transfer function

The procedure of ANN is divided into 2 part following

1. Learning part: Historical information is put into the learning system to create a neural network which use to forecast output by the internal relation between input and target values. Learning procedure is divided into 2 part included (1) feedforward calculation from input to hidden to output (2) feed backward calculation for adjusting weight and bias

2. Testing part: Another input is tested with a neural network which creat in learning the part and use feeds forward calculation for adjusting the weight of each input.

Input information is divided into 3 part for use in the learning procedure, testing procedure and validation which check the accuracy of forecasts. If all data for learning is not accurate, the forecasting results are not accurate. The learning processes have many methods such as Scale Conjugate Gradient method (SCG), Levenberg-Marquardt method (LM) and Bayesian Regularization method(BR) [13]. This paper will show to compare with each method on the next topic.

3. COMPARING LEARNING METHODS

This paper, a comparison between the three learning methods, i.e., SCG, LM, and BR, cooperation with ANN for load forecasting is presented. The forecasting period is 30 days or 720 hours. ANN shows the appropriate learning method for power forecasting. The input and output are separated into three parts including training, testing, and validation. Dry bulb and dew points are the input and load of a system is the output for load forecasting. The information is separated into three parts 70%, 20% and 10% for training, a validation, and testing, respectively. This procedure is done for selecting the most appropriate learning method for power forecasting. All the analytical works are done via MATLAB software version R2017a. The results of load forecasting from each learning methods are shown in Fig.2. As seen from load forecasting results, the most appropriate learning method is the BR method because of the less error following Table 1.

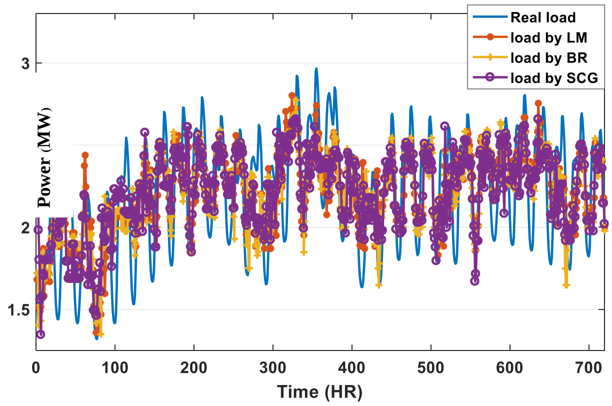
Table 1. The error of load forecasting by ANN using LM BR and SCG

Learning method	Error (%)
LM	9.43
BR	8.98
SCG	9.64

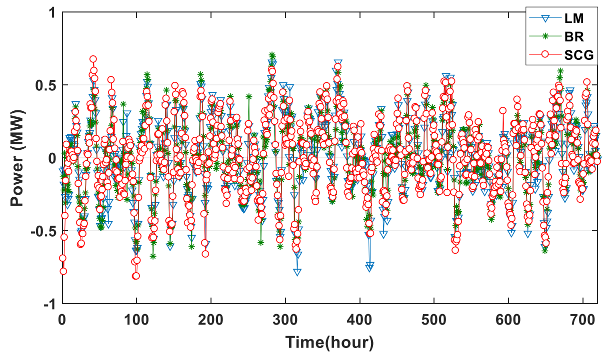
4. VOLTAGE STANDARD AND BESS CONTROL MODE

Voltage Standard

In this paper, voltage standard is set according to the IEEE 1547 standard as shown in Table 2 [14]. The voltage level of each node should maintain between 0.88 p.u. to 1.10 p.u. Otherwise, the power outage may be occurring on the system.



(a)



(b)

Fig.2. (a) Load forecasting using LM BR and SCG methods (b) Error from load forecasting using LM BR and SCG.

Table 2. Clearing Time

Voltage Range (p.u.)	Clearing Time (sec)
$V < 0.50$	0.16
$0.50 \le V < 0.88$	2.00
$1.10 < V < 1.20$	1.00
$1.20 \le V$	0.16

Power flow analysis

For BESS control planning, power forecasting with power flow analysis has been used to simulate a state of the study system.

Power flow analysis procedures are as follows [15].

1. Determine the element values for the passive network components.
2. Determine the locations and the values of all complex power loads.
3. Determine the generation specifications and the constraints.
4. Develop the mathematical model for describing power flow in the power network.
5. Solve the voltage profile for the network.
6. Solve the power flows and power losses in the network.
7. Check for constraint violations

In this paper, voltage each node has been analyzed by equation (6)

$$V_i^{(k+1)} = \frac{\dfrac{P_i^{sch} - jQ_i^{sch}}{V_i^{*(k)}} + \sum y_{ij} V_j^{(k)}}{\sum y_{ij}} \tag{6}$$

where V_i = voltage at bus i (p.u.)

P_i^{sch} = real power at bus i (p.u.)

Q_i^{sch} = reactive power at bus i (p.u.)

The power forecasted using ANN have been analyzed by power flow analysis. The voltage level of each node has been considered for selecting the appropriate mode to control BESS in maintaining the stability of the power system.

Battery controller

A planning method of BESS control for an off-grid system has proposed in this paper. Power forecasting and load flow analysis have used to forecasting and analyzing power and voltage levels on the system. The reason is due to highly fluctuates of power producing from RER. Power forecasting and voltage level have been examined to use for BESS control. BESS control can be divided into two modes including; (1) mode 1 is BESS have enough power to maintain the system stability and (2) mode 2 is BESS have enough power to maintain the system stability. For mode 1, if the power generating from RER is higher than the load demand, then the BESS will be charged as long as State of Charge (SOC) does not exceed 80% (depending on the type of battery) for the longer lifespan of BESS [16]. If the BESS is fully charged (i.e., Soc higher than 80%) then the BESS will be disconnected itself from the system. If the load demand is higher than the generating power from RER, then the BESS will be connected itself to the system. For mode 2, if forecasting process has found that the energy in BESS is not enough for use to maintain the system stability, then BESS will be managed at the highest discharge period before the occurring of instability event to keep the power for using in instability event. An overview of the BESS control methodology is presented in Fig. 3.

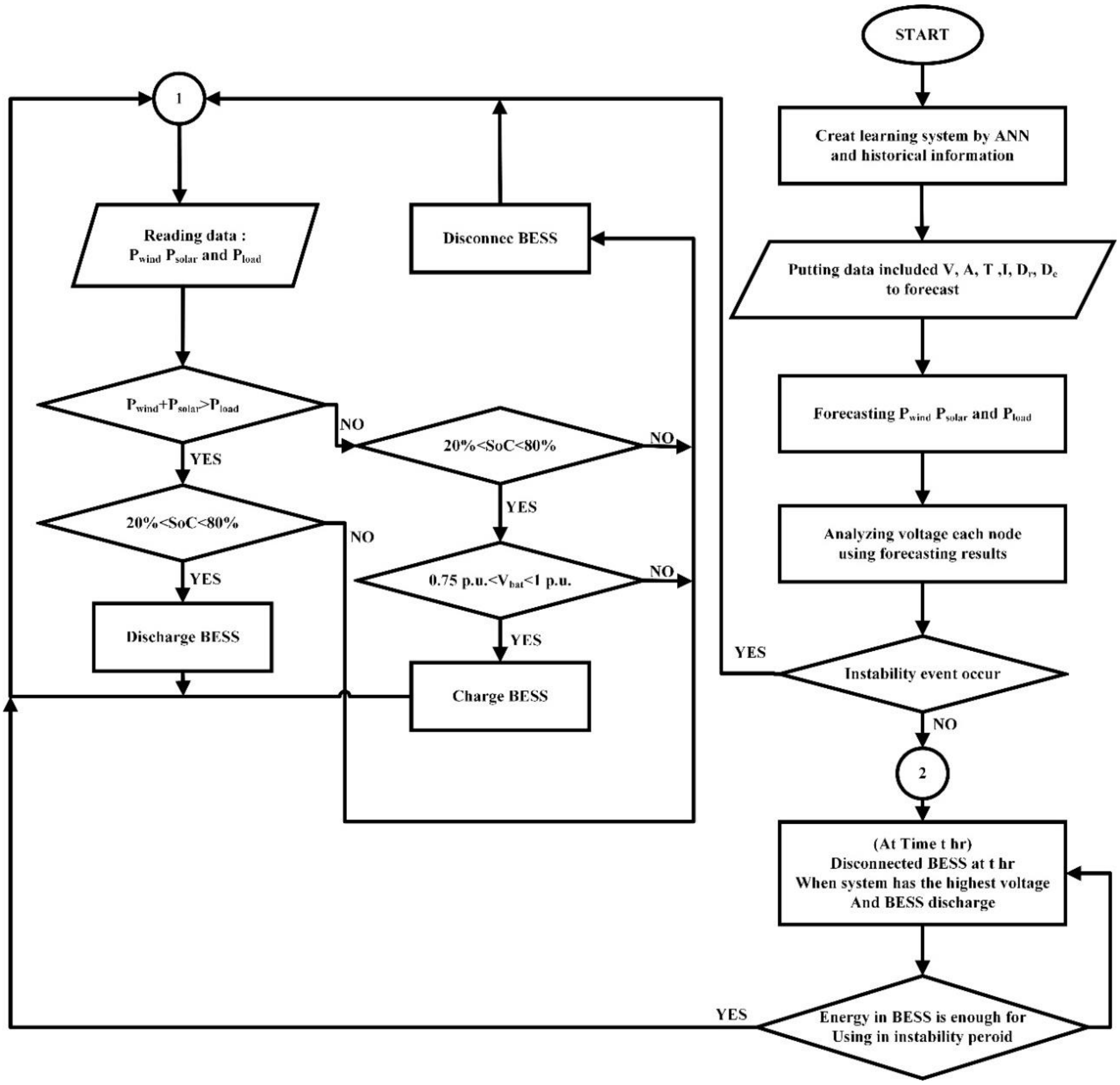


Fig.3. Overview method for planning to manage energy in BESS.

5. A CASE STUDY AND SIMULATION RESULTS

The IEEE 13 node standard test system [21] has been modified to evaluate the proposed technique. The system has modified to the off-grid system having the hybrid renewable energy resources as power generating units. The hybrid renewable energy resources are a Wind turbine 3.5 MW installed at node 2, PV panel 3 MW and BESS 5 MWh installed at node 1 as shown in Fig.4. The Maximum load of this system is approximately 2.9 MW, and parameters in this system have been designed according to weather in a day.

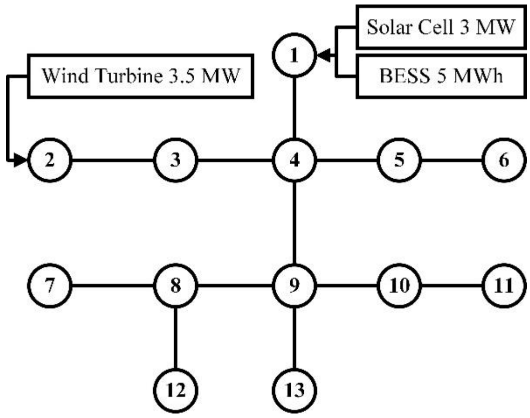
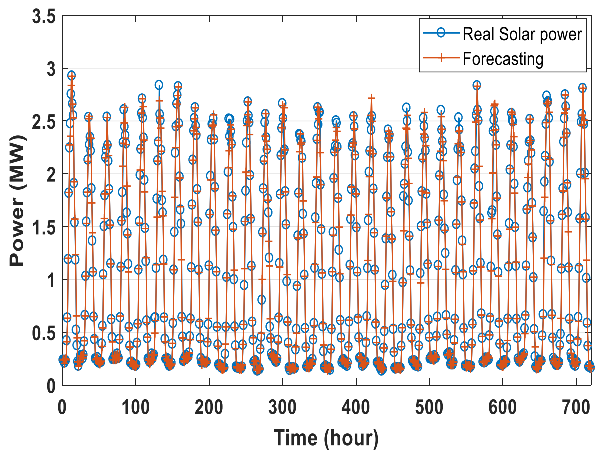
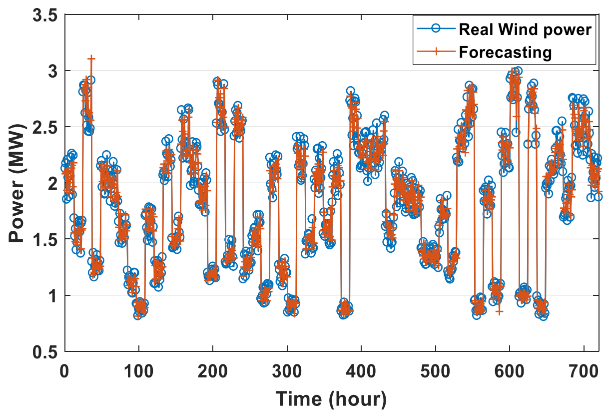


Fig.4. The modified IEEE 13 node standard test system.



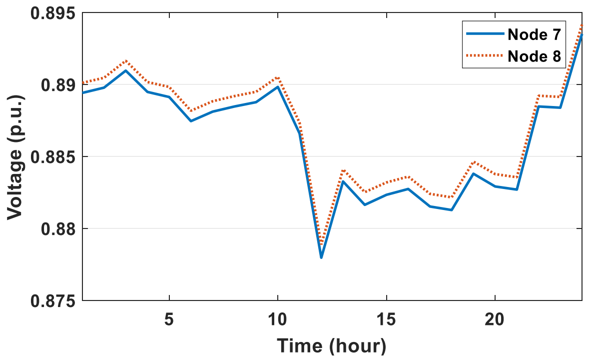
(a)



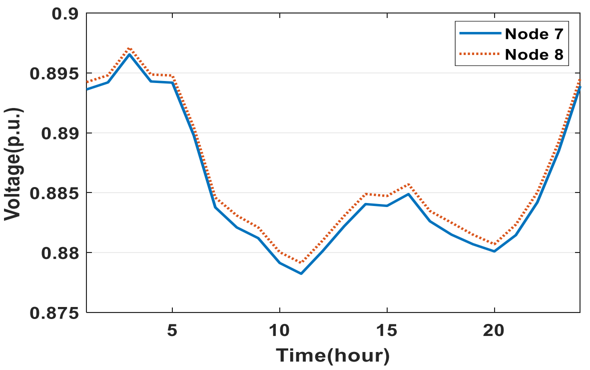
(b)

Fig.5. (a) Wind forecasting (b) Solar forecasting.

For forecast the load demand and the power generating from RER, the weather information is required. This study, the weather information is taken from Lumtaklong area at Amphoe Sikhio, Nakhon Ratchasima province Thailand. The average wind speed is approximately 5.5 m/s, the average solar irradiation is approximately 5 kW/m2, the temperature is between 25-38 ^{o}C, and the air pressure depends on temperature [17-20]. The forecasting results are shown in Fig. 5. As illustrated in Fig. 5, the forecasting results agree with the power generation power from RER. After forecasting, forecasted results of the system have been analyzed by power flow analysis. By using load flow analysis results of node 7 and node 8, The forecasting voltage results are shown in Fig. 6. (a) and the real system results are shown in Fig. 6. (b). As illustrated in Fig. 6 (a), during 11 am to 1 pm, the voltage level at node 7 and node 8 is lower than 0.88 p.u. because of the peak period of load demand. As illustrated in Fig.6 (b), the actual voltage level at node 7 and node 8 is in a range 0.88-0.95 p.u. and approximately agree with those the forecasting results. According to analyzing results, the planning to support the system during an instability period using forecasting results has considered. During 11 am to 1 pm, the voltage level at node 7,8 is lower than the standard level such effects cause the BESS must store enough power to provide when the voltages level lower than 0.88 p.u. The BESS is disconnected from the system during 0 - 4 am to store power for use in the under voltage period because of the highest voltage level, and the BESS has to discharge on the under voltage period. The problem was solved by disconnecting the BESS during 0-4 am to keep power in BESS and connect when the voltage level lower than 0.88 p.u. The actual voltage level at node 7 and node 8 is lower than 0.88 p.u. while using the forecasting results the voltage level is not lower than 0.88 p.u. As illustrated in Fig. 7, the BESS has enough power to maintain the system stability. The off-grid system has no supply power from the main grid. Therefore, a power uses in the off-grid system provided from distributed generation. In this paper, distributed generation in the off-grid system is a wind turbine and a solar cell. The fluctuating power generated from RER depends on weather conditions cause a voltage drop due to lack of power. Although, the BESS has used to decrease the fluctuating power generation from RER. But when weather conditions change, it may lead to power generation lower than power demand and this may cause the voltage to drop lower than the standard level. However, due to the parameters of the system can be forecasted, appropriately power management on the system can be done. The stored power in BESS can be used when instability occurred in the system.



(a)



(b)

Fig.6. (a) Forecasting voltage at the lowest voltage node (b) Voltage in the real event at the lowest voltage node.

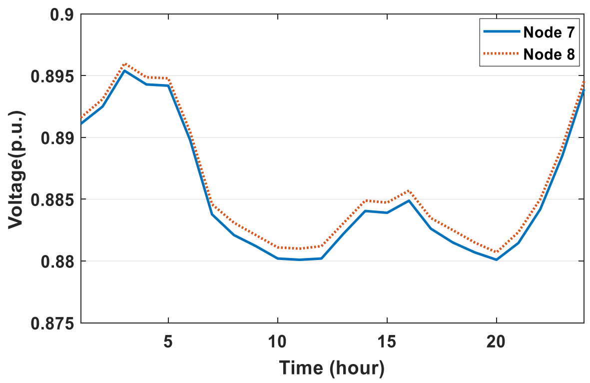


Fig.7. The voltage at the lowest voltage node using the proposed method.

6. CONCLUSION

For the off-grid system which using RER to provide power, this system has to carefully maintain stability because the power generation by RER is fluctuating power cause the BESS has been used to solve the problem. The BESS has not always enough energy to provide load cause the system instability. This paper has been proposed planning to manage power in BESS using ANN to obtain appropriately. power forecasting. ANN has to use the learning method to create a neural network for power forecasting. This paper has been compared the effectiveness of the learning methods which included SCG, LM, and BR. The results show that BR was the most accurate learning method for power forecasting. Then power which is generated by RER were forecasted to analyze by power flow analysis for analysis voltage each bus and planning to manage energy in BESS. From the case study, it is confirmed that the occurring of instability event can be solved by the proposed method. However, the effectiveness of planning depends on the accuracy of the forecasting results because the precise predictions can make the analysis more accurate.

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