# Complementary grid power prediction using artificial neural network in the energy management system of a disaster prevention smart solar microgrid

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## Abstract

The project has installed a disaster prevention smart solar microgrid at Dawu community, Pingtung County, Kaohsiung City which is 1,000 meters above sea level. The energy management system (EMS) in the disaster prevention smart solar microgrid needs to forecast the complementary grid power in order to improve the stability and reliability of the whole system and maximize the profit of operation during peak hours. An advanced meter infrastructure (AMI) has been installed in parallel with the smart solar microgrid which collected important parameters of the system in real-time. In this paper, a back propagation neural networks are applied to predict the complementary grid power by utilizing the load power, the battery voltage, the battery charging/discharging current and the voltage and current from the solar panel. The 1-min data in six months from 1<sup>st</sup> Nov. 2018 to 30<sup>th</sup> Apr. 2019 are collected by the AMI and utilized as input to train the back propagation neural network. The accuracy of the forecasting complementary grid power will be analyzed and evaluated with different method of normalization, the time interval of input data and the number of neural network nodes in the hidden layer. The simulation outputs show that the RMSE achieves the lowest value of 0.0014 in November and 0.0232 in average. The predicting complementary grid power reaches the best MAPE value of 0.1845% in January and 4.3876% in average. In addition, the coefficient of determination achieves the highest value of 0.9998 in February and 0.9598 in average. These achieved simulation outcomes have proved the great effect of varying input parameters on the predicting complementary grid power. The simulation outputs are utilized in the EMS in the disaster prevention smart solar microgrid for predicting higher accurate complementary grid power, improving stability and maximizing profitability of the whole system.

Keywords: forecasting complementary grid power, smart solar microgrid, back propagation neural network, energy management system, short term grid power forecasting.

# 1. Introduction the Disaster Prevention Smart Solar Microgrid and the Energy Management System

Renewable sources with high efficiency energy storage systems are deploying widely in over the world [1]. According to that, the development of the solar power has significantly increased in the recent years in Taiwan. The Taiwanese government has approved a plan in which 20 percent of the total energy is from renewable power and try to achieve the goal of 6.5 gigawatts by 2020 and get the full 20 gigawatts by 2025 [2]. The project in this paper has completed installing a disaster prevention smart solar microgrid in the Dawu Community at Pingtung County, Kaohsiung City, Taiwan which is 1,000 meters above sea level. The Dawu Village tribe often becomes an island due to natural disasters which caused power outages and traffic disruptions. Therefore, the disaster prevention smart solar microgrid has been installed

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which was integrated with the energy management system (EMS) and advanced meter infrastructure (AMI). During the operation of the system, some of important parameters will be collected and transferred to the cloud energy management system through a 4G base station [3]. In order to improve the stability and reliability of the system, a back propagation neural network with the collected data will be applied to predict the complementary grid power. This paper will focus on the analysis and evaluation the change of some parameters in the artificial neural network (ANN) in order to achieve the high accuracy of the predicted complementary grid power by using the Neural Network Toolbox in MATLAB.

The general structure of a disaster prevention smart solar microgrid in this project is shown in Fig. 1. The energy management system (EMS) will take responsible for controlling and managing the whole system. The EMS will control the operation of the 5kW solar-panel power, the 20kWh energy storage system, the main power supplied from Taipower, the 20kW diesel generator and load power such as air conditioner, lighting system, socket and other loads. The EMS also takes responsibility for monitoring and recording some parameters of the system such as the charge/discharge status of the battery pack, the battery voltage and charge/discharge current, the voltage and current from the solar panel, the current to the load and other information. The data will be collected by the AMI and transferred to the cloud energy management system through the 4G base station. The Fig. 2 shows some real components of the disaster prevention smart solar microgrid such as the AMI, the generator, the independent energy store and the automatic transfer switch (ATS) which has been installed completely at Dawu Community.



Fig. 1. The general structure of a disaster prevention smart solar microgrid

The EMS takes an important role in the disaster prevention smart Solar microgrid which manages and controls the power flow in the system [4]. The power dispatch of the EMS is shown in Fig. 3. In case of the islanding mode without the grid power, the EMS utilizes the power from generator, solar power and battery power as the main power source. During the general mode, the EMS will utilize the grid, solar and battery power and maximize the profit of the operation with respect to the peak time and off-peak time. Based on the different level of the load power, it will change the main power source of the whole system. It also decided how much power charges or discharges to the battery and how much complementary power takes from the Taipower grid in order to provide continuously and sufficiently power to the load. If the EMS predicts accurately the complementary grid power, the required equipment will be prepared to run in advance in case of changing operation mode of the whole system. The EMS system evaluates a lot of parameters of the whole system and estimates the value of complementary grid power based on the real-time pricing. Therefore, in order to improve the stability and reliability and maximize the profit in operation of the disaster prevention smart solar microgrid, the value of complementary grid power is required to predict.



Fig. 2. The real components in the project at Dawu Community



Fig. 3. The power dispatch of the energy management system

Much literatures have been applied distinct approaches and methods in the forecasting and estimation of the power flow in the solar micro-grid. The most common techniques were applied ANN and used geographical coordinates, meteorological and solar panel geometry as the input to predict the output of the solar plan [5] - [13]. Yona et al., forecasted the output of solar power based on insolation prediction of

1-day ahead weather reported data and utilized the recurrent neural network, which achieved the average MAE of 0.1327kW forecasting error [14]. Izgi et al., proposed an ANN to forecast output power from a 750W solar panel which achieved the best accuracy of 5 min for short-term and 32 min for long term. The RMSE for the predicting and measuring were in range between 33-55W and 37-63W respectively [15]. Teo et al., integrated an Extreme Learning Machine training algorithm in ANN which achieved the value 3.8564 of RMSE and 0.0798 of standard deviation comparing with the value 4.1096 of RMSE and 0.0946 of standard deviation in the initial model. The higher model performance was achieved by modifying the input variable and increasing the training data [16]. Chen et al., forecasted online 24-h solar power by applying advanced statistical method based on ANN which used meteorological, irradiance, relative humidity and temperature as inputs [17]. However, very little literatures have been applied ANN in forecasting complementary grid power which utilized the endogenous parameters of the system. Khomani et al., applied the mathematical optimization model with real-time prices to predict the power exchanged with main grid. In the scale of microgrid, the simulation outcomes have maximized the profit of operation and utilized the renewable resources in controlling and managing [18].

Previous studies on solar power mostly developed by simulating different ANN models with using different geographical coordinates, meteorological and solar panel geometry as the input. No studies have verified the correlation of complementary grid power with some internal parameters of the solar microgrid such as the load power, the battery voltage, the battery charging/discharging current and the voltage and current from the solar panel in real time. In this case study, the AMI has been installed in parallel with the disaster prevention smart solar microgrid which collected these parameters in real-time. Therefore, the EMS will utilize these real-time colleting parameters and predict the complementary grid power in short-term. This paper will analyze the correlation between the complementary grid power and the colleting parameters by the AMI i.e., load power, the battery voltage, the battery charging/discharging current and the voltage and current from the solar panel by applying a model of ANN. In order to improve the accuracy in predicting the value of complementary grid power, different input data processing is applied. The simulation outputs will support the EMS in predicting not only the value of complementary grid power but also maximize the profit in operation of the whole system.

## 2. Input Data Processing

## 2.1. Input data selection



Fig. 4. The relationship between the power and the voltage collecting data on 23<sup>rd</sup> Feb. 2019

With the support from the AMI system, some important parameters of the system could be collected in every minute and transferred to the could energy management system through the 4G LTE. Therefore, the user could monitor and evaluate the operation and the performance of the system remotely. In addition, the collected data could be utilized with ANN to predict the complementary grid power.

The input data are considered to select base on correlating factors and greatly affecting the output of the ANN. In this paper, the following six data will be collected by AMI and used as inputs to predict the complementary grid power:

- Load power
- Battery voltage
- Battery charging current
- Battery discharging current
- Voltage from the solar panel
- Current from the solar panel.

The predicted value is complementary grid power which is also collected to use as the expected output of the ANN. The whole data are collected every minute in duration of six months from 1<sup>st</sup> Nov. 2018 to 30<sup>th</sup> Apr. 2019. An example of every 10-minutes collecting data shows the relationship between output, the complementary grid power, and the input, the load power, the battery voltage and the solar panel voltage in the Fig. 4. The Fig. 5 shows the relationship between the output data and the remaining current inputs which are the battery charging current, the battery discharging current and the current from solar panel. Before using, the data should be processed by eliminating some extreme set of values which helps increase the accuracy of the ANN. After that, the data were chosen based on the interval time and normalized in the value between 0 and 1 which help the ANN works more efficiently and increases the accuracy of the predicting values.



Fig. 5. The relationship between the power and the current collecting data on 23rd Feb. 2019

In this project, the input data have been collected in every minute but not all the collected data will be utilized as the input of the ANN. After eliminating some extreme values, the input data will be selected base on the time interval of 10, 20 and 30 minutes. The accuracy of the predicted complementary grid power will be analyzed and compared and the best time internal of the input data for the EMS will be chosen with the highest simulation outputs.

## 2.2. Normalization method

The input data is needed to normalize before using in the ANN and the most popular normalization methods are maximum-minimum normalization and Z-Score. The maximum-minimum normalization method will transfer all the input data between the minimum and maximum value which is expressed in (1).

$$Z = \frac{X - X_{min}}{X_{max} - X_{min}} (Z_{max} - Z_{min}) + Z_{min}$$
(1)

where, X,  $X_{min}$  and  $X_{max}$  are the input, the minimum and the maximum value respectively of the collecting data. Z,  $Z_{min}$  and  $Z_{max}$  are the normalized value, the minimum and the maximum normalized value respectively. In this paper, the minimum and maximum normalized value is 0.1 and 0.9 respectively.

In the Z-Score method, the output value is calculated as follow (2).

$$Z = \frac{X - \bar{X}}{s_{\chi}},\tag{2}$$

where,  $\overline{X}$  and  $s_x$  is the mean and the standard deviation of the input data.

The accuracy of the predicted data will be compared with the different above normalized methods of the input data in this case study. Therefore, the best normalization method will be chosen with the highest accuracy and will be used for predicting the complementary grid power in the EMS system.

## 3. Design of Back Propagation Neural Network

The forecasting of the electricity demand becomes more popular with the support of artificial neural network using different techniques, approaches and methods [19]. In this case study, the back propagation neural network (BPNN) will be applied to forecast the complementary grid power. The structure of a back propagation neural network in this case study is shown in the Fig. 6.



Fig. 6. The structure of Back Propagation Neural Network with one hidden layer

The BPNN has three main layers: input, hidden and output layer [20]. The input layer has six input nodes according with six input data in this case study: load power, battery voltage, battery charging current, battery discharging current, voltage from solar panel and current from solar panel. Every input layer node connects with every hidden layer node through a link called the weight value. The input value of every hidden layer node is calculated as equation in (3).

$$net_j = \sum_{i=1}^6 w_{ji} x_i + b_j \tag{3}$$

The output of the hidden layer is calculated basing on an activation function which is chosen to fit the problem. In this study case, a log-sigmoid activation function is used to obtain a nonlinear output [21]. This function is commonly used in the BPNN and is described in the equation (4)

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$$y_j^n = f\left(net_j\right) = \frac{1}{1 + \exp(-\alpha net_j)} \tag{4}$$

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The output of one node in the hidden layer will continue to become an input of other nodes. In this case study, the hidden layer only has one layer and the output of the hidden layer will become the input of the output layer. The output value at the output layer will be compared with the actual value of the complementary grid power and calculated the error. The mean square error (MSE) is calculated as equation (5) and the weight between neural network nodes will be adjusted by using the error back propagation algorithm as the equations (6) and (7).

$$E = \frac{1}{n} \sum_{j=1}^{n} (d_j - y_j^n)^2$$
(5)

$$\Delta w_{ji} = -\eta \, \frac{dE}{dw} \tag{6}$$

$$w_{ji}(t) = w_{ji}(t-1) + \Delta w_{ji},$$
(7)

where,  $w_{ji}$  is the weight value connecting between neural network nodes,  $\eta$  is the learning rate,  $y_j^n$  is the output value of neural network and  $d_j$  is the expected value of the output.

The error is propagated back from the output to the input during the process of adjusting the weight value, which is called the back propagation neural network. The weight value is updated until the error reaches in range of proper value [22].

In this case study, the BPNN only has one layer and the number of neural network nodes in the hidden layer will be changed to observe the effect on the accuracy of the output [23]. The results of prediction will be evaluated by two technical indicators which are root mean squared error (RMSE) and the mean absolute percentage error (MAPE) in equation (8) and (9). In addition, the different level of MAPE is shown in table 1 to evaluate the level of accuracy of the forecasting methods [24].

MAPE	Prediction
$MAPE \leq 10$	High
$10 < MAPE \le 20$	Good
$20 < MAPE \leq 50$	Reasonable
<i>MAPE</i> > 50	Low

Table 1. Difference levels of MAPE

$$RMSE = \sqrt{\frac{1}{n} \sum_{1}^{n} (d_j - y_j^n)^2}$$
(8)

$$MAPE = \frac{100}{n} \sum_{j=1}^{n} \left| \frac{d_j - y_j^n}{d_j} \right|$$
(9)

In addition, the coefficient of determination is also used as an important indicator to evaluate the accuracy of predicting complementary grid power [13]. The coefficient of determination shows approximately the percentage of the observed variation could be explained by the model and is shown in the equation (10).

$$R^{2} = 1 - \frac{\sum_{i=1}^{N} (d_{i} - y_{i})^{2}}{\sum_{i=1}^{N} (d_{i} - \bar{d})^{2}}$$
(10)

# 4. Complementary Grid Power Forecasting and Analysis

The BPNN in MATLAB toolbox is used in order to forecast the complementary grid power with different approaches of the input data. The learning algorithm 'trainlm' is applied which achieves the highest performance and accuracy with others in the MATLAB toolbox [12]. The RMSE, MAPE and the coefficient of determination are used as indicators to evaluate the highest accuracy which will be applied for the EMS in the disaster prevention smart solar microgrid.

## 4.1. Different time intervals of the input data

The input data are selected base on time interval of every 10, 20 and 30 minutes to use as the input of the BPNN and the number of the input data in three cases are the same with more than 6300 input samples. The default of normalization method is the maximum-minimum normalization and the number of the neural nodes in the hidden layer is 20. The result of the simulation is shown in the table 2.

Time interval of input data	RMSE	MAPE (%)	<b>R</b> <sup>2</sup>
10 minutes	0.01472	0.6963	0.9939
20 minutes	0.01316	0.4005	0.9962
30 minutes	0.03971	6.2632	0.9436

Table 2. Results of different time intervals of the input data

The 20 minutes interval input data has the lowest RMSE and MAPE which are 0.01316 and 0.4005% respectively comparing with 10 minutes and 30 minutes interval. In addition, the coefficient of determination of the 20 minutes interval is slightly greater than 10 minutes interval but much higher than the 30 minutes interval. Although the 30 minutes interval has the low RMSE and the coefficient of determination, the MAPE value is significantly high which is 6.2632 comparing with others. In general, the 20 minutes interval input data are the most relevant with the complementary grid power and has the highest accuracy in forecasting. Therefore, the 20 minutes interval data will be chosen as the time interval for the BPNN in the EMS.

### 4.2. Different methods of normalization

The input data is needed to normalize before using as the input in BPNN. In this case study, the most two popular methods, maximum-minimum and Z-Score methods, are used to evaluate the accuracy of the predicting complementary grid power. The 20 minutes interval input data with more than 9700 samples and 20 neural network nodes in the hidden layer are chosen. The simulation result is shown in the table 3.

Table 3. Tesults of different normalization method

Normalization method	RMSE	MAPE (%)	<b>R</b> <sup>2</sup>
Max-min normalization	0.0465	6.5968	0.9470
Z-Score method	0.2140	9.9739	0.9457

From the result of simulation, the maximum-minimum normalization method has the lower RMSE comparing with the Z-Score method which are 0.0465 and 0.214 respectively. The MAPE of the Z-Score method is 9.9739 percent which is in high range but also higher than the max-min normalization. In addition, the coefficient of determination of max-min normalization is also slightly higher than the Z-Score which are 0.947 and 0.9457 respectively. Therefore, the maximum-minimum normalization method will be used to normalize the input data in the BPNN in order to get highest accuracy of the predicting complementary grid power.

## 4.3. Different number of neural networks

Because the number of neural network node depends on the complex of the problems, the number of

the neural network nodes in the hidden layer will vary from 10, 20, 30 and 40 nodes which is used to evaluate the effect on the accuracy of the output [25]. The maximum-minimum normalization method is chosen for the 20 minutes interval data which have more than 9700 samples. The result of simulation in table 4 shows the effect of the number of neural network nodes on accuracy of the predicting value. The 20 nodes of neural network have the lowest RMSE which is 0.0487 comparing with others. In addition, the 10, 30 and 40 nodes have nearly the same value of MAPE which varies from 8.38% to 8.61% but are quite high than the 20 nodes which gets only 6.13%. In addition, the results of coefficient of determination are quite high which got the highest value, nearly 0.95. It means that, with 20 nodes of neural network, 95% of the variability of the input data has been accounted for the complementary grid power and only 5% of the variability is not accounted for. Therefore, the BPNN with 20 nodes is applied in the EMS in order to get the best results of predicting complementary grid power.

Table 4. Result of different neural r	network nodes
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Number of neural network node	RMSE	MAPE (%)	$R^2$
10 nodes	0.0532	8.38	0.9392
20 nodes	0.0487	6.13	0.9500
30 nodes	0.0547	8.55	0.9415
40 nodes	0.0613	8.61	0.9358

Table 5. The summary of RMSE, MAPE and R Square in month

Month	RMSE	MAPE (%)	<b>R</b> <sup>2</sup>
Nov	0.0014	1.6137	0.9793
Dec	0.0073	0.7099	0.9903
Jan	0.0023	0.1845	0.9996
Feb	0.0038	0.2233	0.9998
Mar	0.0594	10.2171	0.8665
Apr	0.0651	13.3771	0.9235
Average	0.0232	4.3876	0.9598



Fig. 7. The results of forecasting data in month

The Fig. 7 and Table 5 show the results of RMSE, MAPE and R square which have been applied 20 minutes interval data, the max-min normalization and the 20 nodes of neural network in month from November, 2018 to April, 2019. The RMSE varies from 0.0014 to 0.0651 between months and gets the average of 0.0232. This standard deviation of the residuals is quite small and the forecasting complementary grid power concentrated closely around the line of best fit. The MAPE is quite small from the Dec. to Feb. but increases up to 10.2171 % and 13.3771 % in Mar. and Apr. respectively. In average,

the MAPE gets 4.3876 % which is in the high range of prediction. The forecasting error is quite small and the prediction accuracy of above forecasting methods has been improved significantly. In addition, the coefficients of determination are quite high and get up to 0.9998 in Feb. The average of coefficients of determination is 0.9598 and quite closely to 1. It means that the variance in complementary grid power could be predicted by 95.98% from the input data. Therefore, the 20 minutes input data, the max-min normalization and the 20 nodes of neural network has improved the accuracy and the stability in predicting complementary grid power.



Fig. 8. The complementary grid power forecasting in a day

The Fig. 8 shows the forecasting and actual complementary grid power in every 20 minutes of a day with the MAPE. The back propagation neural network is simulated by utilizing the maximum-minimum normalization, the 20 minutes time interval and the 20 neural network nodes. The forecasting curve is quite close with actual complementary grid power which has less than 4.5% of the maximum MAPE. Therefore, the accuracy in forecasting complementary grid power by utilizing the back propagation neural network has been improved.

## 5. Conclusion

The EMS in the disaster prevention smart solar microgrid demands the high accuracy of forecasting complementary grid power which used to improve the stability and reliability and maximize the profit of operation of whole system. In this paper, the single layer feed-forward back propagation neural network is utilized to predict the complementary grid power by using internal parameters of the system such as the load power, the battery voltage, the battery charging/discharging current and the voltage and current from the solar panel. The collecting data in six months from 1<sup>st</sup> Nov. 2018 to 30<sup>th</sup> Apr. 2019 are used to training the ANN. In this case study, the higher accuracy of the forecasting complementary grid power is achieved with the maximum-minimum normalization method, the 20 minutes interval of input data and the 20 neural network nodes in the hidden layer. The RMSE achieves the lowest value of 0.0014 in November and 0.0232 in average. The predicting complementary grid power reaches the best MAPE value of 0.1845% in January and 4.3876% in average. In addition, by utilizing the maximum-minimum normalization method, the 20 minutes interval of input data and the 20 neural network nodes in the back propagation neural network, the coefficient of determination achieves the highest value of 0.9998 in February and 0.9598 in average. These achieved simulation outcomes have proved the great effect of varying input parameters on the predicting complementary grid power. The results of this simulation will be utilized in the EMS system in the disaster prevention smart solar microgrid for higher accuracy in predicting complementary grid power and maximize the profit of operation.

# **Conflict of Interest**

The authors declare no conflict of interest.

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