Prediction of PV Power Output and Battery Charging Conditions on OFF Grid Systems MicroHydro Pantai Bantul Yogyakarta Using Rule-Based Algorithm

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Abstract. Energy Management System (EMS) is used as a renewable energy control strategy. This research uses photovoltaics and wind turbines, which is a suitable combination because photovoltaics work during the day while wind turbines can supply batteries that are used at night. The Energy Management System (EMS) in this research consists of photovoltaics, wind turbines, batteries and commercial loads. The system uses an off-grid system with real data from PLTH Pantai Baru Bantul. Prediction of PV power output uses an Artificial Neural Network (ANN), namely Cascade Forward Neural Network, by considering irradiance, PV module temperature, current PV data, which has a Mean Square Error (MSE) of 0.9% with a learning rate of 0.01. The rule base algorithm is used to maximize power from PV renewable energy and wind turbines by implementing a load-shedding scheme so that the resulting power is maximized for charging the battery and maintaining the battery SOC at safe limits with a minimum SOC of 20% and a maximum SOC of 90%. The research is expected to provide recommendations for managing renewable energy using an off-grid system to make it more efficient and reduce dependence on external energy sources..

Keywords: Artificial Neural Network, Cascade Forward Neural Network, Levenberg-marquard, Photovoltaic (PV), Energy Management System (EMS), State of Charge (SOC).

1 Introduction

The dependence on electrical energy increases from year to year, this increase is caused by the growth of factories, buildings, housing, and others. Electricity rates are also

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experiencing growth, so many business institutions are choosing renewable energy as the main alternative, especially solar energy, and wind energy. Renewable energy sources have been widely developed because they have many advantages: cheap operational costs, cleanliness, pollution-free, and easy maintenance, although they require expensive initial investment, this is not comparable to the benefits obtained from using renewable energy.

The PV and Wind Turbine renewable energy hybrid system is a complementary solution to each other's weaknesses and Battery Energy Storage (BES) complements PV and wind turbines thereby maintaining power balance in the electric power system.

PV predictions are very necessary, because the nature of PV is intermittent and depends on weather conditions, such as research carried out to develop probabilistic forecasting based on weather conditions [1]. Probabilistic data sets are historical data obtained from real data collection via inverters and weather measurements. Forecasting PV power output can also use fuzzy as was done by [2]. A hybrid method was also proposed by [3]. PV forecasting was carried out for 24 hours using artificial neural networks. Artificial neural networks have several types of methods, one of which is the one carried out by [4] using a cascade forward neural network by considering the surrounding temperature, radiation, humidity, and wind speed. Using a cascade forward neural network produces a small error that is close to the actual PV power. ANN is based on neural networks, specifically human brain networks. More than one trillion neurons are connected to each other with one trillion synapses so that artificial neural networks can carry out the function of continuously storing knowledge [13].

EMS is discussed in [5] explaining about PV and load estimates which can be evaluated by designing BES charging and discharging in the system for 24 hours. This approach has a very easy concept but does not yet discuss the state of charge (SOC) of the battery.

The EMS) at [6]-[7] uses a Fuzzy Logic Controller (FLC) for a microgrid network connected to hybrid renewable energy (PV and wind turbines) and storage systems. This fuzzy design functions to minimize network fluctuations and extend battery life by keeping the battery SOC at a safe limit with a maximum depth of discharge (DOD) of 50 percent.

The Fuzzy algorithm requires a lot of rules and sluggishness, so it requires an algorithm that is easy to use and fast, one of which uses Dynamic Programming such as [8] which uses a small-scale electricity network operating independently, the small-scale micro network uses renewable and conventional energy such as PV, micro gas turbines and diesel generators. Optimizing the energy produced by renewable energy to charge and discharge the battery uses a rule base algorithm, apart from maintaining the charge and discharge to the battery, it also maintains the SOC at safe limits.

The system uses a predictive approach to be able to regulate generator operation schedules. This aims to minimize blackouts throughout the microgrid system, especially through a load shedding scheme. By using online weather forecasts to predict energy production in the next 48 hours and reduce the duration of outages by around 80% to 100% and still maintain battery SOC at safe limits [10].

The off-grid system in the Energy Management System (EMS) in the proposed method uses renewable energy from PV and wind turbines and energy storage uses batteries. The data used is real data obtained from PLTH Pantai Baru Bantul

Yogyakarta. PV output prediction uses Cascade Forward Neural Network with the Levenberg-Marquardt algorithm to get fast and stable results. Predict PV power output using Irradiance input, ambient temperature, PV module temperature, and PV power with a PV power target one day in the future. Furthermore, EMS is used as a control for determining charge and discharge at safe SOC limits. EMS also regulates the use of PV power, wind turbine power, and battery power, and using a rule-based algorithm can carry out load shedding by determining which loads are needed and which are not needed so that power can be charged to the battery. EMS also regulates battery charging conditions so that they remain within the safe SOC limit.

2 Design Parameters

2.1 Photovoltaic Prediction

Please PV power output predictions are made based on actual data. Accurate forecasting is necessary to evaluate different time horizons. This PV power output estimate starts from one hour to the next few hours and is a short-term estimate, while the medium-term estimate starts from a few hours to the next week and the long-term forecast starts from the next week to the next year. The input and output variables used can be seen in Table 1.

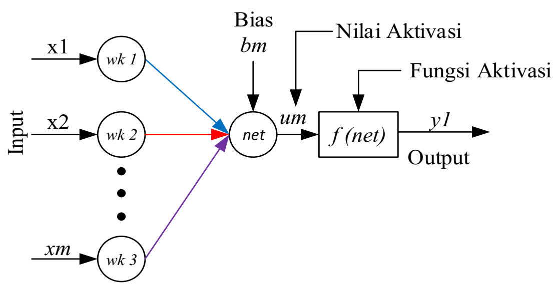

Fig. 1. The structure of ANN

ANN has several types, Such as feed-forward neural networks, multilayer perceptron, cascade forward, etc. Cascade forward is like a feed-forward network in that it is connected directly with weights from the input layer to the output layer. Cascade Forward has a new function. For example, a 3-layer network will have connections from layer 1 to layer 2, layer 2 to 3, and layer 1 to 3, if it has additional connections it will speed up performance where the network will learn the desired output [4].

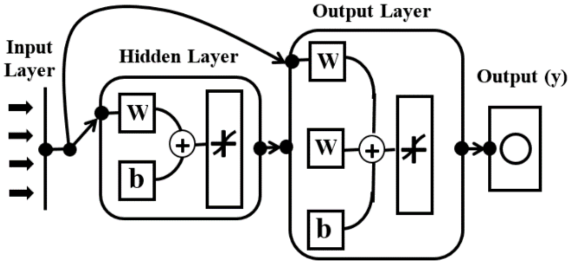

Fig. 2. The Structure of Cascade Forward Neural Network

Table 1. Parameter Input Dan Output

Input	Unit	Target	*Output*
• Power • Irradiation • PV Module Temperature • Current PV Data	kW W/m^2 $°C$ $°C$	PV power 1 day ahead	PV prediction for the next 1 day

The ANN used is a Cascade Forward Neural Network using the Levenberg-Marquardt algorithm. The data used to get prediction results for July 16, 2019, uses training data from July 1, 2019, to July 15 2019, while the data used for testing is data from July 2 2019 to July 16 2019. The target used is PV power for the next 1 day. Time series of daily data are collected every 1 hour starting from 00.00 to 24.00. To predict PV power using learning rates of 0.1, 0.01 and 0.05 using an epoch value of 10,000. The training parameters used are 4 input neuron layers, 10 to 50 hidden neuron layers with 3 hidden layers and 1 output neuron layer and use the Mean Square Error (MSE) performance function. The MSE calculation can be seen in equation 1.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_k - \hat{Y}_k\right)^2 \tag{1}$$

Where Y_k is real data and $\hat{Y}_k$ is data on the predicted value of PV power output. The smaller the MSE value, the better the prediction of PV power output.

The PV power prediction output has the smallest MSE value in training hidden layer 50 at a learning rate of 0.01 with a value of 0.84%, while the largest MSE value occurs at 2.94% in hidden layer 20 neurons at a learning rate of 0.01.

2.2 Wind turbine

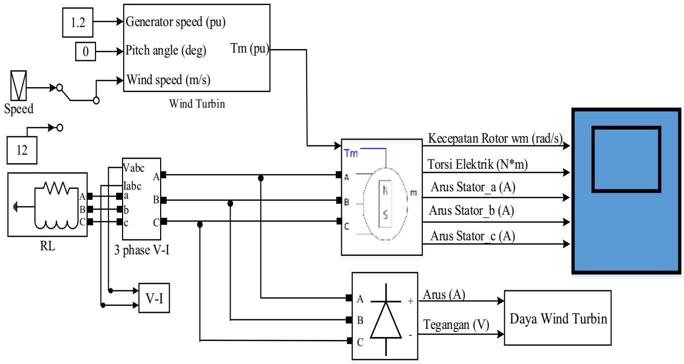

Fig. 3. Wind Turbine Circuit

Figure 3 is a wind turbine design with a total wind turbine capacity of 15 kW. The parameters used are the maximum wind speed of 12 m/s with the base wind speed being 0.73 pu and the base rotational speed being 1.2 pu.

3 Battery Energy Storage (BES)

Please Regulating the use of grids is a strategy for conserving battery energy which aims to avoid excessive use/charging due to the state of charge (SOC) of the battery. The maximum SOC allowed by the battery is 90%, while the minimum SOC is 20%. When the battery SOC has reached 90% it will not charge while the battery SOC is 20% the battery will charge. The limitations in determining battery SOC are formulated as follows:

$$SOC_{min} \leq SOC \leq SOC_{max} \quad (2)$$

$$P_{char\_max} \leq P_{batt} \leq P_{dischar\_max} \quad (3)$$

The battery SOC value of the next interval is shown by the equation (4):

$$SOC\ (t + \Delta T) = SOC(t) + 100\frac{I_B \Delta T}{C} \quad (4)$$

Where,

$SOC(t)$: Temporarily measured value.

$SOC(t + \Delta T)$: Predictions for the horizon ΔT

C : Capacity of BESS

I_B : Current

While I_B has the following equation:

$$I_B = \frac{P_B}{V_B} \quad (5)$$

V_B is the BESS voltage which is considered constant 380V.

PV and Wind Turbines will be supplied to the load and if there is excess power generation, the battery will be charged. The PV renewable energy power is 29.5 kW and the maximum power produced is 14 kW, while the wind turbine power used is 15 kW and the maximum power produced is 8 KW. PV power and wind turbines are assumed to reach maximum power within 4 hours. So, to find out the battery capacity below.

$$P_{Gen} = P_{PV} + P_{WInd} = 14\ kW + 8\ KW = 22\ KW$$

$$C_{Batt} = \frac{E_G}{V_{Batt} D_0 D_{max}} \times 1.25$$

$$C_{Batt} = \frac{(22kW - 14\ kW) \times 4h}{650\ \times 0.8} \times 1.25$$

$$C_{Batt} = 76.92\ Ah$$

Using a battery with a capacity of 20 A requires a battery N_{Batt}:

$$N_{Batt} = \frac{76.92}{20} = 3.84\ \approx 4\ Battery$$

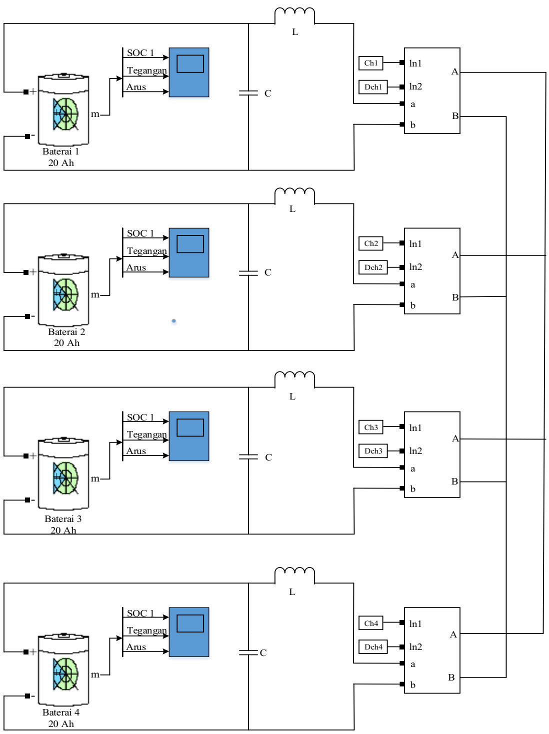

Fig. 4. Battery Storage Wiring

4 Energy Management System (EMS)

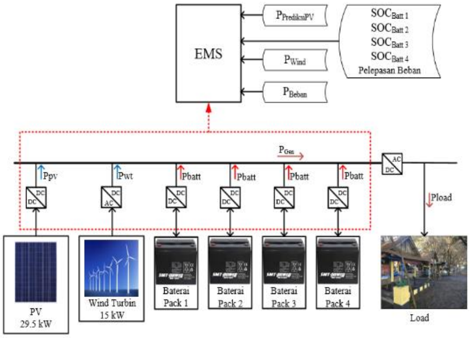

Fig. 5. Block diagram

The Micro hydro (PLTH) generator on Bantul beach produces a total of 44 kWp of power consisting of two sources. PV of 29.5 kW and Wind Turbine of 15 kW. The load supplied by PLTH Pantai Baru Bantul is 14 kW, consisting of Office 3.9 kW, Culinary Stall (West Group) of 2.1 kW, Culinary Stall (East Group) of 2 kW, Culinary Stall (Central Group) of 3 kW, Street Lighting 2 kW and Water Pump 1 kW.

$$P_{Gen} = P_{PV} + P_{WInd} \qquad 3.1$$

Where P_{Gen} is power of renewable energy, P_{PV} is a power of PV dan P_{WInd} is a Power of wind turbine.

EMS as a battery charge and discharge and optimizes the battery charge by carrying out load shedding and if the power is not sufficient for the load requirements it will also carry out load shedding automatically using a rule-base algorithm.
The rule-base algorithm functions to maximize PV and Wind renewable energy power by shedding the load so that power is maximized for charging the battery and still maintains the SOC at safe limits[9]. Power usage will be adjusted by the power produced. If the power produced by the PV and Wind Turbine can supply the load, then the load will be borne by the PV and Wind.

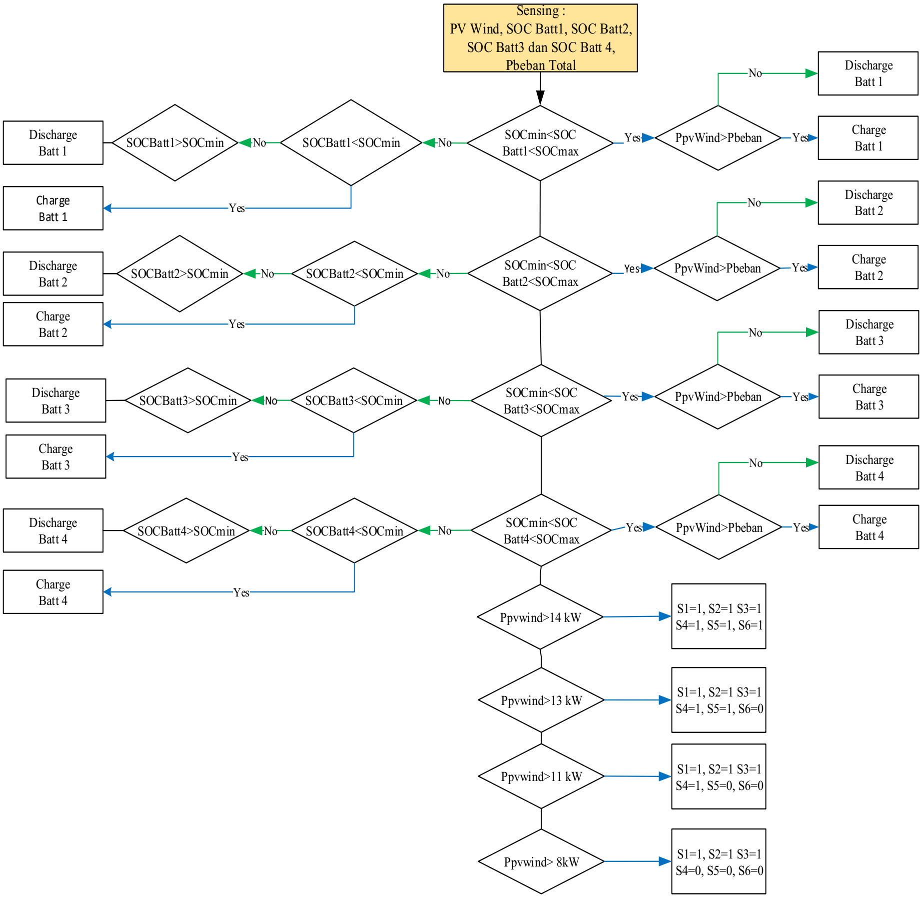

Fig. 6. Example of a figure caption. *(figure caption)*

while the minimum SOC is 20%. If the SOC reaches 20% it will not supply energy to the system and when the SOC is 90% the battery will refuse to charge. If the battery SOC is less than the minimum SOC, it will charge the battery. Conversely, if the battery SOC is greater than the minimum SOC, it will discharge the battery. Meanwhile, if the power produced by PV and Wind is greater than the load power, it will charge the battery if the PV and Wind power is high. generated is less than the load power, so the battery will discharge to the load. There are values of 14 kW, 13 kW, 11 kW and 8 kWa which are the sum of the load values. The value of 14 kW is the total load power used. 13 kW if the power used is Office, Culinary Stall (West Group), Culinary Stall (East Group), Culinary Stall (Central Group) and PJU. The power used is 11 kW for the Office, Culinary Stall (West Group), Culinary Stall (East Group) and Culinary Stall (Central Group). Meanwhile, the power used is 8 kW which is always on, such as the load for the Office, Culinary Stall (West Group) and Culinary Stall (Central Group).

5 Result and Discussion

5.1 Prediction PV With CFNN

The training process shown is taken from the smallest MSE which can be seen in tables 4.4 to 4.6. From the picture, the training iteration process reached 455 iterations with an epoch of 10,000 and a time of 2:23:22 with a performance of $1.00e^{-6,}$ Gradient of $1.00e^{-7}$ and the MU of $1.00e^{10}$.

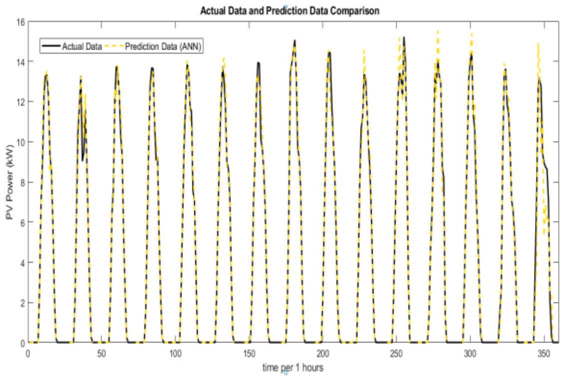

Fig. 7. Testing result

The Cascade Forward Neural Network (CFNN) method with Levenberg-Marquardt is able to provide better MSE at a learning rate of 0.1 with an average of 1.35% while a learning rate of 0.01 with an average MSE of 0.9% and a learning rate of 0.05 with average MSE 1.23%. It can be seen that the CFNN method can provide a better mean square error at a learning rate of 0.01.

5.2 Wind Turbine

The wind turbine at the Pantai Baru Bantul power plant has a total capacity of 15 kW, but 15 kW cannot be optimal because the power of the wind turbine depends on wind speed. If the wind speed exceeds the optimal wind speed, namely 12m/s, the power produced will decrease because it is influenced by the mechanical torque on the turbine and conversely, if it is less than the optimal speed, the power produced will increase.

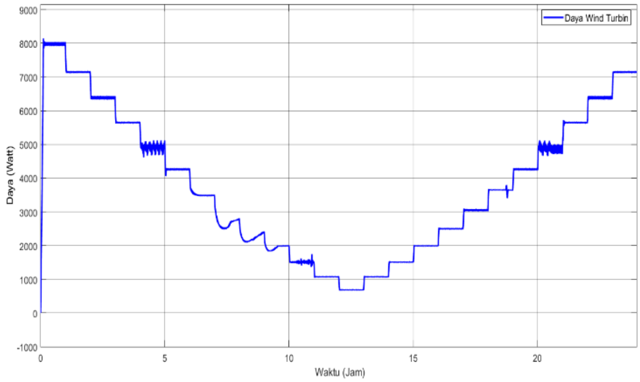

Fig. 8. Power of Wind turbine

Figure 8 shows that the wind turbine power has an optimal power at night of 8 kW at 24.00, while the maximum power reduction during the day at 12.00 is 0.9 kW.

5.3 EMS Using Algorithm Rule Base

EMS regulates load usage which causes an increase or decrease in load. Load shedding in EMS here will reduce the load due to maximizing power to charge the battery and if the power from renewable energy is not sufficient for load needs, apart from that EMS also functions as a charge/discharge for the battery. The algorithm used in EMS is a rule-base algorithm. The EMS results are shown in Figure 9.

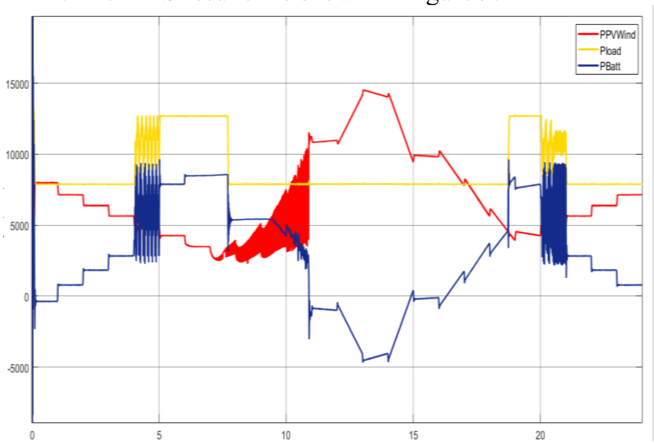

Fig. 9. The results from EMS use a rule-base algorithm

The Simulink simulation in Figure 9 shows that from 00.00 to 04.00 a load of 8 kW is used, consisting of office loads, culinary stalls (west group), and culinary stalls (east group). The 8-kW load is supplied by renewable energy power (PV, Wind) and batteries. From 04.01 to 07.00 the load is increased by 12.5 which consists of office loads, culinary stalls (west group), culinary stalls (eastern group), and culinary stalls (middle group) which causes battery power (blue) and power PVWind (in red) has also experienced improvements. The battery power (blue) experiences oscillations because the load power (yellow) is increased but does not last long and can return to stability. From 07.01 to 19.00 the load is reduced by 8 kW. At 07.00 the battery power (blue) experienced oscillations of up to 2.7 kW, this happened because of the supply from PVWind power (red). The PV wind power reaches its peak at 13.00 at 14.4 kW and the power is optimized for charging the battery up to 4.5 kW. At 14.00 PVwind power (red) the power produced was 14.25 kW and continued to decline until 19.00 reaching 3.93 kW. From 19.00 to 21.00 the load usage (yellow) increases by 12.5 kW so that at 21.01 the load is reduced to a nominal load of 8 kW.

6 Conclusion

The conclusions obtained from the results of the 24-hour PV Prediction research using Cascade Forward Neural Network, the smallest MSE value occurred in Training hidden layer 50 at a learning rate of 0.01 with a value of 0.84% while the largest MSE value occurred at 2.94% in hidden layer 20 neurons in learning rate 0.01. EMS uses a rule-base algorithm for renewable energy generation that is more optimized for charging 4.5 kW batteries, whereas when PV and wind turbine energy is not optimal, battery usage will be maximized so that battery power will discharge to the load to meet the maximum load of 12.5 kW and If the power is not sufficient for the load requirements, the load will be reduced automatically to a minimum load of 8 kW.

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