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Design and Development of a Weather Prediction Device for Solar Power Plant Projects Using a Backpropagation Artificial Neural Network

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Abstract
Planning the installation of a Solar Power Plant (PLTS) requires weather condition information so that projects can be implemented according to plan. However, monitoring weather conditions and forecasting weather for several days to one month ahead have not been optimally utilized as a basis for decision-making in PLTS project planning. Therefore, this study aims to design and develop a weather prediction device based on the Backpropagation Artificial Neural Network (ANN) algorithm so that weather conditions for one month ahead can be predicted accurately. The sensors used were a BH1750 sensor to measure solar light intensity, a BME280 sensor to measure temperature, humidity, and air pressure, a wind-speed sensor, and a rainfall sensor. A total of 10,080 sensor data records were obtained and stored on a microSD module. The data were then processed as inputs for the Backpropagation Artificial Neural Network algorithm to generate weather predictions. The results show that the combination of the Backpropagation Artificial Neural Network algorithm successfully produced a one-month weather prediction with the lowest Mean Absolute Error (MAE) of 0.218595.

Keywords: Solar Power Plant, Backpropagation Artificial Neural Network, Mean Absolute Error

1. Introduction

Electrical energy is a primary necessity for human life today. However, to meet this need, society still relies heavily on conventional, non-renewable, and limited energy sources. Along with population growth and societal development, the use of conventional energy continues to increase, potentially triggering an energy crisis and increasing global temperatures [1]. Examples of conventional energy sources include fossil fuels such as coal, natural gas, and petroleum.

Indonesia faces major challenges in the national energy sector because it remains highly dependent on fossil energy, particularly coal. This has negative environmental impacts, including significant pollution and decreasing reserves of fossil fuels, including coal [2]. Such conditions may create problems for human life in the future. Therefore, efforts are increasingly being made to utilize renewable energy sources for electricity generation. One such renewable energy source is solar energy. Solar energy can be converted into electricity using Solar Power Plant (PLTS) systems.

A Solar Power Plant (PLTS) is a system that generates electricity from sunlight by converting solar radiation using photovoltaic cells. The system receives sunlight and converts it into electrical energy. The stronger the incoming sunlight, the greater the electricity generated [1]. PLTS has advantages over conventional energy because it utilizes sunlight, can be used continuously, and does not cause environmental damage. PLTS systems consist of three types: Off-Grid PLTS, On-Grid PLTS, and Hybrid PLTS. Off-Grid PLTS generates electricity using solar energy without being connected to the electricity grid. Therefore, electricity in this system is generated only from solar radiation and solar panels. On-Grid PLTS uses two electricity sources, namely solar panels and PLN electricity. This system can help reduce electricity costs for homes, offices, or businesses, thereby providing additional benefits to users. Meanwhile, Hybrid PLTS combines PLTS with another electricity generation source [3].

In addition to solar-panel systems and components, weather factors also strongly affect the design and construction of PLTS because solar light intensity, ambient temperature, wind speed, and rainfall can affect the performance and durability of PLTS structures. Weather factors strongly influence project construction, with hot weather accounting for 30.93% and rainy weather for 66.90% [4]. These conditions can cause obstacles such as decreased worker productivity and delays in the installation and commissioning of solar panels.

Therefore, weather prediction is needed in PLTS planning and construction. Weather prediction refers to forecasting atmospheric conditions such as temperature, rainfall, and wind speed over a certain future period [5]. The ability to predict weather is essential to support appropriate decision-making in planning, including determining work schedules in order to minimize the risk of PLTS construction project failures caused by extreme weather [6].

In the implementation of Solar Power Plant (PLTS) projects, a major problem remains: weather-condition monitoring and weather prediction for the following days have not been optimally utilized, even though this information is important for determining the ideal time for planning and installing solar panels. As the number of PLTS projects increases, this problem may further increase the risk of delays and inaccuracies in planning. To address this issue, a device capable of predicting weather conditions for PLTS projects is required.

Previous research has discussed weather prediction using the Random Forest method [7]. The results were relatively good, with an accuracy of 0.71, indicating a 71% success rate in weather prediction. Another study predicted weather using Mamdani- and Sugeno-type Fuzzy Inference Systems and achieved an accuracy of 80.87% [8].

The Backpropagation ANN algorithm was selected because its iterative learning process enables the system to operate effectively and rapidly while minimizing errors and improving prediction accuracy [9]. Therefore, this study designs and develops a weather prediction device capable of forecasting weather up to one month ahead using a Backpropagation Artificial Neural Network algorithm to support more efficient PLTS project installation.

2. Research Method

This study uses a quantitative research method, namely a method that collects measurable numerical data or variables. The data are then analyzed using statistical techniques to identify relationships between variables, make predictions, or identify patterns in the data [10]. In this study, a weather prediction device for PLTS projects was designed and developed. The quantitative method was used to measure data from the BME280 sensor, BH1750 light-intensity sensor, rainfall sensor, and wind-speed sensor. The Backpropagation Artificial Neural Network (ANN) algorithm was then used to predict weather conditions.

2.1 Device Design

The wiring of the weather prediction device for the PLTS project was developed using a Wemos D1 R32 as the data-processing center. In the wiring system, the Wemos D1 R32 is connected to various sensors and modules for data collection. The BME280 and BH1750 sensors are used to measure light intensity, temperature, humidity, and air pressure. A rainfall sensor or tipping-bucket rain gauge is used to detect rainfall, while a wind-speed sensor measures wind speed. The collected data are stored on a microSD module and used as the basis for weather prediction.

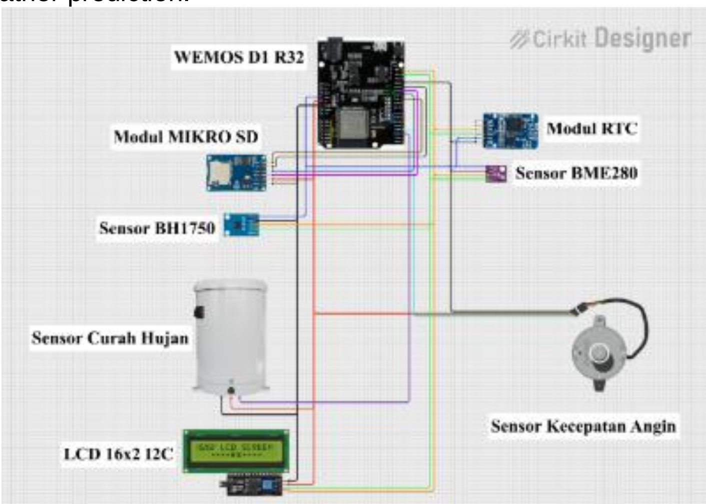

Figure 1. Wiring of the weather prediction device using the Backpropagation ANN algorithm.

The system consists of a Wemos D1 R32 microcontroller, BH1750 sensor, BME280 sensor, rainfall sensor, wind-speed sensor, Real-Time Clock module, and microSD module. When all sensors operate properly, the Wemos obtains data such as light intensity, temperature, humidity, air pressure, rainfall, and wind speed. The resulting data are stored on the microSD module. The Wemos D1 R32 processes the data to produce weather predictions for one month ahead. Finally, the predicted data are sent to the ThinkSpeak platform and displayed on its dashboard.

Figure 2. System flowchart.

The front-view design of the device has a height of 2 meters. The device was designed at this height to obtain maximum wind exposure for the wind-speed sensor. The structure consists of a 1.8-meter pole, four 1-meter metal supports, and a panel box.

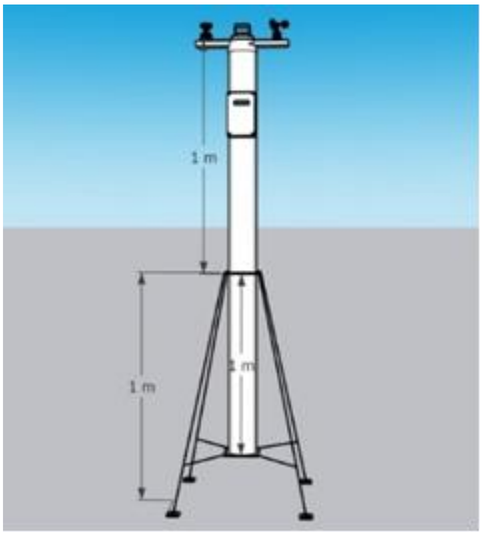

Figure 3. Device design.

2.2 Data Collection Stage

- The data collected in this study were obtained from sensors measuring light intensity, temperature, humidity, air pressure, rainfall, and wind speed. Data were collected over a period of 7 days, resulting in 10,080 data records.
- Training-data collection is the stage of providing data used to train the Backpropagation Artificial Neural Network. Training data help the model learn patterns in the relationships between input and output data. The training data were obtained from the sensor data. Training data generally account for approximately 70–80% of the total data because the amount of training data strongly determines model capability and affects prediction accuracy.
- Test-data collection is the stage of providing data that are not used during training but are instead used to measure the model's prediction capability. Test data are used to evaluate the model's ability to predict new data.
- Data normalization is the process of bringing the scales of values among variables into a comparable range so that each variable is balanced during model training.
- Mean Absolute Error (MAE) is used to measure the difference between predicted and actual values.

3. Results and Discussion

3.1 Sensor Accuracy Testing

Sensor accuracy testing was conducted to determine the ability of each sensor to provide measurements close to actual or reference values. Testing was performed by comparing sensor readings with measuring instruments or reference values used as benchmarks. Each measurement result was recorded, followed by calculation of the error and sensor accuracy percentage.

The error was calculated based on the difference between the sensor reading and the reference instrument reading. The smaller the error, the higher the sensor accuracy. The test results were used as a basis for evaluating sensor performance before implementation in the overall system. A sensor was considered to have good performance when it provided consistent measurements with low error and high accuracy.

Table 1. Solar Light Intensity Data

No	Time	Solar Light Intensity			
		Sensor BH1750	**Lux Meter**	**Difference**	**Error**
1	8.00 17/6/2026	5461	5500	39	0,71%
2	9.00 17/6/2026	5461	5441	20	0,37%
3	10.00 17/6/2026	5461	5526	115	2,08%
4	11.00 17/6/2026	5461	5413	12	0,22%
5	12.00 17/6/2026	5461	5518	57	1,03%
6	13.00 17/6/2026	2861	2975	114	3,83%
7	14.00 17/6/2026	1449	1415	34	2,40%
8	15.00 17/6/2026	6749	6613	136	2,06%
9	16.00 17/6/2026	3913	3997	84	2,10%
10	17.00 17/6/2026	1306	1360	54	3,97%
Average Error %					1,877%

Table 1 presents the solar light intensity data obtained from the BH1750 sensor and a lux meter. The difference between the BH1750 readings and the lux-meter readings was calculated to determine the error and average error. The equation used to calculate the error is as follows:

$$\text{Error} = \frac{Difference}{Instrument\ Reading}\ x\ 100\%$$

Then, calculate the average error using the following equation:

$$\text{Average Error} = \frac{P1+p2+p3+p4+p5+p6+p7+p8+p9+p10}{10}$$

Description: p1, p2, p2,….p10 are the collected error data

Table 2. Temperature, Humidity, and Air Pressure Data

Time	**Temperature, Humidity, and Air Pressure**			
	Sensor BME280	**Measuring Instrument**	**Difference**	**Error**
8.00 12/6/2026	Temperature: 30.3˚C Humidity: 70.6% Air Pressure: 1015.0 hPa	Temperature : 29.4 ˚C Humidity: 67.6% Air Pressure: 1014.2 hPa	Temperature : 0.9 Humidity: 3 Air Pressure: 0.8	Temperature: 3.06% Humidity: 4.44% Air Pressure : 0.0789%
9.00 12/6/2026	Temperature: 32.8˚C Humidity: 72.3% Air Pressure: 1015.1 hPa	Temperature: 33.7˚C Humidity: 70.4% Air Pressure: 1014.3 hPa	Temperature : 0.9 Humidity: 1.9 Air Pressure: 0.8	Temperature: 2.67% Humidity: 2.70% Air Pressure : 0.0789%
10.00 12/6/2026	Temperature: 29.9˚C Humidity: 75% Air Pressure: 1014.8 hPa	Temperature: 30.4˚C Humidity: 71.8% Air Pressure: 1014.0 hPa	Temperature : 0.5 Humidity: 3.2 Air Pressure: 0.8	Temperature: 1.64% Humidity: 4.46% Air Pressure : 0.0789%
11.00 12/6/2026	Temperature: 29.8˚C Humidity: 85.2% Air Pressure: 1015.1 hPa	Temperature: 31.1˚C Humidity: 80.3% Air Pressure: 1014.2 hPa	Temperature : 1.3 Humidity: 4.9 Air Pressure: 0.9	Temperature: 4.18% Humidity: 1.62% Air Pressure : 0.0887%
12.00 12/6/2026	Temperature: 27.4˚C Humidity: 88.7% Air Pressure: 1013.5 hPa	Temperature: 28.7˚C Humidity: 89.5% Air Pressure: 1012.7 hPa	Temperature : 1.3 Humidity: 0.8 Air Pressure: 0.8	Temperature: 4.53% Humidity: 0.89% Air Pressure : 0.0790%
13.00 12/6/2026	Temperature: 27.4˚C Humidity: 88.7% Air Pressure: 1013.5 hPa	Temperature: 28.7˚C Humidity: 89.5% Air Pressure: 1012.7 hPa	Temperature : 1.3 Humidity: 0.8 Air Pressure: 0.8	Temperature: 4.53% Humidity: 0.89% Air Pressure : 0.0790%
14.00 12/6/2026	Temperature: 28.5˚C Humidity: 80.1% Air Pressure: 1012.2 hPa	Temperature: 30.1˚C Humidity: 80.8% Air Pressure: 1011.4 hPa	Temperature: 1.6 Humidity: 0.7 Air Pressure: 0.8	Temperature: 5.32% Humidity: 0.87% Air Pressure : 0.0791%
15.00 12/6/2026	Temperature: 29.2˚C Humidity: 76.9% Air Pressure: 1011.8 hPa	Temperature: 29.2˚C Humidity: 75.5% Air Pressure: 1010.9 hPa	Temperature: 0 Humidity: 1.4 Air Pressure: 0.9	Temperature: 0 Humidity: 1.85% Air Pressure : 0.0890%
16.00 12/6/2026	Temperature: 28.2˚C Humidity: 79.7% Air Pressure: 1012.5 hPa	Temperature: 29.7˚C Humidity: 78.2% Air Pressure: 1011.6 hPa	Temperature: 1.5 Humidity: 1.5 Air Pressure: 0.9	Temperature: 5.05% Humidity: 1.92% Air Pressure : 0.0890%
17.00 12/6/2026	Temperature: 28.1˚C Humidity: 82.4% Air Pressure: 1013.3 hPa	Temperature: 28.5˚C Humidity: 79.9% Air Pressure: 1012.4 hPa	Temperature: 0.4 Humidity: 2.5 Air Pressure: 0.9	Temperature: 1.40% Humidity: 3.13% Air Pressure : 0.0889%
Average Error %				Temperature: 3.238% Humidity: 2.188% Air Pressure: 0.829%

In table 2. BME280 sensor data, namely temperature, humidity, and air pressure data with a measuring instrument (Temperature, Humidity, and Barometric Pressure) meter that produces a fairly small difference and error. Based on the table, the temperature, humidity, and air pressure produced by the BME280 sensor with the measuring instrument (Temperature, Humidity, and Barometric Pressure) will be calculated to determine the difference. The difference data that has been obtained will be used to calculate the error and the average error. The equation used is as follows:

$$\text{Error} = \frac{Difference}{Instrument\ Reading}\ x\ 100\%$$

Then find the average error using the following equation:

$$\text{Average error} = \frac{\text{P1+p2+p3+p4+p5+p6+p7+p8+p9+p10}}{10}$$

Description: p1, p2, p2,….p10 are the collected error data

Table 3. Rainfall Data

Time	**Rainfall**			
	Rainfall Sensor	**Manual Calculation**	**Difference**	**Error**
8.00 12/6/2026	0,0 mm	0,0 mm	0	0
9.00 12/6/2026	0,0 mm	0,0 mm	0	0
10.00 12/6/2026	0,0 mm	0,0 mm	0	0
11.00 12/6/2026	0,0 mm	0,0 mm	0	0
12.00 12/6/2026	0,0 mm	0,0 mm	0	0
13.00 12/6/2026	0,0 mm	0,0 mm	0	0
14.00 12/6/2026	0,0 mm	0,0 mm	0	0
15.00 12/6/2026	0,0 mm	0,0 mm	0	0
16.00 12/6/2026	0,0 mm	0,0 mm	0	0
17.00 12/6/2026	0,0 mm	0,0 mm	0	0
Average Error				0

Table 3. Results of rainfall sensor measurements with manual calculations to determine rainfall which produced zero data because it did not rain when the data was taken.

In Table 4, the wind speed data generated by the wind speed sensor and the anemometer will be calculated to determine the difference. The resulting difference will be used to calculate the error and average error. The equation used is as follows:

$$\text{Error} = \frac{Difference}{Instrument\ Reading}\ x\ 100\%$$

Then find the average error using the following equation:

$$\text{Average error} = \frac{\text{P1+p2+p3+p4+p5+p6+p7+p8+p9+p10}}{10}$$

Description: p1, p2, p2,….p10 are the collected error data

Table 4. Wind Speed Data

Time	Wind Velocity			
	Wind Speed Sensor	**Measuring instrument (A nemometer)**	**Difference**	**Error**
8.00 22/6/2026	0,0 m/s	0,0 m/s	0	0
9.00 22/6/2026	2,2 m/s	2,1 m/s	0,1	4,76%
10.00 22/6/2026	2,9 m/s	2,7 m/s	0,2	7,41%
11.00 22/6/2026	2,1 m/s	2,0 m/s	0,1	5%
12.00 22/6/2026	2,6 m/s	2,5 m/s	0,1	4%
13.00 22/6/2026	2,2 m/s	2,4 m/s	0,2	8,33%
14.00 22/6/2026	3,4 m/s	3,1 m/s	0,3	9,68%
15.00 22/6/2026	2,5 m/s	2,4 m/s	0,1	4,17%
16.00 22/6/2026	2,5 m/s	2,4 m/s	0,1	4,17%
17.00 22/6/2026	2,0 m/s	2,1 m/s	0,1	4,76%
Average Error %				4,87%

3.2 Results of the analysis of the performance of the backpropagation algorithm for predicting the weather for the next 1 month

The results of collecting weather data for 1 week with a recording interval of every 1 minute, resulting in 10,080 data points. The collected data includes sunlight intensity, temperature, humidity, air pressure, wind speed, and rainfall, which are stored automatically by the system. This data will be used to make weather predictions using the ANN Backpropagation algorithm. After the data has been collected, the data will be divided into two groups: training data and test data. The data distribution percentage is 80% training data and 20% test data. Then, the entire data will be normalized using the following equation:

$$normalization\ (x) = \frac{Min\ range + (x - \min value)(mxRange - minRange)}{(Maxvalue - \min value)}$$

Prediction results using the JST Backpropagation algorithm

Table 5. Sensor data processed to be used for predictions

Testing	Hidden Nauron	Weight	Learning Rate	MAE
1	5	0.2	0.9	0.260272
2	10	0.2	0.9	0.277241
3	15	0.2	0.9	0.226095
4	20	0.2	0.9	0.219428
5	25	0.2	0.9	0.218595

Table 5 shows the Backpropagation ANN algorithm testing by varying the number of hidden neurons, namely 5, 10, 15, 20, and 25 neurons. Meanwhile, using a learning rate parameter of 0.9 and an initial weight using a value of 0.2 in each test. The test results show that the use of 5 hidden neurons produces an MAE value of 0.260272, while the use of 10 hidden neurons increases the MAE value to 0.277241. The use of 15 hidden neurons observes a decrease to 0.226095. The decrease in value again is used when using 20 hidden neurons to 0.219428. The final test using 25 hidden neurons produces an MAE value of 0.218595, which is the smallest error value compared to all test results. These results indicate that the configuration with 25 hidden neurons provides the best level of prediction accuracy.

Figure 5 shows the data training process using an artificial neural network with 6 input layers, 25 hidden layers, and 1 output layer. The 6 input neurons represent six weather parameters used as input: light intensity, temperature, humidity, air pressure, wind speed, and rainfall. Meanwhile, 1 output neuron generates weather prediction results.

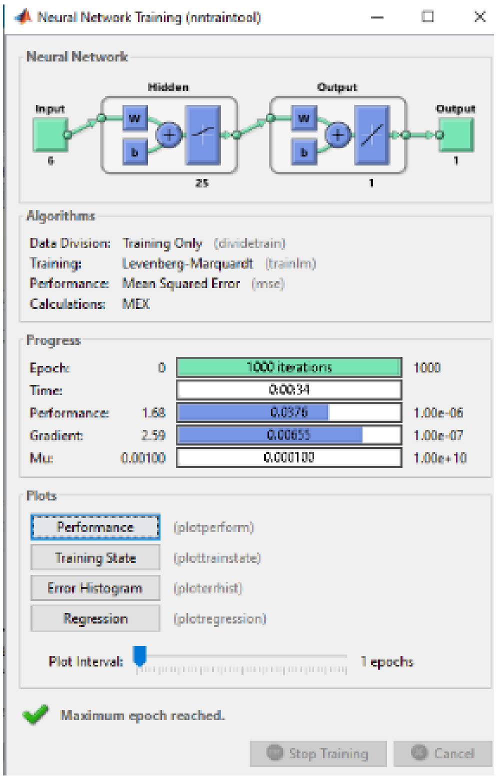

Figure 5. The training process of the JST backpropagation algorithm

In Figure 6, the histogram shows error values around the zero error line, indicated by the orange vertical line. This indicates that the network's prediction results have a small difference from the target value, allowing the model to learn the data pattern well.

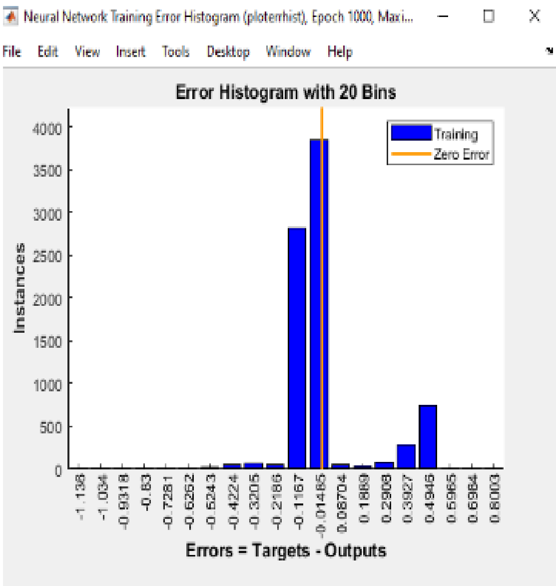

Figure 6. Histogram of error value

4. Conclusion

After knowing the results of the design, testing, and analysis of the weather prediction tool using the JST Backpropagation algorithm , the following conclusions were obtained:

- The accuracy of the sensors used for weather prediction tools for the next 1 month such as the BH1750 sensor or sunlight intensity sensor which produces an average error of 1.887%. The BME280 sensor or sensor detects temperature, humidity, air pressure which produces an average error of 3.238% Temperature, 2.188% Humidity, Air Pressure 0.829%. Then the wind speed sensor produces an average error of 4.487% and the rainfall sensor produces an average error of 0%. So all the sensors used have good accuracy.
- The results of the performance using only the ANN backpropagation algorithm using 10,080 total data that has been processed using the ANN network architecture by varying different hidden neurons 5, 10, 15, 20, 25 with a learning rate of 0.9 and a weight of 0.2 produced the smallest MAE value of 0.218595 with a network architecture of 25 hidden neurons, a learning rate of 0.9, a weight of 0.2 and the largest MAE value is 0.277241 with a network architecture of 10 hidden neurons, a learning rate of 0.9, a weight of 0.2. So data processing using the ANN backpropagatian algorithm has proven successful in making predictions with small MAE values.

After analyzing the weather prediction tool using the JST Backpropagaton algorithm, suggestions were obtained for information in further research, including:

- Adding a wind direction sensor to determine the wind direction.
- Data collection is increased again by 1-2 months to make predictions more accurate.
- Add grounding to the tool because the tool is placed outdoors to prevent it from being struck by lightning.
- The output category in the JST algorithm adds a cloudy category, which previously only included sunny and rainy.

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