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Load Control Battery Strategy based on Backpropagation and Simulated Annealing Training Performance

***Abstract**. Nowadays, the light control system only uses scheduling so if the season changes the system becomes less effectivity. This study aims to compare the backpropagation (BP) and simulated annealing (SA) algorithm training performances for the ANN system. The selection of the ANN method for estimating the intensity of solar radiation is because it can estimate the daily or hourly average solar radiation with high accuracy. In order to find out the best performance, this research compares BP and SA algorithms based on their Mean Square Error (MSE) and Absolute Error (AE) values. Based on the results, this study shows that MSE and AE values for SA are better than BP. The MSE value of SA is 0.047338156 lower than BP, while the AE value of SA is 19.26% lower than BP. The results of this study prove that for training on a supervised control system using ANN, simulated annealing could be prioritized in the active power load control strategy.*

***Streszczenie.** Obecnie system sterowania oświetleniem opiera się wyłącznie na harmonogramie, zatem w przypadku zmiany pory roku skuteczność systemu staje się mniejsza. Celem tego badania jest porównanie wydajności uczenia algorytmu propagacji wstecznej (BP) i symulowanego wyżarzania (SA) dla systemu SSN. Wybór metody SSN do szacowania natężenia promieniowania słonecznego wynika z faktu, że pozwala ona z dużą dokładnością oszacować średnie dobowe lub godzinne promieniowanie słoneczne. Aby określić najlepszą wydajność, w badaniu tym porównano algorytmy BP i SA w oparciu o wartość błędu średniokwadratowego (MSE) i błędu bezwzględnego (AE). Na podstawie wyników badanie to pokazuje, że wartości MSE i AE dla SA są lepsze niż BP. Wartość MSE SA jest o 0,047338156 niższa niż BP, natomiast wartość AE SA jest o 19,26% niższa niż BP. Wyniki tego badania dowodzą, że w przypadku szkolenia w nadzorowanym systemie sterowania wykorzystującym SSN, symulowane wyżarzanie może mieć priorytet w strategii sterowania obciążeniem mocą czynną. (**Strategia kontroli obciążenia baterii oparta na propagacji wstecznej i symulowanym wyżarzaniu**)*

Keywords: Light control, ANN, Backpropagation, Simulated annealing
Słowa kluczowe: Sterowanie światłem, SSN, propagacja wsteczna, symulowane wyżarzanie.

Introduction

Indonesia is a tropical country with the potential for solar energy of 536 GW, of which the utilization is only 152 MW or about 0.028% [1][2]. As a type of renewable energy, solar energy has advantages compared to others, namely the ease of implementation. This ease of implementation is utilized by the provinces of DKI Jakarta, Central Java and Bali to utilize solar cells as rooftops [1]. The obstacle when applying solar energy is the fluctuating intensity of solar radiation that affects the output of electrical energy produced. The current technology to overcome fluctuations in the intensity of solar radiation is Maximum Power Point Tracking (MPPT), where this technology obtains maximum power output [3][4][5].

Using MPPT is only to make the output power maximum but unable to overcome fluctuations in the intensity of solar radiation on lighting lamps. The solution to this problem is to adjust the power output of the lamp. This setting uses Pulse Width Modulation (PWM) to adjust the lamp brightness. Setting the amount of lamp power can use a scheduling system based on needs so that its use is more optimal [6][7][8][9]. The optimal lighting control system with this scheduling does not yet use solar cells, because solar cells can save electricity and reduce carbon emissions [10]. The power consumption control system for lighting lamps with a solar cell source still uses much on-off control without considering how much power the battery receives from the solar cell [11][12][13]. When the weather changes, the intensity of solar radiation also changes, so the control of lighting becomes not optimal. This problem needs to be solved so that the arrangement of lighting with solar cell sources can be more optimal when the intensity of solar radiation changes.

Various methods with estimation approaches to estimate solar radiation intensity for optimal solar cell design have been proposed using the artificial neural network (ANN) method. The choice of the ANN method for estimating solar radiation intensity because it can estimate daily or hourly average solar radiation with high accuracy [2][14][15][16]. In the previous studies, the estimation of solar radiation intensity using the ANN method used ambient temperature, relative humidity, wind speed, wind direction, duration of solar radiation, latitude, longitude and month as input parameters [2][15][16][17]. ANN can estimate solar radiation intensity reasonably because it collaborates in a complex way between input and output to produce optimal results [16].

Another ANN capability is predicting current data in a time series form and calculate the use of wasted energy [18][19]. Sensor and embedded technologies are used to obtain current value and identify electrical equipment that is operated using ANN [18]. An important process that must be carried out by a supervised ANN is the training process, one of which uses the backpropagation (BP) algorithm [20][21]. ANN using BP algorithm training can perform object recognition with accuracy above 95% [22][23]. Apart from using the BP algorithm, the ANN training process can also use the metaheuristic algorithm. ANN training using metaheuristic algorithms in image recognition research can work better than BP [24].

In the previous study [25], light load control was carried out using a zero-order fuzzy sugeno method with the addition of a simple linear regression-based estimator to predict the remaining battery usage time. The use of fuzzy has been proven able to increase the duration of battery use up to approximately 17 hours at an initial condition of 55.82 Wh by adjusting the load power used. In this study, a preliminary study carried out as a form of development from previous research. Fuzzy logic-based light load control has weaknesses because it is not adaptive and depends on expert system updates (rule base) [26][27].

Based on this, it is necessary to determine the ANN training algorithm for problems with the control system for controlling lamp power with battery charging input from solar cells. The contribution of this research is the comparison of the ANN training methods between backpropagation (BP) and simulated annealing (SA). The comparison will determine the suitable method for controlling lamp power with solar cell sources. In this research, two parameters that become crucial to conclude the suitable method are Mean Squared Error and Absolute Error.

Method

Research design

This study applies the ANN network structure model for lighting power regulation systems with battery charging input from solar cells. The network structure has 3 inputs, 2 hidden layers each with 9 neurons and 1 output, as shown in Figure 1. The choice of the ANN method is because it has good accuracy for estimating solar radiation intensity when it is implemented [2]. This ANN is conducting training with the dataset in Table 1, using the BP and SA algorithms. During the training process, the mean square error (MSE) value between BP and SA algorithms is compared with different epoch values.

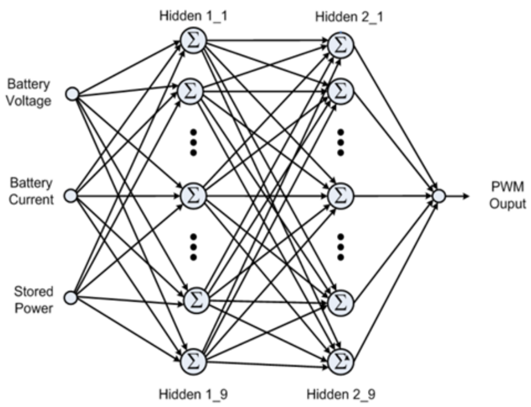

Fig. 1. Block system design of ANN control

The first layer is the input layer of ANN, which receives data directly in the form of voltage, current and stored power. The number of nodes in the input field represents the dimension of the vector [28]. The hidden layer consists of a certain number of nodes, this research uses 9 nodes, each of which is connected to every node in the input layer with a certain weight. Each node in the hidden layer is connected to the output node, the output node in this research uses PWM.

Prototype Design

Block system hardware ANN for controlling lamp power settings with solar cell sources as shown in Figure 2. The sensors used are current sensors ACS712 5A and voltage sensors using the voltage divider method [12][13][25]. The processing unit uses Arduino and ESP8266 microcontrollers connected to the firebase. This system uses a source of electrical energy from a 20Wp solar panel as well as a charge controller and 12 Ah battery. Current and voltage sensors are also used to obtain electrical power values. ESP8266 is used to receive data that has been obtained from the Arduino microcontroller and send it to Firebase to store the data as a data logger. This data logger is used to store battery current, battery voltage, power stored, and PWM out data, as shown in Table 1.

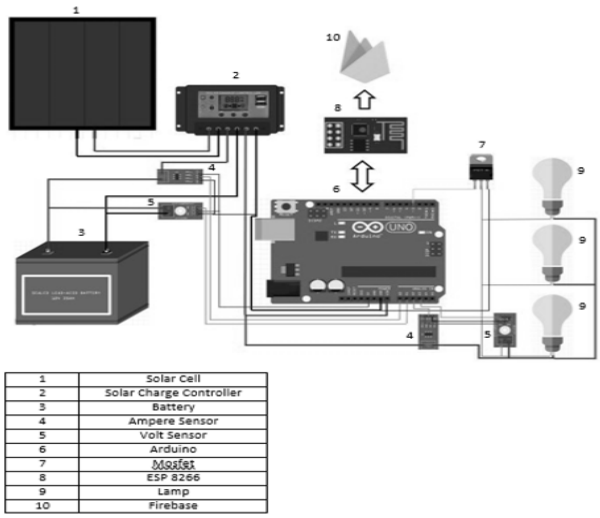

Fig. 2. Block system hardware.

Table 1. Dataset of ANN Control System

No	Battery Current (A)	Battery Voltage (V)	Power Stored (Watt)	PWM Out (%)
1	0.62	13.22	53.09	90.20
2	0.44	13.21	50.99	47.06
3	0.54	13.16	48.83	19.61
4	0.62	13.13	47.11	19.61
5	0.59	13.09	44.77	19.61
6	0.59	13.06	43.17	19.61
7	0.28	13.05	41.07	78.43
8	0.36	13.02	39.46	39.22
9	0.28	13	37.94	39.22
10	0.36	12.99	36.68	19.61
11	0.3	12.96	35.22	19.61
12	0.33	12.94	33.85	19.61
13	0.3	12.92	32.4	19.61
14	0.28	12.9	31.37	35.29
15	0.33	12.87	29.83	19.61
16	0.33	12.84	28.62	19.61
17	0.33	12.81	27.11	19.61
18	0.57	12.78	25.71	19.61
19	0.22	12.83	23.99	54.90
20	0.2	12.8	22.32	54.90
21	0.25	12.78	20.63	54.90
22	0.54	12.69	18.99	15.69
23	0.25	12.73	17.1	39.22
24	0.22	12.72	15.78	39.22
25	0.28	12.64	14.12	23.53
26	0.25	12.65	13.48	17.65

Result and Discussions

In this section, system reliability is tested with the following procedures: i) Create a computer application for ANN training between BP and SA algorithms using the dataset in Table 1, and ii) Compare the results of the two types of ANN training in terms of the Mean Square Error (MSE) and Absolute Error (AE) values in percentage (%).

Computer application for ANN training with BP and SA algorithms

An application to compare the ANN training process with the BP and SA algorithms is run on a computer that has the specifications of Core I5 RAM 16GB Hard disk SSD 480GB. The results of the application design to test this ANN training are shown in Figure 3. The testing process for this ANN training comparison between the BP and SA algorithms is activated together so that the MSE results can be seen on the charts in the application program.

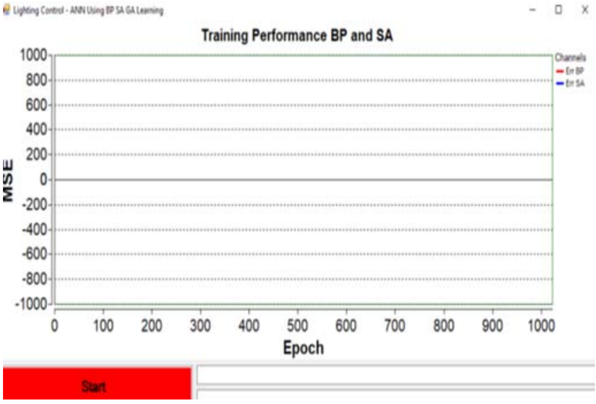

Fig. 3. Application of Training ANN

The first test in this research compares BP and SA training algorithms using 1000 epochs, for results as shown in Figure 4.

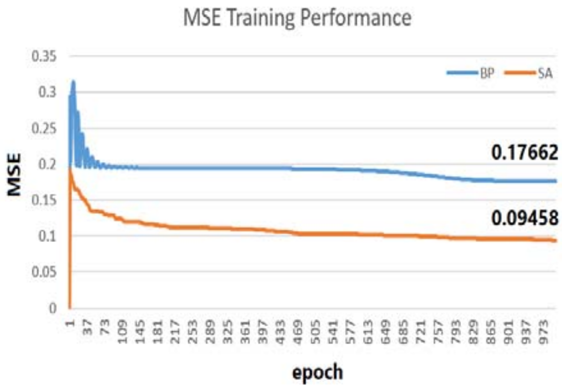

Fig 4. Application of Training BP and SA Algorithm using 1000 epoch

Based on Figure 4, during the ANN training process using Table 1, SA has a value of MSE = 0.09458 while BP = 0.17662, MSE results for SA convergence faster than BP. Figure 5, is the result of the BP and SA algorithm training tests using 1500 epochs.

Fig. 5. Application of Training BP and SA Algorithm using 1500 epoch

The test results with 1500 epochs have an MSE value for SA = 0.08011 and BP = 0.17495. The next test uses 2000 epochs for the ANN training process.

Fig. 6. Application of Training BP and SA Algorithm using 2000 epoch

The test results with 2000 epochs have an MSE value for SA = 0.08071 and BP = 0.10705. Based on Figure 6 above, the MSE for SA goes straight to convergence, while BP needs to reach above 1400 epochs to get it.

Comparison of ANN training using BP and SA Algorithm

The overall results of the MSE comparison of the ANN training process using the BP and SA Algorithm with epochs 1000, 1500, 2000, 2500, and 3000, are shown in Table 2 and Figure 7 below.

Table 2. MSE result using BP and SA

No	Epoch	MSE	
		BP	SA
1	1000	0.176624	0.094584
2	1500	0.174956	0.080115
3	2000	0.107046	0.08071
4	2500	0.101898	0.081078
5	3000	0.099236	0.086582
Average		**0.131952**	**0.084614**

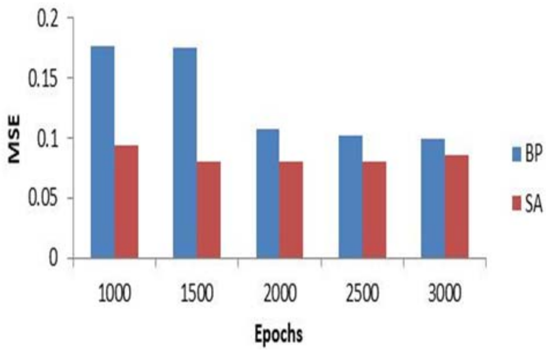

Fig 7. ANN training using BP and SA Algorithm

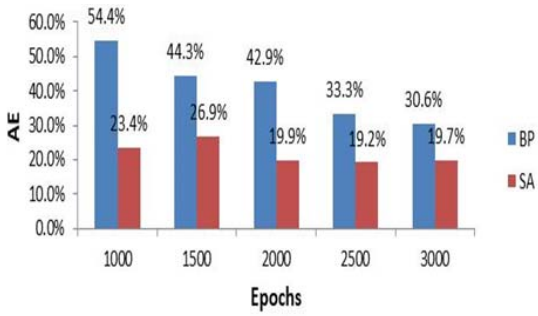

Fig. 8. Comparison output using BP and SA algorithms

Based on these results on figure 7, SA is better in testing than BP. MSE on SA tends to be more stable for the training process dataset in Table 1, while BP during 2000 epochs MSE starts to get better. The average of the tests in Figure 6 obtained BP = 0.131952 and SA = 0.084614. The results in Figure 8 below are a comparison between the target output and training output with BP and SA.

Based on these results, SA is better in testing than BP. AE on SA tends to be more stable for the training process dataset in Table 1. The average of the tests in Figure 8 obtained BP = 41.09 % and SA = 21.83%.

Conclusions

A comparison of ANN training using BP and SA algorithms has been carried out in this study. The dataset used is battery current, battery voltage, power stored, and PWM for the ANN control system. Based on the test results using different epoch values, SA can produce a lower MSE value of 0.047338156 compared to BP. A comparison of AE values from SA and BP shows that the average AE in SA is 19.26% lower. Based on the results of the ANN training test, it can be concluded that SA is better than BP in the case of a lamp control system with ANN.

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