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Daily Electrical Energy Forecasting in Rooftop Photovoltaic Systems: A Case Study

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Forecasting, photovoltaic, renewable energy

Abstract

The tropical climate provides room for optimizing solar energy. However, the ability in functionality is not optimal because the existing photovoltaic has not been investigated how much energy is produced. This research provides precise daily predictions for the sustainability of Photovoltaic energy. The resulting photovoltaic energy will undergo a predictive model by comparing NASA data with the predicted results from observational data. First, the mean square error (MSE) step is carried out with the smallest target value, determining the value of the correlation coefficient from training, validation and test data. The resulting prediction is at a validated daily energy of 9.46 in epoch 124. The prediction success is 99.98% for 4500 days with a standard of 2.2 x 105 kWh.

1. Introduction

Indonesia has a tropical climate with abundant sunlight intensity. The right light intensity can be enjoyed from 06.00 WIB to 17.30 WIB with clear weather conditions. Sunny weather can produce solar energy which has the potential for renewable energy [1,2]. Renewable energy has so far become scalable for home energy to large industries [3]. Because its benefits are not optimal, it is necessary to make accurate daily predictions [4–6].

The importance of predicting daily Photovoltaic for planning energy estimation from solar panels [7–9]. Solar panels that refer to weather conditions and the intensity of sunlight have a great opportunity to be used in Surakarta. Both of these conditions have a dependence on solar brightness and weather factors [10,11]. With reference to these factors, fluctuation values can be identified clearly and have the opportunity to optimize energy use.

Optimizing Photovoltaic energy has various strategic steps, first with Meta Learning Extreme Learning Machine optimized with Golden Eagle Optimization and Logistic Map (MGLE-ELM) and the average time imputation algorithm improves the radiation time forecasting performance in Thailand by 93.07% on the coefficient of determination than previous findings [7]. Radiation time will be affected by ambient conditions regarding carbon emissions, network flow, and individual indirect carbon emissions on a 30-bus system

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considering electricity carbon emissions [4]. Existing carbon emissions are part of the 9-10 km^2 Photovoltaic module design with a COE cycle of 0.063 /kWh [12,13]. This cycle can increase by 70% with an area of 220 m2 [14]. in another study, the actual performance of the photovoltaic module was 19.38% with an efficiency of 17% while using an aluminum heat sink and forced air cooling technique, micro inverter [15,16].

Designing the right module for refrigerated photovoltaic will be more complex by integrating it into the predicted power grid using machine learning to improve prediction accuracy. [3]. Prediction accuracy has been carried out using ARIMA-Gumbel (GP) which is significant to produce predictions of 73.73%, GSRML-GP3 plays a role of 15.25% in the hybrid model for solar photovoltaic [17]. In addition to hybrid, the SVM and GPR models in predicting solar photovoltaic power are 98% of the coefficient of determination [18]. The determined value is inseparable from the forecasting correction for the MAE value of 13.34 > 9.87; MSE 1517 > 930; RMSE 1517 > 30.497 and COD 93.5% > 95.9 in predicting photovoltaic energy [16].

Precise energy predictions can increase the growth of renewable energy by 24.8% [19]. With the growth of renewable energy, 27.7% efficiency can be achieved in the STC Photovoltaic module with different climatic conditions between 1–1.9°C [20]. The growth of energy used in the photovoltaic module requires a training model of 12 units to predict accurately on a daily basis [21]. However, these 12 units will be more complex with the climatic-weather-forecasting combination using the corrected ANN 96% [22].

To improve the research that has been done before, it is necessary to compare the power generation from NASA compared to the ANN model. This comparison uses a test simulation of 10 units, 500 units, 500 units, 1000 units and 2000 units. This test simulation has never been done on previous findings. Of course, this will get the accuracy of the ANN model which is almost in accordance with NASA data for 11 years (2012–2022).

This study predicts the daily energy generated by photovoltaic in Surakarta. This prediction will have an impact on more efficient energy optimization due to the ability to store large amounts of energy that will continue for the future. This energy treatment will be carried out using historical solar energy reference data from NASA. Historical data will be processed in an artificial neural network to produce the most accurate predictions for the future.

Daily Photovoltaic predictions can contain model errors of artificial neural networks. This model can predict the right energy capacity for use in the Surakarta area, thereby reducing dependence on limited fossil energy and potential environmental damage. Daily Photovoltaic Predictions contain accurate information for renewable energy generators in the Surakarta area. Power grid administrators can plan more efficient energy allocation, appropriate energy storage, expanded energy distribution, and the ability to meet energy demand during weaker hours of solar energy production.

2. Methods

The methods sections often come disguised with other article-specific section titles but serve a unified purpose: to detail the methods used in an objective manner without the introduction of interpretation or opinion. The methods sections should clearly tell the reader how the results were obtained. They should be specific. They should also make adequate reference to accepted methods and identify differences. The governing principle is as follows: Describe all of the techniques used to obtain the results in a separate, objective Methods section [23].

2.1 Design

The research design uses quantitative. This design shows that ANN is a tool for generating patterns from training activities [24,25]. The training carried out is in the form of classification from ANN [16], accurate predictions and estimates [26], precise network pattern recognition [27], control and optimization, language processing, and pattern recognition over continuous time [28]. This research will focus on predictions and estimates using the hidden units that have been described above.

2.2 Study Area

Surakarta is a tropical climate area. This city is located at the coordinates Latitude -7.57; Longitude 110.82; DMS 7°34′31.759″S 110°49′27.578″E with an area of 44.04 Km2 as shown in Fig 1. Surakarta has two seasons, namely hot from December to March and rainy from January to February. Daily temperatures range from 22°C to 35°C, and the monthly average wind speed is around 9.25 knots from September to April, reaching 10 knots, while the air pressure and humidity are 1011.4 Mb and range from 69% to 87%, respectively.

Fig. 1 *Study case location in Surakarta, Indonesia*

2.3 Instrument

The instruments in this study will facilitate the process of observing secondary data, data processing, analysis of research results, and discussion. The first instrument used is NASA data (2010-2021) for reference in predictions from solar energy observation data, MATLAB software for processing NASA data and observations, and the ANN model application to show prediction findings and estimate photovoltaic energy.

2.4 Procedure

The first procedure of this research is to collect data about sunlight from NASA (2010-2021) [22]. Observation data is collected from solar energy potential, determines the definition of input and target, normalizes data into binary sigmoid, divides data for the training process on ANN with the data being tested, and inputs data into the training process.

The second procedure is to determine the ANN training using the initial weight initialization, determine the activation function, back propagation training, determine the smallest MSE value as the network architecture [29], re-testing to obtain forecasting results of energy potential from photovoltaic in Surakarta.

We use MATLAB's built-in tools to train, test and validate the neural network. Data adequacy can determine accurate results, the amount of data to produce sufficient data points using a reference number of days as input. Neural network training was developed using the MATLAB algorithm. This algorithm was developed to sort data, normalized and un-normalized data to create a good model. This research uses the Levenberg – Marquardt back propagation algorithm as the basis for creating the algorithm because it has high speed and effectiveness. The neural networks used in this research are made into 5 different types, namely 10, 500, 1000, 1500, and 2000 neurons in one hidden layer to get the most optimal network architecture with near perfect regression plots, the average square error (R^2) is low, and the tendency to over-fitting is reduced. These results show a comparison between NASA data (target) and ANN prediction results (output).

As a loss function in this model, the mean squared error is estimated using [30].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - y_i)^2 \quad (1)$$

N is the total data or rows in the data group, Yi is the input data (NASA data), and yi is the prediction from the neural network.

The strength of the relationship between predicted data and input data is sought as a statistical parameter. This relationship is sought using regression correlation [31].

$$R = \frac{\sum_{i=1}^{n}(Y_i - \tilde{Y}_i)(y_i - \tilde{y}_i)}{\sqrt{\sum_{i=1}^{n}(Y_i - \tilde{Y}_i)^2 \sum_{i=1}^{n}(y_i - \tilde{y}_i)^2}} \quad (2)$$

Table 1 *ANN models*

Network Type	Network
Neurons Size	10, 500, 1000, 1500 and 2000
Performance	Mean squared error (MSE)
Algorithm	Levenberg-Marquest Algorithm

The ANN model was trained using 6664 data points from measured samples collected over a ten-year period (2010–2021). In this research, the data was then divided into three parts: the first part was the training part, with 75% of the data, 15% of the training data, and 15% of the validation data.

Using a normalization method, the noise levels in the dataset were scaled to a standard range of 0 to 1 during the data organization and cleaning process. Modifying various features in the machine learning model makes the mean-squared error (MSE) appear reduced. Data conditioning is done by normalizing the values so that they do not go out of line, such as 0.1 and 0.9. The approach is taken by changing the values into an input and output scale between 0.1 and 0.9. This normalization is done by applying the Equation below [32]:

$$P_n = 0.1 + \frac{(0.9 - 0.1)(P - P_{min})}{(P_{max} - P_{min})} \quad (3)$$

P_n is the normalized value of P, P_{max} is the maximum value of P and P_{min} is the minimum value.

After training, testing and data validation with a neural network, the resulting data must be normalized according to the initial data. This is done by applying the equation below.

$$P = \frac{(P_n - 0.1)(P_{max} - P_{min})}{(0.9 - 0.1) + P_{min}} \quad (4)$$

where P is the unnormalized value of P_n.

The back propagation and Levenberg-Marquardt algorithms are the most popular algorithms for building first generation conditional networks. Several studies have been carried out using artificial neural networks in various classification and optimization cases [33–38]. In this research, back propagation is used as a multilayer neural network algorithm. When the backpropagation technique is applied, the values in the network are changed to move in the negative direction of the gradient of the sum of the squared errors. The error vector for a network with input, x, weights, w, targets, t, and outputs, o, is given as [22]:

$$[e] = [e] - [t] \quad (5)$$

in a back propagation neural network, the weights are then modified as follows:

$$w_{t+1} = w_t - \eta \frac{1}{2}\frac{\partial e^T e}{\partial x} \quad (6)$$

where η is referred to as the learning parameter. The use of the momentum parameter μ is recommended in similar research [22]. The weights will be updated with the new rules after the momentum parameters are implemented [22]:

$$w_{t+1} = w_t - \eta \frac{1}{2}\frac{\partial e^T e}{\partial x} + \mu\,(w_t - w_{t-1}) \tag{7}$$

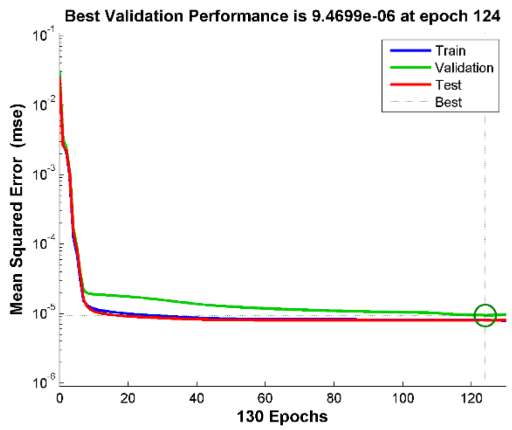
In the research we carried out, the Levenberg – Marquardt algorithm was used as the basis. This is a development of the Gauss – Newton principle. This rule is used to modify the Gauss – Newton method in determining neural network training weights. [22]:

$$W_{n+1} = W(n) - (J(n)^T J(n))^{-1} J(n)^T e(n) \tag{8}$$

where J is the Jacobian matrix defined as [41]:

$$J = \left[\frac{\partial e_1}{\partial w_1}\ \frac{\partial e_1}{\partial w_2} \cdots \frac{\partial e_1}{\partial w_m}\ \frac{\partial e_2}{\partial w_1}\ \frac{\partial e_2}{\partial w_2} \cdots \frac{\partial e_2}{\partial w_m}\ \vdots\vdots\vdots\ \frac{\partial e_n}{\partial w_1}\ \frac{\partial e_n}{\partial w_2} \cdots \frac{\partial e_n}{\partial w_m} \right] \tag{9}$$

The result of the matrix inversion product is affected by the momentum parameter μ. The method used to calculate the sum of squared errors will decide this parameter. If the error is reduced, the argument is split by some scalar.



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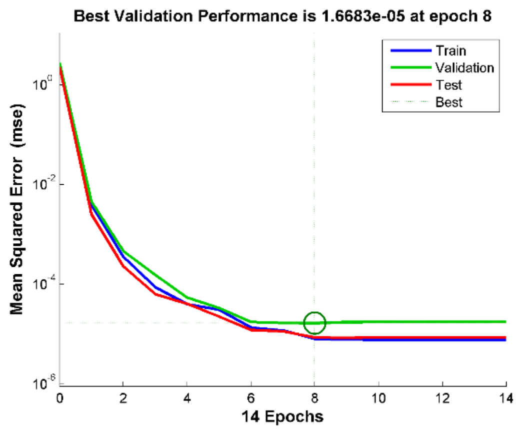

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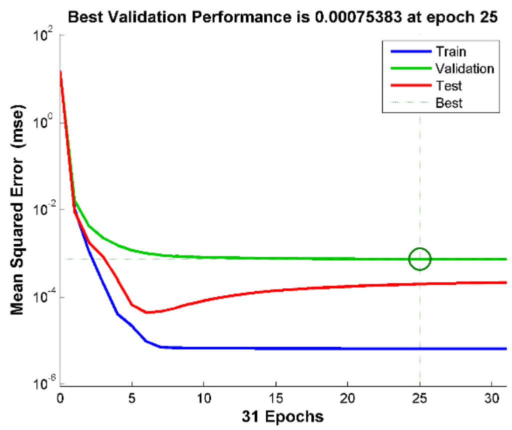

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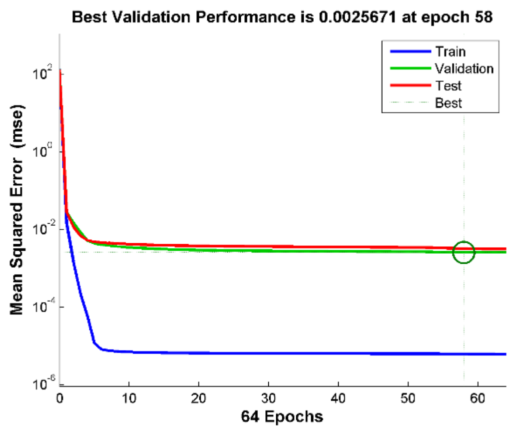

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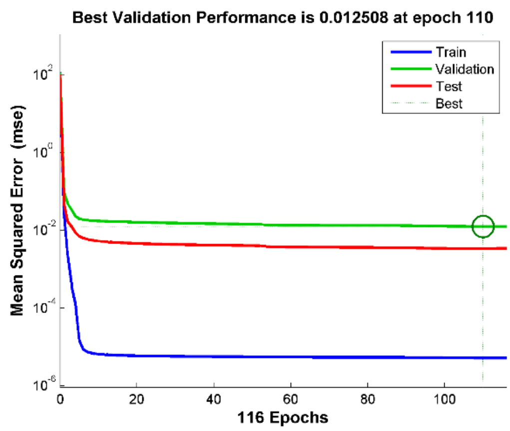


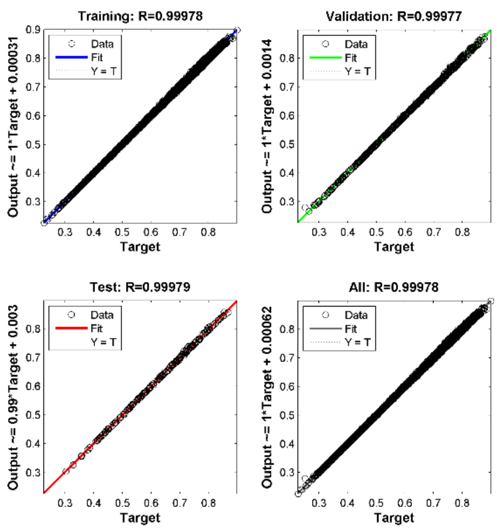
(e)

Fig. 2 *Mean squared error on (a) 10 neurons; (b) 500 neurons; (c) 1000 neurons; (d) 1500 neurons; (e) 2000 neurons*

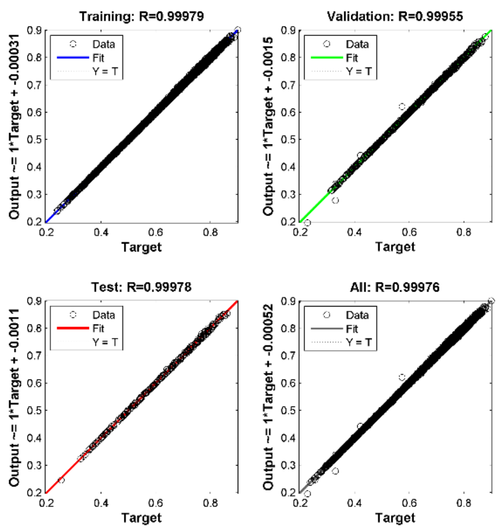
3. Results

Results and discussion as a part that examines and discusses the results of the Mean Squared Error (MSE) in section 1, Comparison of Training and Validation in section 2, and the predicted value of Power Generation (kWh) in section 3. The results from MSE show the best validation performance. With this MSE, it can be stated that the stability of the validation results, the best test, and the training are in Figure 3 in parts (a) and (b). Meanwhile, Figure 3 (c) shows that the validation value is in nomination 102 at the 31st epoch. However, the value of the train with the best test is below the nomination. Figure 3 (d) shows that the stability of the validation and the best test is balanced. However, the train brought a balance value of 10-2 with an epoch of 60. Figure 3 (e) states that the validation exceeded far from the best tar and train of between 10-4 and 10-2 at the 25th epoch.

Part of Fig. 4 shows that the comparison of training, validation, and test values is more than 0.9000. However, the success of these three values is superior in Fig. 4 (a) because the test value is 0.99979. However, the overall value of the correlation coefficient is more than 0.9000. Therefore, the three values are closely related to the data set and the hidden unit used.



(a)



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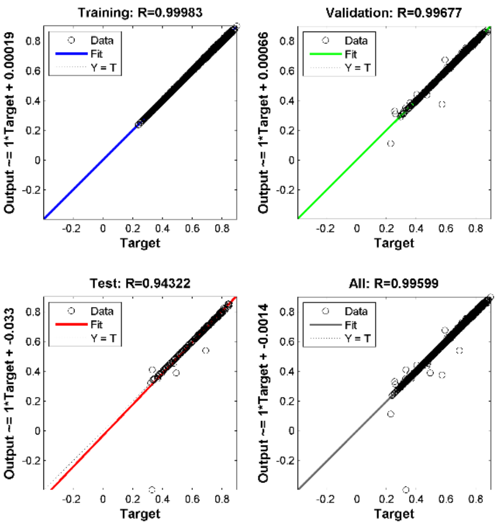

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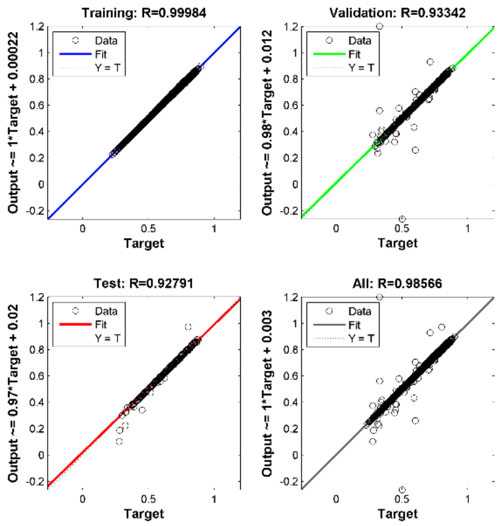

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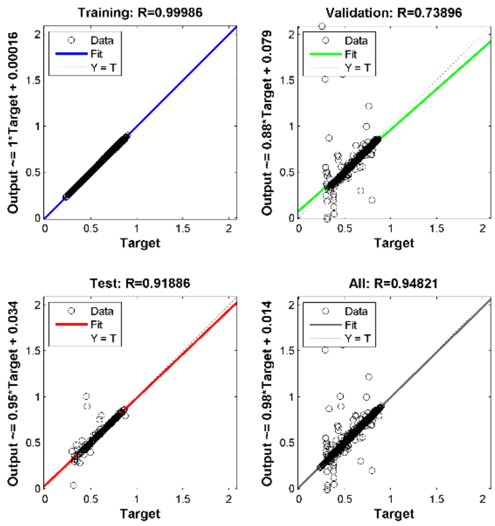
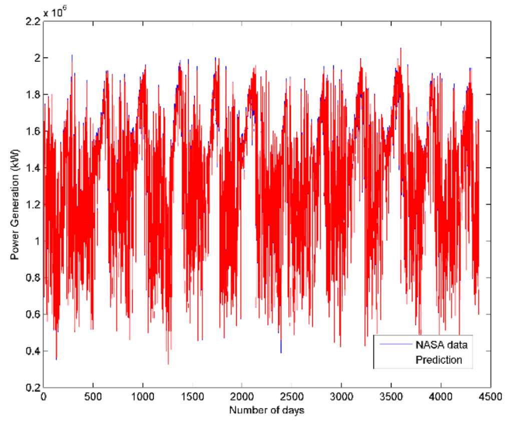


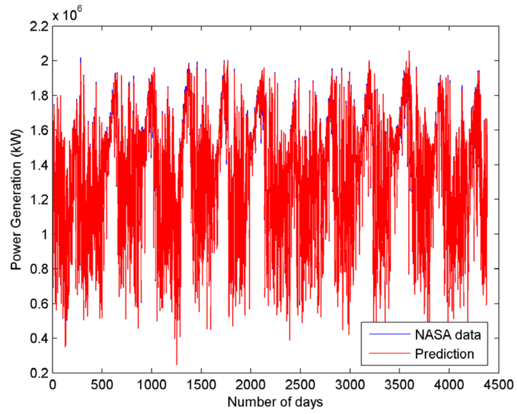
(e)

Fig. 3 *Coefficient of correlation between the dataset and the line of fit for (a) 10 neurons; (b) 500 neurons; (c) 1000 neurons; (d) 1500 neurons; (e) 2000 neurons*

Fig. 5 shows a very small prediction error. This error occurs because the correlation coefficient is in the range of 0.900 to 1.000. This shows that predictions will be difficult to resemble real conditions. Daily energy generated by photovoltaics on validation 9.46×10-6 di epoch 124 with an R-value of 0.99979 is closely related to the numbers of days for 4500 days from NASA with the resulting ANN model. Evidence of ANN accuracy in Fig. 5(a) does not show the blue color as NASA data because of the accuracy it reaches 99.98% with standards 2.2×105 kWh.



(a)



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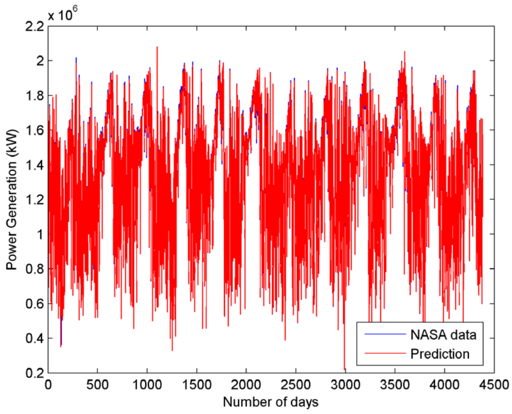

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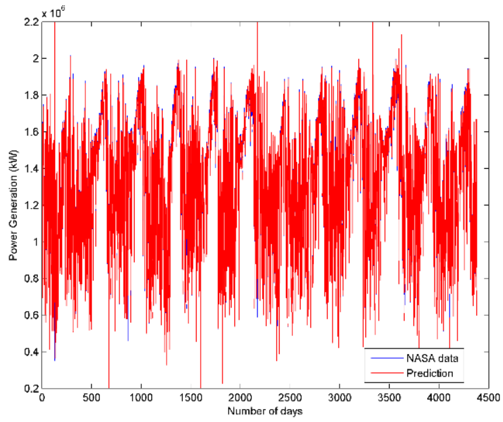

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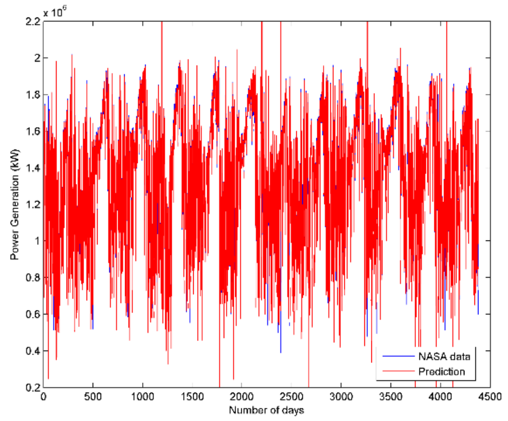

(e)

Fig. 4 *Number of day power generation data NASA vs ANN model on (a) 10 neurons; (b) 500 neurons; (c) 1000 neurons; (d) 1500 neurons; (e) 2000 neurons*

4. Conclusions

This study predicts that the daily energy generated by photovoltaics is validated at 9.46 in epoch 124 in Surakarta. This prediction will impact more efficient energy optimization because the accuracy for 4500 shows a 99.98% determination value on the ability to store large amounts of energy, which continues for the future at the standard 2.2×105 kWh.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: Delfianti contributed to the ***conceptual, design and editing****. Rovianto contributed to the writing* ***manuscript and analysis****. Harsito contributed to the* ***concenptual, writing manuscript and analysis****. Pradana assisted in* ***analysis and visualized****, Pongajow assisted in* ***visualized and produced figures****. Joshua contributed in* ***visualized and program running****. All authors reviewed the results and approved the final version of the manuscript.*

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