An evaluation of the artificial neural network based on the estimation of daily average global solar radiation in the city of Surabaya

Adi Kurniawan[1], Anisa Harumwidiah[2]
[1]Department of Marine Engineering, Institut Teknologi Sepuluh Nopember, Indonesia
[2]Study Program of Electric Technology, Universitas 17 Agustus 1945 Surabaya, Indonesia

ABSTRACT

The estimation of the daily average global solar radiation is important since it increases the cost efficiency of solar power plant, especially in developing countries. Therefore, this study aims at developing a multi layer perceptron artificial neural network (ANN) to estimate the solar radiation in the city of Surabaya. To guide the study, seven (7) available meteorological parameters and the number of the month was applied as the input of network. The ANN was trained using five-years data of 2011-2015. Furthermore, the model was validated by calculating the mean average percentage error (MAPE) of the estimation for the years of 2016-2019. The results confirm that the aforementioned model is feasible to generate the estimation of daily average global solar radiation in Surabaya, indicated by MAPE of less than 15% for all testing years.

Corresponding Author:

Adi Kurniawan
Department of Marine Engineering
Institut Teknologi Sepuluh Nopember
Jalan Raya ITS, Keputih, Sukolilo, Surabaya 60111, Indonesia
Email: adi.kurniawan@ne.its.ac.id

1. INTRODUCTION

Surabaya, the second biggest city in Indonesia, is famous for its high temperature and humidity. It is also ranked second highest global solar radiation among the big cities with a daily average of 5.29 kWh/m^2 [1]. However, this potential is yet to be utilized, as there is no big or even medium scale photovoltaic (PV) power plant in Surabaya. In Indonesia, only 152 MW PV has been installed by November 2019, which is less than 0.1% of 536 GW potential [2]. Despite the recent continuous decrease in the price of the PV panel [3], [4] the total cost of PV power plant is quite expensive for developing countries such as Indonesia. Moreover, most of the equipment of the PV energy systems such as the panels and power electronic converters are not produced in Indonesia. Therefore, an efficient design and operation is required in order to increase the cost efficiency of the system [5].

The information of the availability of the global solar radiation holds a significant role in building efficient design and operation on PV energy systems [6]. The amount of daily average global solar radiation has been widely applied for various studies which includes investigating the feasibility of solar power plant [7] optimal sizing of the energy storage systems [8], [9] determination of the optimal tilt angle [10]-[12], and designing energy management system [13]. However, the data of measured solar radiation is limitedly available. Furthermore, some design processes demand the prediction of the future global solar radiationTherefore, the prediction or estimation of the global solar radiation is necessary [14], [15].

Numerous approaches have been proposed to estimate the amount of solar radiation on horizontal plane. Empirical models such as linear, quadratic, cubic, logarithmic, and exponential regression have been widely used since 1940's [16], [17]. Recent methods employ machine learning algorithm in the form of artificial neural network (ANN) [18]-[20], gradient boosting tree (GBT) [21], genetic programming (GP) [22], [23], and support vector machine [24], [25] among others. In comparison with other estimation method,multi-layer perceptron ANN is one of the most popular since it solves high non-linearity, complex, and time-varying problems [26] and it has also been proven to have higher accuracy [27], [28].

Various meteorological parameters were used as inputs for ANN to estimate the daily average global solar radiation. The choice of parameters includes the availability of the data, its effect to the estimation accuracy, and the thought of complexity or simplicity of the network. The common weather parameters used as the input includes sunshine duration, cloudiness, temperature, humidity, and wind speed. Other parameters besides meteorological data are position (latitude and longitude) and altitude of the city, as well as the number of month [29], [30].

This study aims to investigate the feasibility of the common multi layer perceptron ANN to estimate the daily average global solar radiation using Surabaya meteorological data. The analysis of the results will help generate recommendations to improve the accuracy of the estimation model. The contribution of this paper is to generate an ANN model to estimate the daily average solar radiation for Surabaya city using available meteorological data.

In section 2, the detail of the proposed method is explained. Meanwhile, the explanation of he comparison results between measured and estimated daily average solar radiation is presented in section 3. The section 4 contains the conclusion of the findings in this research.

2.   RESEARCH METHOD

The available weather parameters used as input for the neural network are minimum temperature (T_{min}), average temperature (T_{avg}), maximum temperature (T_{max}), average relative humidity (RH), precipitation (Pr), sunshine duration (SD), and average wind speed (WS). These parameters were taken from the database of Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG). The weather parameters of Surabaya are measured in Tanjung Perak Maritime Meteorology Station and are available as day-to-day metric and are, then converted into a daily average per month for the input of the network. The additional input data is the number of the month (j), since the daily average solar radiation on each month may vary due to the rainy and dry season. The output of the network is the daily average global solar radiation on a horizontal surface (G). The data were obtained from the NASA Power database, in the form of total solar radiation per day, it was then converted to the daily average amount for each month. The structure of the network is presented in Figure 1. Due to the minimum error during the training process, three numbers of neurons in hidden layers are selected.
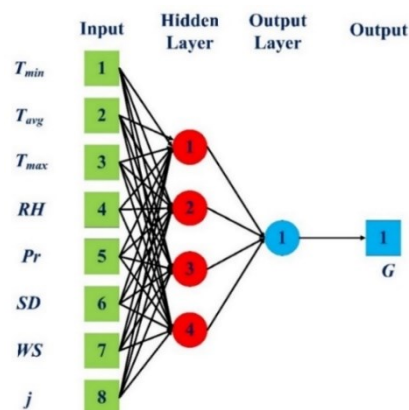

Figure 1. Configuration of ANN to predict the global solar radiation

The ANN was trained using an unfiltered 5-years data from January 2011 to December 2015. 60 samples of input-output correlation data were utilized for the training process. The training process to determine the appropriate weight value for each connection between neurons was carried out based on its convergence and stability speed according to the Levenberg-Marquardt method [30], in order to minimize errors defined as:

$$MSE = \frac{1}{n}\sum_{k=1}^{n} e_k^2 = \frac{1}{n}\sum_{k=1}^{n}(t_k - y_k)^2 \tag{1}$$

where n is the total number of samples of the output parameter, k is the index of the output samples, e is the error of the output, t is the target value of the output from the data, and y is the output value obtained from the calculation of the ANN [31]-[33].

To evaluate the effectiveness of the trained ANN, a comparison is made between estimation and measured value for 2016-2019 data. The ANN is used to calculate the estimation of daily average global solar radiation per month by applying the weather parameters data of 2016-2019. The results were then compared with the actual global solar radiation from the NASA Power database for the same month of the same year with the statistical parameter calculated as the mean average percentage error (MAPE) for each year as follow:

$$MAPE = \frac{1}{12}\sum_{j=1}^{12}\left|\frac{Gp_j - Gm_j}{Gm_j}\right| \times 100\% \tag{2}$$

where j is the index of the month, Gp is the estimated value of the daily average solar radiation per month taken from the result of the ANN, and Gm is the measured value of the daily average solar radiation taken from NASA. The MAPE has been used in previous studies as a parameter to measure the accuracy of solar radiation estimation using ANN [28].

3. RESULTS AND DISCUSSION

The ANN training process shows a good correlation between the target from the data and the output of the ANN, indicated by a regression value of 0.967 as shown in Figure 2. It also indicates that the five years training data have a strong correlation between the inputs and the output. The graphical comparisons between the estimated and measured daily average global solar radiation per month for 2016-2019 years are shown in Figure 3 and it indicate that the estimation values tend to be lower than measured ones. The differences are especially larger during the peaks of dry season between July and October. In contrast, the highest similarity was observed in the peaks of rainy season between December and February. Given the large difference of daily average precipitation during dry (1.89 mm) and rainy season (9.35 mm) per year in 2011-2015, the division of the ANN training for each season will improve the accuracy of the estimation.

The statistical results of MAPE for each year are presented in Table 1. The error is on the increase for the more recent year, this is as a result of the increase in the measured daily average solar radiation in Surabaya between 2016 and 2019. The measured values are 4.8 kWh/m^2 in 2016, 4.98 in 2017, 5.3 in 2018, and 5.48 in 2019. Meanwhile, the input parameters are somewhat stable for each year. For example, in the same period, the average temperatures are 29.04, 28.55, 28.78, and 29.02°C respectively.
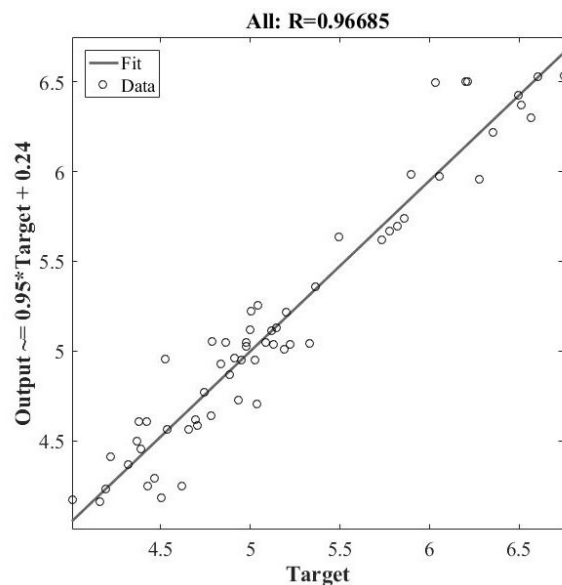

Figure 2 Graphics of regression between target and the output during the ANN training process
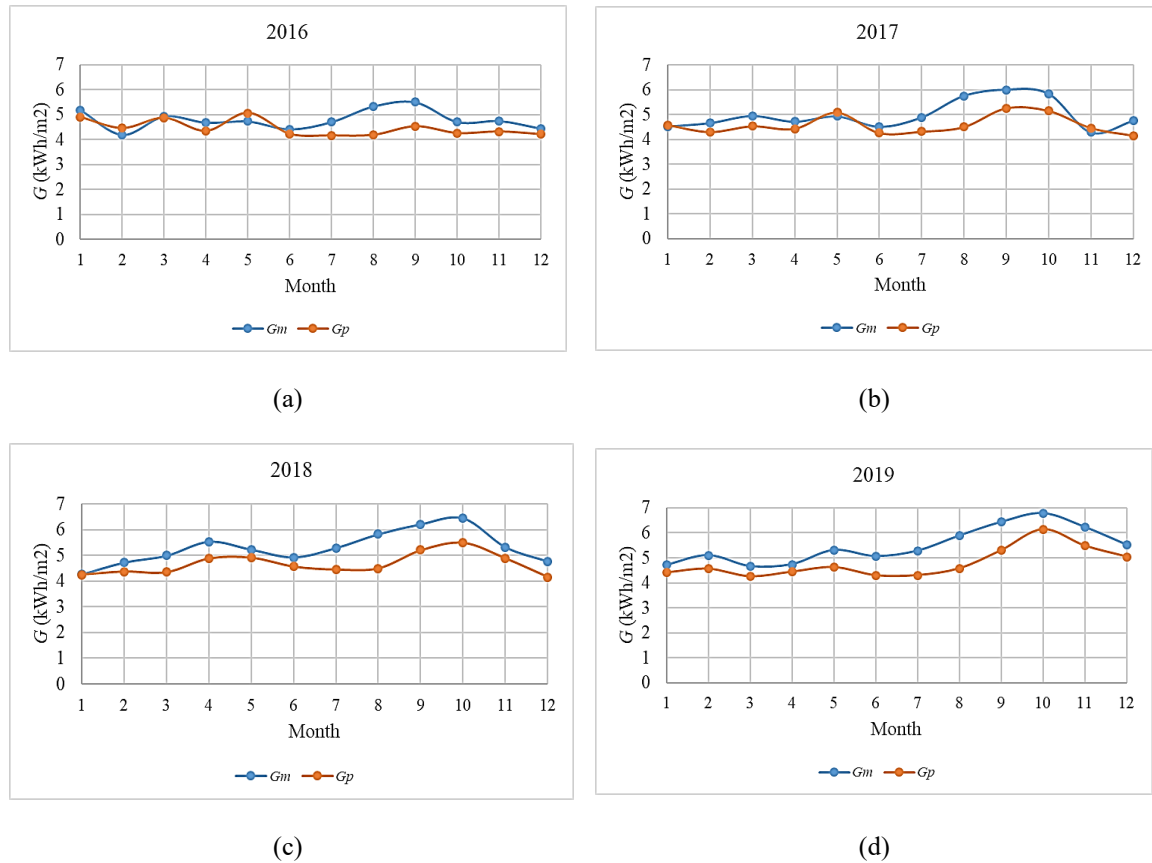
(a)

(b)

(c)

(d)

Figure 3. Graphical comparisons between measured and estimated daily average solar radiation per month for
the year of; (a) 2016, (b) 2017, (c) 2018, and (d) 2019

Table 1. Statistical results of the daily average solar radiation estimation model for Surabaya

Year	MAPE (%)
2016	8.77
2017	8.82
2018	11.38
2019	12.41

In order to evaluate the capability of the ANN model to estimate the daily average global solar radiation in Surabaya, one need to compare the MAPE acquired in this study with the results from the previous studies. The MAPE in this study is clearly higher than average of 6.89% achieved for the cities in India [34], 5.47% of Japan [35], 4.49% of Saudi Arabia [20], 5.21% of Iran [36], and 5.38% of Malaysia [27]. However, the MAPE results for 2016 and 2017 in this study are classified under high accurate prediction, while the results for 2018 and 2019 are classified as good estimation according to Lewis classification [34]. The value of MAPE in this study also lower than similar study in Fez, Morocco, in which the best achieved MAPE is 21.77% [37].

4.   CONCLUSION

The results from this study indicate that the estimated value of the solar radiation from the ANN can approach the value of the measured one, as proven by MAPE (less than 20). Therefore, the common multi layer perceptron ANN estimator model with the available meteorological data is reliable to estimate the daily average global solar radiation for the city of Surabaya. However, the improvement of the accuracy of the estimator is highly possible when two separate ANN are trained and applied separately for dry and rainy season. The increase in errors over the past year also suggests that a limitation in the number of previous years to be used for the training process is required to estimate solar radiation over a given year.

5.   FUTURE WORK
In the next step, the accuracy improvement of the ANN estimator needs to be designed by applying classification method for dry and rainy season. Further, the ANN estimator with location as the inputs will also designed to be able to estimate the daily average solar radiation in all area in Indonesia.

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