An Estimation of hourly average solar radiation using artificial neural network in the city of Surabaya

A Kurniawan¹*, E S Koenhardono¹, I R Kusuma¹, J Prananda¹, S Sarwito¹ and A A Masroeri¹

¹Department of Marine Engineering, Institut Teknologi Sepuluh Nopember, Surabaya 60111 Indonesia

*e-mail: adi.kurniawan@ne.its.ac.id

Abstract. To maximize the effectiveness of solar energy systems installed on the ship, the panels need to be positioned on their optimal inclination angle. To determine this angle, information on hourly average solar radiation is required in addition to position and direction data. However, the amount of hourly solar radiation is not continuously measured in Indonesia. This study proposed a method to estimate the hourly solar radiation for any month. This is based on Artificial Neural Network (ANN) with the month and the hour required for the estimate and the previous daily average solar radiation as the input. The proposed ANN method was validated by comparing the estimation results with the measured hourly average solar radiation in Surabaya from May to July 2020. Its effectiveness was affirmed with the coefficient of determination ($R^2$) of 0.983 or higher for each of the three observed months.

1. Introduction

Indonesia is a maritime state located on the equator, therefore a solar-assisted ship is very suitable to be used as a major mode of transportation [1], [2]. However, limited available space to install the photovoltaic (PV) panels on the ship forced the engineers to maximize the efficiency of the PV system [3], [4]. One possible method to maximize the efficiency of this system is by installing the panels on their optimal inclination angle and not on a horizontal position [5].

To determine this angle, the information of hourly solar radiation is required while the ship is sailing. In contrast to the daily average solar radiation, the measurement of hourly solar radiation is not continuously performed in Indonesia [6], which reduces the possibility of determining the optimal inclination angle of PV panel on ship sailing in the Indonesia area.

Nevertheless, with the recent technologies, the use of estimation techniques helped to overcome the problem of limited information on solar radiation. Several methods were validated to accurately predict the amount of hourly solar radiation, either based on physical or historical statistical models [7]–[12]. However, each of them requires information on weather parameters that are difficult to access in Indonesia, such as the hourly clearness index among others.

This study proposed a new estimator for the hourly average solar radiation based on artificial neural network. The ANN was utilized either as an estimator of the daily average [13], [14], or hourly solar radiation [15], [16] and this is more suitable to be used in this region since it only requires three inputs which are easily accessible in Indonesia. These inputs include the month and the hour when the estimation is required and also the previous amount of the daily average solar radiation. Furthermore,
this estimation technique enables the determination of the PV panel inclination angle installed on the ship sailing in Indonesia, which in turn reduces the operational fuel cost and greenhouse gas emissions by cutting the usage of diesel generator.

2. Material and Method

The structure of the proposed ANN method to estimate the hourly average solar radiation is presented in Figure 1. As mentioned in section 1, there are three inputs for the ANN and the data of daily average solar radiation of the previous month is easily accessible from NASA Power database.

![Figure 1. Structure of the proposed ANN.](image)

The ANN was trained using the data of the daily average solar radiation in the city of Surabaya from January to December 2019. The number of hours is selected from the earliest sunrise (5 AM) to the latest sunset (5 PM), resulting in a sample size of 156 for each input-output parameter. In addition, the Levenberg-Marquardt backpropagation method was adopted to train the ANN, which represents a fast and stable convergence [17]. Meanwhile, the stopping criteria of this method is the minimization of mean squared error (MSE) defined

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

with $n$ as the total number of samples, $k$ is the index, $e$ is the error of the output, $t$ is the target value of the output taken from the data, and $y$ is the estimated output value obtained from the ANN [18].

The minimum MSE during training was reached after 27 iterations as shown in Figure 2. The MSE itself reaches the value of 1000. It is understandable since the daily solar radiation is in the order of thousands Wh/m². The training of ANN is stopped when the error is stop to decrease, indicated by the gradient. Furthermore, the good agreement between the estimated and target value of the output from the training data was confirmed by 0.996 regression value as presented in Figure 3. The white dots are the representation of plotting between the actual target value in horizontal axis and the output value of the ANN for the same input in vertical axis. The straight diagonal black line is the regression line that approach the distribution of data plot. If the output of the ANN can be exactly same with the target data, then the line will touch all the dots and the value of $R$ will be 1.
3. Result and Discussion
The proposed method was validated by comparing the estimation results with the measured hourly average solar radiation for May, June, and July 2020 in Surabaya. Also, the graphical comparisons for each month are shown in Figure 4 to 6. It showed a high similarity between predicted and measured values, especially for July. For May and June, although there is gap between the estimated and measured value, but the curves of the estimated value have same pattern with the measured value. Furthermore, the predicted values tend to be higher than the measured, especially during the peak sunlight between 10 AM and 1 PM.

Figure 2. Error performance of ANN training.

Figure 3. Regression line of ANN training.
Figure 4. Comparison of predicted and measured hourly solar radiation in Surabaya for the month of May.

Figure 5. Comparison of predicted and measured hourly solar radiation in Surabaya for the month of June.

Figure 6. Comparison of predicted and measured hourly solar radiation in Surabaya for the month of July.
Further validation of the proposed method was done by calculating the statistical parameter in the form of the coefficient of determination ($R^2$) for each month as follow:

$$R^2 = 1 - \frac{\sum_{h=1}^{20}(G_{\text{meas}(h)} - G_{\text{pred}(h)})^2}{\sum_{h=1}^{20}G_{\text{pred}}^2}$$

(2)

where $G_{\text{meas}}$ is the measured value of hourly solar radiation, $G_{\text{pred}}$ is the predicted value of hourly solar radiation, and $h$ is the index of hour.

The $R^2$ of each month is listed in Table 1 and the lowest $R^2$ is 0.983 for the estimation of May. The similar result is obtained for the estimation of June, but more accurate result is obtained for the estimation of July, with $R^2$ of 0.999. For comparison, the MARS method generates an average $R^2$ of 0.912 [8] while the best $R^2$ for various regression methods is 0.93 [11].

### Table 1. Statistical results of hourly solar radiation estimation in Surabaya for the year of 2020.

| Month | $R^2$ |
|-------|-------|
| May   | 0.983 |
| June  | 0.985 |
| July  | 0.999 |

### 4. Conclusion

This study aims to develop an estimation method of hourly solar radiation, which may be utilized for various purposes such as determining the optimal inclination angle of PV panels installed on ship. The determination of the optimal inclination angle on ship based on the estimation of solar radiation using land data has been proposed by the research in Japan. Therefore, it is possible to apply the similar method using the data of solar radiation in Indonesia. The proposed method is applicable for use in Indonesia since all the required inputs are accessible. Furthermore, the accuracy of the proposed method was validated by comparing the predicted with the actual measured value of hourly average solar radiation. Meanwhile, the calculation of the statistical parameters also indicates a good performance of the estimation method.

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