Two-step artificial neural network to estimate the solar radiation at Java Island

Adi Kurniawan[1], Eiji Shintaku[2]
[1]Department of Marine Engineering, Institut Teknologi Sepuluh Nopember, Indonesia
[2]Department of Transportation and Environmental Systems, Hiroshima University, Japan

Article Info

ABSTRACT

The availability of information about solar radiation characteristics, particularly solar radiation predictions, is important for efficiently designing solar energy systems. Solar radiation information is not available in Indonesia because official measurements have not been conducted by the Indonesian Meteorological, Climatology, and Geophysical Agency (BMKG). In this study, a new two-step artificial neural network (ANN) is proposed to estimate both the daily average and hourly solar radiation at Java Island, Indonesia. The input parameters for the daily average solar radiation estimation are the location and time required, along with five selected monthly meteorological parameters that BMKG predicts for the subsequent month. The selected meteorological parameters are temperatures, relative humidity, and precipitation. The estimated daily average solar radiation is then used as the input parameter of the hourly solar radiation estimation along with the local time and location. The ANN training was conducted using two years of data, 2018 and 2019, from Surabaya and Jakarta, while the validation was performed in the same cities for January through July 2020. The accuracy of the proposed method is comparable to previous studies with an average R2 of 98.70% for the daily average solar radiation estimate and 97.44% for the hourly solar radiation estimate.

Corresponding Author:

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

1. INTRODUCTION

As of November 2019, Indonesia has utilized only 152 MW or 0.028% of its abundant 536 GW solar energy potential through solar energy systems [1]. A lack of official solar radiation measurements could be one of the factors contributing to the slow development of solar energy systems, as optimal designing becomes more difficult without this information [2]. This problem could be overcome by generating an accurate solar radiation estimator for a specific location.

Estimates of solar radiation have been used in various optimal solar energy design. The annual solar radiation calculation has been used to determine the ideal location to build a photovoltaic system [3, 4]. The monthly total, or daily average, solar radiation is required for the optimal sizing of solar panels or storage systems [5-7], while determining panel installation angles calls for the hourly solar radiation [8].

Various methods have been proposed to estimate either the daily average or hourly solar radiation. The artificial neural network (ANN) method for estimation is one of the most popular methods for the daily average prediction due to its high accuracy [9, 10]. While a wider range of methods has been used to estimate

hourly solar radiation, ANN-based methods have also been applied with accurate results. Those methods include multilayer perceptron [11], deep learning [12], adaptive neuro-fuzzy [13, 14], Jordan recurrent [15] and comparison of various methods [16]. However, those aforementioned methods cannot be used for estimating solar radiation in Indonesia because they require meteorological input parameters that are not measured by Indonesian Meteorological, Climatology, and Geophysical Agency (BMKG). The unavailable input parameters are hourly cloud cover, clearness index, atmospheric pressure, and visibility.

The objective of this study is to build a solar radiation estimator using an ANN-based method and the meteorological data types available in Indonesia. Because no hourly weather information is available, the hourly solar radiation estimator relies on the daily average solar radiation in the same month. Therefore, a two-step ANN is required. The first ANN (ANN-1) predicts the daily average solar radiation using the selected monthly weather parameters, while the second ANN (ANN-2) predicts the hourly solar radiation using the output of ANN-1. Both the training and the validation of the ANNs were performed using data from the cities of Jakarta and Surabaya, which are located on Java Island. The cities were selected because they have the largest electricity demand in Indonesia. The results of this research can be used to help solar energy system designers to build high-efficiency photovoltaic systems in Indonesia, especially on Java Island.

2.   RESEARCH METHOD

In this study, a two-step ANN is proposed to estimate the amount of solar radiation at Java Island. ANN-1 estimates the amount of the daily average solar radiation, which is then used by ANN-2 to estimate the hourly solar radiation in the same month. The configuration of the two-step ANN is depicted in Figure 1. The meteorological data for training both networks were from 2018 and 2019 from the city of Jakarta, which is located in the western part of Java Island, and Surabaya, which is the capital of East Java province. The ANNs were built in MATLAB environment using neural network toolbox. The selection of the input and the number of hidden neurons are explained in the sub-sections. To get the estimation result, the ANN model was added to the Simulink and was executed with the meteorological data of Surabaya and Jakarta for January through July 2020 as the input. The validation of the accuracy of the model was performed by comparing the estimation results with the measured solar radiation in the same period.
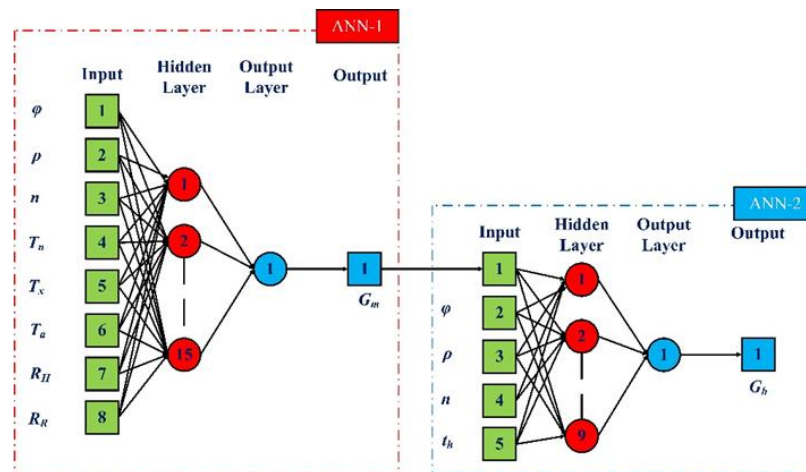

Figure 1. Configuration of the proposed method

2.1. ANN-1 design

ANN-1 estimates the daily average solar radiation by using the inputs of month, geographical position, and meteorological data of daily average minimum, maximum, and average temperature, relative humidity, and precipitation. These meteorological data were selected because BMKG forecasts these data for the subsequent month. Thus, using these meteorological data allows for the estimation of the daily average solar radiation for the following month. The geographical positions of latitude and longitude were included because the position of the sun, and thus the solar radiation, varies for different locations in the same month. The daily solar radiation data for training ANN-1 was taken from the NASA power database. The data was converted into the daily average solar radiation, with each day in a defined month assumed to have equal solar radiation. Detailed information about the input-output parameters is presented in Table 1.

Table 1. Parameters of ANN-1

Parameter	Notation	Unit	Min.	Max.	Ave.
Latitude	φ	°	-7.25	-6.21	-6.73
Longitude	ρ	°	106.85	112.75	109.8
Month number	n		1	12	6.5
Minimum temperature	T_n	°C	23.05	27.4	26.23
Maximum temperature	T_x	°C	30.36	36.37	33.1
Average temperature	T_a	°C	27.53	31.38	28.83
Relative humidity	R_H	%	61.54	82.43	73.8
Precipitation	R_R	mm	0	21.52	5.29
Daily average radiation	G_m	kWh/m^2	4.09	6.79	6.16

The number of hidden neurons in ANN-1 was chosen by comparing the regression value (R) during training for various numbers of neurons in the hidden layer. The candidates for the number of the hidden neurons are determined by the rules [17]:

$$h \geq \frac{2}{3}i + o \tag{1}$$

$$h < 2i \tag{2}$$

where h is the number of the hidden neurons, i is the number of the inputs, and o is the number of the outputs.

With eight inputs and one output, the number of hidden neurons is between six and 15. ANN-1 was trained ten times for each number of hidden neurons. The comparison of the highest R for each number of hidden neurons is shown in Figure 2. According to this analysis, the preferred number of hidden neurons for ANN-1 is 15. The training regression line of the preferred ANN structure is shown in Figure 3. The feed-forward Levenberg-Marquardt method was chosen to train ANN-1 due to its speed and stable convergence [18]. The iteration-stopping criteria were based on the minimum mean squared error (MSE), which is calculated as (3).

$$\text{MSE} = \frac{1}{n}\sum_{k=1}^{n} e_k^2 = \frac{1}{n}\sum_{k=1}^{n}\left(t_k - y_k\right)^2 \tag{3}$$

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.
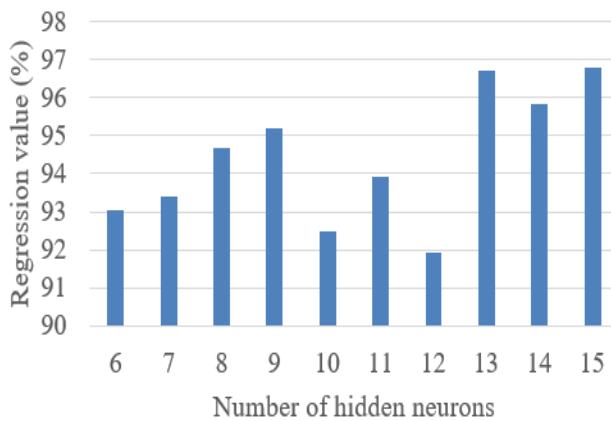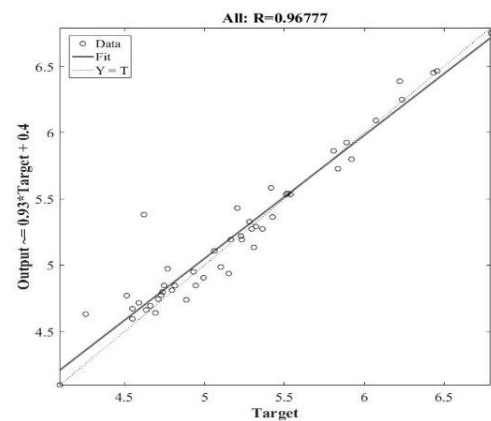

Figure 2. Comparison of regression values for ANN-1

Figure 3. Regression line for ANN-1 training

2.2. ANN-2 design

ANN-2 estimates hourly solar radiation based on the daily average solar radiation, geographical position, month, and local hour. The advantage of this method is that it does not require any hourly weather parameters as input, which are not measured and recorded by BMKG. The hourly solar radiation data for the ANN-2 training was taken from the commercial Solcast website for the cities of Jakarta and Surabaya in

2018 and 2019. The raw data were converted into the average of hourly solar radiation in each month. Detailed information about the input-output parameters is listed in Table 2.

Table 2. Parameters of ANN-2

Parameter	Notation	Unit	Min.	Max.	Ave.
Local time hour	t_h		5	18	11.5
Hourly solar radiation	G_h	Wh/m^2	0	998.03	391.9

Using the same method as described in section 2.1, the number of hidden neurons for ANN-2 was also determined by comparing R values for candidates determined using (1) and (2). The range of the number of hidden neurons was between four and nine, and nine was selected as the number of hidden neurons due to having the highest R, as shown in Figure 4. The regression line during the ANN-2 training with nine hidden neurons is depicted in Figure 5.
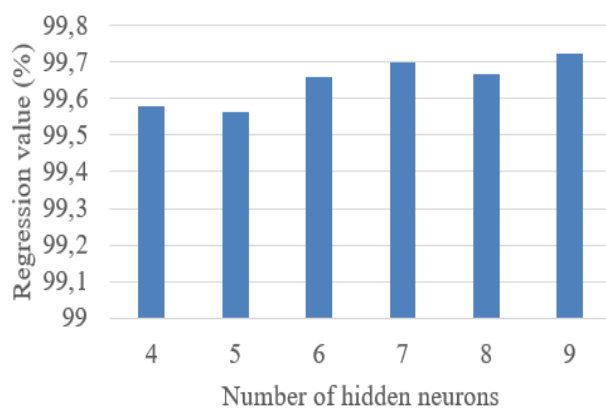

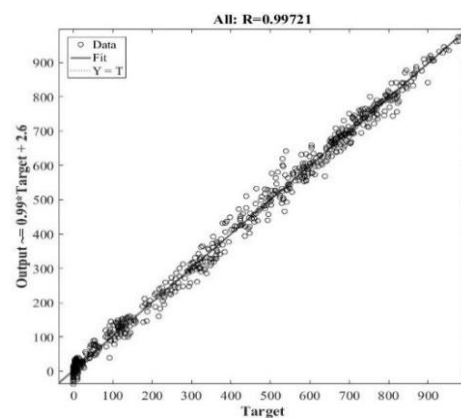Figure 4. Comparison of regression values for ANN-2

Figure 5. Regression line for ANN-2 training

3. RESULTS AND DISCUSSION

Validation of the proposed method was completed by comparing the estimated results from each ANN with the measured solar radiation in Jakarta and Surabaya for January through July 2020. Although the comparison was not performed for a full year, the selected months include portions of the rainy season (October-April) and the dry season (May-September) on Java Island. The accuracy of each ANN is measured by coefficient of determination R^2, which is calculated as (4).

$$R^2 = \left(1 - \frac{\sum G_{meas} - G_{pred}}{G_{pred}^2}\right) \times 100\% \tag{4}$$

where G_{meas} is the measured value of the solar radiation and G_{pred} is the estimated value of the solar radiation. R^2 is selected as it is one of the most frequently used parameters to measure the accuracy of solar radiation prediction [9]. Therefore, by calculating the R^2, the accuracy of the proposed method could easily be compared with the accuracy of the methods from previous studies.

3.1. Accuracy of daily average solar radiation estimation

The accuracy of the proposed method was validated by a minimum value of R^2 of 97.86%, as shown in Table 3. A higher value of R^2 indicates that the estimated value is more accurate; a 100% value can be achieved if all the estimated values are equal to the measured values. The graphical comparisons of the daily average solar radiation are shown in Figures 6 and 7. The estimation accuracy for Surabaya is higher than for Jakarta, which indicates that the solar radiation in Surabaya is more predictable and is more strongly correlated with the input parameters than in Jakarta. In both cases, the estimations for January and February produces higher error than for the other months. Considering the error distribution, an improvement for estimation during rainy season is recommended for the future research.

Table 3. Daily average solar radiation estimation accuracy

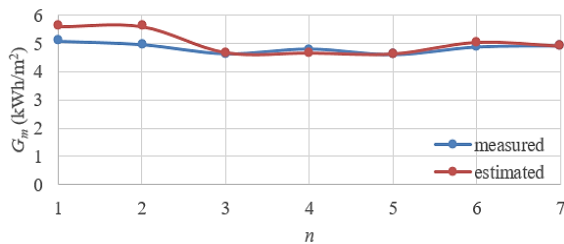| City	n	$G_{m\text{-}meas}$	$G_{m\text{-}pred}$	R^2
Surabaya	1	5.08	5.6	
	2	4.96	5.6	
	3	4.64	4.67	
	4	4.81	4.66	99.55%
	5	4.61	4.63	
	6	4.88	5.04	
	7	4.92	4.90	
Jakarta	1	4.46	5.51	
	2	4.41	5.51	
	3	4.68	4.57	
	4	4.64	5.14	97.86%
	5	4.13	4.93	
	6	4.44	4.83	
	7	4.69	4.51	

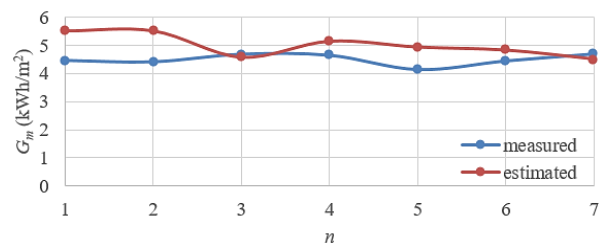Figure 6. Comparison of measured and estimated daily average solar radiation in Surabaya for 2020

Figure 7. Comparison of measured and estimated daily average solar radiation in Jakarta for 2020

The estimated values of daily average solar radiation tend to be higher than the measured values. This is due to that the measured solar radiation in 2020 is considerably lower than in 2018-2019, while the values of input parameters tend to be equal. The accuracy of the daily average solar radiation estimation on Java Island might be increased if other meteorological parameters are involved. Previous studies have indicated that sunshine duration and cloud cover percentage significantly correlate with the amount of solar radiation [19, 20]. However, while the daily sunshine duration is measured, the predicted value is not recorded by BMKG. Therefore, this parameter could not be included as an input for an estimate of the daily average solar radiation for the following month. Compared with the R^2 of the daily average solar radiation estimates from previous studies, the accuracy of the proposed method is comparable, as shown in Table 4.

Table 4. Comparison of proposed daily average solar radiation estimation with previous studies

Author	Method	Location	Average of R^2
Proposed	ANN	Indonesia	98.70%
Marzouq et al. [21]	ANN	Morocco	97.16%
Gurlek and Sahin [22]	ANN	Turkey	98.88%
Teke and Yildirim [23]	Cubic Regression	Turkey	59.60%
Behrang et al. [24]	ANN	Iran	99.57%

3.2. Accuracy of hourly solar radiation estimation

The measured and estimated hourly solar radiation was compared on an hourly basis for an entire day from 12 AM to 11:59 PM. However, in Surabaya, the earliest sunrise is between 5 AM and 6 AM and the latest sunset is between 5 PM and 6 PM for the entire year. Jakarta has a wider range of sunrise and sunset times, with the earliest sunrise occurring between 5 AM and 7 AM and the latest sunset occurring between 5 PM and 7 PM.

The graphical comparisons between the estimated and measured values are presented in Figures 8 and 9. The horizontal axis is the number of data points, which represents the number of the hour for each month. For example, data point number 1 represents 1 AM in January, while data point number 25 represents 1 AM in February. Although the lines are not perfectly equal, the shapes tend to be similar. Unlike in daily average estimation, the results on hourly estimates are more varied. The estimated values in Surabaya tend to be higher, while the estimated values in Jakarta tend to be lower than the measured values. Since both of daily

average estimates in Surabaya and Jakarta are higher than the measured values, the results of hourly estimation indicate that there is limitation of the estimation accuracy when the meteorological input is limited to the daily average radiation only. Figures 8 and 9 also indicate that like in the daily average estimation, the error are higher for the estimation on rainy season.
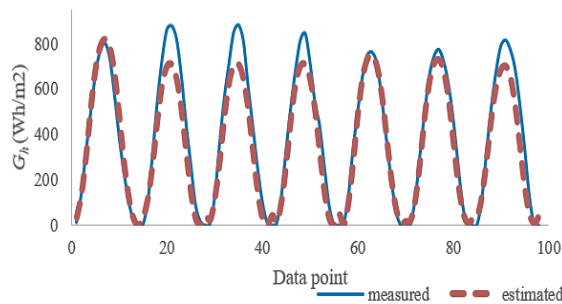

Figure 8. Comparison of measured and estimated hourly solar radiation in Surabaya for 2020
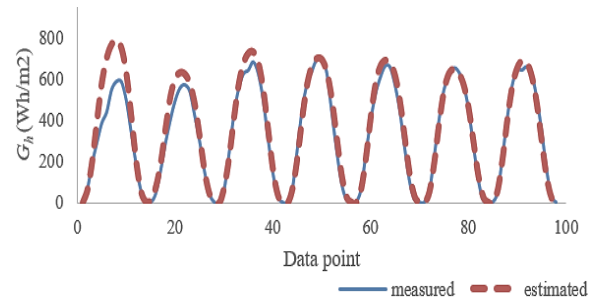
Figure 9. Comparison of measured and estimated hourly solar radiation in Jakarta for 2020

The R2 for the estimated hourly solar radiation for each month are listed in Table 5. The values are lower than for the daily average solar radiation because the estimation of hourly solar radiation is more difficult. For the hourly solar radiation, the estimation accuracy for Jakarta is higher than Surabaya, meaning that the correlation between the daily average solar radiation and hourly solar radiation in Jakarta is higher than in Surabaya. A comparison of the R2 achieved in previous studies with the proposed method is shown in Table 6. This comparison suggests that the accuracy of proposed method is higher than that of previous studies.

Table 5. Hourly solar radiation estimation accuracy

City	n	R^2
Surabaya	1	99.48%
	2	93.05%
	3	94.18%
	4	96.64%
	5	98.88%
	6	98.71%
	7	93.83%
Jakarta	1	92.41%
	2	97.87%
	3	99.44%
	4	99.70%
	5	99.50%
	6	99.50%
	7	99.55%

Table 6. Comparison of proposed hourly solar radiation estimation with previous studies

Author	Method	Location	Average of R^2
Proposed	ANN	Indonesia	97.44%
Li *et al.* [25]	MARS	Hong Kong	91.23%
Paulescu & Blaga [26]	Clustering	Romania	93%
Hocaoglu & Serttas [27]	Mycielski-Markov	Turkey	84.13%

4. CONCLUSION

The goal of this study was to propose a method to accurately estimate both the daily average and hourly solar radiation in Indonesia, where the official measurements are not available from BMKG. The proposed method not only estimates the radiation profile for each month based on the previous history but also can be used to predict daily average and hourly solar radiation for the subsequent month, using meteorological parameter inputs available from BMKG. Due to the unavailability of hourly weather parameter measurements, the estimation of hourly solar radiation is only based on the daily average solar radiation and the time and location in which the estimation is required. The proposed method is also capable

of estimating the solar radiation for multiple cities, at least on Java Island, by employing latitude and longitude as input parameters. The accuracy of the proposed method has been validated by calculating the R2 and comparing it with the results from previous studies in the same field of study. The comparisons show that the proposed method generates better accuracy than most of the references with average R2 of 98.91% for daily average estimation and 97.44% for hourly estimation. Because the proposed method produced a greater error in the peak of the rainy season than in the dry season, it may be possible to improve the proposed method by using a clustering method that treats the dry and rainy seasons separately.

REFERENCES

[1]   Insitute for Essential Services Reform, "Indonesia Clean Energy Outlook: Tracking Progress and Review of Clean Energy Development in Indonesia," *Jakarta: Institute for Essential Services Reform (IESR)*, 2019.
[2]   B. D. E. Mahdi, H. Abdelatif, and M. A. Zafrane, "An interactive approach for solar energy system: Design and manufacturing," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 5, pp. 4478-4489, 2020.
[3]   A. Calcabrini, H. Ziar, O. Isabella, and M. Zeman, "A simplified skyline-based method for estimating the annual solar energy potential in urban environments," *Nature Energy*, vol. 4, no. 3, pp. 206-215, 2019.
[4]   A. Z. Abass and D. A. Pavlyuchenko, "The exploitation of western and southern deserts in Iraq for the production of solar energy," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 6, pp. 4617-4624, 2019.
[5]   D. F. Al Riza, S. I. U. H. Gilani, and M. S. Aris, "Standalone photovoltaic systems sizing optimization using design space approach: Case study for residential lighting load," *Journal of Engineering Science and Technology*, vol. 10, no. 7, pp. 943-957, 2015.
[6]   C. Yao, M. Chen, and Y.-Y. Hong, "Novel Adaptive Multi-Clustering Algorithm-Based Optimal ESS Sizing in Ship Power System Considering Uncertainty," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 307-316, 2018.
[7]   A. N. Azmi, N. Bin Salim, and A. B. Khamis, "Analysis of an energy storage sizing for grid-connected photovoltaic system," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 16, no. 1, pp. 17-24, 2019.
[8]   A. Kurniawan and E. Shintaku, "Determining the optimal inclination and orientation angles of solar panels installed on ship," *International Journal of Renewable Energy Research*, vol. 10, no. 1, pp. 45-53, 2020.
[9]   M. Marzouq, H. El Fadili, Z. Lakhliai, and K. Zenkouar, "A review of solar radiation prediction using artificial neural networks," *2017 International Conference on Wireless Technologies, Embedded and Intelligent Systems (WITS)*, Fez, 2017, pp. 1-6.
[10]   A. Kurniawan and E. Shintaku, "Estimation of the Monthly Global, Direct, and Diffuse Solar Radiation in Japan Using Artificial Neural Network," *International Journal of Machine Learning and Computing*, vol. 10, no. 2, pp. 253-258, 2020.
[11]   G. Notton, C. Voyant, A. Fouilloy, J. L. Duchaud, and M. L. Nivet, "Some applications of ANN to solar radiation estimation and forecasting for energy applications," *Applied Sciences*, vol. 9, no. 1, 2019, Art. no. 209.
[12]   M. A. Jallal, S. Chabaa, and A. Zeroual, "A new artificial multi-neural approach to estimate the hourly global solar radiation in a semi-arid climate site," *Theoretical and Applied Climatology*, vol. 139, no. 3-4, pp. 1261-1276, 2020.
[13]   H. S. Hussein, "Global solar radiation prediction using a combination of subtractive clustering algorithm and adaptive neuro-fuzzy inference system: A case study," *Journal of Engineering Science and Technology*, vol. 15, no. 3, pp. 1652-1669, 2020.
[14]   S. Salisu, M. W. Mustafa, M. Mustapha, and O. O. Mohammed, "Solar radiation forecasting in Nigeria based on hybrid PSO-ANFIS and WT-ANFIS approach," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 6, pp. 3916-3926, 2019.
[15]   A. A. Firdaus, R. T. Yunardi, E. I. Agustin, T. E. Putri, and D. O. Anggriawan, "Short-term photovoltaics power forecasting using Jordan recurrent neural network in Surabaya," *TELKOMNIKA Telecommunication, Computing, Electronics and Control*, vol. 18, no. 2, pp. 1089-1094, 2020.
[16]   A. Khosravi, R. N. N. Koury, L. Machado, and J. J. G. Pabon, "Prediction of hourly solar radiation in Abu Musa Island using machine learning algorithms," *Journal of Cleaner Production*, vol. 176, pp. 63-75, 2018.
[17]   J. Heaton, "Artificial Intelligence for Humans," Volume 3: Deep Learning and Neural Networks," *Chesterfield: Heaton Research, Inc*, 2015.
[18]   A. Kurniawan and E. Shintaku, "A Neural Network-Based Rapid Maximum Power Point Tracking Method for Photovoltaic Systems in Partial Shading Conditions," *Applied Solar Energy*, vol. 56, no. 3, pp. 157-167, 2020.
[19]   K. Bouchouicha, N. Bailek, M. E. S. Mahmoud, J. A. Alonso, A. Slimani, and Abdallah Djaafari, "Estimation of Monthly Average Daily Global Solar Radiation Using Meteorological-Based Models in Adrar, Algeria," *Applied Solar Energy*, vol. 54, no. 6, pp. 448-455, 2018.

[20] A. Koca, H. F. Oztop, Y. Varol, and G. O. Koca, "Estimation of solar radiation using artificial neural networks with different input parameters for Mediterranean region of Anatolia in Turkey," *Expert Systems with Applications*, vol. 38, no. 7, pp. 8756-8762, 2011.

[21] M. Marzouq, Z. Bounoua, A. Mechaqrane, H. E. Fadili, Z. Lakhliai, and K. Zenkouar, "ANN-based modelling and prediction of daily global solar irradiation using commonly measured meteorological parameters," *IOP Conference Series: Earth and Environmental Science*, vol. 161, no. 1, 2018.

[22] C. Gurlek and M. Sahin, "Estimation of the Global Solar Radiation with the Artificial Neural Networks for the City of Sivas," *European Mechanical Science*, vol. 2, no. 2, pp. 46-51, 2018.

[23] A. Teke and H. B. Yildirim, "Estimating the monthly global solar radiation for Eastern Mediterranean Region," *Energy Conversion and Management*, vol. 87, pp. 628-635, 2014.

[24] M. A. Behrang, E. Assareh, A. Ghanbarzadeh, and A. R. Noghrehabadi, "The potential of different artificial neural network (ANN) techniques in daily global solar radiation modeling based on meteorological data," *Solar Energy*, vol. 84, no. 8, pp. 1468-1480, 2010.

[25] D. H. W. Li, W. Chen, S. Li, and S. Lou, "Estimation of hourly global solar radiation using Multivariate Adaptive Regression Spline (MARS)-A case study of Hong Kong," *Energy*, vol. 186, 2019, Art. no. 115857.

[26] E. Paulescu and R. Blaga, "Regression models for hourly diffuse solar radiation," *Solar Energy*, vol. 125, pp. 111-124, 2016.

[27] F. O. Hocaoglu and F. Serttas, "A novel hybrid (Mycielski-Markov) model for hourly solar radiation forecasting," *Renewable Energy*, vol. 108, pp. 635-643, 2017.

BIOGRAPHIES OF AUTHORS

Adi Kurniawan was born in Surabaya, Indonesia in 1989. He received the B.Eng. and M.Eng. degrees in electrical engineering, power systems, from Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia, in 2011 and 2013, respectively. He received the Dr.Eng. Degrees from Department of Transportation and Environmental Systems, Hiroshima University, Japan, in 2020. He is now the head of Marine Electrical and Automation Systems Laboratory in Department of Marine Engineering of ITS, in which he has been a lecturer since 2014. His research interest includes renewable energy systems and control of power converters. He is currently working toward high efficiency maximum power tracking for PV system for ship application.

Eiji Shintaku was born in Hyogo, Japan in 1966. He received the B.E., M.E. and Dr. Eng. degrees in naval architect from Kyushu University, Japan, in 1989, 1991 and 1995, respectively. He is an Associate Professor at the Department of Transportation and Environmental Systems, Hiroshima University, Japan. His research interests include development of structural monitoring devices for large scale structure, control of marine equipment, electric propulsion system for ship. He is a member of The Japan Society of Naval Architects and Ocean Engineers, The Japan Institute of Marine Engineering and The Robotics Society of Japan.