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# Estimation of Hourly Solar Radiations on Horizontal Surface from Daily Average Solar Radiations Using Artificial Neural Network

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*Abstract*— **Hourly solar radiation information is necessary to increase the effectiveness of photovoltaic (PV) energy systems. However, compared with daily average solar radiation, the measurement of hourly solar radiation is much less available. In this study, a multilayer perceptron artificial neural network based on daily average solar radiation is proposed to estimate the amount of hourly solar radiation. The proposed method also relies on the location of the PV system, the hour when the estimate is needed, and the month when the estimate is needed. Two separate networks were built to estimate hourly direct solar radiation and hourly diffuse solar radiation, the summation of which is the estimated value of global hourly solar radiation. The networks were trained using three years of data from 2016 to 2018 from five locations around Japan. The data were taken from the website of the Japan Meteorological Agency (JMA). The number of hidden neurons for each network was determined by comparing the regression value obtained during the training process. The proposed method was validated by comparing the estimated value with the actual measured solar radiation value for each month in 2019 for the same five locations used for training the networks. The reliability of the proposed method was confirmed with the minimum $R^2$ of 0.951 for the estimation of hourly direct solar radiation and 0.983 for hourly diffuse solar radiation. Further improvement in the accuracy of estimating the daily peak radiation value is considered to improve the total accuracy of the estimation model in the future.**

*Keywords*— **Diffuse solar radiation; direct solar radiation; global solar radiation; multilayer perceptron; renewable energy; solar energy forecasting.**

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## I. INTRODUCTION

Photovoltaic (PV) panels for solar-to-electric energy conversion have been commercially available for over 60 years. In the last decade, the use of these devices in fields as diverse as the domestic, industrial, and transportation sectors has grown rapidly due to campaigns for cleaner energy sources and concerns over the depletion of fossil fuels [1]–[6]. Although PV panels are widely used, research into methods for increasing the efficiency of such systems is still ongoing, as the high price and low efficiency of PV cells force the development of efficient topologies, control, and management systems, or a combination of the above, to decrease the cost/energy ratio of PV-based energy sources [7], [8].

One method to decrease the cost-to-energy ratio of a photovoltaic (PV) power system is to undergo optimal planning before building the system. Solar radiation availability information for the precise location where a PV energy system will be built is necessary for optimal planning. The required solar radiation availability information varies, depending on the main purpose of optimal planning of the PV power system.

Simple analyses, such as determining the ideal location to install a PV system, only require annual solar radiation yield data [9]. More advanced analyses, such as optimal sizing of a PV panel or the energy storage system, call for daily average solar radiation information [10]–[13]. More detailed analyses, such as determining the most productive installation angles of a PV panel on a ship, need hourly solar radiation data [14], [15]. However, solar radiation data is limited in some locations due to the price of the measurement devices. To date, some countries have no available solar radiation measurements.

Japan, which ranked fifth in the world with a 7 GW installed PV system, has monthly global solar radiation data for 157 locations. However, hourly direct and diffuse solar radiation measurement is limited to only five locations, namely Sapporo, Ishigakijima, Minamitorishima, Tateno, and Fukuoka [16]. As the availability of the hourly solar radiation data is limited to these locations, a sophisticated method to estimate the hourly solar radiation for other locations is necessary to improve the efficiency of solar energy systems in all installation locations.

Prediction of hourly solar radiation can be approached with either physical models or statistical models. Physical models are primarily derived from a mathematical equation using the amount of solar radiation in a certain location, while statistical models use past data to estimate the same parameter for the future based on selected inputs. Although the process for designing statistical models is simpler than for physical models, the statistical models have better accuracy, especially for short-term prediction [17]. This led to the significant increase of the investigation studies of the statistical model applied to estimate hourly solar radiation worldwide, compared with a physical model.

Many types of statistical models with various input parameters have been proposed to estimate hourly solar radiation around the world. Some prominent methods include clustering and classification techniques with hourly clearness index as the input [18], a simple regression model using the clearness index and relative sunshine [19], and a multivariate adaptive regression spline (MARS) technique with ten weather parameters as inputs [20]. The most recent notable methods include the use of a modification of empirical model [21], a hybrid of regression [22], [23], and autoregressive integrated moving average (ARIMA) [24]. Additionally, machine learning algorithms, particularly artificial neural networks (ANN), are widely used to predict hourly solar radiation.

The prediction accuracy of multiple machines learning algorithms, including support vector regression (SVR), multilayer feed-forward neural network (MLFFNN), fuzzy inference system (FIS), radial basis function neural network (RBFNN), and adaptive neuro-fuzzy inference system (ANFIS), has been investigated using inputs of humidity, pressure, wind speed, temperature, and local time. In an investigation of solar radiation prediction for Abu Musa Island, Iran, the SVR model gave the most accurate result [25]. A more simple multilayer perceptron backpropagation neural network with multiple weather parameters, including temperature, humidity, wind speed and direction, precipitation, sunshine duration, atmospheric pressure, declination, zenith angle, and extraterrestrial solar radiation, has been validated in Bouzareah, Algeria, and Odeillo, France [26], while a multi-neural model with an input combination of air temperature, humidity, precipitation, wind speed, and acquisition hour, has been validated to predict the hourly solar radiation in Agdal, Morocco.

Although the methods above are proved to be accurate in estimating hourly solar radiation, multiple weather inputs are required, limiting the methods' usefulness. In locations where even one of the required input parameters is not accessible, the estimate cannot be generated, or the accuracy may decrease. Therefore, an estimation model with high accuracy but require as few as possible input is desired.

In this study, a new multilayer perceptron backpropagation neural network is proposed. Unlike other methods, the only required weather input is the daily average or monthly global solar radiation. While not every location has daily average solar radiation measurements, the probability of the input's availability is higher than using multiple weather input data.

The purpose of this study is to investigate if the proposed method, which held an advantage in the required input, has sufficient accuracy compared with other previous methods. With the high accuracy results and few required inputs, this method can be relied on to produce estimates of solar radiation where the data are not available. The explanation of the proposed method is detailed in section 2, while the validation of the method, including the comparison with other methods, is presented in section 3. Section 4 contains a discussion of the findings of this study as well as possible future works.

## II. Materials and Method

This study's estimation of hourly solar radiation uses daily average solar radiation as one of the input parameters. The coordinate positions (latitude and longitude) of the location being estimated are also used as input parameters, as the ANN is trained using data from multiple locations in Japan. The other input parameters are the month and the hour for which the estimate is needed. Since Japan has four seasons, the sunrise and sunset time, sunshine duration, and amount of hourly solar radiation are different for each month. However, in this study, the amount of solar radiation in a given hour is assumed to be equal for all days in the same month. This is because the input data of daily average solar radiation uses the average value in a month.

Limiting the input data to the five parameters above is one of the advantages of the proposed method. Weather parameters such as temperature, precipitation, or wind speed are not required for the estimation. However, if the monthly solar radiation data are not available, the monthly solar radiation must be estimated before using the proposed model, which may require those weather parameters.

To generate a more accurate ANN to estimate hourly direct and diffuse solar radiation, each was estimated in this study using its own ANN, instead of using one ANN with multiple outputs. The estimated amount of hourly global solar radiation can then be calculated as the sum of the hourly direct solar radiation and the hourly diffuse solar radiation. The structure of this study's ANN model is shown in Fig. 1.

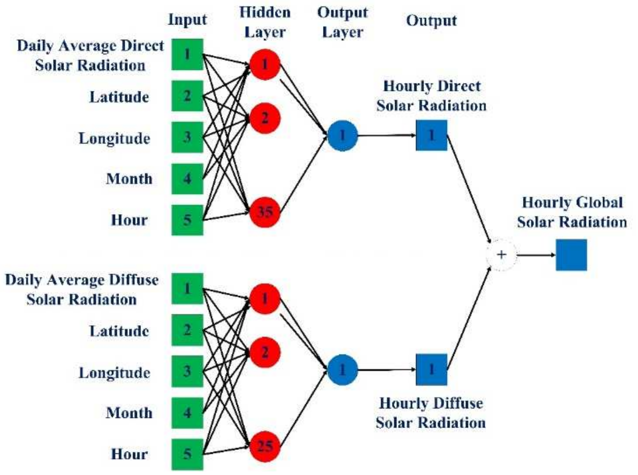



Fig. 1 Structure of the proposed ANN model

The target output was the average solar radiation for each hour, between Japan's earliest sunrise (5 AM) and the latest sunset (8 PM). The training data were the average hourly solar radiation measurements from three years (January 2016 through December 2018) in five locations, resulting in 960 samples for each data parameter.

Data used were taken from Japan Meteorological Agency's website. The five locations where the hourly solar radiations are available are spread around Japan, from the Northwest (Fukuoka), Southwest (Ishigakijima), Central (Tateno), North East (Sapporo), and South East (Minamitorishima).

The number of hidden neurons in each model was determined by the highest regression value (R) during the training process. The comparisons of regression values during the training process for hourly direct and diffuse solar radiation are listed in Table I.

TABLE I
COMPARISON OF REGRESSION VALUES FOR DIRECT AND DIFFUSE SOLAR RADIATION ESTIMATION

| Number of Hidden Neuron | $R_{direct}$ | $R_{diffuse}$ |
|---|---|---|
| 5 | 0.973 | 0.992 |
| 10 | 0.984 | 0.995 |
| 15 | 0.992 | 0.996 |
| 20 | 0.983 | 0.996 |
| 25 | 0.976 | **0.997** |
| 30 | 0.994 | 0.996 |
| 35 | **0.996** | 0.996 |
| 40 | 0.992 | - |
| 45 | 0.993 | - |

According to the comparisons, the highest regression value, and thus the number of hidden neurons, for direct and diffuse radiation is 35 and 25, respectively. The investigation for the optimal number of hidden neurons for direct solar radiation is stopped on 45 neurons because the value tends to be lower after the optimal number has been found. The investigation of the optimal value of hidden neurons for diffuse solar radiation is stopped at 35 neurons due to the same cause.

The regression lines between the target and the output from the ANN for the chosen models are shown in Fig. 2 and Fig. 3.

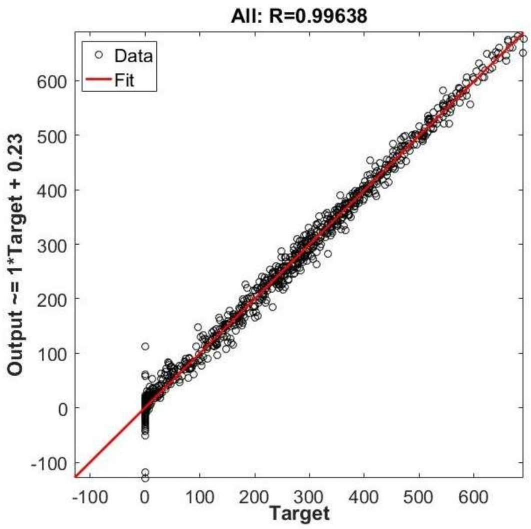



Fig. 2 Regression line of the ANN training for direct solar radiation estimation

The lines show good agreement between the target solar radiation taken from the data, with the estimate of solar radiation generated by the ANN model for the same input conditions. The lowest accuracy occurs when the solar radiations are supposed to be 0 in the early morning or before sunset, but the ANN produces non-zero estimates. It is to be noted that the ANN may produce negative solar radiation estimation. However, a filter is applied in the system algorithm after the ANN to limit the lower estimation result to be zero since negative solar radiation does not exist in reality

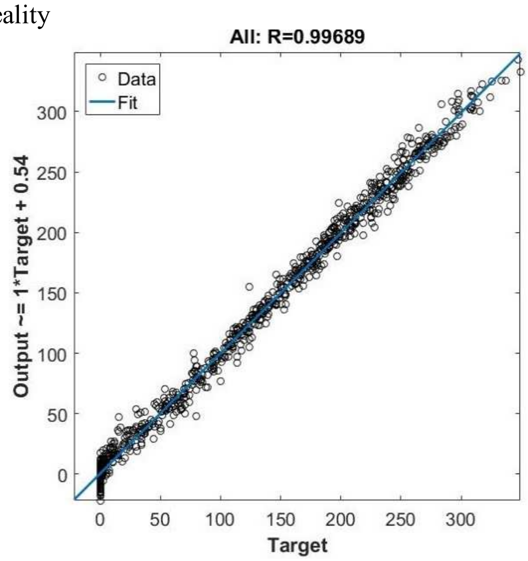



Fig. 3 Regression line of the ANN training for diffuse solar radiation estimation

To validate the effectiveness of the proposed ANN model, the coefficient of determination ($R^2$) was calculated for the estimation using 2019 actual measurements. The following formula was used to calculate the coefficient of determination:

$$R^2 = 1 - \frac{\sum_{h=5}^{20}(G_{meas(h)} - G_{pred(h)})^2}{\sum_{h=5}^{20} G_{pred}{}^2} \quad (1)$$

$R^2$ was chosen because it is one of the most frequently used methods to measure the accuracy of solar radiation estimates using an ANN method [11]. For further validation, the $R^2$ result of this study was also compared with the $R^2$ from previous studies. In this study, the $R^2$ are calculated separately between the estimation results of direct and diffuse solar radiation. The calculations are performed for each month for each location, resulting 120 values of $R^2$ in total.

## III. RESULTS AND DISCUSSION

This study's proposed method has been validated by comparing the estimated 2016 through 2018 data with the actual hourly solar radiation measurements in 2019. The comparison has been done for each month in all five cities, with the statistical results shown in Table II. As shown in the table, the lowest $R^2$ for the hourly direct solar radiation estimate is 0.9513, which corresponds to the city of Fukuoka in January. The estimate for hourly diffuse solar radiation was more accurate, with 0.9831 as the lowest $R^2$ calculated for the city of Tateno in January. The average $R^2$ for the estimated hourly diffuse solar radiation is 0.9958, which is considerably higher than 0.9854 for the estimated hourly direct solar radiation.

TABLE II
STATISTICAL RESULTS FOR HOURLY SOLAR RADIATION ESTIMATION PER MONTH FOR SAPPORO, FUKUOKA, ISHIGAKIJIMA, MINAMITORISHIMA AND TATENO

| Location | Month | $R^2$ | |
|---|---|---|---|
| | | $G_b$ | $G_d$ |
| Sapporo | 1 | 0.9583 | 0.9961 |
| | 2 | 0.9829 | 0.9979 |
| | 3 | 0.9855 | 0.9974 |
| | 4 | 0.9885 | 0.9950 |
| | 5 | 0.9898 | 0.9953 |
| | 6 | 0.9961 | 0.9954 |
| | 7 | 0.9718 | 0.9942 |
| | 8 | 0.9630 | 0.9922 |
| | 9 | 0.9765 | 0.9957 |
| | 10 | 0.9569 | 0.9974 |
| | 11 | 0.9900 | 0.9943 |
| | 12 | 0.9686 | 0.9937 |
| Fukuoka | 1 | 0.9513 | 0.9982 |
| | 2 | 0.9825 | 0.9965 |
| | 3 | 0.9727 | 0.9980 |
| | 4 | 0.9955 | 0.9932 |
| | 5 | 0.9945 | 0.9976 |
| | 6 | 0.9851 | 0.9985 |
| | 7 | 0.9727 | 0.9941 |
| | 8 | 0.9858 | 0.9886 |
| | 9 | 0.9819 | 0.9955 |
| | 10 | 0.9966 | 0.9981 |
| | 11 | 0.9956 | 0.9971 |
| | 12 | 0.9930 | 0.9949 |
| Ishigakijima | 1 | 0.9839 | 0.9976 |
| | 2 | 0.9851 | 0.9962 |
| | 3 | 0.9741 | 0.9974 |
| | 4 | 0.9712 | 0.9975 |
| | 5 | 0.9530 | 0.9980 |
| | 6 | 0.9932 | 0.9971 |
| | 7 | 0.9852 | 0.9958 |
| | 8 | 0.9892 | 0.9977 |
| | 9 | 0.9865 | 0.9977 |
| | 10 | 0.9947 | 0.9992 |
| | 11 | 0.9938 | 0.9978 |
| | 12 | 0.9649 | 0.9988 |
| Minamitorishima | 1 | 0.9882 | 0.9956 |
| | 2 | 0.9959 | 0.9965 |
| | 3 | 0.9959 | 0.9981 |
| | 4 | 0.9933 | 0.9950 |
| | 5 | 0.9919 | 0.9949 |
| | 6 | 0.9984 | 0.9929 |
| | 7 | 0.9929 | 0.9978 |
| | 8 | 0.9976 | 0.9969 |
| | 9 | 0.9971 | 0.9946 |
| | 10 | 0.9964 | 0.9941 |
| | 11 | 0.9940 | 0.9946 |
| | 12 | 0.9871 | 0.9939 |
| Tateno | 1 | 0.9976 | 0.9831 |
| | 2 | 0.9957 | 0.9941 |
| | 3 | 0.9958 | 0.9959 |
| | 4 | 0.9929 | 0.9966 |
| | 5 | 0.9965 | 0.9976 |
| | 6 | 0.9928 | 0.9968 |
| | 7 | 0.9701 | 0.9963 |
| | 8 | 0.9836 | 0.9954 |
| | 9 | 0.9908 | 0.9975 |
| | 10 | 0.9883 | 0.9923 |
| | 11 | 0.9963 | 0.9958 |
| | 12 | 0.9876 | 0.9936 |

Compared with the results from previous studies, which analyzed both physical and statistical models, the estimate generated by the proposed model is significantly more accurate. The MARS method [20] gives the average $R^2$ of 0.9123 for the estimate of hourly global solar radiation in Hong Kong, while the regression technique resulted in an $R^2$ of 0.93 to predict the diffuse solar radiation in Romania [19]. Meanwhile, the hybrid Mycielski-Markov model obtained an $R^2$ of 0.8413 for an estimate for one hour in the future [27].

The example of graphical comparisons between the estimated and measured hourly solar radiation for each month, represented by one month per season, is shown in the example of actual measured solar radiations in Fig. 4 and Fig. 5, only for January in Sapporo and July in Fukuoka. The graphical comparisons show that the model generated an estimated solar radiation value similar to the actual measurements. The estimated value does not tend to be dominantly above or below the measured value. However, the estimation was limited to generating a smooth bell-shaped curve with one peak value, while the actual hourly radiation curves sometimes have multiple peaks and valleys, especially for direct solar radiation. As a result, the prediction tends to be less accurate during the peak radiation periods than the few hours after sunrise and before sunset.

The results from previous similar studies show that the estimations of solar radiation always have one peak, as resulted in this study [19], [20], [27]–[29]. The estimation result with multiple peaks in a day is not available, even for the model that uses various weather data as the input. However, it does not close any possibility to develop a more advanced model that can estimate solar radiation closer to the actual measured radiation in the future study, including generating multiple peaks of solar radiation estimation.

Each graphic shown in the result of this study is shaped based on the linearization of the input-output based on the three-years data between 2016-2018. Since the input contains the geographical position, the generalization of ANN gives the results that tend to be similar to the data on the same site during the same month and hour. For example, in Fig. 4 (a) the peak of direct solar radiation in January occurs at 11 AM. According to the Japan Meteorological Agency (JMA) data, the peak of direct solar radiation in Sapporo in January between 2016-2018 also occurs at 11 AM. The validations have also been performed in some other graphics which not shown in this paper.

The estimation results of single-peak hourly radiation are also supported by the formula of solar hour angle, which increases 15° per hour during the morning and decreases 15° per hour during the afternoon, and reaches the peak during the local noon [30]. Excluding real weather conditions where the factors such as clouds may appear, the amount of solar radiation should be proportional to the solar hour angle that reaches a peak during the local solar noon. The formula to calculate solar hour angle is as follow:

$$\omega = 15(12 - L_{ST}) \quad (2)$$

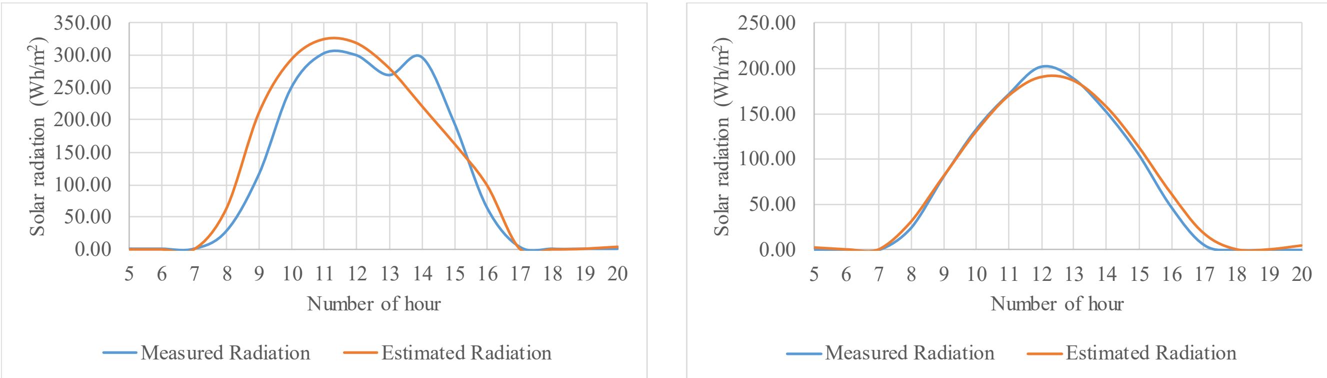
where $L_{ST}$ is local solar time, which can be calculated by:

$$L_{ST} = LT + \frac{ET}{60} + \frac{4}{60}(L_S - L_L) \quad (3)$$

where $LT$ is the local standard time, $L_S$ is the standard meridian for a local zone, $L_L$ is the longitude of the location in which solar radiation is analyzed, while *ET* is the equation of time.

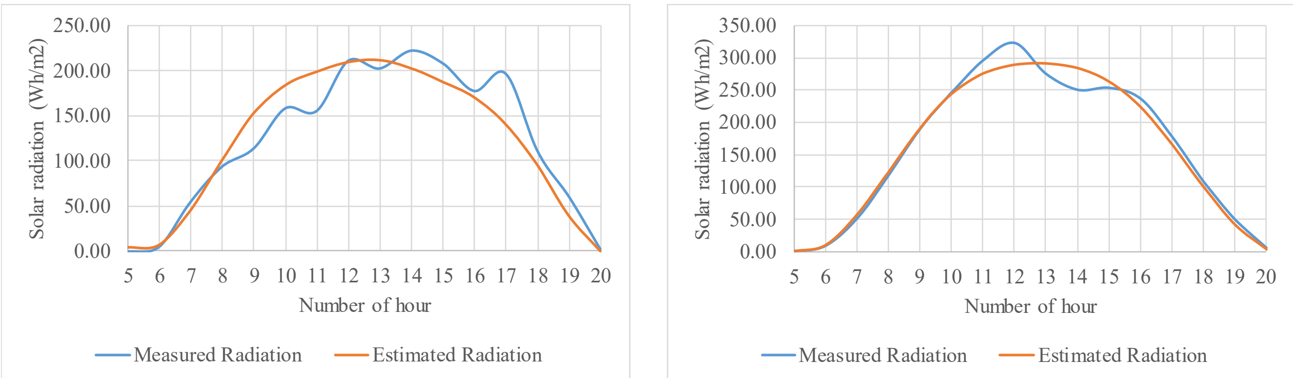
The example of comparison graphics between direct and diffuse solar radiation is January in Sapporo, which is in winter, and the comparison for July in Fukuoka, which is in summer. The multiple peaks are very likely caused by the cloud-covered sky during some intervals, especially for an estimate for July in Fukuoka. Even though July is included in the summer category, it is to be noted that rains are frequently pouring in July in Japan.

The influence of cloud for the presented graphics of measured solar radiation is strong because the graphics are only taken from one-year measurement, compared with the three-year measurement used for the training of ANN.




(a) (b)

Fig. 4 Comparison of hourly solar radiation for January in Sapporo (a) Direct radiation (b) Diffuse radiation




(a) (b)

Fig. 5 Comparison of hourly solar radiation for July in Fukuoka (a) Direct radiation (b) Diffuse radiation

## IV. Conclusion

This study proposes a new ANN-based method to estimate hourly direct and diffuse solar radiation. The information of hourly direct and diffuse solar radiation information is important to maximize solar energy conversion efficiency for various applications. However, this information is frequently limited, mainly due to economic reasons. Thus, the estimated model of hourly solar radiation held a significant role in improving the solar energy system's overall efficiency. The advantage of this method is that it requires only daily average solar radiation data, which are more accessible than other potential input parameters.

This study investigated using solar radiation data in Japan; the most accurate ANN model to predict the hourly direct solar radiation consists of 35 hidden neurons, while the hourly diffuse solar radiation model uses 25 hidden neurons. The optimum number of a hidden neuron may vary depending on the location where the investigation is performed. The validation of the proposed method has been performed by calculating the $R^2$ for each day in 2019, broken down by month, for five locations in Japan. The results show that the proposed method can estimate at least as accurately as previous methods, especially for diffuse radiation estimates. The graphical hour-to-hour comparisons between the estimated and actual measured values also show good similarity. A method to improve the accuracy of estimating the daily peak radiation value could be considered for future research. One possible recommendation is to apply deep learning ANN instead of the single hidden layer used in the current study.

## Nomenclature

| | | |
|---|---|---|
| $G_b$ | direct solar radiation | Wh/m$^2$ |
| $G_d$ | diffuse solar radiation | Wh/m$^2$ |
| $G_{meas}$ | measured value of solar radiation | Wh/m$^2$ |
| $G_{pred}$ | predicted value of solar radiation | Wh/m$^2$ |
| R | regression value | |
| $R^2$ | coefficient of determination | |
| Subscripts | | |
| h | Number of hours | |

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