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ANN-Based Model for Daily Solar Radiation Prediction with A Low Number of Hidden Neurons And Optimal Inputs

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Abstract

Solar radiation has been the focus of many studies over the past years due to its usefulness in clean energy generation through photovoltaic (PV) systems. For both standalone and grid-connected PV systems, it is necessary to have solar radiation information beforehand (accurate prediction) as it is used for the PV systems design, for making power dispatching plans, for potential future PV system feasibility, etc.… In this article, an Artificial Neural Network (ANN)-based model for daily global solar radiation prediction is proposed. This model is trained with a backpropagation algorithm and make prediction using meteorological variables as inputs. While keeping the accuracy at high level, the model is built using a low number of neurons in the ANN's hidden layer and most effective input variables. As a result, the proposed model is simpler as compared to many existing models. First, the minimum and the maximum numbers of hidden neurons are calculated. Second, results of numerical simulations based on a trial-and-error method can show us the low number of hidden neurons and the optimal inputs for the model. A simple model is preferred when the performance level is not affected. In addition, a simple model is easy to implement and requires lower computer's capacity; which is beneficial economically.

Keywords: *Neural networks; photovoltaic systems; prediction; solar radiation; weather variables*

1. Introduction

Global warming and environmental pollution due to greenhouse gas emission in the atmosphere represent a significant threat for humans. In this twenty first century, securing energy sources while protecting the environment is an important challenge [1]. Moreover, continuing to develop technologies to increase efficiency in energy production and distribution is necessary. Solar energy, among others, can help to address the greenhouse gas emission issue with the aim to protect the environment. In recent years, a large number of photovoltaic (PV) systems have been deployed across the world as mega solar plants or micro-grids. In Japan, the government is planning to integrate a total amount of 53 GW by 2030 [2]. Also, the solar energy is one of the most important renewable energy sources for a large number of southern Europe countries such as Spain and other locations in the same longitude, such as Saudi Arabia or India [3]. With the expected integration of high amounts of solar power, reliable predictions of solar power generation are increasingly needed as a tool for efficient management and operation strategies of PV systems as well as for solar energy trading [4]. Solar radiation is a key element for clean energy generation by PV systems. But as we know, the solar radiation is intermittent by nature and it is difficult to accurately determine its value in the future. The output power of PV systems is greatly affected by weather conditions. In fact, the output of renewable energy systems changes constantly and/or significantly according to the conditions and the characteristics of the location where they are installed; which makes it difficult to exactly determine how much benefit in terms of generated power can be obtained from these systems [3]. With a view to making PV systems' operation more stable and reliable, predicting solar radiation is necessary. The operators of these PV systems need to predict the output power by using solar radiation prediction information to maintain the balance between demand and supply of electric power in the near future. In addition, for PV systems with battery storage, the prediction is helpful to schedule the charging process of the batteries at the most appropriate time to optimize the proportion of power supplied and stored at any time, and thus avoid the loss of usable energy [4]. Meteorological variables can be used as inputs to determine solar radiation ahead of time through an appropriate modeling. Many methods for solar radiation prediction exist in the literature: expert systems (ESs), fuzzy logic (FLs), genetic algorithms (GAs), artificial neural networks (ANN) and other hybrid models [5]. The relationship between meteorological variables and solar radiation is non-linear. ANN method is perfectly suitable for modeling such cases. In fact, the ANN technique can deal with both linear and nonlinear

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problems [6]; which makes it a suitable choice for this study. The prediction model proposed in this study provides good accuracy and is less complex (use lower number of inputs and hidden neurons) as compared to many other existing models in the field of solar radiation prediction. The selection of input variables is made by a trial-and-error method through multiple numerical simulations in "R studio" with a dataset containing meteorological variables from Kofu City, Japan. The selection of a better combination of inputs is a crucial step because these inputs have a significant impact on the model performance. In addition, it is advantageous to use simple models when the accuracy level that they can provide is high. Model complexity does not necessarily mean higher performance as we can see in the comparison section (Table 6) between our model and many others. The goal of this study is to develop a ANN model that makes prediction with good accuracy and offers structural simplicity. In other words, while keeping the model accuracy at good level, we make the model structure simpler by using a lower number of hidden neurons and a lower number of input variables. A simple model offers many advantages as it is easy to implement, to understand and requires lower computer capacity, which is a substantial economic benefit. The number of neurons in the hidden layer is determined by an experimental formula provided in the section 4.1 of this manuscript and then, the lowest number is determined after evaluating the model performance through the calculation of errors values in each case.

2. Brief description of ANN

In this section, we will be briefly describing the ANN as it is the method used to build our model. We chose to use a feed-forward ANN structure because it is simple and easy to implement. This choice also contributes to the overall goal of this research which is 'building an accurate and simple ANN model for predicting solar radiation'. Moreover, the *back-propagation algorithm* is widely used to train feedforward neural networks. We have therefore used it to train our model.

2.1. ANN operation principle

Artificial Neural Network is one of the most interesting programming paradigms invented in the last several years [6]. The ANN imitates the functioning of a human brain. Which means that ANN learns from examples (input data provided during the training process) and understand how to solve similar problems in the future.

Similarly, to the biological neuron, the ANN defines the neuron as a central processing unit which makes a mathematical operation and provide one output value using a set of input values. The output of a neuron is a function of the weighted sum of the inputs added to a random number called 'the bias'. As an illustration case, a neuron called '*perceptron*', performs a basic operation where the neuron is activated (output=1) if the total amount of signals received from other neurons exceeds an activation threshold. This can be described by the following equation:

$$Yj = \sum_{i=1}^{n} AiXi + B \quad (1)$$

Here: j is the number assigned to the neuron, Yj is the output of neuron j, n is the number of inputs of the neuron, i is an index, Ai is the weight, Xi is the input and B is the bias.

In this study, meteorological variables represent the inputs (Xi) and solar radiation represents the output (Yj). 'Weights' in the ANN are the most important parameters in the conversion of an input into an output. These weights are numerical parameters that determine how strongly each of the neurons affects the other. Moreover, the 'bias' is an additional value that is used to adjust the neuron's output along with the weighted sum of the inputs as indicated in (1). The role of the entire artificial neural network is merely the calculation of the outputs of all neurons, which is an entirely deterministic calculation[5]. The ANN calculates the weights and bias values for each neuron and save them for future utilization.

2.2. ANN structure

In general, ANNs are made of the following three layers: one input layer, one or more hidden layers and one output layer as shown in Figure 1.

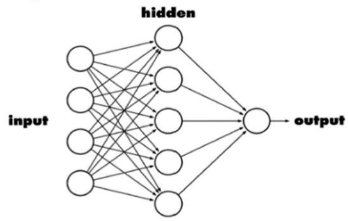

Figure 1: ANN structure

In this figure, neurons are represented by *circles*. Each neuron is connected to all neurons of the previous layer. The input neurons form the *input layer*, the middle layer(s) which performs the processing is(are) called the *hidden layer(s)*, and the output neuron(s) form the *output layer*. The hidden layer converts the inputs to the desired output.

Feed-forward structure: in this ANN structure, signal flows only in one direction. The input signals are sent in the network through the input layer, then, after being processed, they are transferred to the next layer, just as indicated in Figure 2. The arrows in the figure shows the direction of signals flow.

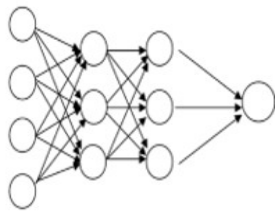

Figure 2: Feed-forward ANN

2.3. ANN training process

Before using ANNs, they must undergo a training process. 'Training the ANN' means providing the network with some sample data and modifying the weights to approximately determine the desired function of the ANN [7]. Two main training techniques are used: *supervised learning* and *unsupervised learning.*

a. *Supervised learning*: the input data and the desired output data are provided to the ANN. The response of the ANN to the inputs is then measured. The *weights* and *biases* are adjusted to narrow down the difference between the actual and desired values of outputs.

b. *Unsupervised learning*: in this method, only inputs are supplied. The ANN modifies the weights so that same inputs can produce same outputs. The ANN identifies the patterns and differences in the inputs without any assistance from outside. The unsupervised learning method is used when the values of the predicted variable are not available in the dataset. In our case, the predicted value is solar radiation and its values from past years are available in our dataset. Therefore, we have used the supervised learning method. Besides, the steps through which the learning process is carried out in a neural network is named '*learning algorithm*'. There are many different learning algorithms. The different algorithms have different characteristics and performances in terms of memory requirements, processing speed, and numerical precision.
c. *Activation function*: An activation function is a mathematical function which converts the input to an output for each neuron. Many activation functions can be used for neural networks such as linear function, unit step, sigmoid, hyperbolic tangent etc.… For instance, in the case of the sigmoid function, the output value of a neuron is given by:

$$Yj = \frac{1}{1 + \exp\left(-\sum_{i=1}^{n} AiXi + B\right)} \quad (2)$$

With all variables as defined in (1).

3. Literature review

The following studies are presented in this manuscript with the intention to comparing them with our model (Table 6). The presented studies are selected based on performance evaluation parameters used (*RMSE*: Root Mean Square Error; *MBE*: Mean Bias Error), in order to allow an easy comparison with our model. Geographical and meteorological variables are used as inputs in these studies. Each developed model has its main characteristics such as: *number and nature of inputs*, *number of hidden neurons* and *statistical parameters* (errors).

Angela et al. (2011) [8] have used only one variable, the "*sunshine duration"* as an input to the ANN model. A five-year dataset (2003-2008) was used for training and testing the model. The final model had one hidden layer with 65 neurons with a RMSE=0.521 and a correlation coefficient of 0.963.

Alharbi, M. (2013) [9] three different variables (temperature, humidity, and daily date code) were used as inputs to ANN model. In addition, the model was trained and tested with a three-year dataset (2009-2011). The models included three layers with the number of neurons going from 60 to 83 in the hidden layer. The study reached a conclusion that the best prediction was achieved when all the three input variables were used. The best model had 80 neurons in the hidden layer. The RMSE value was 7.5% and the correlation coefficient was 0.986.

Wang et al. (2011) [10] used diffused radiation, temperature, relative humidity, and time, as input parameters to the ANN models. The model was aimed at short-term solar radiation forecasting in Golden, CO, USA. The most accurate model was made of two hidden layers with 18, 13 neurons respectively; the RMSE value was 0.0331.

Mubiru et al. (2008) [11] have used latitude, longitude, altitude, sunshine hours, cloud cover, and maximum temperature data as inputs to the ANN model. The model was used to predict the monthly average daily global solar radiation in Uganda. In the model, a dataset covering three years from April 2003 to December 2005 had been used. The study reached a conclusion that the best model was the one with 15 hidden neurons and one hidden layer using the Levenberg–Marquardt training algorithm. This model had R^2 and RMSE of 0.974 and 38.5% respectively.

Sozen et al. (2004) [12] used latitude, longitude, altitude, months, mean sunshine duration, and mean temperature as input parameters to the ANN model to forecast the solar radiation in Turkey. The highest mean absolute percentage error was used for the validation of the model. The error value was around 6.74% and the absolute fraction of variance, R^2 value was 99.89% for the testing stations.

Tymvios et al. (2005) [13] used the same input parameters as Sozen et al. (2004) for training seven ANN models to predict the solar radiation upon a horizontal surface. The ANN models included one and two hidden layers and the number of neurons between 23 and 77. The ANN model with two hidden layers (23 and 46 neurons respectively) turned out to be the best model. The mean biased error (MBE) value was 0.12% and the root mean square error (RMSE) value was 5.67%. This research used a seven-year-span dataset (1986-1992) collected at Athalassa, Cyprus.
Table 6 (see page 4) provides comparison results of these models and our model.

4. Prediction model construction

Details about our global solar radiation prediction model are presented here. As mentioned before, a dataset from Kofu city, Yamanashi prefecture in Japan is used. The dataset covers a 6-year-period from January 2010 to December 2015 and contains 10 daily variables: *average temperature (Tav)*, *maximum temperature (Tmax)*, *minimum temperature (Tmin)*, *total precipitation (Precip)*, *average wind speed (WSav), maximum wind speed (WSmax), average vapor pressure (VPav), average humidity (Hav), cloud cover (CC)* and *solar radiation(GSR).*
The construction of the model is done in the four steps presented below:

Step 1: Determining the maximum and minimum numbers of hidden neurons: the number of neurons in the hidden layer is calculated using an experimental formula provided in equation (3) below.

Step 2: Finding the best combination of meteorological variables(inputs): Each variable is first used individually as inputs of the ANN model and then combined with the others. This is done to determine which variables provide better prediction accuracy. After simulations of our code in R studio, we can determine the best variables combination through error calculation.

Step 3: Building the ANN model using inputs of step 1 and 2: The **construction** of our model involves "training" the network with known input/output data available in our dataset, and then "testing" the constructed model with different data.

Step 4: Comparing our model to existing models: our model's structure and performance is compared to other models in the field of solar radiation prediction (Table 6).

4.1. Number of neurons in the hidden layer

In this study, finding the good number of hidden neurons and the best combination of input variables are crucial steps. The number of neurons in the hidden layer is determined using an experimental formula as follows [8]:

$$m = \sqrt{(n + l)} + \alpha \; ; \quad (3)$$

With: m**:** number of neurons in the hidden layer, n: number of input neurons, l: number of output neurons and α a constant (with $1 < \alpha < 10$). Our model is designed using a low number of neurons in the hidden layer. This number can be determined by (3) primarily, then the network is debugged over. In our case, if n=3 and l =1 then m can vary from 3 to 12. If n=2 and l=1, then m will vary within same limits (after rounding up to the nearest decimal). The best model is chosen after analyzing simulation results from R studio. Statistical indicators which include *RMSE* and *MBE* are used for this purpose in this paper. The results of these simulations are provided below.

4.2. Selection of inputs

As explained above (step 2), each meteorological variable is first used individually as input to determine its contribution to the GSR prediction. For the case of one variable (one input), good results can be obtained with three neurons in the hidden layer. Table 1 shows simulation results for each meteorological variable. Based on these results, we can see that '*WSav*', '*WSmax*', '*Tmax*' and '*Hav*' can make prediction with a lower value of error (*RMSE*).
It means that, these inputs have more impact on *GSR* prediction than other inputs. In the next step, these four inputs are combined in pairs (two by two) for GSR prediction.

Table 1: GSR prediction with 1 input variable

Model	Input	Output	Neurons	RMSE (%)
ANN_1.1	*Tav*	GSR	3	6
ANN_1.2	*Tmax*	GSR	3	5.5
ANN_1.3	*Tmin*	GSR	3	6.5
ANN_1.4	*Precip*	GSR	3	6.2
ANN_1.5	*WSav*	GSR	3	5.3
ANN_1.6	*WSmax*	GSR	3	5.4
ANN_1.7	*VPav*	GSR	3	6.6
ANN_1.8	*Hav*	GSR	3	5.7
ANN_1.9	*CC*	GSR	3	6

Table 2 shows the prediction results using two variables as inputs. In the same way, we can see that using two variables as inputs provides better accuracy (lower *RMSE*) than one variable. 'ANN_2.4' and 'ANN_2.6' make prediction with better results because the *RMSE* values are the lowest. Next, we will combine these variables three by three to see if we can further bring down the error value. Table 3 provides the results of this simulation. When we compare the results of Table 2 and Table 3, we clearly see that using three inputs provide higher accuracy.

Table 2: GSR prediction with 2 input variables

Model	Input	Output	Neurons	RMSE (%)
ANN_2.1	*WSav, WSmax*	GSR	3	5.2
ANN_2.2	*WSav, Tmax*	GSR	3	4.5
ANN_2.3	*WSav, Hav*	GSR	3	5.0
ANN_2.4	*WSmax, Tmax*	GSR	3	4.4
ANN_2.5	*WSmax, Hav*	GSR	3	5.1
ANN_2.6	*Tmax, Hav*	GSR	3	3.5

Table 3: GSR prediction with 3 input variables

Model	Input	Output	Neurons	RMSE (%)
ANN_3.1	*Tmax, Hav, WSmax*	GSR	4	3.3
ANN_3.2	*Tmax, WSmax, WSav*	GSR	4	3.2
ANN_3.3	*Tmax, Hav, WSav*	GSR	4	3.5
ANN_3.4	*Hav, WSmax, WSav*	GSR	4	5.0

The lowest value of *RMSE* is obtained when we use '*Tmax*', '*WSmax*' and '*Hav*' as input variables (ANN_3.1).
However, from Table 2 we can see that *RMSE*=3.5% for 'ANN_2.6' and from Table 3 we have *RMSE*=3.3% for 'ANN_3.1'.
These two *RMSE* values are just slightly different. Therefore, one may choose to use two meteorological variables as inputs (ANN_2.6) instead of three variables (ANN_3.1) for simplicity reason. Knowing that simplicity is one of our goals in this work, we choose to use '*Tmax*' and '*Hav*' as inputs for GSR prediction. The graph below (Fig.4) shows the results of daily solar radiation prediction by our ANN model. On the vertical axis we have the numerical values of solar radiation (MJ/m^2) and on the horizontal axis we have different days when the prediction is made (541 days in total on this diagram). The comparison between actual and predicted values is also shown. As we can see, the difference between the actual value (blue) and the predicted value (gray) is not so big for most of the days.

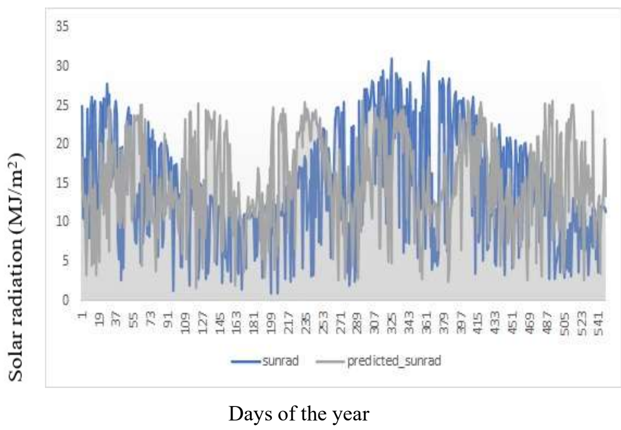

Figure 4: Comparison between actual and predicted values of daily solar radiation

4.3. Effect of neuron number on GSR prediction

Several numerical simulations of our model have shown that the high number of neurons does not increase the GSR prediction accuracy. Table 4 and Table 5 show prediction results with higher number of neurons for 2 and 3 input variables.
We can see that increasing the number of neurons of our model does not necessarily result in better accuracy and results in GSR predictions regardless of the combination of input variables.

Table 4: High number neurons result for 2 input variables

Model	Input	Output	Neurons	RMSE (%)
ANN_5	*Tmax,Hav*	GSR	10	3.54
ANN_5	*Tmax,Hav*	GSR	22	3.53
ANN_5	*Tmax,Hav*	GSR	30	3.53
ANN_5	*Tmax,Hav*	GSR	40	3.53

Table 5: High number neurons result for 3 input variables

Model	Input	Output	Neurons	RMSE (%)
ANN_4	*Tmax,Hav,WSmax*	GSR	10	3.3
ANN_4	*Tm,Hav,WSmax*	GSR	20	3.4
ANN_4	*Tm,Hav,WSmax*	GSR	30	3.3
ANN_4	*Tm,Hav,WSmax*	GSR	50	3.4

4.4. Performance evaluation (errors calculation)

During the testing process, the predicted values of daily global solar radiation are generated by our ANN model. Then, the predicted values are compared with actual values available in the dataset through error analysis. In this study, we have used two statistical quantities namely, the Mean Bias Error (*MBE*) and the Root Mean Square Error (*RMSE*) to evaluate our model's performance. The *MBE* is defined by:

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(Yi - Xi) \qquad (4)$$

Where, *i* is an index, *Yi* is the ith predicted value, *Xi* is the ith actual value, and *n* is the number of observations. The MBE provides information on the average deviation of the predicted values from the corresponding actual data and can give an indication on the long-term performance of the model. A positive MBE value shows the amount of overestimation in the predicted global solar radiation and vice versa. If the MBE value is low, this indicates a good prediction [8]. The model developed in this study provides an *MBE* value of **7%**. This means a very low overestimation in the prediction of daily solar radiation.

On the other hand, the *RMSE* is defined by:

$$RMSE= \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Yi - Xi)^2} \qquad (5)$$

With all the variables as defined in (4).

The *RMSE* gives an indication on the short-term performance of the model. It also represents a measure of the variation of predicted values around the measured data. The lower RMSE value is, the higher the performance of the model will be[8]. The model developed in this study provides a RMSE value of 3.5%.

4.5. Comparison between the RMSE of the proposed model and other existing models

In this section, we present a performance comparison between our model and other existing models. Basically, our model is compared to the models that use similar performance indicator (*RMSE*). Our model is implemented with a lower number of neurons in the hidden layer while providing a good accuracy. The table below show comparison results. The proposed model (last row) is built with three layers, two input variables (*maximum temperature* and *average humidity*) and three hidden neurons.

Table 6: Results of comparison with other models

Inputs	Layers	Neurons	RMSE (%)	Authors
Sm, St, Tmax	4	69	5.67	Tymvios et al. (2005)
Tav, R	4	55	13.14	Mellit et al. (2010)
GSR, t, Hrel, Tav	4	79	3.3	Wang et al. (2011)
Sm	3	65	52	Angela et al. (2011)
D	3	83	18.53	Allarbi M. (2013)
D, Tav, Hrel	3	75	7.91	Allarbi M. (2013)
L, l, A, Sm, CC, Tm	3	15	38.5	Muribu et al. (2008)
Sm	3	65	52.1	Karoro A. et al. (2011)
Tmax, Hav	3	3	3.5	Our model

Where: *St Theoretical daily sunshine duration, Sm: Measured daily sunshine duration, L: Longitude, l: latitude, A: Altitude, R: Correlation coefficient, D: day, Hrel: relative humidity, t: time, GSR: Global Solar Radiation.*

5. Conclusions

In this manuscript, an ANN-based model has been proposed for daily GSR prediction. Our model's main advantage is its simplicity due to the low number of inputs and neurons used. Simple models are easy to understand and implement. Moreover, simple models offer an economic benefit because the required computer's power is lower. Numerical simulations of our R code (in R studio) can help us to select the combination of the most influential input variables and the suitable number of hidden neurons through a trial-and-error method. The performance of our model can be verified through the calculation of the *RMSE* value (3.5%) and *MBE* the value (7%). In comparison to many existing models, our model is simple and provide a good accuracy. For future study, we propose to make the selection of the most effective input variables by using a statistical method such as factor analysis, decision three, etc. and compare the results.

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