Jr. of Industrial Pollution Control 34(2)(2018) pp 2206-2210
www.icontrolpollution.com
Research Article

PREDICTION OF SOLAR ENERGY PRODUCED UNDER DIFFERENT SYSTEM AND ENVIRONMENTAL CONDITIONS FOR JORDANIAN STATIONS USING ARTIFICIAL NEURAL NETWORK

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(Received 03 December, 2018; accepted 26 December, 2018)

Key words: Solar energy, Artificial neural network, Environmental conditions.

ABSTRACT

Solar energy; as one of renewable energy sources, is of high importance mainly for countries with high temperature and long sunshine duration. However, environmental conditions and system parameters affect the output of the solar panels in different geographical locations in any country. Solar energy stations available in different locations in Jordan have been investigated, using artificial neural network (ANN). Analysis of several inputs (variables) identified were employed to indicate their relative significance to the output such as latitude, altitude, sunshine duration (SSD) and global solar radiation (GSR). ANN shows proficiency in the prediction of the original experimental data for all the solar stations. In the simulation, the energy gain increases with the increase in the GSR which is one important environmental condition and the perfect fit (R value 0.9961) indicates that the network output is close to targets. It can be concluded that the provided ANN model predicts power variable close to measured value. The uniqueness of this work is that it predicts the important output of the solar stations based on the logical arrangement of detailed parameters that are found in all operational units of the system.

INTRODUCTION

Solar energy as renewable energy source has significant contribution in providing constant source of energy, mainly for countries with high temperature and long shining time. Solar energy provides clean source of energy such as wind (Lei, *et al.*, 2009; Schilling and Esmundo, 2009; Greiser, *et al.*, 2009), tidal (Assad, *et al.*, 2017; Assad, *et al.*, 2016), geothermal energy sources (Lund and Boyd, 2016; Barbier, 2002; Bani-Hani, 2017). Solar energy and photovoltaic utilization has been investigated thoroughly in the literature sources (Reddy, *et al.*, 2013; Li, *et al.*, 2016; Muñoz, *et al.*, 2017; Jean, *et al.*, 2015).

Most of the investigations of the solar energy utilization are experimental (Bani-Hani and Abidoye, 2016). Researchers are trying to find suitable applications for solar energy (Bani-Hani, 2016). These experimental data can be validated against theoretical results and vice versa. However, because of the presence of strong computing tools such as the Artificial Neural Networks (ANNs) the experimental data can be validated and predicted (Abidoye, *et al.,* 2016). This will help in better analysis of the renewable energy systems for energy sustainability. The renewable energy outputs are variable due to parameters affecting the systems that are known as characteristic of their sources. Electrical power system; for example, is facing a difficulty of integrating these variable power sources into the existing power grids (Akinyele, *et al.*, 2014).

Artificial neural networks (ANNs) have played an important role in solving many complex real-world problems such as pattern classification, clustering, approximation, forecasting, optimization, control (Garth, *et al.*, 1996; Goodacre, *et al.*, 1994; Grieser, *et al.*, 2015; Hecht-Nielsen, 1990; Geeraerd, *et al.*, 1998; Hajmeer, *et al.*, 1996; Hajmeer, *et al.*, 1997; Hajmeer, *et al.*, 1998; Jain, *et al.*, 1996; Pham, 1994).

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Nowadays, ANNs can be used to solve problems that are difficult for human beings. They can extract the desired information directly from the data to overcome the limitations of the conventional approaches.

Neuron is the fundamental processing element of a neural network. Basically, an artificial processing neuron receives inputs from the environment, combines them in a special way, performs generally a non-linear operation on the result, and then obtains the final result (Haykin, 1994).

Additional layer(s) of neurons placed between the input layer (containing input nodes) and the output neuron are needed to cope with nonlinearly separable problems. This architecture is known as multilayer perceptron (MLP) architecture (Hecht-Nielsen, 1990). These intermediate layers are named hidden layers because they do not interact with the external environment. In addition, their nodes are called hidden nodes.

Training step is an important subject in ANN. There are two types of ANN learning models existing, the supervised and unsupervised learning. Supervised learning presents the input to the network along with the desired output. The model adjusts the weights and the network attempts to produce the desired output. In unsupervised learning, the ANN do not rely on the use of target data instead tries to find an underlying structure (Sözen, *et al.*, 2004).

There are different algorithms for training: back-propagation algorithm (Rumelhart, *et al.*, 1986) gradient descent and gradient descent with momentum, which are often slow for practical problems (Sozen, *et al.*, 2004). Faster algorithms such as conjugate gradient, quasi-Newton, and Levenberg–Marquardt use standard numerical optimization- techniques (Sozen, *et al.*, 2004).

ANN MODELING

In this paper, the ANN model was used to predict the power variable based on different solar data variables. The data were obtained for solar stations in Jordan (Hrayshat, 2009). The data required were altitude, latitude, longitude, solar sunshine duration (SSD), global solar radiation (GSR). In addition, the environmental conditions where the system parameters include the solar panel specifications. All of these conditions and parameters will affect the electricity generated in each solar station. (Fig. 1) shows the multilayer feed forward ANN model used.

The model is consisted of an input layer with five neurons (5 variables), a hidden layer with ten neurons and an output layer with one neuron.

The ANN architecture used five neurons to

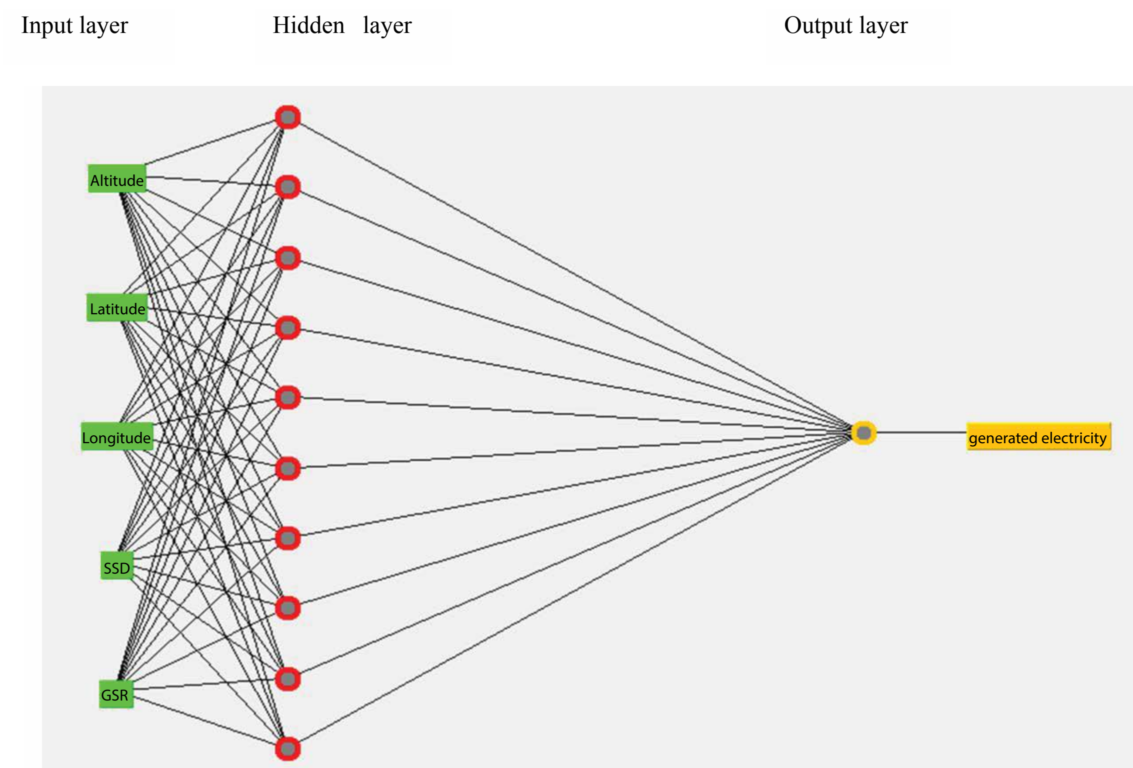

Fig. 1 ANN architecture for the generated electricity prediction.

receive five inputs representing Altitude, Latitude, Longitude, SSD, and GSR. The output layer consists of one output neuron representing the power (generated electricity). There are one or more hidden layers between input and output layers generally.

The artificial neural network fitting tool (nftool) was used to model the ANN. It consists of a standard two layers feed forward neural network trained with Levenberg–Marquardt (LM) algorithm and is suitable for static fitting problems. The input and target data were randomly divided to 70%, 15%, 15% training, testing and validation respectively.

The ANN model data undergo training and validation. The testing set was used to measure the performance of the network in producing the outputs.

The performance plot shows the mean square error (MSE) with respect to the number of epochs. Mean Square Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error. The performance plot indicates MSE in training, testing and validation data.

RESULTS AND DISCUSSION

The performance plot of the ANN is demonstrated in (Fig. 2). The x-axis shows the number of iterations and Y-axis demonstrates the mean square error (MSE). As shown, the MSE becomes minimum as the number of epochs is increasing and there is no major over fitting near epoch 4 (where best validation performance has taken place). A green circle sign (at fourth epoch) indicates that the best validation performance obtained, and three other epochs do not have any effect on the optimization of the result. (Fig. 3) shows the error histogram of the collected data. It

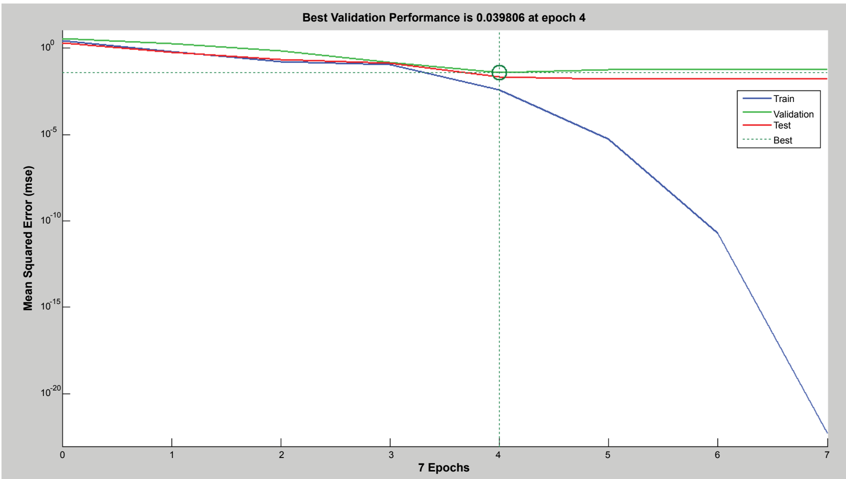

Fig. 2 Performance plot of the ANN model.

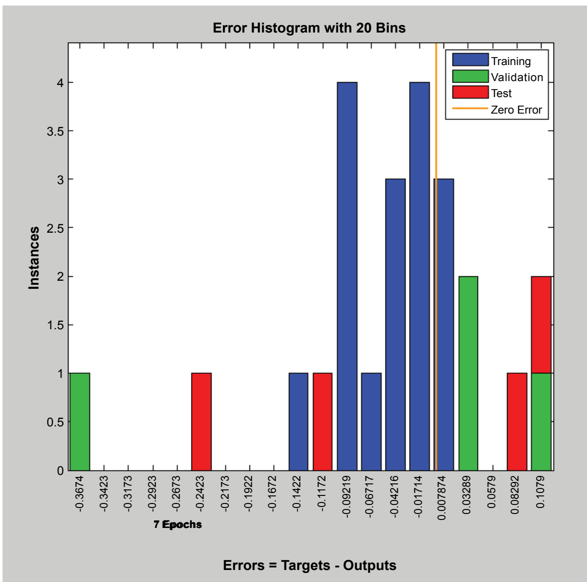

Fig. 3 Error histogram of the ANN model.

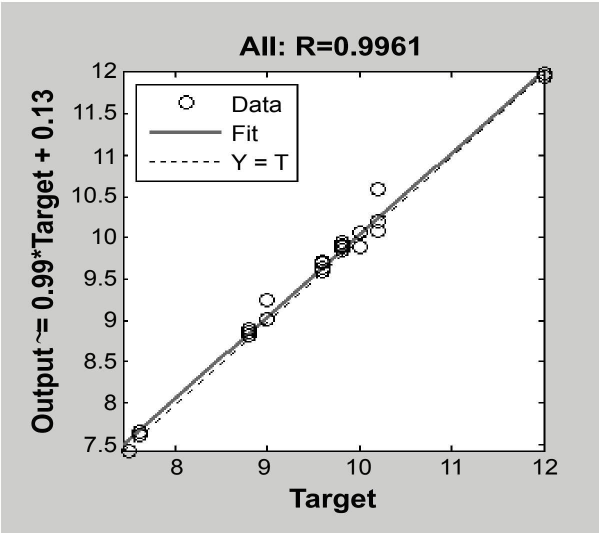

Fig. 4 The regression plot of the ANN model.

illustrates how much the data (training, test, and validation) is belonging to various error values.

The correlation coefficient (R-value) measures the correlation between outputs and targets of the ANN model (Fig. 4). An R value of 1 means a close relationship and 0 for a random relationship. The perfect fit (here R value 0.9961) indicates that the network output is close to targets.

CONCLUSION

System and environmental parameters are affecting the output parameter of the solar stations at different locations in Jordan. The energy output (electricity) has been calculated and investigated, using artificial neural network (ANN). Among many variables identified, statistical analysis showed the relevance of selected parameters to the different outputs. ANN shows comparable results in the prediction of the original experimental data for all the stations and solar cells used. As a result, the energy output increases with the increase in the environmental parameters. ANN is a significant tool to predict the output power (electricity) generated from different solar stations. The results are comparable. The environmental conditions have more effect on the output than the system conditions.

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