Rev. Roum. Sci. Techn.– Électrotechn. et Énerg.
Vol. **68**, *3*, pp. 313–316, Bucarest, 2023

Thermotechnique et thermoénergétique
Thermotechnics and Thermal Energy

DEVELOPMENT OF BACKPROPAGATION ALGORITHM FOR ESTIMATING SOLAR RADIATION: A CASE STUDY IN TURKEY

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Keywords: Solar radiation; Estimation; Artificial neural network; Backpropagation.

Solar energy is vital in replacing fossil fuels and reducing greenhouse gas emissions with significant potential. Engineers, architects, and farmers require accurate information about solar radiation to develop solar energy systems. It is common for meteorological services worldwide to measure the duration of sunshine and air temperature. Despite this, worldwide solar radiation measurements are extremely rare, and some information needs to be included. Estimating solar radiation at sites with no own station becomes vitally critical. In the literature, various models have been developed to estimate solar radiation. The artificial neural network (ANN) model is commonly used to estimate global solar radiation. This study generates a backpropagation algorithm annually to estimate global solar radiation in Adana using the meteorological data obtained from Turkish State Meteorological Services. ANN model was developed using the data for the 2014, 2015, and 2016 years with the MATLAB program. The data for 2017 is used for testing the model. The developed model and real data are compared depending on the R^2 value. As a result of the study, the R^2 obtained by training the data was calculated as 0.9019. The R^2 value derived from test data was calculated as 0.7277. Considering these results, the estimation study was satisfactory.

1. INTRODUCTION

The sun is the most significant energy source for the global ecosystem Solar energy has become an efficient solution to the world's energy challenges and is one of the most important renewable sources. Solar energy is a huge alternative energy source for safety and the environment. It provides energy to the earth more than humankind needs. These properties make it the most significant alternative source of energy in the face of consuming energies [1].

Solar radiation is utilized in the design and evaluation of solar energy devices. For the development, installation, and examination of the performance of solar energy devices, it is necessary to know about solar radiation [2]. In addition, the sizing of photovoltaic systems and the estimation of their performance are provided by reliable and calculated solar radiation data. However, collecting solar radiation data is laborious and costly, leading researchers to forecast and model solar radiation data using meteorological data in different methods [3].

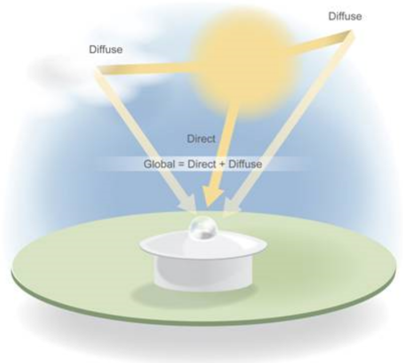

Fig. 1 – Components of global solar radiation.

The entire quantity of solar energy absorbed by the Earth's surface, commonly represented in W/m^2, is known as global solar radiation (GSR). The sum of direct, diffuse, and reflected solar radiation is defined as global solar radiation. Direct solar radiation reaches the Earth's surface directly through the atmosphere, diffuse solar radiation is distributed and reflected solar energy reaches a surface. It is reflected on nearby surfaces [4]. The representation of consisting global solar radiation is shown in Fig. 1. However, because ground-reflected radiation is usually insignificant compared to direct and diffuse, global radiation is said to be the sum of direct and diffuse radiation only as in Equation (1):

$$GSR = Direct\ Solar\ Radiation + Diffuse\ Solar\ Radiation \quad (1)$$

Many different fields of engineering use artificial neural networks. Studies on ANN demonstrate that modeling provides important benefits in interpreting solar radiation data. This is especially true in cases where this data is needed, such as establishing a regional solar power plant. Within this context, ANN is the ideal method to apply. The following is a review of studies that have been published on this topic. Srivastava et al. [5] carried out a study to highlight the importance of solar radiation estimation by integrating solar power plants with conventional power plants. A 6-day solar radiation forecast was made by assigning nine inputs: time, minimum temperature, maximum temperature, average temperature, dew, rain, wind, atmosphere, and azimuth angle. In the ANN, the structure created, a comparison was made using the methods of feedforward, backpropagation, deep learning, and model-averaged neural networks. As a result, the model-averaged neural network gave the best accuracy.

Sivaneasan et al. [6] developed a solar energy estimation algorithm by creating a 3-layer artificial neural network consisting of input, hidden, and output layers with fuzzy logic pre-processing. The accuracy of the proposed estimation algorithm was examined and compared with other artificial neural network algorithms.

A solar forecasting methodology is proposed that aims to pave the way for greater use of solar energy using solar data from the Fortaleza region by Lima et al. [7]; multilayer perceptron (MLP) backpropagation artificial neural network (ANN) was preferred as the estimation method. As a result, this study obtained the best ANN performance as 41.9 % of

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DOI: 10.59277/RRST-EE.2023.68.3.11

the predictions obtained up to 5 % error, and the mean absolute percentage error was 6.11 %.

Ahuja et al. [8] created an ANN using the Levenberg Marquardt algorithm and back propagation concept for solar radiation energy estimation. Although only one hidden neuron layer exists in the system, the average of 2-, 12- and 24-hour data was taken to increase the prediction accuracy. As a result of the article, a successful estimation algorithm with ANN 2.7 % MAPE and 97 % accuracy has been developed.

Mohamed [9] created an artificial neural network model to validate and predict global solar radiation data for three cities in Egypt. The developed ANN structure is based on two algorithms: backpropagation with momentum and learning rate coefficients and basic backpropagation. In conclusion, their study showed that the ANN-based model is an efficient method with higher sensitivity.

In this study, the aim is to estimate the global solar radiation with a backpropagation algorithm for Adana. Solar radiation estimation is a widely discussed topic in the literature, and various methods have been examined to achieve the most accurate results. It is possible to obtain a unique result for each data set, selected input, and method. In this study, an estimation process based on meteorological data between 2014 and 2017 for the Adana region was performed using the backpropagation algorithm. In the continuation of the paper, an error analysis is achieved to observe the accuracy of the developed algorithm. First, specifically solar energy was considered an important renewable energy source. The demand for solar radiation data grew in tandem with the expanding usage of solar energy and the difficulties of acquiring data on solar radiation. Subsequently, some studies on this subject in the literature were included.

The second part of this paper discusses the structure of artificial neural networks and the backpropagation algorithm. Methodology, graphs, and equation models were produced in the third part using MATLAB to illustrate our developed ANN structure. The Results and Discussion section of the paper compares our results with real data. This paper aims to contribute to the literature on estimation topics.

2. **METHODOLOGY**

Artificial neural networks have recently become popular in various usage areas in the literature. It is a useful model in many disciplines, such as pattern recognition, forecasting, clustering, and classification [10]. The purpose of forming artificial neural networks is to develop a machine learning system based on the biological model and activity of the brain [11]. In these neural networks, simple units called neurons connect to form larger structures. The function and behavior of the developed network are determined by the weight values of the connections between neurons [12].

The utilization areas of artificial neural networks can be listed as classification, speech, vision, and pattern recognition and control systems. In this study, artificial neural networks, encountered in many different areas of use, are used in solar radiation estimation. Artificial neural networks, which work by imitating the nervous systems of the human brain, consist of simple elements called neurons that connect and operate. Each neuron processes information by receiving it from other neurons to which it is connected and produces an output signal that is converted to other neurons with the help of an activation function. A specific neuron output results from the weighted input and the activation function. Figure 2 illustrates the working process of an ANN. ANN is described in the flowchart with step-by-step instructions. In Fig. 3, a basic artificial neuron structure is given. The output of any neuron is also created with the help of the following eq. (2) [13]:

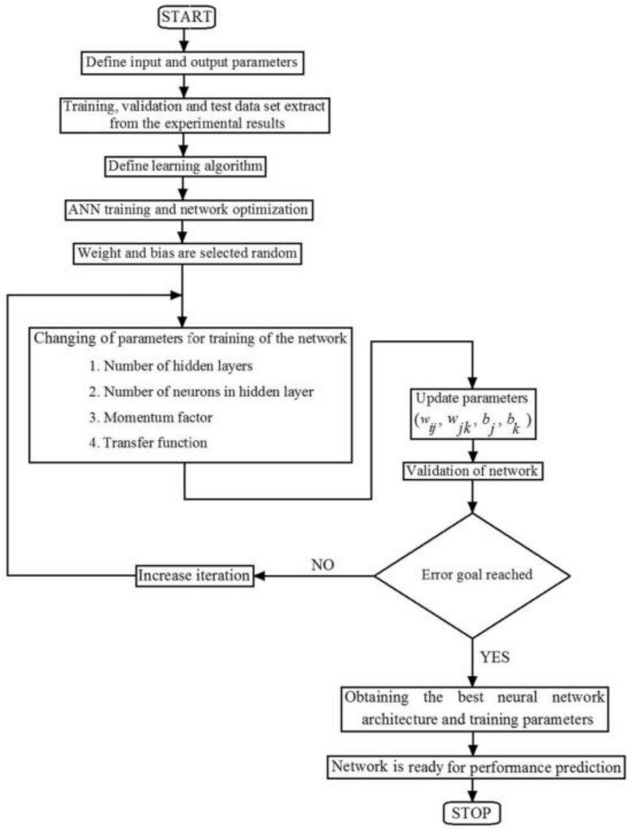

Fig. 2 – ANN flowchart [14].

$$s_i = \Sigma^n{}_{j=1} = x_j w_{ij} + b_j \,, \qquad (2)$$

where $y_j = f(s_i)$.

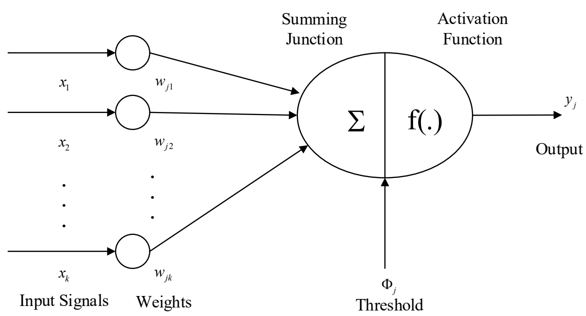

Fig. 3 – Basic structure of a simple artificial neuron.

Backpropagation is an artificial neural network technique that utilizes supervised learning and is popular due to its advantages in the learning process. The backpropagation algorithm is used for training. Backpropagation algorithms are known for their simplicity and ease of application, even when dealing with complex data. The backpropagation algorithm has superior computing properties to other learning algorithms (such as Bayesian learning). The training process for backpropagation neural networks is like that for other neural networks. When performing the training process with backpropagation, the weights are adjusted iteratively to minimize errors [15]. Artificial neural network backpropagation is one of the sub-areas of artificial intelligence appropriate for estimation [16]. The backpropagation (BP) algorithm is one of the most widely used neural network models and has a trained multi-layer feedforward network structure compared to the error BP algorithm. The BP network can be used to learn and store many mapping relationships of the generated model. In addition, the mathematical equation describing these mapping relationships need not be explained beforehand. The BP network adopts the steepest descent method, which adjusts the network's weight value and threshold value to obtain the minimum squared error sum of the learning rule [17].

3. RESULTS AND DISCUSSION

An ANN structure was created using the backpropagation algorithm for the daily global solar radiation estimation using the Adana region meteorological data. In this structure, inputs are taken as daily average temperature, daily average relative humidity, and daily sunshine duration. The dataset used for the estimation is from the Turkish State Meteorological Service. The observed parameter as output is the daily global solar radiation. Figure 4 illustrates the constructed structure in detail. The arrows in red indicate the function of the BP algorithm. With the aim of the ANN structure to perform its function more straightforwardly, the dataset used is normalized by assigning values between 0 and 1.

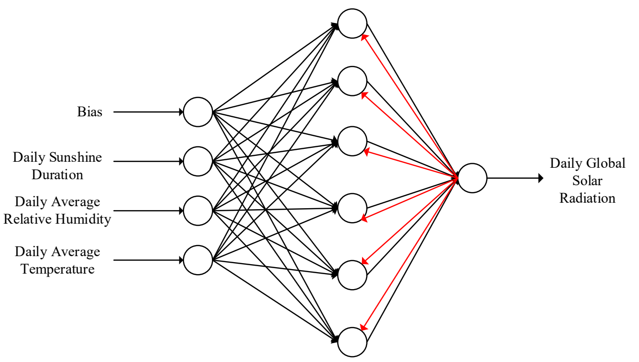

Fig. 4 – ANN structure of estimating daily global solar radiation with BP algorithm.

2014, 2015, and 2016 data were used as train datasets, and 2017 data were considered test data. As a result of the ANN structure developed by using the MATLAB program, the graphical results of the estimated output and real output values for the trained and tested datasets are shown in Fig. 5, 6.

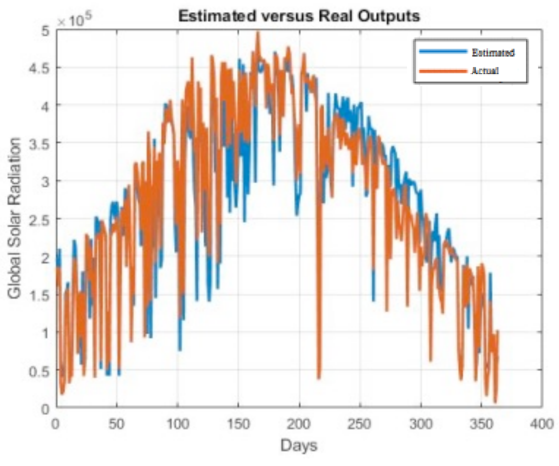

Fig. 5 – Trained estimated outputs *vs* real outputs.

In Fig. 5, estimated outputs and real outputs comparison were achieved. (R) represents the correlation between the predictor variable and the response variable. Consequently, the aim to calculate the error between estimated output and real output coefficient of determination (R^2) value is calculated as ($R \times R$) 0.9019. This value shows that the accuracy of estimation is successful.

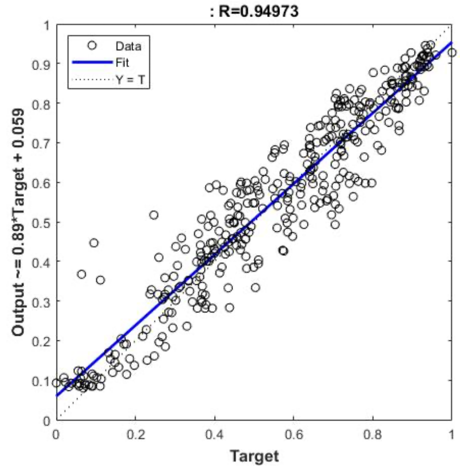

Fig. 6 – R value of the trained dataset.

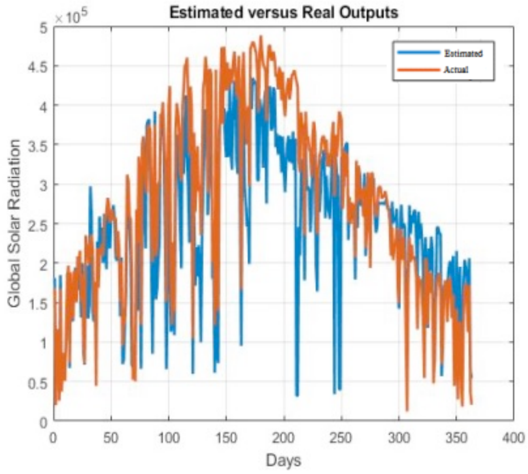

Fig. 7 – Tested estimated outputs *vs* real outputs.

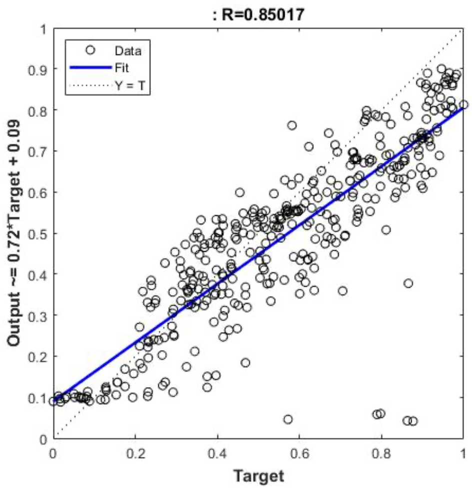

Fig. 8 – R value of the tested dataset.

This value shows that the accuracy of estimation is successful. Fitted linear regression models are referred to as linear models. A regression model describes the connection between a response and a set of predictors. According to the tested dataset results, a linear regression equation has been developed. This equation shows the correlation between the predictor variable and the response variable.

$$y = 0.716x + 0.08974\,. \tag{3}$$

Data from 2014, 2015, and 2016 were utilized for training, and estimation was made in the MATLAB program using 2017 data for the testing. A model was developed with the test data, as seen in eq. (3). The y parameter represents the estimated output. The coefficient of determination R value of the developed model was 0.85017.

4. CONCLUSIONS

In this paper, an estimation for daily global solar radiation has been achieved by using 2014-, 2015-, 2016- and 2017-year data of daily sun. The 2017 year is used as test data. Using the MATLAB program, estimated and real outputs of trained and test datasets have been compared. (R^2) values show that the estimation of ANN is accurate with (R^2 = 0.9019) for the trained dataset and (R^2 = 0.7227) for the test dataset. According to the (R^2) value, it is found that our calculations are quite accurate to estimate global solar radiation for Adana. The results demonstrate that the ANN model is highly effective at accurately predicting daily global solar radiation, with high accuracy in both the trained and test datasets. The comparison results showed that the outputs of the ANN model were very close to the real outputs. This indicates that the ANN model could accurately estimate the global solar radiation for Adana province.

Received on 28 January 2022

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