ESKİŞEHİR TECHNICAL UNIVERSITY JOURNAL OF SCIENCE AND TECHNOLOGY
A- APPLIED SCIENCES AND ENGINEERING

2023, 24(2), pp. 141-154, DOI: 10.18038/estubtda.1184918

RESEARCH ARTICLE

MODELLING OF DIFFERENT MOTHER WAVELET TRANSFORMS WITH ARTIFICIAL NEURAL NETWORKS FOR ESTIMATION OF SOLAR RADIATION

Kübra KAYSAL[1,*], Fatih Onur HOCAOĞLU[2]

[1,2] Electrical Engineering Department., Engineering Faculty, Afyon Kocatepe University, Afyonkarahisar, Turkey

ABSTRACT

In recent years, the interest in renewable energy sources has increased due to environmental damage and, the increasing costs of fossil fuel resources, whose current reserves have decreased. Solar energy, an environmentally friendly, clean and sustainable energy source, is one of the most important renewable energy sources. The amount of electrical energy produced from solar energy largely depends on the intensity of solar radiation. For this reason, it is essential to know and accurately predict the characteristics of the solar radiation intensity of the relevant region for the healthy sustainability of the existing solar energy systems and the systems planned to be installed. For this purpose, a two-stage forecasting model was developed using the hourly solar radiation intensity of 2014 in a region in Turkey. In the first stage of the study, the second month of each season was selected to investigate the seasonal effects of the region and large, medium, and small-scale events in the study area were examined using discrete wavelet transform. The performances of different mother wavelets in the Artificial Neural Network model with Wavelet Transform (W-ANN) are compared in the second stage. July, the most successful estimation result in seasonal solar radiation intensity was obtained. The most successful RMSE values for January, April, July and October were 65,9471W/m^2, 74,3183 W/m^2, 54,3868 W/m^2, 78,4085 W/m^2 respectively, the coiflet mother wavelet measured it.

Keywords: Artificial neural networks, Wavelet transform, Mother wavelets, Solar radiation estimation

1. INTRODUCTION

Energy has a vital role in the development of countries and in raising the welfare level of humanity. Various factors such as advancing technology, increasing population and industrialisation are increasing the energy need in the world. In the development of countries, an uninterrupted, cheap, and high-quality energy supply is needed. In daily life, energy is used in various ways such as kinetic, mechanical, electricity, heat, hydraulic, solar, and wind. These types of energy are obtained from various sources by different methods. Energy sources are obtained from fossil fuel and renewable energy sources [1,2]. Most of the world's energy needs are met by fossil fuels. In our country, a large part of the energy consumption is obtained from fossil fuels such as lignite and oil. In addition to the negative effects of these resources, which have high costs, on the country's economy, it is foreseen that their current reserves will be depleted shortly. In addition, considering the harmful effects of fossil fuel sources on the environment, such as air pollution, acid rain, and climate change, it is thought that renewable energy sources, which are cleaner and sustainable, will increase the share of production [3,4].

Solar energy, one of the renewable energy sources, is a low-cost, high-energy potential and environmentally friendly energy type. This energy, whose usage area is increasing day by day, has started to be the focus of researchers with various studies such as solar energy, electricity production estimation, hydrogen production, and increasing the efficiency of photovoltaic systems [5]. For this reason, it is envisaged that large-scale photovoltaic power plants will be widely established with developing technology and investment support. Solar radiation estimation is an essential factor of

*Corresponding Author: kubra543@hotmail.com
Received: 05.10.2022 Published: 21.06.2023

photovoltaic systems that are used effectively in energy production. While solar radiation directly affects efficiency, it has an essential place for investors in terms of proper planning, system installation, design and sustainability [6,7]. Solar energy varies according to regional, temporal and weather events. Due to this variable structure, problems such as voltage fluctuations and instability arise in the network and reduce the reliability of electricity generation from solar energy [8]. For this reason, establishing accurate and reliable models to predict solar radiation intensity has been a popular research topic from past to present and it continues to inspire researchers to develop various prediction models.

Gabralı [3] performed the prediction modelling of wind and solar energy potential with Wavelet Transform Artificial Neural Networks (W-ANN) in his study. In the study, first of all, the input data is divided into subcomponents by wavelet transform. The correlation values between the obtained sub-components were calculated, and the component with high correlation was given as the input of the Artificial Neural Network (ANN). The results obtained from the W-ANN model were successful compared to the ANN model created without transformation. Guermoui et al. [9] have estimated solar radiation using daily temperature data for the Algerian region. The study estimated solar radiation intensity using the support vector machine model corrected with 3-year temperature data. The results were found to be quite successful. Mohammadi et al. [10] used the Wavelet Transform-Support Vector Machine model for solar radiation intensity estimation in their study, in which they contributed to the literature. The success rate of the proposed hybrid model was 97.4%, higher than the other models. According to Falayi et al. [11] performed wavelet power spectrum analysis for Nigerian solar radiation studies. The results of the tests show that the aperture coefficient and sunshine duration stand out with high wavelet coefficients, while turbidity and cloudiness increase in low wavelet coefficients. According to the results, it was seen that cloudiness has a significant effect on solar radiation. Ferkous et al. [12] proposed the Wavelet-Gaussian Process Regression model for solar radiation estimation. For the analysis, 4 years of real-time solar radiation data from the Algerian region is used. Different types of mother wavelet models were established, and the results were compared. The best result in estimation was obtained with the coiflet1 mother wavelet. Belmahdi et al. [13] estimated one month ago solar radiation using time series models. Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models were used for forecasting. It has been determined that the ARIMA model is suitable for the city of Tetouan in estimating solar radiation. According to Rabehi et al. [14] created a prediction model using a new hybrid combination of these methods with enhanced Decision Trees, Multilayer Perceptrons, and Linear Regression in their study. The study used input data such as extraterrestrial radiation, daily minimum and maximum average temperatures, and sunshine duration ratio to estimate daily solar radiation. The multilayer sensor model has been identified as suitable for solar radiation estimation. In their study, Faisal et al. [15] made a radiation estimation using the solar radiation intensity data they measured from five different cities in Bangladesh. In analysis, three various networks have been developed, namely Recurrent Neural Network (RNN), Long-Short-Term Memory (LSTM), and Gated Repetitive Unit (GRU). The performance of the developed models was compared according to the Mean Absolute Percent Error (MAPE) performance criterion. As a result, GRU gave the best result among the three models, with an error value of 19.28%. Belmahdi et al. [16] compared the performance of various machine learning methods for solar radiation estimation. Global solar radiation data measured at Abdelmake Faculty of Science was used in the study. The most successful performance was obtained from Feed Forward Neural Networks (FFNN) and the ARIMA model among the various selected machine learning algorithms. Malik et al. [17] used ANN algorithms for solar radiation and wind speed estimation. The study discusses the benefits and limitations of various ANN models. As a result of the study, it has been seen that Levenberg Marquardt and Bayesian algorithms are very effective in estimating nonlinear properties such as solar radiation and wind speed. On the other hand, Monjoly et al. [18] estimated one hour after solar radiation using wavelet decomposition method, and various multiscaling decomposition models. As a result of the study calculated the rRMSE value for the Wavelet Decomposition and ANN hybrid prediction model as 7.86%, and the success value as 72.08%.

Some researchers have used a single estimation method for solar radiation estimation. For example, Wang et al. [19] used the ANN model to estimate the solar radiation intensity considering different weather conditions. In another study, Wang et al. [20] used a directly explicable neural network-based model to predict solar radiation intensity using meteorological, geographic, and time series data. Husein and Chung. [21] used the LSTM model for solar radiation estimation. Mutavhatsindi et al. [22] used Feedback Artificial Neural Network (FFNN), LSTM, and Support Vector Regression to estimate solar radiation intensity. Experiments proved that the FFNN model was more successful. Researchers have designed hybrid models to solve solar radiation prediction problems in recent years. Singla et al. [23] estimated solar radiation using deep learning methods based on Wavelet transform. As a result of the experiments, the Wavelet-Bidirectional LSTM deep learning model was found to be more successful. Meng et al. [24] proposed a new smart hybrid model for solar energy prediction using wavelet transform package and Generative Adversarial Networks (GANs). Guermoui et al. [25], a hybrid model of support vector machine and artificial bee colony algorithms, applied for global solar radiation estimation, and successful results were obtained. Huang et al. [26] used hybrid deep neural networks with wavelet transform for hourly solar irradiance estimation. The method yielded successful results.

In summary, single and hybrid forecasting methods are frequently used in solar radiation forecasting. However, all methods have advantages and disadvantages. Although single estimation methods give successful results in estimation, estimation accuracy is not as high as hybrid methods. Hybrid models are relatively robust, but it is difficult to determine the appropriate structure. An advanced prediction technology should be designed by examining the characteristic structure of solar radiation with variable characteristics very well. This study aims to investigate the potential of solar energy and predict solar radiation intensity using the Wavelet Transform Artificial Neural Network (W-ANN) model. The significance of energy resources for the advancement of energy and the development of nations is underscored. However, factors such as advancing technology, increasing population, and industrialization contribute to the growing demand for energy. Consequently, there is a pressing need for a continuous, cost-effective, and reliable energy supply. Solar energy is a cost-effective, high-potential, and environmentally friendly type of renewable energy. The utilization of this energy source is expanding day by day, and research related to solar energy is focused on various aspects such as solar energy generation, electricity production forecasting, hydrogen production, and improving the efficiency of photovoltaic systems. Solar radiation estimation is an important factor for effectively utilizing photovoltaic systems in power generation. Solar radiation, which directly impacts efficiency, holds a significant position for investors in terms of proper planning, system installation, design, and sustainability. It is known that current prediction models face challenges in terms of accuracy and reliability. Due to the variable nature of solar energy, issues such as voltage fluctuations and network instability arise, thereby reducing the reliability of electricity generation from solar energy. Hence, the development of precise and dependable models for estimating solar radiation intensity has been a popular research topic throughout history, motivating researchers to explore various prediction models.

This study aims to examine the solar radiation intensity characteristics seasonally for the design of solar energy systems in a particular region. Another aim of the study is to compare the performance of different types of mother wavelets in solar radiation intensity prediction for the Wavelet Transform Artificial Neural Network prediction model. For these purposes, one-year real-time solar radiation data were analysed with the help of wavelet transform. The solar radiation intensity data in the study area was arranged seasonally and the events affecting the potential of this energy were tried to be determined. In addition, hourly frequency short-term forecasting was carried out with solar radiation data. In the two-stage forecasting model, in the first stage, the data are analysed with different types of mother wavelet models, and divided into approximation and detail components. Obtained detail components were presented as input to the ANN model. MATLAB R2020a software was used to create models and test data. According to the results obtained, the most successful result for the W-ANN model was measured with the coiflet1 mother wavelet. This study was conducted to make an important contribution to solar radiation forecasting by evaluating the performance of different forecasting methods, and understanding seasonal variability for solar system design. In addition, he is investigating the use of advanced forecasting technologies such as wavelet transform and artificial neural networks in solar radiation estimation.

2. MATERIAL AND METHODS

2.1. Dataset

In this study, solar radiation intensity data from the Turkish Meteorology General Directorate (TMGM) measured between January 1, 2014 and December 31, 2014 belonging to the Van region were used. A total of 8760 real-time data at an hourly frequency were analysed with the help of various wavelet transforms, and trained with Artificial Neural Networks. 80% of the 8760 data were used as training data, and 20% were used as test data. When the hourly data given in Figure 1 are examined, it is observed that the solar radiation intensity does not have a certain trend, and shows sudden changes due to various reasons.

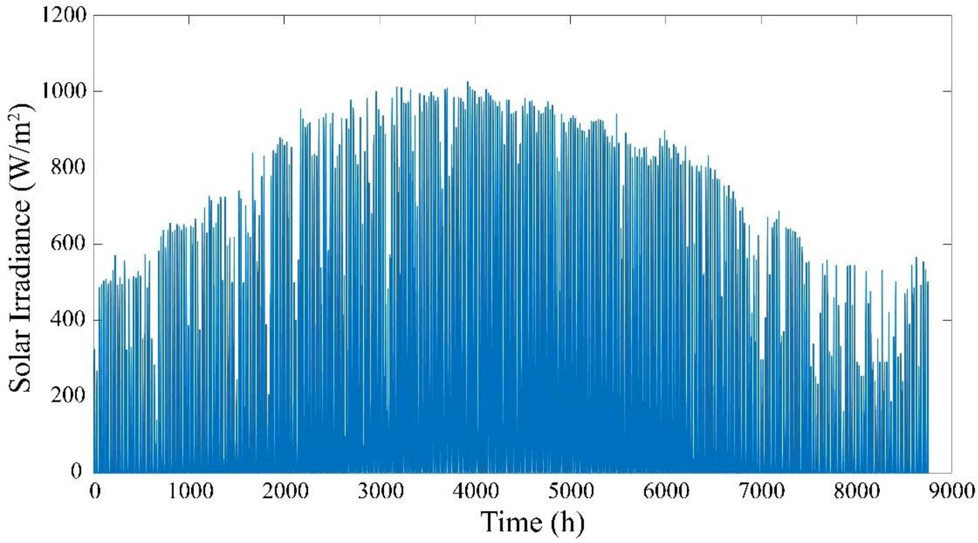

Figure 1. Hourly solar irradiance data between January 1, 2014, and December 31, 2014

2.2. Wavelet Transform

One of the widely known methods of signal processing is the Fourier transform. The most significant disadvantage of the Fourier transform is that time information is lost while obtaining information on the frequency axis. Time information in variable structured signals is essential for establishing and testing various systems. Unlike the Fourier transform, the wavelet transform allows a signal to be studied in both frequency and time axis. With the wavelet transform, it is possible to calculate both the high and low-frequency components of the signal in a specific time interval. In this way, the examination of the systems whose frequency changes over time, and the analysis of their instantaneous changes can be done very sensitively [27].

Wavelet transform decomposes a signal or data into wavelets at various stages. The most important parameter of this transformation is the mother wavelets. The signal is multiplied by a function called the master wavelet, which can be translated in time, and changed in width. Some mother wavelet functions used in wavelet transform are given in Figure 2.

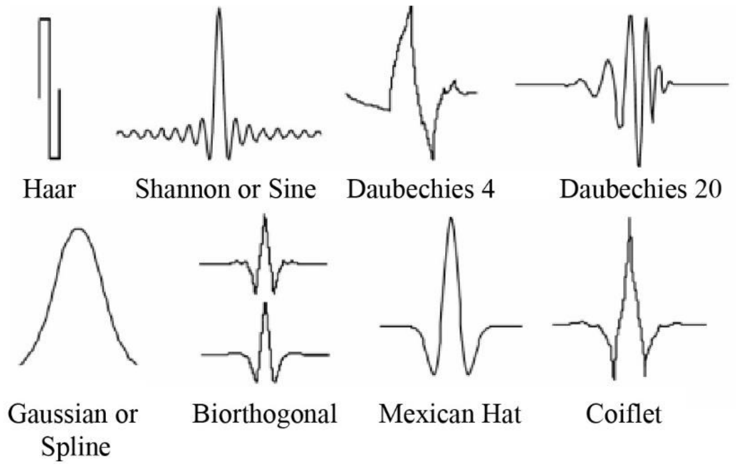

Figure 2. Various mother wavelets [28]

Discrete wavelet transform (DWT) has the advantage of calculating the wavelet coefficients at the selected scale and time interval. This way, the processing load caused by forming many coefficients will be reduced. The DWT function, which is re-expressed with the selected scale value, and used for the discrete wavelet transform, is given in equation 1 [29,30].

$$W_{m,n}\left(\frac{t-\tau}{s}\right) = s_0^{-m/2} W\left(\frac{t-n\tau_0 s_0^m}{s_0^m}\right) \tag{1}$$

In the equation, τ is the translation value, s is the scaling value, W is the mother wavelet transform function, m is the wavelet's translation, and n is the scaling parameter. s_0 is the shift step, and its value is greater than 1. τ_0 is the translation value in the time axis. The decomposition process of the signal repeats sequentially, and makes it possible to decompose it to the desired level [30]. The sequential iteration process is shown in Figure 3.

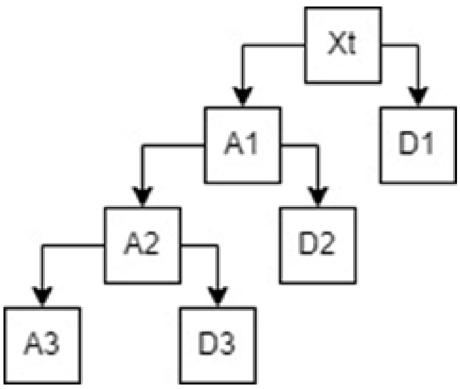

Figure 3. Sequential decomposition analysis

The decomposed signal (x_t) value is expressed in equation 2 according to the decomposition level.

$$\begin{aligned} x_t &= A_1 + D_1 \\ &= A_2 + D_2 + D_1 \\ &= A_3 + D_3 + D_2 + D_1 \end{aligned} \tag{2}$$

A low pass and high pass filter are used to decompose the time series signal. As a result, the signal is divided into one approximation (A) component, and as many detail (D) components as it is decomposed from the level. Low-frequency values in the signal give the approximation component, while high-frequency values give the detail components [31]. While low-frequency components reveal the seasonal changes in solar radiation intensity or the climatic character of the region, high-frequency components mostly reflect the characteristics such as suddenly changing cloudiness.

2.3. Artificial Neural Networks

Artificial neural networks are structures that have been developed inspired by the structure, and operation of the human brain. They are connected to each other by connections with various neuron structures and weights. ANNs are computer programs that mimic biological nerve cells. They can self-learn, memorise, and establish relationships between information [32]. A simple neural network consists of an input layer, a hidden layer, and an output layer. An example of ANN is given in Figure 4.

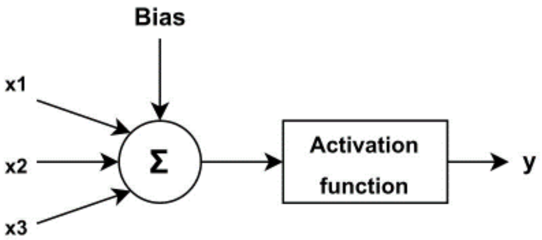

Figure 4. ANN Model

In an ANN model, each input value is multiplied by its own weight (w) and summed. The total value is applied to an activation function, and the output value is obtained. Starting from the explanation, equation 3 is obtained [33].

$$y = \sum_{i=1}^{N} x_i * w_i \tag{3}$$

In the equation, y represents the output value, x represents the input value, and w represents the weights. It is observed in various studies in the literature that pre-processing the input data increases the prediction success in ANN models [34]. To increase the prediction success in the study, a hybrid model was created by using wavelet transform and artificial neural networks together. In this context, a short-term estimation study was made for the solar radiation intensity in the study. In the W-ANN model, Haar, Coiflet (Coif1), Daubechies (Db1) and Symlets (Sym1) mother wavelet functions, which are frequently used in the literature, are used to evaluate the predictive performance of various mother wavelets used in wavelet transform [31].

3. APPLICATION AND RESULTS

In this section, a seasonal analysis of solar radiation intensity has been carried out to design solar energy systems in a particular region. Detail components obtained from various mother wavelet functions are presented as input to artificial neural networks, and short-term solar radiation intensity estimation is made.

3.1. Data Exploration

In the first stage, in order to reveal the seasonal effects of the solar radiation intensity data measured between January 1, 2014 and December 31, 2014, the second month of each season was selected, and analyzed on a monthly basis. April representing the spring, July representing the summer, October representing the autumn, and January representing the winter season were selected, and the events affecting the temporal change of solar radiation intensity were examined. Removing other months from the data reduces the processing load in wavelet transform and modelling process. In the second stage, to see the effects of different mother wavelet analyses on the prediction performance, discrete wavelet analysis was applied to the solar radiation intensity data for April, July, October and January with four different mother wavelet functions. In the third stage, the detail components of the signal, which are divided into approximation and detail components with different mother wavelet functions, are presented as input to the ANN model. In the ANN model, 80% of the input data was used as training data and 20% as test data.

Root Mean Square Error (RMSE) error criterion was used to evaluate the performance of W-ANN hybrid models. The RMSE formula is given in equation 4.

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}(y_n - \widehat{y_n})^2}{N}} \tag{4}$$

In the equation, y_n is the actual value observed in time in the data, and $\widehat{y_n}$ is the predicted value.

3.2. Wavelet Analysis Results

In the study, the second month of each season was chosen to represent the four seasons. April, July, October and January data are separated from the main data. Since the data is recorded in hourly periods, there are between 720 and 744 data records in a month, depending on the months with 30 or 31 days. No data loss was observed within months. The discrete wavelet transforms investigated large, medium and small-scale events in the study area. The original data s is represented by the approach component a and the detail component d. Of the detail components, $\boldsymbol{d_1}$ small, $\boldsymbol{d_2}$ medium and $\boldsymbol{d_3}$ describe large-scale events. Large-scale events have low frequency and long period, while small-scale events have high frequency and short period [3].

Figure 5 shows the detail and approximation components as a result of the discrete wavelet analysis of solar radiation intensity for April. There is a periodicity in solar radiation intensity throughout the month. The solar radiation intensity decreased on the 10th, 13th and 20th days of the month. The effect of all scale events can be mentioned during the month under review.

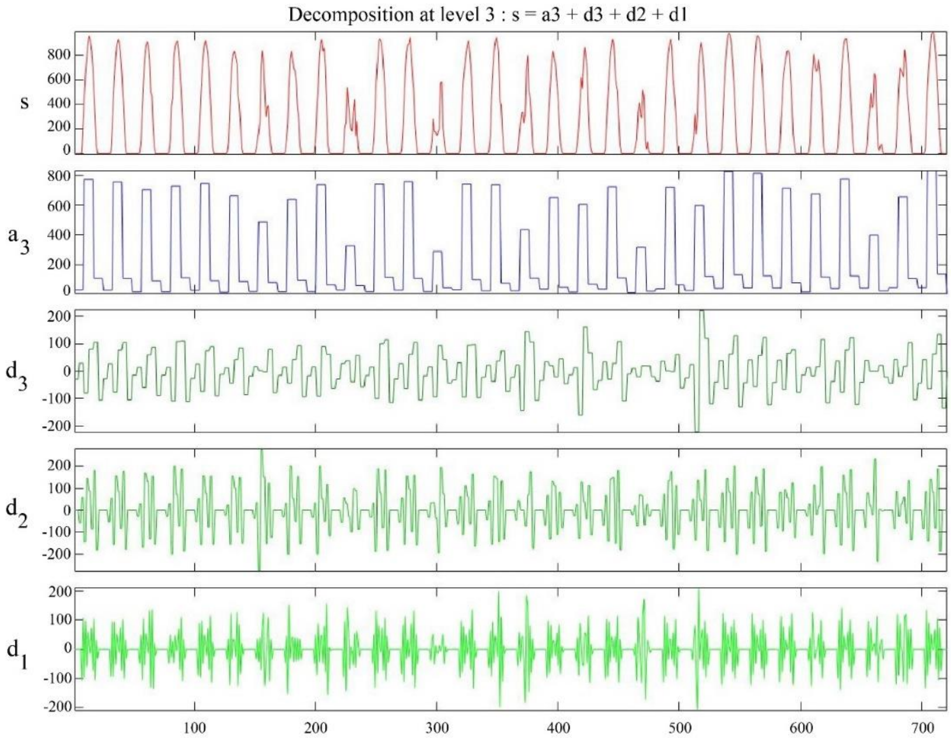

Figure 5. Discrete wavelet analysis of solar radiation intensity for April

Figure 6 shows the detail and approach components as a result of the discrete wavelet analysis of solar radiation intensity for July. On the 5th and 23rd days of the examined month, a decrease in solar radiation intensity occurred with the effect of large and small-scale events.

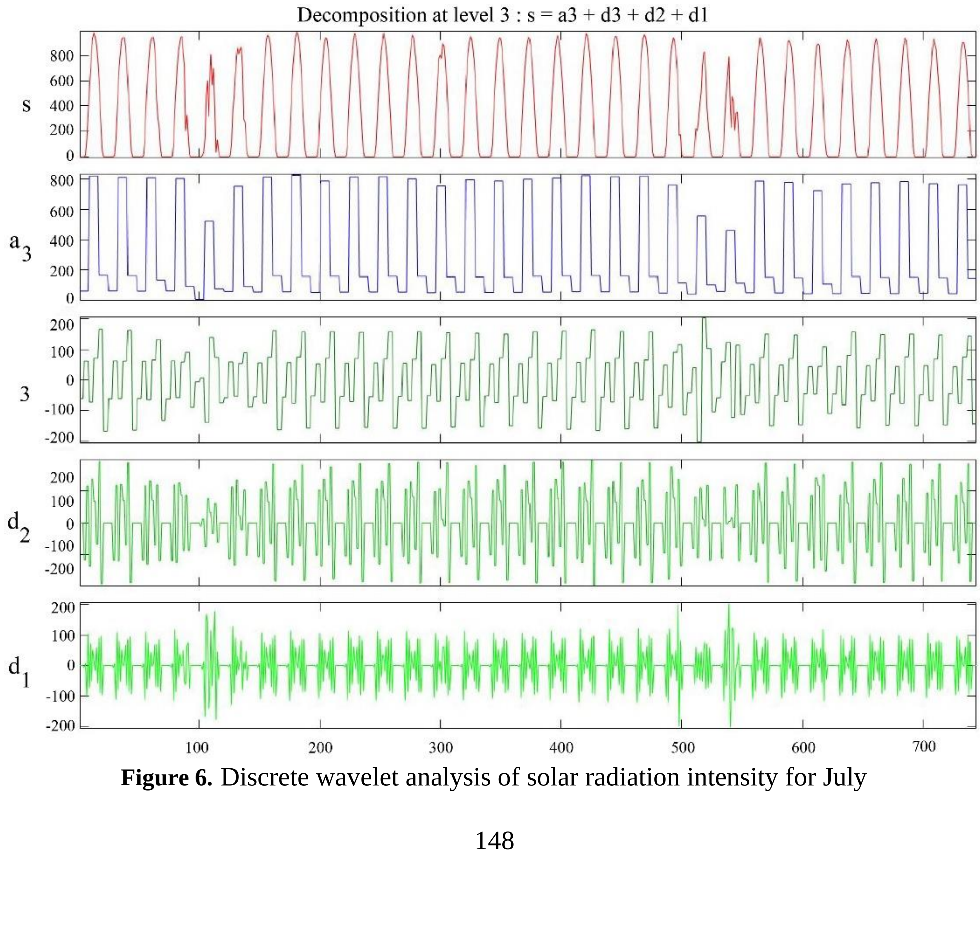

Figure 6. Discrete wavelet analysis of solar radiation intensity for July

Figure 7 shows the detail and approach components as a result of the discrete wavelet analysis of solar radiation intensity for October. It is seen that there is a decrease in the solar radiation intensity in the middle of the month examined and the events in all three scales have an effect.

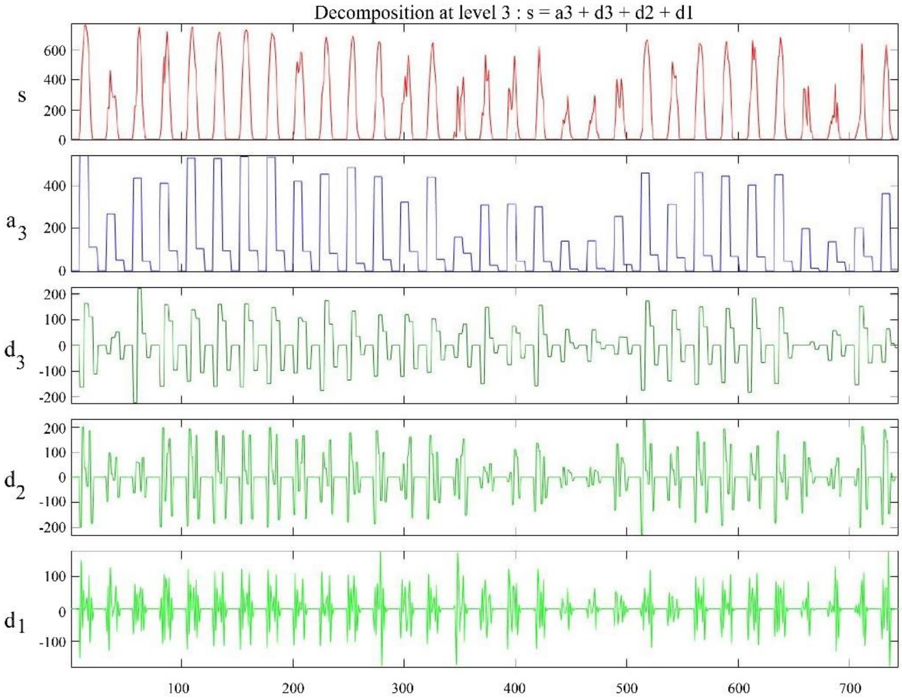

Figure 7. Discrete wavelet analysis of solar radiation intensity for October

Figure 8 shows the detail and approximation components as a result of the discrete wavelet analysis of solar radiation intensity for January. The effect of small-scale events can be seen on the first two days of the month and the 26th-28th days of the month.

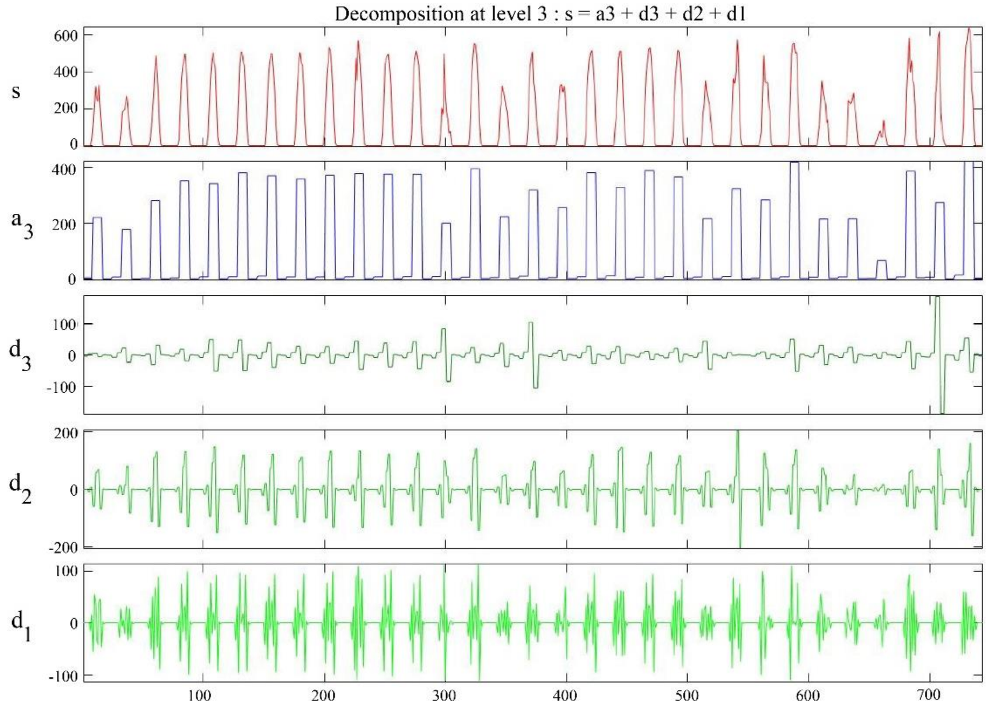

Figure 8. Discrete wavelet analysis of solar radiation intensity for January

3.3. W-ANN Estimation Results

In this study, the W-ANN model's data were first divided into subcomponents with four different mother wavelet transforms. The aim is to observe which mother wavelet gives more effective results in the ANN model. The data is subdivided, each from Level 5, using sym1, db1, haar, and coif1 mother wavelets. Each subcomponent was used as input for the ANN model. Thus, for each mother wavelet component, the short-term solar radiation intensity was estimated in the ANN model, and the most suitable mother wavelet type for the model was determined. In Figure 9-12, the Coif1 mother wavelet and the observation-forecast graphs of the months obtained from the ANN are given.

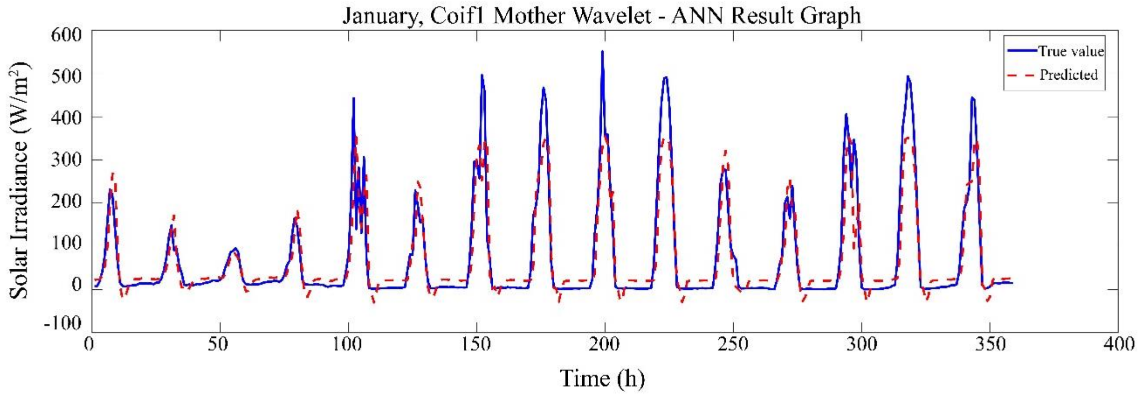

Figure 9. Coif1 mother wavelet ANN observation-predict graph for January

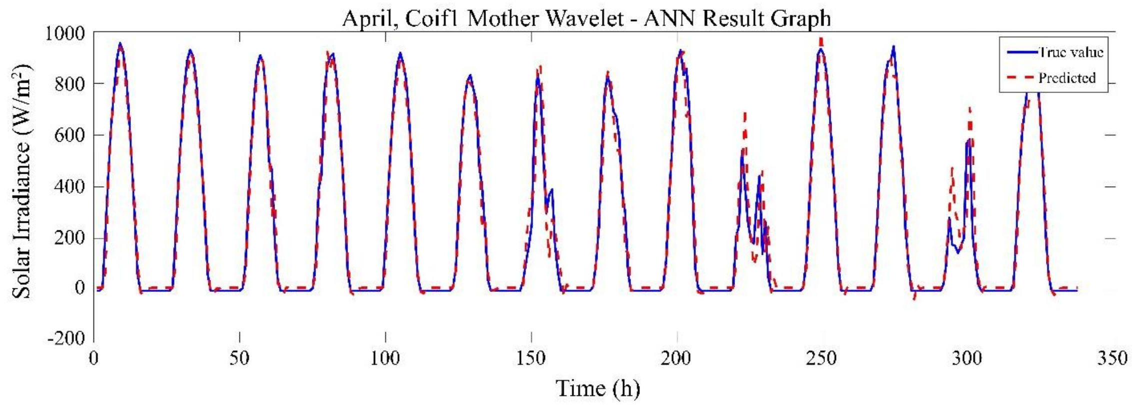

Figure 10. Coif1 mother wavelet ANN observation-predict graph for April

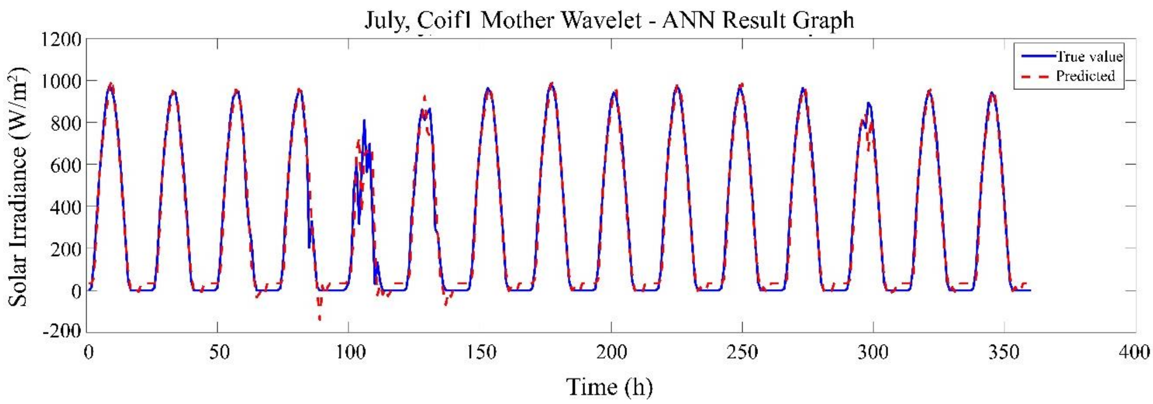

Figure 11. Coif1 mother wavelet ANN observation-predict graph for July

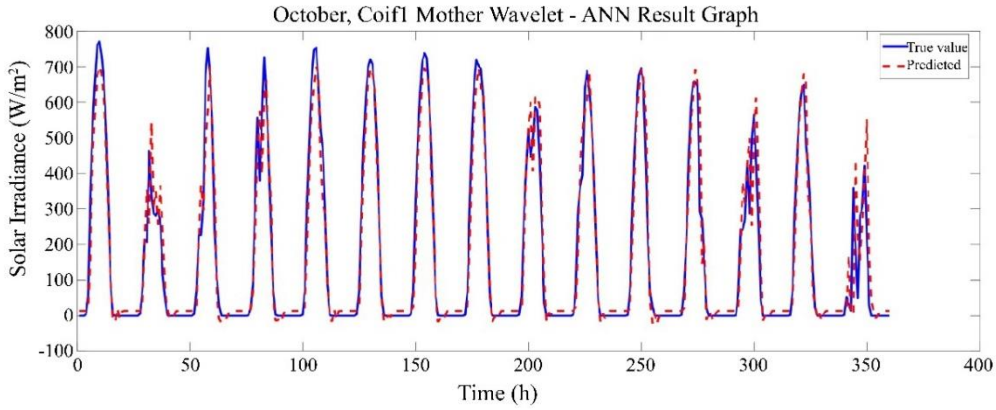

Figure 12. Coif1 mother wavelet ANN observation-predict graph for October

4. DISCUSSION

In this study, data separated from the fifth level to its sub-components with four different main wavelet transforms are presented as input to the ANN model. The short-term solar radiation was estimated with each main wavelet presented to the artificial neural network. The RMSE values of the model were calculated to determine the most suitable main wavelet type. The error values of the ANN models created with each mother wavelet are shown in Table 1. According to the results, in the estimation study of wavelet transform ANN models, the Coif1 mother wavelet was more successful for all selected months. The best results every month were obtained from July.

Table 1. Comparison of solar radiation (W/m^2), mother wavelet ANN error values

Months	Mother Wavelet-ANN Model RMSE Results (W/m^2)			
	Sym1	**Db1**	**Haar**	**Coif1**
January	67,9561	79,8354	74,3543	**65,9471**
April	74,5663	75,0166	85,9196	**74,3183**
July	61,3040	56,1864	58,2133	**54,3868**
October	84,1517	82,1218	80,1521	**78,4085**

The general results of the study are as follows:

1- In the study, periodic patterns of solar radiation intensity in four different seasons were examined using discrete wavelet analysis.
2- Solar radiation intensity data of April, July, October and January are separated, and detail and approximation components are obtained by wavelet analysis.
3- The detail components d1, d2 and d3 represent large, medium and small-scale events.
4- Periodicity was observed in solar radiation intensity in April, and decreases were detected on the 10th, 13th and 20th days.
5- In July, on the 5th and 23rd days, the solar radiation intensity decreased due to large and small-scale events.
6- In October, there was a decrease in solar radiation intensity around the middle of the month, and the effects of events at all scales were observed.
7- In January, the effects of small-scale events were observed on the first two days and on the 26th to 28th days.
8- According to the W-ANN prediction results, the Coif1 wavelet yielded more successful results compared to other wavelet types.
9- Among all months, the best prediction results were obtained for the month of July.

This study emphasises that the modelling should be done seasonally and monthly as much as possible to obtain reliable and successful results in solar radiation intensity estimation studies, since meteorological events vary seasonally. In addition, early warning systems against fluctuations in solar energy systems with variable characteristics can be developed by developing estimation models that can obtain reliable and accurate results with W-ANN models with different mother wavelet structures designed in the study. It is expected that the results obtained in this study will increase the efficiency of solar energy systems, and will also be a roadmap for the systems planned to be established for the active region and other regions with similar characteristics to this region in the future. These results show that discrete wavelet analysis and W-ANN model are an effective method to understand and predict the periodic patterns of solar radiation intensity in different seasons.

CONFLICT OF INTEREST

The authors stated that there are no conflicts of interest regarding the publication of this article.

AUTHORSHIP CONTRIBUTIONS

Kübra KAYSAL: Conceptualization, Formal analysis, Conception and design of study: analysis and/or interpretation of data, Drafting the manuscript, revising the manuscript critically for important intellectual content, Approval of the version of the manuscript to be published.**Fatih Onur HOCAOGLU:** Conceptualization, Formal analysis, Conception and design of study: analysis and/or interpretation of data, Drafting the manuscript, revising the manuscript critically for important intellectual content, Approval of the version of the manuscript to be published.

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