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Next-Month Prediction of Hourly Solar Irradiance based on Long Short-Term Memory Network

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Abstract

Today, in parallel with the population growth and the advancement of technology, development concerns have started to arise in terms of country administrators. Therefore, alternative solutions to classical energy sources are sought. Renewable energy sources are one of the preferred energy sources today. The popularity of renewable energy sources, including solar energy, is increasing day by day. Solar energy has the potential and accessibility to spread faster than other renewable energy sources. Since Türkiye is located in a region with a high potential in terms of solar energy, which is generally called the sun belt, it is a right decision to prefer solar energy as an energy source in our region. In this study, time series prediction using Long Short-Term Memory (LSTM) Network method is used for short-term solar irradiance estimation. In order to demonstrate the success of the results, a comparison was made with the Artificial Neural Network (ANN) method. Finally, prediction results of solar irradiance were compared with statistical tests and error analyzes were given in numerically.

Keywords: Long short-term memory, Solar irradiance, Time series prediction, Solar energy

Uzun Kısa Dönemli Bellek Ağına Dayalı Saatlik Güneş Işınımının Gelecek Ay Tahmini

Öz

Günümüzde nüfus artışına ve teknolojinin ilerlemesine paralel olarak ülke yöneticileri açısından kalkınma kaygıları ortaya çıkmaya başlamıştır. Bu nedenle klasik enerji kaynaklarına alternatif çözümler aranmaktadır. Yenilenebilir enerji kaynakları günümüzde önerilen enerji kaynaklarından biridir. Güneş enerjisi de dahil olmak üzere yenilenebilir enerji kaynaklarının popülaritesi her geçen gün artmaktadır. Güneş enerjisi, diğer yenilenebilir enerji kaynaklarından daha hızlı yayılma potansiyeline ve erişilebilirliğine sahiptir. Türkiye genel olarak güneş kuşağı olarak adlandırılan güneş enerjisi potansiyeli yüksek bir bölgede yer aldığından bölgemizde enerji kaynağı olarak güneş enerjisini tercih etmek doğru bir karardır. Bu çalışmada, kısa dönem güneş ışınımı tahmini için Uzun Kısa Süreli Bellek (LSTM) Ağı yöntemi kullanılarak zaman serisi tahmini kullanılmıştır. Sonuçların başarısını ortaya koymak için Yapay

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Sinir Ağları (YSA) yöntemi ile karşılaştırma yapılmıştır. Son olarak güneş ışınımının tahmin sonuçları istatistiksel testlerle karşılaştırılmış ve hata analizleri sayısal olarak verilmiştir.

Anahtar Kelimeler: Uzun kısa süreli hafıza, Güneş ışınımı, Zaman serisi tahmini, Güneş enerjisi

1. INTRODUCTION

One of the causes of many negative natural events experienced today is the climate crisis that has arisen due to carbon emissions. More and more fossil fuels are used to increase the increasing energy demand, and so the amount of carbon released to nature increases. Energy is an important factor for the continuity of nature and social life. As a result of the increase in the amount of greenhouse gas emissions due to human activities and the change in the concentration of natural greenhouse gases, the problem of climate change has reached significant dimensions. Climate change due to global warming is cited as a cause of many problems, from melting glaciers to changes in climate zones, from drought to changes in the ecological system. Solutions to this problem are being sought on both a global and national level. One of the recommended methods to meet the great demand in the energy field today is the use of renewable energy sources. Countries encourage the use of renewable energy because it is "clean energy". Recently, carbon border adjustment mechanism has come to the fore as a solution to the carbon emission problem. Companies doing business with industrialists in the EU are interested in this issue. When they use carbon emission-based methods during their production processes, they will face some sanctions during export. For this reason, companies are searching ways to meet their energy needs with more environmentally friendly methods.

Considering the climatic conditions and geography of Türkiye, the use of renewable energy sources is also important in reducing environmental problems caused by greenhouse gas emissions and reducing foreign dependency in the field of energy. Many countries, including Türkiye, are developing different applications to increase the use of environmentally friendly and sustainable energy sources. Solar energy is one of Türkiye's main renewable energy sources [1]. With the widespread use of solar energy, many studies are made today on the estimation of solar radiation values. In this study, long short-term memory (LSTM) method, which is one of the deep learning approaches that has been used frequently in recent years, has been applied for the estimation of hourly values of the solar radiation in our country.

There are many studies on solar radiation in the literature. Angstrom was the first to propose the idea that the intensity of solar radiation could be calculated [2]. With the energy issue gaining importance day by day, studies in this field have reached different dimensions over time. There are many studies that developed empirical models for solar radiation estimation [3-6]. In addition to the excessive use of Artificial Neural Networks (ANNs) in this field, many data mining techniques are also successfully used to predict solar radiation. To forecast global radiation for Seeb locations, AI-Alawi and AI-Hinai [7] used a multilayer feed forward network. In the study, back propagation method was used to train the artificial neural network. In artificial neural network architectures, the signals that are given to the input layer change depending on the structure of the problem. In this study, mean values of wind speed, and sunshine hours, pressure, relative humidity, temperature, vapor pressure, and location, month were used as signals sent to the first layer. At the end of the study, it is seen that the mean MAPE ranged between 5.43 and 7.30. Solar radiation estimation is studied globally, as well as on a country-by-country and even regional basis. Real data from target regions are generally used in this field. Mellit and Pavan [8] proposed a useful technique for forecasting solar irradiance based on the ANN model, which could estimate the solar irradiance 24 hours in advance using the current values of the mean daily solar irradiance and ambient air temperature. The results obtained at the end of the study were evaluated for sunny and cloudy days. In [9] using latitude, longitude, the number of days in the week, and the sunshine ratio as input variables, Khatib et al developed a multilayer perception model to forecast the clearness index in Malaysia. The neural network used is designed in a feed-forward structure. In Saudi Arabia, Alharbi [10] employed neural networks to estimate solar radiation and compared the results with classical training and Extreme Learning Machines (ELM). Pang et al [11] suggested a recurrent neural network model to research the role of new deep learning techniques in accurate solar radiation prediction. In 2011, the monthly average global solar radiation on a horizontal surface was calculated for the Gusau, Nigeria region [12]. Meteorological data was used as a forecasting method with feed forward back propagation neural network. While solar radiation is used as output parameter, maximum ambient sunshine duration, relative humidity and temperature are used as input signals. The predicted and measured levels of the global sun's radiation are given at the end of the study, emphasizing the success of the method.

In addition to these studies, the LSTM algorithm is applied frequently for solar radiation prediction. Recent developments in the LSTM algorithm offer a new perspective to address this issue. Qing and Niu [13] estimated hourly solar radiation values with the LSTM method, using the weather forecast values of the same time period as input data in their studies. Kara [14] used the LSTM method for the daily solar radiation estimation problem. The data of Çorum - Türkiye region is used and obtained results compared with different machine learning models. When the prediction performance of the LSTM model is compared with traditional machine learning models, it is stated that the LSTM results are more successful. Yildirim et al estimated one-hour-ahead solar radiation with different methods based on neural network using PV data from the Tarsus region in Türkiye in 2023 [15]. Numerical and graphical comparisons made at the end of the study show that the LSTM method is the most successful method for one hour forward solar radiation estimation. In the study in 2023 [16], the LSTM method was preferred to estimate the Global horizontal solar Irradiation (GHI). Real data of Erfoud Moroccan city were used. The major goal is to simultaneously estimate hourly and sub-hourly GHI using only endogenous historical data over different time horizons. Two scenarios have been preferred: a yearly performances scenario that takes into account all climatic conditions and a seasonal performances scenario that distinguishes between the climatic conditions that define each season of the year. In the study, LSTM was compared with NN and (Random Forest) RF methods. Even with the high variability of GHI, the LSTM network is the most robust method. In comparison to ANN models, LSTM has good performance and high stability. In another study in 2023 [17], Short-Term Solar Irradiance estimation was made using three different estimation methods. When the results were examined using various error criteria, it was observed that the isolated convolutional neural network (CNN-1D) and LSTM methods were more successful. In this study, short-term solar irradiance estimation is aimed utilizing time series prediction using LSTM Network approach.

2. MATERIALS AND METHODS

Long Short-Term Memory (LSTM) is a specific recurrent neural network (RNN) proposed by Hochreiter and Schmidhuber for modeling temporal sequences [18]. The backpropagation mechanism used by RNN structures during calculation may cause problems in error backflow, whereas the LSTM method provides long-range dependencies. The memory blocks shown in Figure 1 have an important place during the information flow. In their structures, they contain special multiplying units called gates to control the flow of signal and memory cells that store the temporary state of the network. The gates in the LSTM architecture as follows [19]:

- The forget gate: The forget gate classifies the data as either being kept or being thrown away.
- The input gate: The cells are updated by the input gate.

- The output gate: The next concealed state is decided by the output gate.

Moreover, LSTM features an internal memory unit and gate structure to circumvent the RNN training difficulties of vanishing gradient and exploding gradient.

It is critical to calculate particular values in order for the architecture to function. Assume that the variables f_t for the forget gate, S for the candidate internal state, i_t for the input gate, h_t for the memory cell state, o_t for the output gate and C_t for the internal memory of the unit are all present. Figure 1 displays a few of these variables.

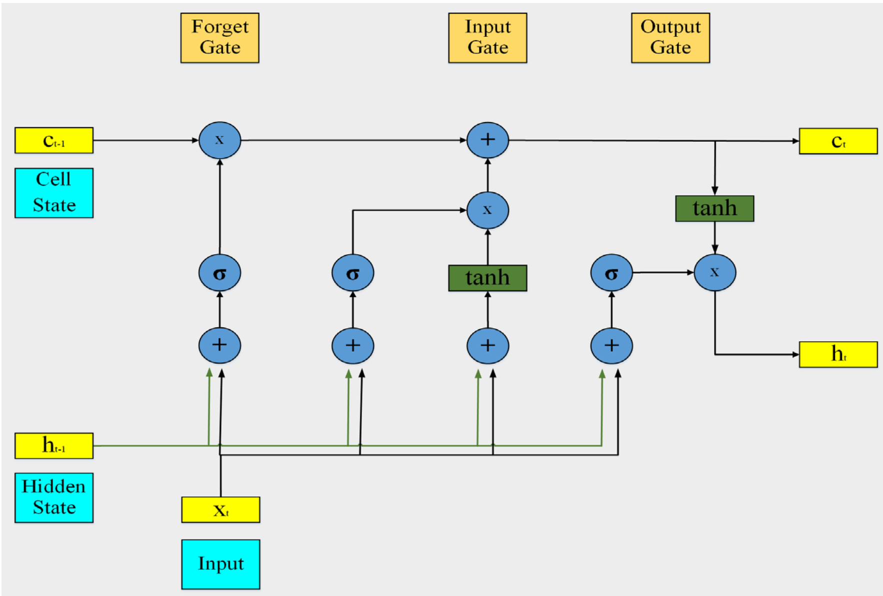


Figure 1. The structure of the LSTM Network method

In this situation, recursive equations of the LSTM method are defined as follows:

$$f_t=\sigma\left(W_f X_t+U_f h_{t-1}+b_f\right) \quad (1)$$

$$i_t=\sigma\left(W_i X_t+U_i h_{t-1}+b_i\right) \quad (2)$$

$$S = \tanh(W_c X_t + U_c h_{t-1} + b_c) \quad (3)$$

$$C_t = i_t S_t + f_t S_{t-1} \quad (4)$$

$$o_t = \sigma(W_o X_t + U_o h_{t-1} + V_o C_t + b_o) \quad (5)$$

$$h_t = o_t \tanh(C_t) \quad (6)$$

Here:

- σ and tanh are the activation functions,
- X is the memory cell's input vector at time t,
- W_i, W_c, W_o, W_f, U_c, U_i, U_f, U_o, and V_o are weightes of the neural wetwork.
- b_f, b_c, b_i, and b_o are biases.

In addition:

$$\sigma= \frac{1}{1+e^{-X}} \quad (7)$$

Equations 1,2, and 5 in this section defines the input, forget and output gates. Using these equations representing the gates, it is decided which part of the newly calculated candidates will be allowed to pass and which part will be forgotten.

Artificial Neural Network (ANN) is another technique applied in this study. ANNs are machine learning methods developed by modeling the neural structures of the brain in a computer environment. Inspired by the functioning of the human brain, many different neural network models have been proposed. When the studies in literature are examined, it is seen that ANN models are frequently preferred in the solution of forward prediction problems.

The ANN structure generally consists of 3 layers, as shown in Figure 2; input layer, hidden layer and output layer. The signal from the outside is received through the input layer to the neural network structure. It is then transmitted to the output layer via the hidden layer, and as a result of the network, it is transmitted to the external environment via the output layer. The number of neurons in the hidden layer is chosen through trial and error in order to get the best results, whereas the number of neurons in the input layer and the output layer is chosen depending on the nature of the problem.

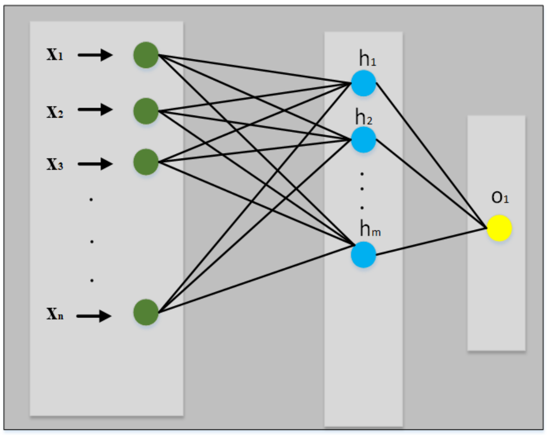


Figure 2. Architecture of Artificial Neural Network with 3 layers

3. RESULTS AND DISCUSSIONS

The data set used in this study was created with real-time data from a 1 MW PV plant. Two different artificial neural network models were used in the estimation phase in the study made with the data obtained by collecting 5-month irradiation data (January - May) from the solar power plant. The data were taken from the PV panel at one-hour intervals. The time series data set of solar radiation was used in the study. The prediction is aimed with Long Short-Term Memory (LSTM) Neural Network by using 4-month data in the training phase and 1-month data in testing phase. In order to show the accuracy in time series data model, comparison was made with the Artificial Neural Network (ANN) method. At the end of the study, 3 different error criteria, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were used in the comparison of the results obtained with the two methods. The error criteria used are as follows:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e(t)| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(e(t)\right)^2} \tag{9}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{X_{desired}-X_{actual}}{X_{actual}}\right| \tag{10}$$

where n refers to the number of samples in the dataset and e refers to the error between predicted and actual values. $X_{desired}$ and X_{actual} are the real value and the predicted value in the data set, respectively. Table 1 displays the results of the ANN and LSTM algorithms using the error criteria. The linear regression values of the estimation results are also given in Table 1.

Table 1. Performance results of LSTM and ANN methods

Error Criteria	LSTM	ANN
RMSE	142.8028	168.9314
MAE	86.1236	122.9337
MAPE	45.0233	64.1112
Regression	0.90186	0.85993

The graphical results of solar irradiation prediction are given in Figure 3. As seen in the figure, the estimation results obtained with LSTM are more consistent with the actual values. When the results are examined, it is seen that there is a more successful approach with the LSTM method, especially at the peak point.

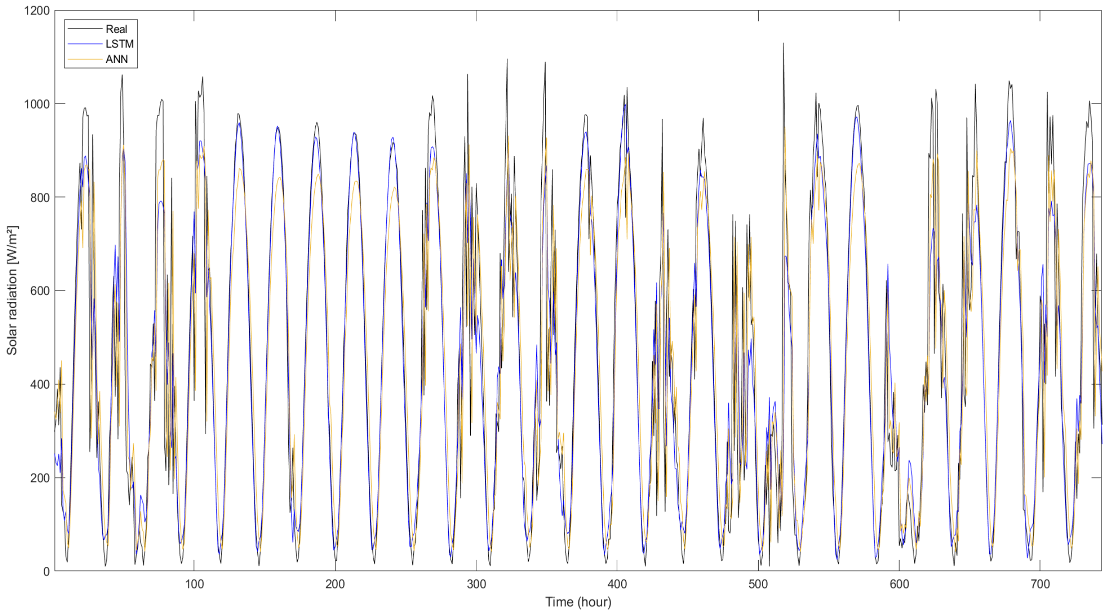
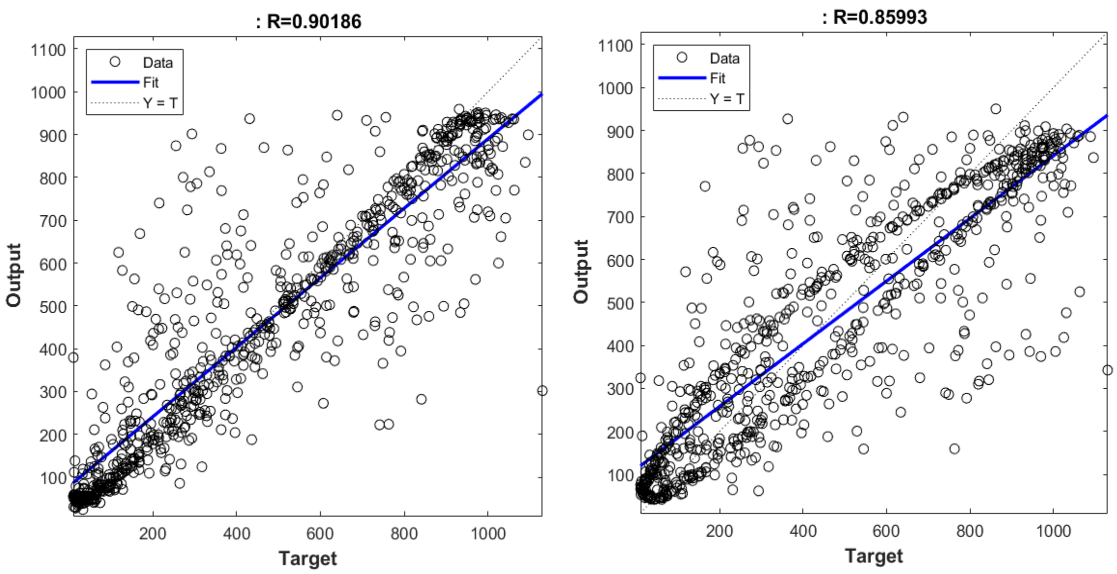


Figure 3. Predicted solar irradiation using an LSTM network

The results of the two estimation methods are given with the linear regression results. Regression is the process of fitting models to data. The simplest and most common type of regression is linear regression since its graph shows a straight line. The regression graphs of the estimation results obtained with LSTM and ANN for solar radiation are given in Figure 4.



(a) (b)

Figure 4. Regression graphs with (a) LSTM method (b) ANN method

4. CONCLUSIONS

The amount of energy resources currently being used is expected to be insufficient given the daily rapid increase in the global energy supply. Renewable energy sources are being increasingly sought after as a solution to this issue. Solar energy, which is seen as a limitless resource, is the most widely used of these techniques. This study aims to estimate the levels of solar irradiation obtained from PV panels. The recently popular LSTM Network method has been preferred for the estimation process. A comparison was made with the ANN method to measure the success of the method. From the values obtained according to the error criteria, it is seen that both methods are within the acceptable error values but LSTM is more successful. In addition, it was determined that the LSTM method would provide closer values than ANN. When the graphical results are examined, it is seen that the LSTM method is more successful at peak points.

The recommendation for further study is to develop the combination of LSTM and Convolutional Neural Network (CNN) models.

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