Yuzuncu Yil University
Journal of the Institute of Natural & Applied Sciences
https://dergipark.org.tr/en/pub/yyufbed

Research Article

Modeling of Monthly Mean Solar Energy Potential using Artificial Neural Network

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Abstract: The aim of this study is to develop an artificial neural network (ANN) model for accurately predicting monthly mean solar radiation and irradiance for Mersin (36.8^o N, 34.6^o E, Türkiye). The prediction of monthly mean solar radiation and irradiance was made by using two different ANN (NN-1 and NN-2) models with different input parameters and thus, a dual solution strategy for the monthly mean solar radiation and irradiance forecasts was presented. The ANN models were trained for the target parameters (monthly mean solar radiation and irradiance) at each month of the year. The training, testing and validating for both models were conducted using the data obtained for the period from 2004 to 2024. The performance results of these alternative models compared with each other. The accuracy of the models to predict the monthly mean solar radiation and irradiance are identified based on root mean square errors (RMSE) and cross-correlation coefficients (R). The NN-2 model has smaller RMSE values and has bigger R values. That is, the NN-2 model has higher prediction success with lower prediction error for both monthly mean solar radiation and irradiance intensity. The presence of two models may be advantageous for more precise forecasting situations and the NN-2 model can be chosen for such cases. In addition, the application of the NN-2 model proposed in this study can be extended to other locations.

Keywords: Artificial neural network, Modelling, Solar irradiance, Solar radiation

Yapay Sinir Ağı Kullanılarak Aylık Ortalama Güneş Enerjisi Potansiyelinin Modellenmesi

Öz: Bu çalışmanın amacı, Mersin (36.8^o N, 34.6^o E, Türkiye) için aylık ortalama güneş radyasyonu ve ışınım şiddetini doğru bir şekilde tahmin etmek için bir yapay sinir ağı (YSA) modeli geliştirmektir. Aylık ortalama güneş radyasyonu ve ışınım şiddetinin tahmini, farklı giriş parametrelerine sahip iki farklı YSA (NN-1 ve NN-2) modeli kullanılarak yapılmış ve böylece aylık ortalama güneş radyasyonu ve ışınım şiddeti tahminleri için ikili bir çözüm stratejisi sunulmuştur. YSA modelleri, yılın her ayında hedef parametreler (aylık ortalama güneş radyasyonu ve ışınım şiddeti) için eğitilmiştir. Her iki model için eğitim, test ve doğrulama işlemleri 2004-2024 yılları arasında elde edilen veriler kullanılarak gerçekleştirilmiştir. Birbirine alternatif olan bu modellerin performans sonuçları birbirleriyle karşılaştırılmıştır. Aylık ortalama güneş radyasyonu ve ışınım şiddetini tahmin eden modellerin doğruluğu, kök ortalama karekök hatalarına (RMSE) ve çapraz korelasyon katsayılarına (R) dayanarak belirlenmiştir. NN-2 modeli daha küçük RMSE değerlerine ve daha büyük R değerlerine sahiptir. Yani, NN-2 modeli hem aylık ortalama güneş radyasyonu hem de ışınım yoğunluğu için daha düşük tahmin hatasıyla daha yüksek tahmin başarısına sahiptir. İki modelin varlığı daha hassas tahmin durumları için avantajlı olabilir ve bu gibi durumlar için NN-2 modeli seçilebilir. Ayrıca, bu çalışmada önerilen NN-2 modelinin uygulaması diğer konumlara genişletilebilir.

Anahtar Kelimeler: Güneş ışınımı, Güneş radyasyonu, Modelleme, Yapay sinir ağı

Received: 26.03.2025
Accepted: 30.05.2025

How to cite: Timoçin, E. (2025). Modeling of monthly mean solar energy potential using artificial neural network. *Yuzuncu Yil University Journal of the Institute of Natural and Applied Sciences*, *30*(2), 512-523. https://doi.org/10.53433/yyufbed.1665961

1. Introduction

In recent years, while technological and economic developments have increased global energy demand in worldwide, fossil energy sources are not enough to meet this demand. To overcome this situation, scientists and engineers have focused their work on discovering new energy sources and developed countries have begun to use renewable energy sources to meet their energy needs. The main renewable energy sources are solar, wind and geothermal energies. Among these, the source with the highest energy potential is solar energy. In addition, unlike fossil fuels, solar energy is an energy source that is both sustainable and non-polluting while generating energy. Due to these advantages, the popularity of this power source continues to increase day after day (Dupont et al., 2020; Holechek et al., 2022).

Since Türkiye is located between latitudes 36° N and 42° N, it is country rich in terms of the potential to benefit from solar energy. Türkiye has an annual average sunshine duration of 2373 hours (7.5 hours daily) and an annual solar energy potential of 1527 kWh/m² (4.2 kWh/m² daily). The major solar energy regions of Türkiye are South Eastern Anatolia Region and the Mediterranean regions and the utilization potential from the solar energy of these regions are at a size which needs to be examined importantly (Kaygusuz & Sarı, 2003). In this context, Mersin (36.8° N, 34.6° E) is one from provinces of Türkiye that have maximum solar radiation potential. Turkey has a substantial solar energy potential; however, it is not being utilized to its full capacity for energy production. Therefore, the number of areas where solar energy is applied should be increased without delay.

The increase in the utilization of solar energy has increased the interest in the estimation of solar energy parameters. Because solar energy models are very effective tools used to benefit from solar energy systems at the highest level. In addition, inaccuracies in solar energy prediction cause significant economic losses and constrain the national expansion of renewable energy. For these reasons, estimating the amount of solar radiation and irradiance that are the main input parameter for solar energy systems is very important (Nawab et al., 2023).

So far, there have been many attempts by different researchers to predict solar radiation data over short and long terms for a location or a region in both Türkiye and other regions of the world. A neural network model was developed for the estimation of global solar radiation all over Saudi Arabia. The results show that the solar radiation model is applicable (Mohandes et al., 1998). The relationship between monthly mean global solar radiation and geographical and meteorological parameters for Elazığ was investigated and a 9% deviation from the actual values was determined (Toğrul & Onat, 1999). Regression analyses were performed to estimate monthly mean solar radiation for Türkiye, and statistically significant results were obtained from the proposed equations (Toğrul & Toğrul, 2002). A numerical model was developed to estimate global solar radiation using humidity data. This study showed that global solar radiation strongly depends on sky clearness (Yang & Koike, 2002).

The solar energy potential for Türkiye was estimated using artificial neural networks (ANNs). In this study, the ANN model developed for solar radiation produced more accurate estimates than the regression models proposed for Türkiye and other countries (Sözen et al., 2004). The applicability of 50 models available in the literature was tested for estimating the monthly average daily global radiation of Konya (Menges et al., 2006). A hybrid deep learning model was developed to estimate daily average solar irradiance, and the study investigated both the performance and applicability of the proposed approach. The findings indicate that the hybrid model can be effectively utilized for accurate daily solar irradiance prediction (Eşlik et al., 2024). Artificial neural network models have been developed to estimate global monthly mean solar radiation using meteorological data. In the studies, some statistical indicators such as high correlation coefficients, low mean deviation and the RMSE were obtained between the estimated and actual data. These statistical results reveal that there is a strong agreement between the estimated data and the measured data (Jiang, 2008; Mubiru & Banda, 2008; Rehman & Mohandes, 2008; Chaouachi et al., 2009; Fadare et al., 2010; Mubiru, 2011; Priya & Iqbal, 2015; Kılıç, & Kumaş, 2016; Neelamegam & Amirtham, 2016). The annual average solar radiation values (kWh/m²) was estimated for various test locations across Turkey using two different machine learning techniques. The results demonstrated that solar radiation can be accurately predicted using machine learning methods (Demirgül et al., 2024).

Artificial neural network models were developed to estimate solar radiation potential in Türkiye by using geographic and meteorological data as input parameters. When the predicted data obtained from the proposed models were compared with the real measured data, it was revealed that the models gave quite appropriate results for solar radiation estimation in selected regions (Solmaz & Ozgoren, 2012; Arslan & Bayhan, 2016; Şenkal, 2016; Kaplan, 2017; Kulcu et al., 2017).

In this study, considering the meteorological data and solar data, it was presented a dual solution strategy for the monthly mean solar radiation and irradiance forecasts in Mersin. It was used two different ANN models (named as NN-1 and NN-2) which have different input parameters. It was used meteorological data as input parameters in NN-1 model. On the assumption that there is no better indicator of solar radiation behavior than itself, it was used solar radiation data as input parameters in NN-2 model. Input parameters used in the proposed NN-2 model have been used for the first time to predict solar radiation potential. The input parameters, output parameters and the structures of NN-1 and NN-2 models used in this study are explained in detail in the section 2. The models were developed as alternatives to each other and their performance results were compared with each other. The results of models are presented in section 3.

2. Material and Methods

2.1. Overview of the artificial neural network

An artificial neural network consists of one input layer, one or more hidden layers and one output layer. The unknown parameters of a neural network are the weights that can be found by training with different algorithms on known input-output layers. Therefore, a database of examples with input and output values is required to train a neural network. (Fletcher, 1990; Haykin, 1999a; Haykin 1999b).

A two-layer feed-forward architecture and a multi-layer perception algorithm were used to train both models developed for this study. Figure 1 shows the architecture diagrams of the NN-1 and NN-2 models with two hidden layers.

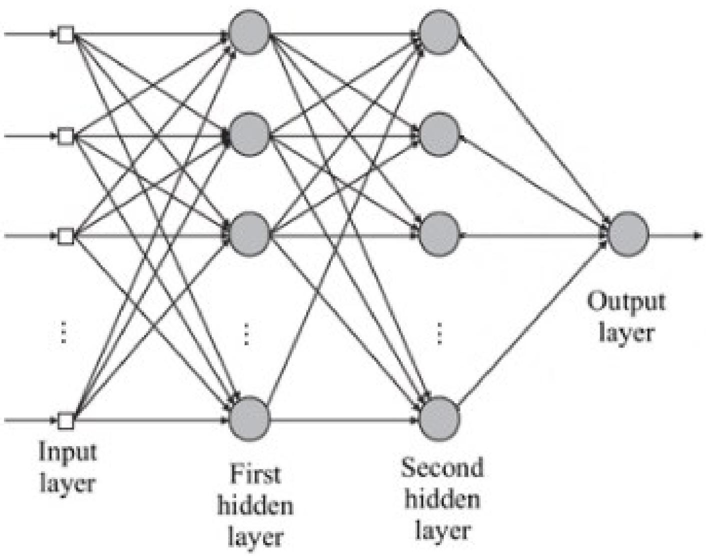

Figure 1. Architecture diagrams of the NN-1 and NN-2 models with two hidden layers.

The hidden layers have six neurons in NN-1 and NN-2 models forecasting the monthly mean solar radiation and irradiance values. The NN-1 and NN-2 models use hyperbolic tangent sigmoid functions in the hidden layer and a linear function in the output layer. Equation 1 shows the function that defines the network structure.

$$O_k = v_{ok} \sum_{j=1}^{q} v_{jk} \tanh(w_{oj} + \sum_{i=1}^{p} w_{ij} x_i) \qquad (1)$$

where O_k, υ_{jk} and w_{oj}, p and q is the output of the kth output unit, the networks network weights, the number of network inputs and the number of hidden units, respectively. During the training phase, the model adjusts the weights to minimize the difference between the obtained outputs and the desired outputs, using the expression given in Equation 2.

$$E = \sum_{k=1}^{r} \sum_{e=1}^{n} (d_{e,k} - o_{e,k})^2 \tag{2}$$

where r is the number of network outputs and n is the number of training examples (Fletcher, 1990; Haykin, 1999a; Haykin,1999b). The data used in this study was divided randomly, and 70% of the data was used to train the models, 15% to test the models, and 15% to validate the models.

2.2. Inputs and outputs of the NN-1 and NN-2 models

In this work, raw data used in constructing the inputs were extracted from Solar Radiation Data Center (SODA, 2025). The data considered include the years from 2004 to 2024. The inputs used in the NN-1 and NN-2 models are summarized in Tables 1-3. The outputs for both models are monthly mean solar radiation and irradiance data. The Z-score method was used to detect outliers in the data. Possible outliers were limited to prevent them from negatively affecting the accuracy of the model (Hastie et al., 2009). The solar radiation and solar radiation data used in the study were examined in detail for missing data before the analysis. As a result of the preliminary control and verification processes, no missing observations were found in both data sets throughout the time series. Therefore, no completion method was needed in the preprocessing step.

Table 1. Inputs of the NN-1 used to predict monthly mean solar radiation and irradiance

No	**Input Parameter**
1	Monthly mean temperature
2	Monthly mean relative humidity
3	Monthly mean pressure
4	Monthly mean wind speed
5	Monthly mean wind speed direction
6	Monthly mean rainfall
7	Monthly mean clear sky
8	Month

Table 2. Inputs of the NN-2 used to predict monthly mean solar radiation

No	**Input Parameter**
1	Monthly lower decile of solar radiation
2	Monthly upper decile of solar radiation
3	Monthly 1st quarter of solar radiation
4	Monthly 2nd quarter of solar radiation
5	Monthly 3rd quarter of solar radiation
6	The ratio of monthly 2nd quarter of solar radiation to monthly lower decile of solar radiation
7	The ratio of monthly 2nd quarter of solar radiation to monthly upper decile of solar radiation
8	The ratio of monthly 2nd quarter of solar radiation to monthly 1st quarter of solar radiation
9	The ratio of monthly 2nd quarter of solar radiation to monthly 3rd quarter of solar radiation
10	Trigonometric Sine component of the month
11	Trigonometric Cosine component of the month

Table 3. Inputs of the NN-2 used to predict monthly mean solar irradiance

No	**Input Parameter**
1	Monthly lower decile of solar irradiance
2	Monthly upper decile of solar irradiance
3	Monthly 1st quarter of solar irradiance
4	Monthly 2nd quarter of solar irradiance
5	Monthly 3rd quarter of solar irradiance
6	The ratio of monthly 2nd quarter of solar irradiance to monthly lower decile of solar irradiance
7	The ratio of monthly 2nd quarter of solar irradiance to monthly upper decile of solar irradiance
8	The ratio of monthly 2nd quarter of solar irradiance to monthly 1st quarter of solar irradiance
9	The ratio of monthly 2nd quarter of solar irradiance to monthly 3rd quarter of solar irradiance
10	Trigonometric Sine component of the month
11	Trigonometric Cosine component of the month

In the NN-1 model, the month of year (m) from 1 to 12 is used to learn seasonal variations. However, the NN-1 model has the problem of not seeing the time series data as contiguous because the m values for December and January are numerically far apart. To address this issue related to the representation of months in the NN-1 model, the months were transformed into two separate input features in the NN-2 model: the trigonometric sine component of the month ($\mathrm{Sin}(2\pi m/12)$) and the trigonometric cosine component of the month ($\mathrm{Cos}(2\pi m/12)$). When used together, these components provide the necessary cyclical continuity while also offering a unique input representation for each month of the year.

3. Results

As performance measures of models, we calculated RMSE values and R between the forecast and observed monthly mean solar radiation and irradiance values. Equation 3 and equation 4 are defining the respective measures:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(O_i - M_i)^2}{N}} \tag{3}$$

In Equation 3, O_i, M_i, and N represent the model output result, the observed and measured data, and the total number of observations, respectively.

$$R = \frac{C\,(o, m)}{C(o, o).\,C(m, m)} \tag{4}$$

In Equation 4, C(o, m), C(o, o) and C(m, m) are the cross-covariance function and auto-covariance functions, respectively. The cross-covariance function (C(o, m)) describes the statistical relationship between observed and modeled data, while the auto-covariance functions ((C(o, o) and C(m, m)) quantify the internal variability within the observed and modeled datasets. The R values range between -1 and 1, indicating how well the modeled data corresponds to the observed data (Wackernagel, 1995). Table 4 shows performance results for two ANN models which have different input parameters from 2004 to 2024. Considering RMSE of two models, as shown in Table 4, it is clearly seen that the error values of NN-2 model are very smaller than the errors of NN-1 for both solar monthly radiation and irradiance. In addition, considering R between the predicted and observed target parameters, it is clear that the NN-2 model results are nearer to 1 than those of the NN-1 model. That is, the NN-2 model has the highest prediction success since it has the lowest prediction error values for both monthly solar radiation and irradiance.

Table 4. Performance results of NN-1 and NN-2 models from 2004 to 2024

	Radiation (MJ/m²)		Irradiance (W/m²)	
	NN-1	NN-2	NN-1	NN-2
RMSE	0.84	0.21	0.78	0.17
R	0.932	0.986	0.951	0.992

How the cumulative distribution of the error variation changes is very important in revealing the performance of the model. Figure 2 shows cumulative distributions of the RMSE between forecast and observed monthly mean radiation values for NN-1 and NN-2 models from 2004 to 2024. Considering Figure 2, the cumulative distribution of the RMSE values for the NN-2 forecast results shows very smaller values when compared with the errors of the NN-1.

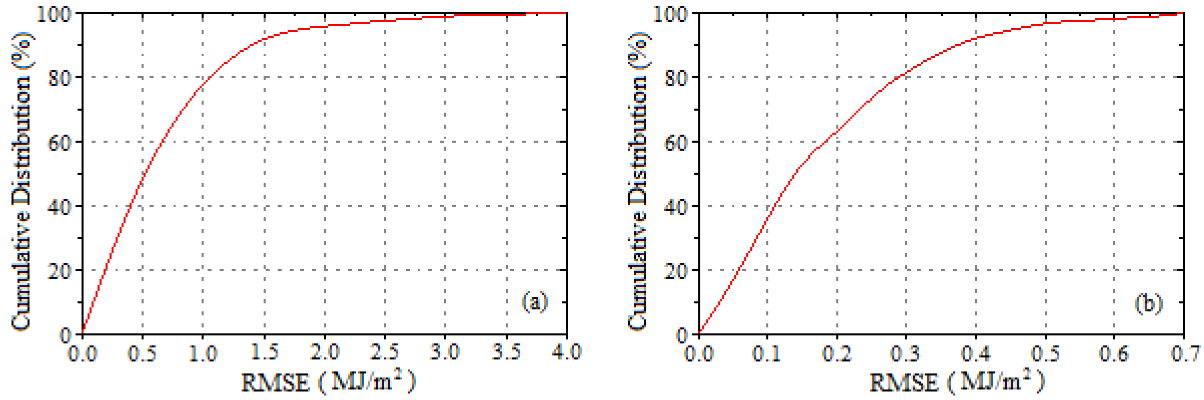

Figure 2. Cumulative distributions of the RMSE between predicted and observed monthly mean radiation values from 2004 to 2024: (a) for NN-1, (b) for NN-2.

Figure 3 shows cumulative distributions of the RMSE between predicted and observed monthly mean irradiance values for NN-1 and NN-2 models from 2004 to 2024. Considering Figure 3, similarly to the results in Figure 2, the cumulative distribution of the RMSE for the NN-2 forecast results shows very smaller values when compared with the errors of the NN-1.

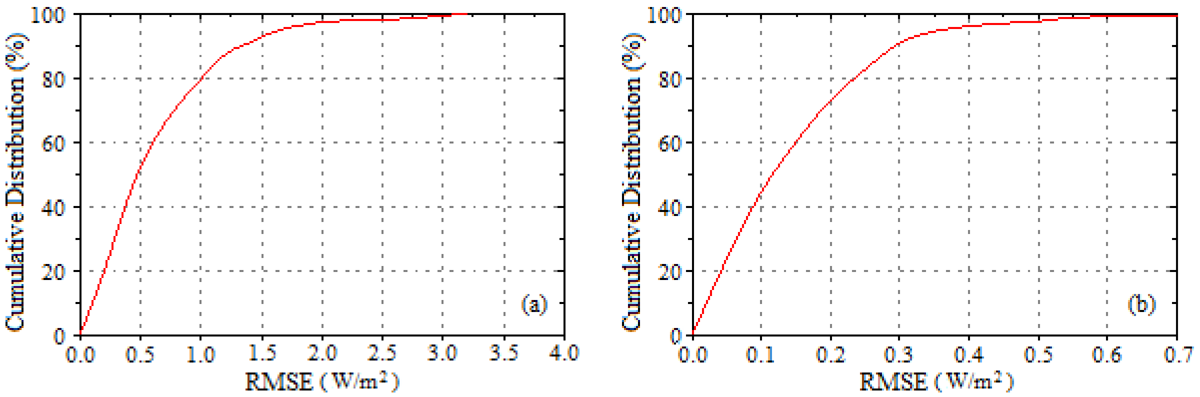

Figure 3. Cumulative distributions of the RMSE between predicted and observed monthly mean irradiance values from 2004 to 2024: (a) for NN-1, (b) for NN-2.

The scatter diagrams reveal the overall performance of the model as well. Figure 4 and Figure 5, respectively, show scatter diagram of the predicted monthly average radiation and irradiance versus observed monthly average radiation and irradiance for NN-1 and NN-2 models from 2004 to 2024. When the scatter diagrams in Figure 4 and Figure 5 are compared, they show that the best fit line in the NN-2 model results for both monthly radiation and irradiance have a slope closer to 1 and the deviations of the scatter points are smaller than that of NN-1 model. That is, NN-2 predicted values for both monthly radiation and irradiance give the best forecasting matching with the actual data along the fitting line.

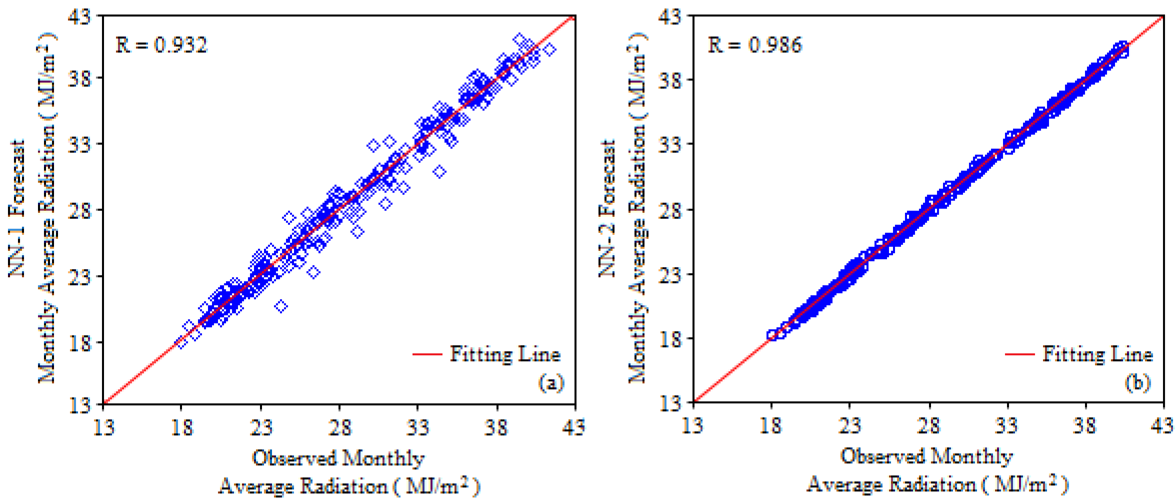

Figure 4. (a) Scatter diagram of the NN-1 predicted monthly average radiation according to observed monthly average radiation from 2004 to 2024, (b) Scatter diagram of the NN-2 predicted monthly average radiation according to observed monthly average radiation from 2004 to 2024.

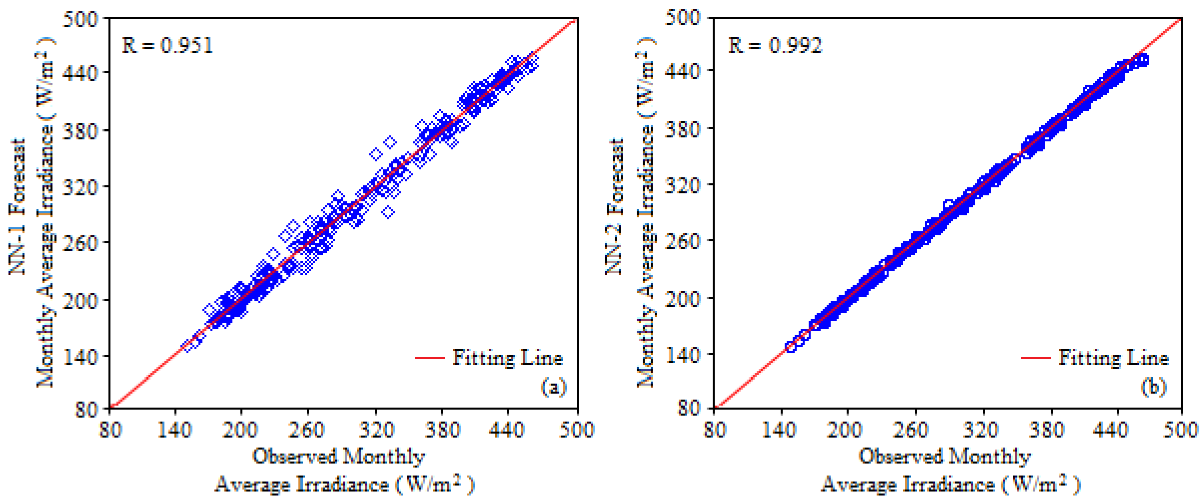

Figure 5. (a) Scatter diagram of the NN-1 predicted monthly average irradiance according to observed monthly average radiation from 2004 to 2024, (b) Scatter diagram of the NN-2 predicted monthly average radiation according to observed monthly average irradiance from 2004 to 2024.

Figure 6 and Figure 7, respectively, show monthly changes of RMSE of predicted radiation and irradiance with NN-1 (red bars) and with NN-2 (blue bars) from 2004 to 2024. Monthly RMSE results enable the evaluation of short-term forecasting accuracy and help identify seasonal or month-specific variations in model error. Considering the RMSE for two models, it is clearly seen that the error values of NN-2 model are very smaller than the errors of NN-1 for both monthly radiation and irradiance during all months. That is, the NN-2 model has the highest prediction success with the smallest forecasting error for both monthly radiation and irradiance for all months. When the error values of each month for both radiation and irradiance are compared with each other, it is seen that RMSE values have the smallest values in August while the biggest values in April for both models.

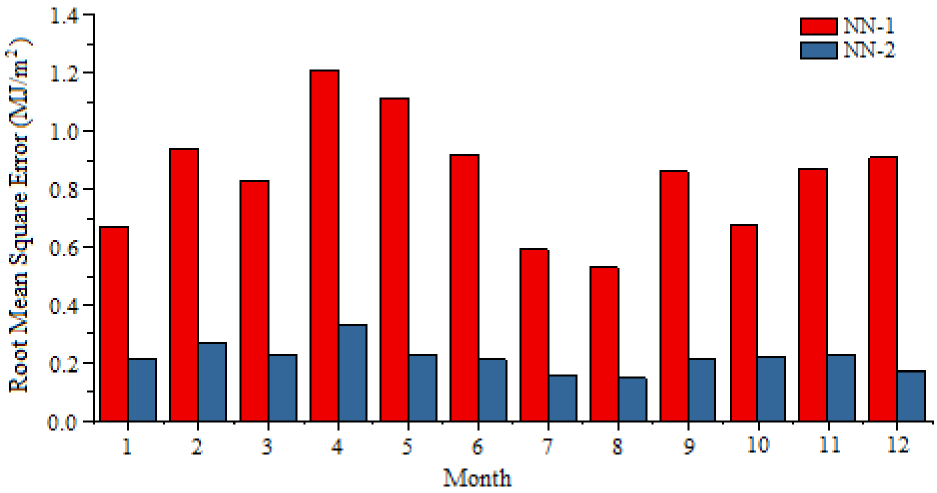

Figure 6. Monthly root mean square errors of predicted radiation with NN-1 (red bars) and with NN-2 (blue bars) from 2004 to 2024.

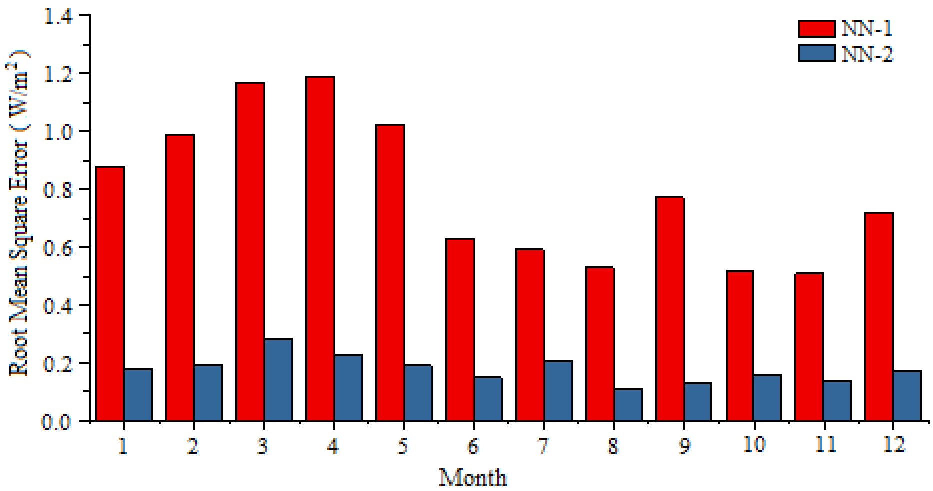

Figure 7. Monthly root mean square errors of predicted irradiance with NN-1 (red bars) and with NN-2 (blue bars) from 2004 to 2024.

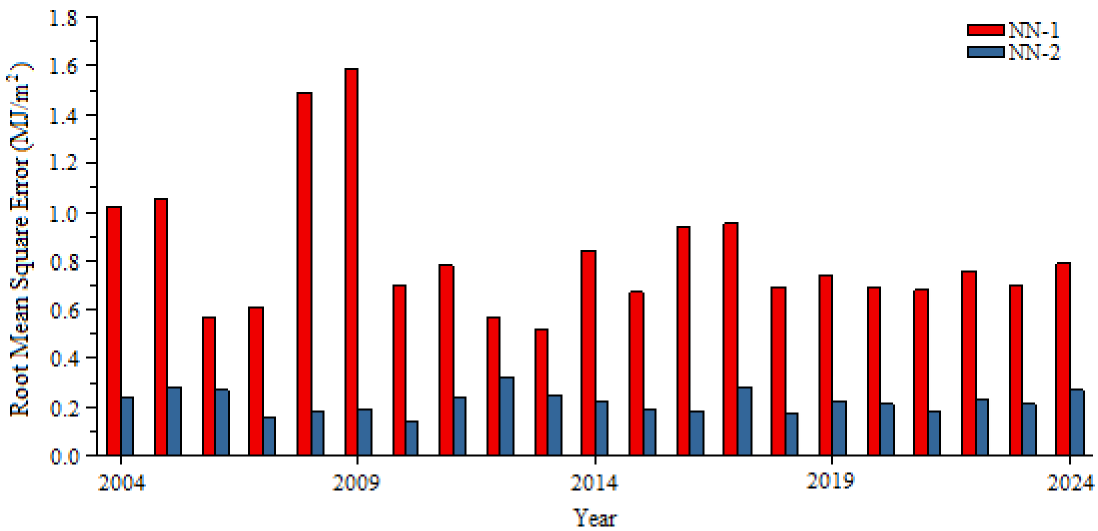

Figure 8. Yearly root mean square errors of predicted radiation with NN-1 (red bars) and with NN-2 (blue bars) from 2004 to 2024.

Figure 8 and Figure 9 show yearly changes of RMSE of predicted radiation and irradiance with NN-1 (red bars) and with NN-2 (blue bars) from 2004 to 2024, respectively. Annual RMSE values provide a broader perspective on long-term model reliability and overall performance consistency. Considering the RMSE for two models, it is clearly seen that the error values of NN-2 model are very smaller than the errors of NN-1 for both radiation and irradiance during all years. That is, the NN-2 model has the highest prediction success since it has the lowest prediction error values for both radiation and irradiance values during the period from 2004 to 2024.

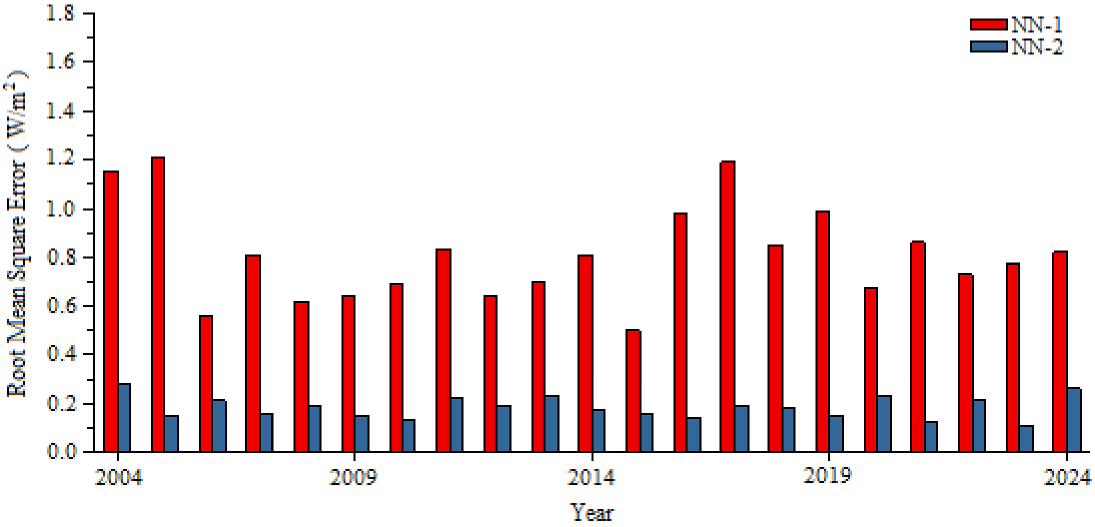

Figure 9. Yearly root mean square errors of predicted irradiance with NN-1 (red bars) and with NN-2 (blue bars) from 2004 to 2024.

Figure 10 and Figure 11 compare the predicted monthly mean radiation and irradiance values from the NN-1 and NN-2 models with the observed monthly average radiation and irradiance values during 2024 in Mersin. Considering the temporal variations of the observed NN-1 and NN-2 model predicted values shown in Figure 10 and Figure 11, it was once again shown that the NN-2 predicted values are in very good agreement with the observed values with smaller error values for both target parameters. In both sites, it can be said that NN-2 model is a model with higher prediction success than the NN-2 model.

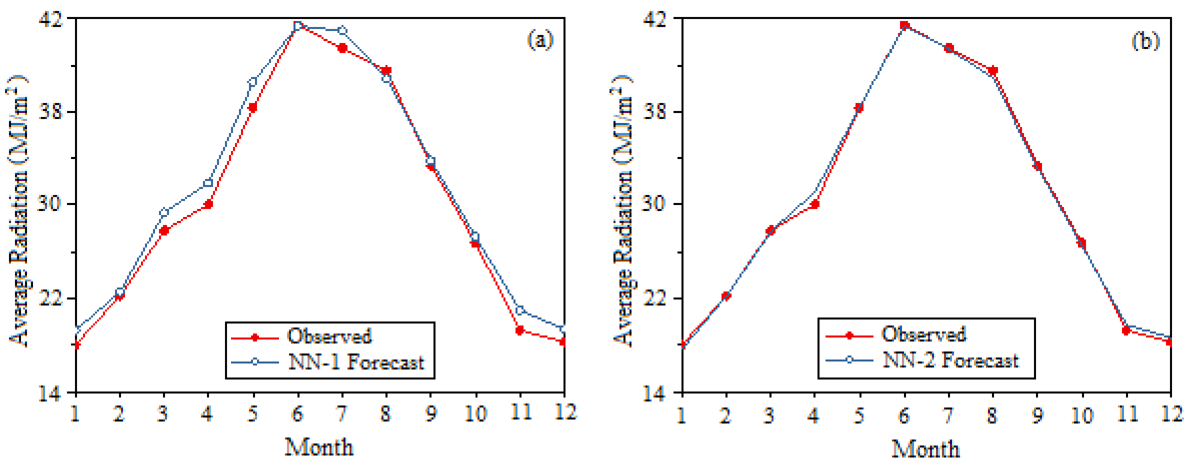

Figure 10. Monthly variations of the observed and predicted average radiation values during 2024: (a) for NN-1, (b) for NN-2.

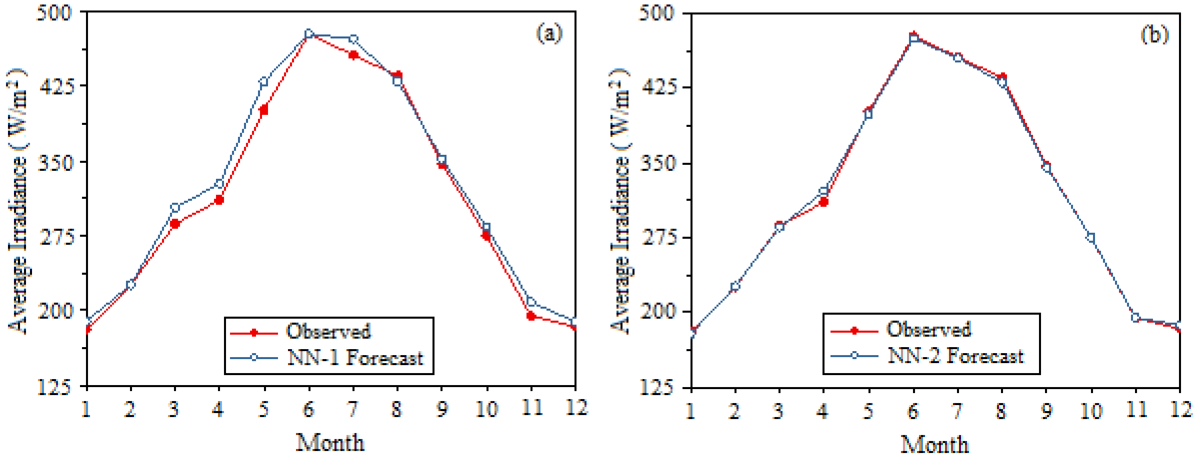

Figure 11. Monthly variations of the observed and predicted average irradiance values during 2024: (a) for NN-1, (b) for NN-2.

4. Discussion and Conclusion

In this study, two artificial neural networks having different input parameters were developed and applied to forecasting of monthly mean solar radiation and irradiance over Mersin. For this purpose, it is presented a dual solution strategy for the monthly mean solar radiation and irradiance forecasts. In the NN-1 model is used meteorological parameters as input parameters, while in the NN-2 model is used solar radiation and irradiance parameters as input parameters. The performance results of the models, which are alternatives to each other, were compared. Statistical test results show that the accuracy of NN-2 model is higher than NN-1 model in prediction of monthly mean solar radiation and irradiance. The results of this study show that using only solar radiation parameter instead of using a large number of different meteorological parameters can be increased the accuracy of the estimation and solar energy potential as required to design solar energy systems can be more accurately estimated with NN-2 model. The presence of two models may be advantageous for more precise forecasting situations. In such cases, the NN-2 model can be chosen.

The proposed model has strong potential not only for accurate solar radiation and irradiance forecasting but also for improving the practical aspects of solar energy system design and operation. Its capabilities in supporting optimal site selection, system sizing, and real-time performance prediction make it a valuable tool for engineers and planners. Moreover, it offers significant advantages in optimizing battery storage operations based on predicted solar input, improving storage capacity utilization, and contributing to the development of more efficient and intelligent solar energy systems.

Acknowledgements

The author would like to thank the Solar Radiation Data (SODA) team to providing solar radiation and irradiance data at their web site. This research was supported by Mersin University Scientific Research Projects Support System (BAP-Project No: 2020-1-AP4-4084).

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