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Enerji Vadisi Optimizasyonu Tabanlı Yapay Sinir Ağı Kullanılarak Güneş Radyasyonu Tahmini: Türkiye'nin KOP Bölgesi İçin Bir Vaka Çalışması

Ömer Özcan[1]* Mehmet Çeçen[2] Muhammed Karaaltun[3] Mehmet Hacıbeyoğlu[3]

[1] Necmettin Erbakan University, Vocational School of Technical Sciences, Department of Big Data Analytics, Konya, Türkiye
[2] Selcuk University, Ilgın Vocational School, Department of Electric and Energy, Konya, Türkiye
[3] Necmettin Erbakan University, Faculty of Engineering, Department of Computer Engineering, Konya, Türkiye

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ÖZET

Güneş enerjisi, enerji güvenliği, çevresel sürdürülebilirlik ve fosil yakıtlara bağımlılığın azaltılması açısından günümüzde en önemli yenilenebilir enerji kaynaklarından biri olarak kabul edilmektedir. Güneş enerjisi sistemlerinin etkin şekilde planlanabilmesi ve optimize edilebilmesi için güneş radyasyonunun doğru tahmin edilmesi büyük önem taşımaktadır. Ancak birçok bölgede uzun dönemli ve güvenilir meteorolojik verilerin sınırlı olması, güneş radyasyonu tahmin çalışmalarını zorlaştırmaktadır. Bu çalışmada, Türkiye'nin önemli tarım, sanayi ve enerji bölgelerinden biri olan Konya Ovası Projesi (KOP) Bölgesi için güneş radyasyonu tahmini amacıyla Enerji Vadisi Optimizasyon Algoritması (Energy Valley Optimization-EVO) ile optimize edilmiş Yapay Sinir Ağı (YSA) modeli önerilmiştir. Çalışmada Konya, Karaman, Aksaray, Nevşehir, Niğde, Kırşehir ve Yozgat illerine ait 1990–2024 yılları arasındaki 34 yıllık meteorolojik ve coğrafi veriler kullanılmıştır. Veri seti, NASA POWER projesinden elde edilen enlem, boylam, rakım, sıcaklık, nem, yüzey basıncı ve yağış gibi değişkenleri içermektedir. Önerilen EVO-YSA modeli, yapay sinir ağı ağırlıklarının klasik gradyan tabanlı yöntemler yerine EVO algoritması ile optimize edilmesine dayanmaktadır. Bu yaklaşım, yerel minimumlara takılma problemini azaltarak modelin küresel optimum çözümlere ulaşma olasılığını artırmaktadır. Ayrıca Levy Flight mekanizmasının kullanılması, keşif ve sömürü dengesini geliştirerek optimizasyon performansına katkı sağlamaktadır. Model performansı, Levenberg–Marquardt (LM) ve Scaled Conjugate Gradient (SCG) eğitim algoritmalarıyla eğitilen geleneksel YSA modelleriyle karşılaştırılmıştır. Sonuçlar, önerilen yöntemin en iyi yapılandırmada yaklaşık 0,95 korelasyon katsayısı (R) ve 0,0754 ortalama kare hata (MSE) değeri elde ederek karşılaştırılan yöntemlerden daha başarılı olduğunu göstermiştir. Ayrıca 10 bağımsız deney sonucunda elde edilen performans üstünlüğü istatistiksel testlerle doğrulanmıştır. Elde edilen aylık güneş radyasyonu tahminleri, NASA POWER verileriyle yüksek uyum göstermiş ve KOP Bölgesi'ndeki şehirlerin güneş enerjisi potansiyelinin güvenilir şekilde modellenebildiğini ortaya koymuştur. Çalışma sonucunda geliştirilen EVO-YSA modelinin, meteorolojik verilerin sınırlı olduğu bölgelerde güneş enerjisi potansiyelinin belirlenmesi, fotovoltaik sistem planlaması ve yenilenebilir enerji yatırımlarının desteklenmesi için etkili bir karar destek aracı olarak kullanılabileceği değerlendirilmiştir.

Solar Radiation Forecasting Using Energy Valley Optimization Based Artificial Neural Network: A Case Study for KOP Region of Türkiye

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ABSTRACT

Solar energy has emerged as one of the most important renewable energy resources for ensuring energy security, promoting environmental sustainability, and reducing dependence on fossil fuels. Accurate estimation of solar radiation is essential for the efficient planning, design, and operation of photovoltaic systems and other solar energy applications. However, the limited availability of long-term and reliable meteorological observations in many regions poses a significant challenge for solar radiation forecasting. To address this issue, this study proposes an Artificial Neural Network (ANN) model optimized using the Energy Valley Optimization (EVO) algorithm for estimating solar radiation potential in the Konya Plain Project (KOP) region of Türkiye.The proposed EVO-ANN model was developed using 34 years (1990–2024) of geographical and meteorological data obtained from NASA's Prediction of Worldwide Energy Resources (POWER) project. The dataset includes information from seven provinces within the KOP region Konya, Karaman, Aksaray, Nevşehir, Niğde, Kırşehir, and Yozgat incorporates variables such as latitude, longitude, altitude, air temperature, humidity, atmospheric pressure, precipitation, and temporal information. Unlike conventional ANN training approaches that rely on gradient-based optimization methods, the proposed model employs the EVO algorithm to optimize network weights, thereby reducing the risk of convergence to local minima and improving global search capability. Furthermore, the integration of the Levy Flight mechanism enhances the balance between exploration and exploitation during the optimization process. The performance of the proposed model was evaluated and compared with ANN models trained using the Levenberg–Marquardt (LM) and Scaled Conjugate Gradient (SCG) algorithms. Experimental results demonstrated that the EVO-ANN achieved superior predictive performance, reaching a correlation coefficient (R) of approximately 0.95 and a minimum mean square error (MSE) of 0.0754 in the best-performing configuration. Statistical analyses conducted over ten independent runs confirmed the superiority of the proposed approach. Monthly solar radiation estimates also showed strong agreement with NASA POWER measurements across all cities in the KOP region. The findings indicate that the EVO-ANN model provides a reliable and effective framework for solar radiation estimation, particularly in regions with limited meteorological observations. The proposed approach can support renewable energy planning, photovoltaic system deployment, and solar resource assessment, while also offering a transferable methodology for similar geographical regions worldwide.

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*** Corresponding Author:** Ömer Özcan, *oozcan42@gmail.com*

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INTRODUCTION

The importance of renewable energy has increased in recent years, primarily due to energy security, economic sustainability and environmental problems [1,2]. As countries endeavor to fulfill their energy requirements sustainably, the significance of renewable energy becomes increasingly vital, acting as a fundamental element for future energy security and environmental management [3,4]. Renewable energy consumption significantly enhances economic growth and sustainability, benefiting countries by providing cleaner energy sources and a positive correlation between renewable energy consumption and economic performance [5,6]. The shift from fossil fuels to renewable energy sources such as solar, wind, geothermal, wave, and hydropower has been recognized as an essential method for mitigating greenhouse gas emissions and promoting sustainable economic growth. This transition not only alleviates environmental degradation but also strengthens energy autonomy by reducing dependence on imported fuels, thus allowing countries to develop autonomous energy strategies [7].

Renewable energy, particularly solar energy, is gaining prominence as a sustainable, clean, and cost-effective alternative to traditional fossil fuels [8]. Photovoltaic (PV) systems, primarily harnessed through solar energy, have gained traction as a reliable source of electricity due to advancements in technology, policy support, and financial incentives. Solar photovoltaic technology converts sunlight directly into electricity, contributing significantly to the reduction of greenhouse gas emissions [9]. The International Renewable Energy Agency (IRENA) projects that the global renewable energy potential will increase substantially, with solar energy playing a central role in this growth [10]. The versatility of solar energy applications extends beyond large-scale power plants, enabling deployment in decentralized systems like solar trees and rooftop installations [11–13]. These systems not only provide electricity but also enhance energy independence and resilience against power outages. Implementing solar energy technologies can lead to significant cost savings over time, reducing reliance on imported fuels and lower electricity bills for consumers. The complementary nature of solar energy with other renewable sources, such as wind, enhances the stability and reliability of power generation. Hybrid systems that combine solar and wind energy optimize energy output and reduce variability, maintaining a balanced and resilient energy grid [14,15]. Solar energy is of paramount importance for electric energy generation, offering a sustainable solution to the global energy crisis. As technological advancements continue to improve efficiency and reduce costs, the role of solar energy in achieving energy independence and environmental sustainability will only become more significant [16].

The scarcity of comprehensive meteorological data is a significant challenge in accurately calculating solar radiation, which is crucial for applications such as solar energy generation and climate studies. To address this issue, various methodologies have been developed, including regression models, machine learning techniques, satellite data utilization, empirical models, and Geographic Information System (GIS) integration [17,18]. Regression models correlate solar radiation with historical data, while machine learning techniques offer better estimations under limited data conditions [19]. Satellite data provides a high-resolution dataset for mapping global solar radiation, especially in regions with sparse or non-existent ground-based measurements. Empirical models use temperature and sunshine hour data to estimate solar radiation, validating its accuracy against measured data. GIS integration enhances the accuracy of solar radiation estimations by using digital elevation models, accounting for local topographical variations that influence solar exposure [20]. These methods not only enhance the accuracy of solar radiation estimations but also provide viable solutions in scenarios where direct measurements are unavailable [21].

Artificial neural networks (ANN) and machine learning (ML) techniques have been widely used to estimate solar radiation, enhancing prediction accuracy and efficiency [22]. These methodologies are crucial for designing and optimizing solar energy systems, particularly in regions with limited

meteorological data [23,24]. ANNs can effectively utilize historical data to train models that predict solar radiation for photovoltaic system dimensioning, incorporating complex non-linear relationships. Khatib and Elmenreich [23] proposed a generalized regression neural network (GRNN) model that generates hourly solar radiation data from daily measurements, emphasizing its simplicity and improved accuracy over empirical methods. The integration of various machine learning algorithms has been shown to enhance solar radiation estimation. Hybrid models combining different machine learning techniques yield better results in estimating global solar radiation at specific locations, such as South African stations. Ensemble methods can significantly improve forecasting performance during extreme climate events. In addition to ANNs, other machine learning techniques such as support vector machines and decision trees have been employed in solar radiation forecasting. Viscondi and Alves-Souza conducted a case study in Brazil, where they utilized various ML algorithms to predict incident solar radiation [25]. Kim et al. demonstrated the application of boosting decision trees and recurrent neural networks for solar radiation forecasting [26]. Uzun's research on ANN models in Turkish cities illustrates the potential for localized solar radiation predictions, which can inform energy planning and resource management. The application of artificial neural networks and machine learning techniques in solar radiation estimation presents a promising avenue for enhancing the accuracy and reliability of solar radiation forecasts.

Nevertheless, a clear gap remains in the literature. Most ANN-based solar radiation studies rely on gradient-based training algorithms such as Levenberg-Marquardt (LM) or Scaled Conjugate Gradient (SCG), which are sensitive to initial weights and prone to convergence to local minima, potentially limiting prediction accuracy [23,25,26]. The use of metaheuristic optimizers for ANN weight optimization in solar radiation estimation—especially in regions with diverse meteorological and geographical conditions such as Türkiye’s KOP—has not been sufficiently explored. Furthermore, systematic comparison of such hybrid models against conventional training algorithms under identical data and network structures is often lacking.

Türkiye's solar radiation potential is significant, with an average of 3.6 kWh/m² of solar radiation daily and approximately 2640 hours of sunshine annually [27]. Accurate data is crucial for designing and optimizing solar energy systems, contributing to Türkiye's energy needs and sustainability goals [28]. Empirical models have been developed to estimate solar radiation across different regions, with ANN being employed to enhance accuracy in regions with limited direct measurements [28,29]. However, there are several shortcomings, such as uniformity of data across diverse climatic regions and limited input parameters. To address these issues, localized models incorporating a wider range of meteorological variables and real-time data collection methods are needed [30]. Enhanced data collection through satellite imagery and ground-based measurements can improve the accuracy of solar radiation estimates. Integrating machine learning techniques with traditional empirical models can provide more robust predictions tailored to specific regions within Türkiye [31,32]. By leveraging advanced technologies and localized approaches, Türkiye can optimize its solar energy utilization and contribute to a more sustainable energy future.

The necessity of using a metaheuristic such as Energy Valley Optimization (EVO) for training the ANN is twofold. First, gradient-based algorithms minimize the error function in a local neighborhood and can converge to suboptimal weights, whereas EVO performs a global search over the weight space and can escape local minima [33]. Second, when combined with Levy flight, EVO strengthens exploration and improves the balance between exploration and exploitation, which is beneficial when optimizing the many weights of an ANN [34]. Thus, EVO is a well-founded choice for optimizing ANN weights in solar radiation estimation, where high accuracy is required despite limited or heterogeneous meteorological data.

The original contribution of this study is threefold. First, it proposes an ANN whose weights are optimized by the Energy Valley Optimization algorithm (EVO-ANN) for estimating shortwave downward solar radiation in the KOP region of Türkiye, using 34 years of geographical and meteorological data from NASA's POWER Project [35]. Second, it provides a systematic, statistically supported comparison of EVO-ANN with ANNs trained by Levenberg-Marquardt and Scaled Conjugate Gradient under identical network architectures and data splits, demonstrating clear gains in correlation coefficient (R) and mean square error (MSE). Third, it delivers monthly solar radiation estimates for seven KOP cities (Konya, Karaman, Aksaray, Nevşehir, Niğde, Kırşehir, Yozgat), supporting regional renewable energy planning. The aim of this study is therefore to estimate the solar radiation values of central Anatolian cities in the KOP region using this EVO-ANN approach.

MATERIALS AND METHODS

In this study, an ANN and optimization-based regression model was proposed to estimate the solar energy potential of the geographical region of the Konya Plain Project (KOP) [36]. The overall workflow of the proposed methodology is presented in Figure 1. The proposed model predicts the amount of solar radiation with high accuracy, taking into account the geographical and 34-years meteorological data of the region.

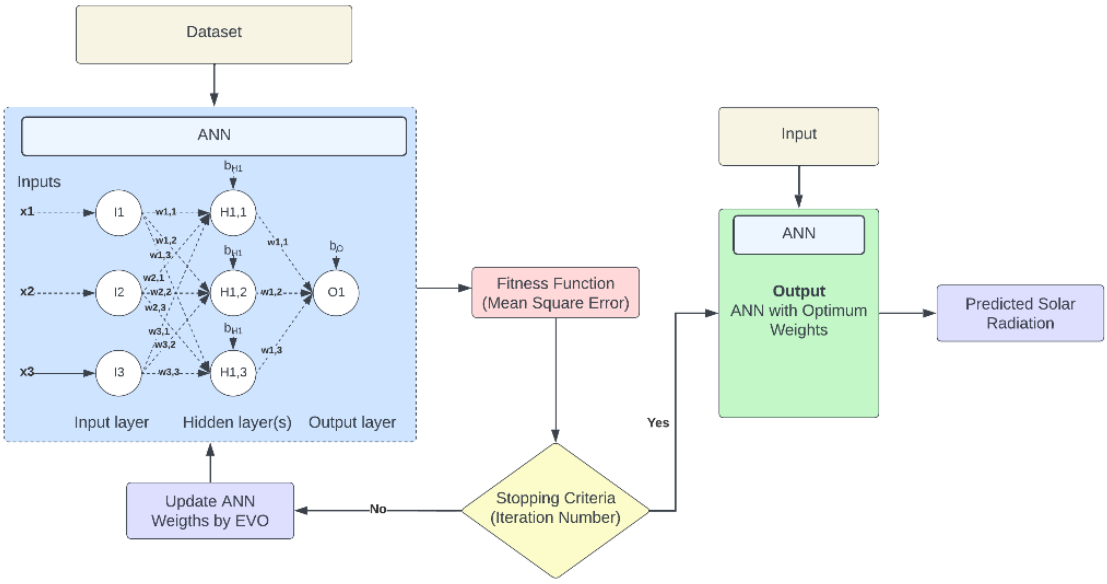


Figure 1
EVO-ANN based solar radiation prediction method

Model description

The proposed EVO-ANN is an ANN model in which optimal weights are calculated with Energy Valley Optimizer (EVO). The model takes geographical and meteorological data as input and updates the weights of the ANN with the EVO algorithm until the stopping criterion is met. As a result, by using the ANN model with the optimum weights, the amount of solar energy falling on the surface for any location within the KOP region can be estimated.

Data collection and locations

In this study, meteorological data provided by The POWER Project supported by NASA [37] and geographical information about the cities of Konya, Karaman, Aksaray, Nevşehir, Niğde, Kırşehir and

Yozgat located in the KOP geographical region have been used [36]. Location and altitude information about the cities are given in Table 1.

Table 1
Cities locational information in KOP Türkiye

Order	City	Latitude (deg)	Longitude (deg)	Altitude (m)
1	Karaman	37.175	33.228	1250
2	Konya	37.866	32.483	1026
3	Aksaray	38.368	34.0369	900
4	Nevşehir	38.624	34.723	1250
5	Niğde	37.966	34.683	1208
6	Kırşehir	39.150	34.166	985
7	Yozgat	39.820	34.804	1418

The KOP region is one of the important tourism, industrial and agricultural production regions for Türkiye [38]. In addition, thanks to the high solar energy potential of the region given in Figure 2 and Figure 3, studies on solar energy production in the region have increased in recent years [39,40]. Türkiye's largest solar power plant with a capacity of 1350 MWe was completed and put into operation in the KOP region, which is the priority investment region for solar energy investments, in 2023 [41].

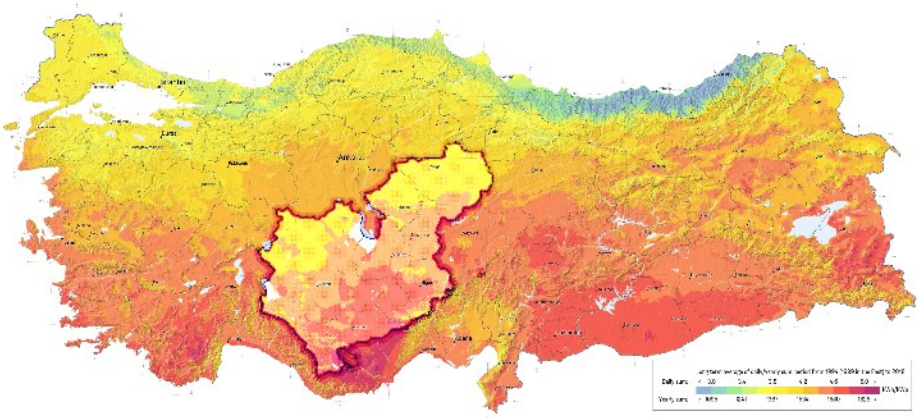


Figure 2
Solar radiation map of Türkiye and KOP region [42]

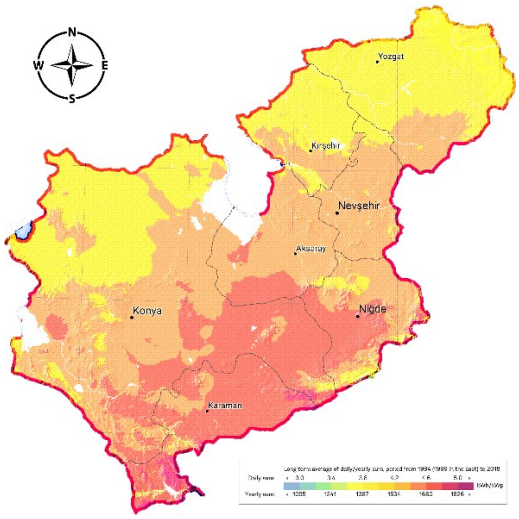


Figure 3
Cities in KOP Türkiye [42]

The data provided by the NASA POWER Project consists of 34 years of meteorological and

geographical data between 1990-2024 and consists of the structure in Table 2.

Table 2
Dataset structure

Title	Description
Latitude	The geographic coordinate that specifies the north–south position of a point on the Earth's surface
Longitude	The geographic coordinate that specifies the east–west position of a point on the Earth's surface
Altitude	The height above sea level
Year	The year in which the data was collected
Mo	The month in which the data was collected
Dy	The day of the month when the data was collected
ALLSKY SFC SW DWN	All Sky Surface Shortwave Downward Irradiance (in kWh/m²/day)
T2m	The air temperature measured 2 meters above ground level (in °C)
Qv2m	The specific humidity at 2 meters above ground level (in g/kg)
Ps	The atmospheric pressure at the Earth's surface (in Pascals)
Prectotcorr	The total corrected precipitation amount (in mm/day)

The data set, consisting of 12555 lines of data for each city, consists of a total of 87885 lines. During the tests, 20% of this data set was used as test, 60% as train and 20% as validation data.

Data preprocessing

The NASA POWER dataset is gap-filled, and no missing values were encountered in the variables used; therefore, no imputation was applied. All inputs (latitude, longitude, altitude, year, month, day, T2m, Qv2m, Ps, Prectotcorr) and the target (ALLSKY SFC SW DWN) were normalized to the interval [0, 1] using min-max normalization. For each variable, the minimum and maximum were computed on the training set only for that run, and the transformation $(x - x_{\min})/(x_{\max} - x_{\min})$ was applied to the training, validation, and test sets so that no information from the test set influenced the model or the scaling.

Data split and validation

The combined dataset was randomly split into 60% training, 20% validation, and 20% test. The objective is to model the relationship between meteorological and geographical inputs and solar radiation rather than to forecast a single long time series; a random split therefore allows the model to be evaluated across different calendar periods and conditions. To reduce dependence on a single partition and to support statistical comparison, each network configuration was run 10 times with different random seeds (and thus different train/validation/test splits); the mean, standard deviation, minimum, and maximum of R and MSE over these 10 runs are reported in Table 3. To avoid data leakage, the test set was not used in any training, validation, or model selection step. Normalization

parameters (minimum and maximum per variable) were computed on the training set only for each run and then applied to the validation and test sets, so that test data did not influence scaling or model fitting.

Design of the artificial neural network model

ANNs are mathematical models developed inspired by the working principles of the human brain and perform tasks such as learning, recognition and classification [43]. ANNs generally consist of an input layer, one or more hidden layers and an output layer as shown in Figure 4. The neurons in each layer take the values coming from the neurons in the previous layer, weigh them and transfer them to the next layer with the help of an activation function. The output of each neuron is obtained by the weighted sum of the inputs from the previous layer according to the equation given in Equation 1, and then the final output is obtained by applying an activation function.

$$F_{net} = \sum_{i=1}^{n} w_i * x_i + b \tag{1}$$

In Equation 1, n refers to the number of neurons in the previous layer, w_i refers to the input weights, x_i refers to the input values, b refers to the bias value. Activation function is applied to the F_{net} value and the final output is obtained. In the proposed method, the sigmoid function given in Equation 2, widely used in the literature, was used as the activation function [44].

$$F(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

ANNs are widely employed not only in classification tasks but also in a broad range of regression problems, including financial forecasting [45], real estate valuation [46], energy consumption and demand prediction [47], medical and healthcare-related estimations [48], and marketing and sales forecasting [49].

It is not possible to find historical meteorological data for every region of the surface in large areas such as the KOP region. For this reason, EVO-ANN model, has been proposed to calculate the solar energy potential on any date and any surface in the KOP region. The EVO-ANN model, whose ANN part is given in Figure 4, takes location, altitude, year, month, day, temperature, humidity, surface pressure and rainfall information as input as given in Figure 4 and estimates the amount of solar energy falling on the surface in (ALLSKY SFC SW DWN) as output. The network architecture tested number of hidden layers and neurons per layer are given in Table 3. The hidden and output layers use the sigmoid activation function (Equation 2). In the proposed EVO-ANN, weights are optimized by EVO; within each fitness evaluation, the ANN is trained on the training set for a fixed number of epochs (250) with mini-batch updates, and the validation set is used to monitor generalization. The optimizer used for this internal training is Root Mean Square propagation with learning rate 0.001. For the comparison models (Model 1 and Model 2), the same architecture and data splits were used, with Levenberg-Marquardt and Scaled Conjugate Gradient as the training algorithms [50].

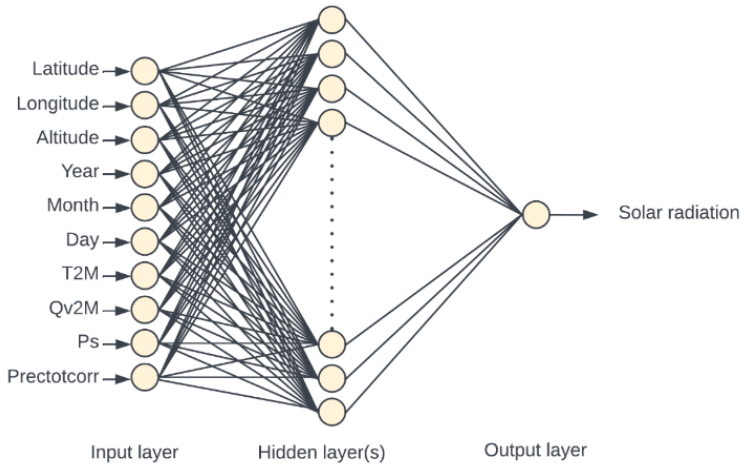


Figure 4
ANN schematic diagram for solar radiation prediction

To produce the best results on a given task with ANN models, ANNs must be trained with forward or back propagation algorithms or other optimization techniques. The main purpose of the training is to optimize the weight and bias values of the ANN by correctly analyzing the relationships between inputs and outputs [43]. In the proposed EVO-ANN model, ANN weights are updated by EVO according to the error rate measured by Mean Square Error (MSE) between the input and output given in Equation 3, as seen in Figure 1.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - y'_i)^2 \tag{3}$$

In Equation 3, n refers to the number of samples in the data set, y_i refers to the actual value, and y'_i refers to the predicted value.

Energy valley optimization (EVO) algorithm

The EVO algorithm is a physics-inspired metaheuristic optimization method based on energy minimization principles. This energy minimization is often considered equivalent to finding the optimal solution of the optimization problem [33]. In the proposed EVO-ANN method, the Levy Flight equation given in Equation 4, which has been seen in studies that the EVO algorithm helps to establish a more effective exploration and exploitation balance, has been applied [34].

$$L(s,\lambda) = \frac{\lambda * \Gamma(\lambda) * \sin((\pi * \lambda)/2)}{\pi * s^{1+\lambda}} \tag{4}$$

In Equation 4, λ is the Levy distribution constant and is taken as $\lambda = 1.5$ in this study, Γ and s represent the gamma function, and step length respectively. Levy Flight is a random walk model that effectively explores the solution space by making jumps. The pseudo code of the EVO algorithm with Levy Flight applied is given in Algorithm 1.

In Algorithm 1, the probability coefficient used as a condition for the application of Levy Flight is taken as $probability = 0.1$. $\beta = 1$ controls the movement of particles in the direction of energy decrease during the position update phase. $\alpha = 1$ represents dense, positively charged particles and allows the algorithm to make large jumps, such as the Levy flight, which increases its global search ability. $\varepsilon = 1$ adds a random factor to the agents' position update step. $\lambda = 1.5$ Levy allows the agent to make long jumps in the solution space during flight. This allows the algorithm to explore a large search

space without getting stuck in local minima, improving the global optimization process.

Algorithm 1
EVO algorithm with Levy Flight

Initialize population $\{X_i\}_{i=1}^{N}$ randomly within bounds

Evaluate fitness $F_i = f(X_i)$ for all agents and set X_{best}

For $t = 1\ to\ T$:

For each agent i:

$X_i' = X_i + \beta(X_{best} - X_i) + \varepsilon.rand()$

$if\ rand() < p: X_i' = X_i + \alpha.Levy(\lambda)$

Apply boundary handling to X_i'

If $f(X_i') < f(X_i): set\ X_i \leftarrow X_i'$

Update X_{best}

Return X_{best}

The EVO parameters used in this study are as follows. The population size (number of agents) was set to 10 and the maximum number of generations to 50. Each agent encodes the full vector of ANN weights and biases; the search bounds for each weight were $[-1,1]$. The Levy flight probability p was 0.1; the parameters $\beta = 1$, $\alpha = 1$, $\varepsilon = 1$, and $\lambda = 1.5$ were used as in Algorithm 1. The fitness of an agent is the MSE (Equation 3) of the ANN on the training set after setting the weights to that agent's position and performing the internal training (epochs) described above. The run was stopped when the maximum number of iterations was reached.

Evaluation criteria

In this study, the MSE given in Equation 3 and R metrics given in Equation 5 were used as evaluation criteria. MSE is a type of metric that expresses the difference between predicted and actual values, widely used in the literature. As the difference between the estimated and the actual value decreases, the MSE value decreases. R is the correlation coefficient used to measure the degree of linear relationship between two variables. The closer the absolute value of the R value is to 1, the stronger the relationship between two variables.

$$R = \frac{n * (\sum x * y) - (\sum x) * (\sum y)}{\sqrt{[n * \sum x^2 - (\sum x)^2][n * \sum y^2 - (\sum y)^2]}} \quad (5)$$

In Equation 5, the value n represents the number of data pairs.

RESULTS

In order to get the best solar energy results from the proposed EVO-ANN model, ANNs with different hidden layer models were created and tested. Then, monthly estimates were obtained for all cities and compared with the measured solar energy values.

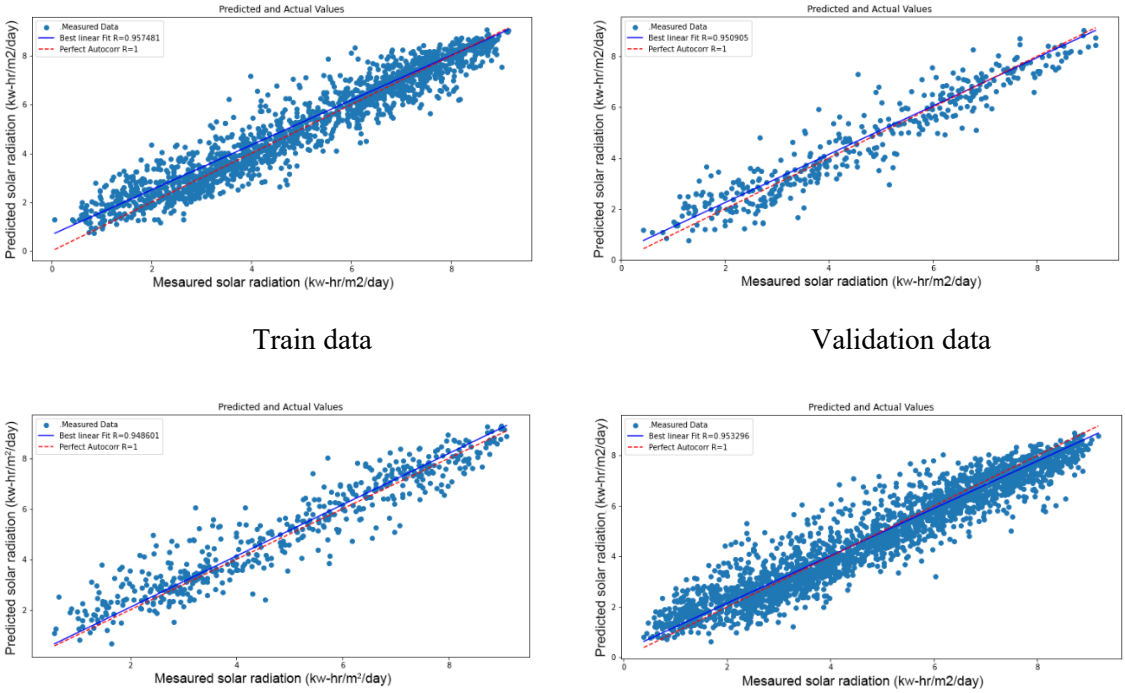


Figure 5
Performance of the best trained network

Network optimization

The performance of the proposed EVO-ANN under different network architectures is summarized in Table 3. Single-layer networks with 20, 15 and 10 neurons and two-layer networks with 20x20, 15x15, and 10x10 neurons were evaluated. Each configuration was run 10 times; for each run, R and MSE were recorded and the maximum, minimum, mean, and standard deviation across runs were reported. The 95% confidence intervals (CI) for the mean R and mean MSE were computed as $\bar{x} \pm t_{9,0.025}\,(s/\sqrt{10})$, where $\bar{x}$ and s are the sample mean and standard deviation over the 10 runs and $t_{9,0.025}$ is the two-tailed critical value of the t-distribution with 9 degrees of freedom. For the best EVO-ANN configuration (15×15 neurons), the 95% CI for mean R (all data) is [0.9521, 0.9527] and for mean MSE is [0.0754, 0.1265]; for Model 1 (20 neurons, all data) the 95% CI for mean R is [0.9386, 0.9396].

To compare Model 1 (LM), Model 2 (SCG), and the proposed EVO-ANN, the Friedman test was applied to the 10 paired runs at each comparable architecture, using R and MSE as outcomes. When the Friedman test indicated $p < 0.05$, pairwise post-hoc comparisons used the Wilcoxon signed-rank test. For the 15x15 architecture, the Friedman test yielded $\chi^2(2) = 18.2$, $p = 0.0001$ for R and $\chi^2(2) = 20.0$, $p < 0.0001$ for MSE; Wilcoxon tests gave $p = 0.005$ (EVO-ANN vs. Model 1) and $p = 0.005$ (EVO-ANN vs. Model 2) for both R and MSE. For the best EVO-ANN configuration (15x15), test-set residuals (predicted minus actual) had mean -0.002 kWh/m²/day and standard deviation 0.275 kWh/m²/day. Training, validation, test, and all-data diagnostics for the best-trained network appear in Figure 5.

Table 3 lists mean all-data R and MSE by architecture and trainer. By aggregate rank on those means, the proposed EVO-ANN is first, Model 1 second, and neurons yielded the strongest means among the architectures tested. For the proposed EVO-ANN, the highest mean all-data R occurs the 15x15 two-layer configuration and the lowest mean all-data MSE for the single hidden layer with 15 neurons.

Mapping of solar radiation in Türkiye

Solar radiation mapping is a key step for identifying priority regions for photovoltaic deployment, grid planning, and regional energy policy. In Türkiye, the spatial distribution of solar resources is driven by a combination of latitude, continentality, topography, and cloudiness regimes; therefore, a nationwide perspective is necessary to interpret local estimates and to position regional case studies within the broader resource landscape. Figure 2 presents the solar radiation map of Türkiye and highlights the KOP region within this context [42]. The map indicates that Central and Southern Anatolia exhibit relatively high irradiance potential compared with the Black Sea coastal belt, where persistent cloudiness and higher humidity reduce incoming shortwave radiation. These large-scale patterns are consistent with earlier solar potential mapping efforts based on measured and modeled datasets [51]. In this study, mapping is operationalized through monthly aggregation of the dataset used for model evaluation. Specifically, test records were grouped by month and city, evaluated on the trained EVO-ANN, and then summarized as monthly mean values. The resulting city-level monthly means are reported in Table 4, where measured (NASA POWER) and predicted values are juxtaposed. This representation provides a compact "map" of the solar resource over space (across KOP cities) and time (across months), allowing direct comparison of seasonal cycles and inter-city gradients. The same comparison is shown graphically in Figure 6 to make the seasonal envelope and deviations easier to interpret. Across all cities, the expected seasonal behavior is observed: minimum irradiance occurs in winter months (December–February), increases through spring, peaks in summer (June–August), and then decreases in autumn. Importantly, the month-to-month shapes are similar across KOP cities, while the amplitude differs by location and altitude (Table 1), reflecting the combined effects of synoptic cloud patterns and local geography. From a planning standpoint, this seasonal structure implies that PV generation in the KOP region will be strongly summer weighted, which is beneficial for meeting cooling-related electricity demand but also highlights the need for flexibility solutions for winter months. Finally, the mapping perspective also clarifies why the KOP region is a meaningful case study. As shown in Figure 3, the selected cities span a considerable portion of Central Anatolia, covering different elevations and microclimatic conditions within a high-potential corridor. Given the region's increasing solar investments and its strategic role in agriculture and industry, presenting solar radiation estimates in a spatio-temporal (city-by-month) mapping format supports actionable comparison among candidate locations and provides a transferable template for extending the approach to other regions of Türkiye with limited ground observations.

Table 3
Network performance

Model			Model 1 [50]						Model 2 [50]						Proposed EVO-ANN					
Trainer			LM						SCG						EVO					
Number of hidden layers			1			2			1			2			1			2		
Number of neurons			20	15	10	20 by 20	15 by 15	10 by 10	20	15	10	20 by 20	15 by 15	10 by 10	20	15	10	20 by 20	15 by 15	10 by 10
Coefficient of correlation (R-value)	Training data	Mean	0.9405	0.9398	0.9374	0.9431	0.9422	0.9412	0.9170	0.9122	0.9089	0.9192	0.9120	0.9107	0.9496	0.9462	0.9463	0.9569	0.9522	0.9500
		Std	0.0012	0.0013	0.0011	0.0006	0.0017	0.0008	0.0077	0.0060	0.0052	0.0041	0.0132	0.0078	0.0009	0.0001	0.0002	0.0004	0.0	0.0002
		Max	0.9424	0.9420	0.9396	0.9445	0.9457	0.9429	0.9314	0.9182	0.9206	0.9250	0.9230	0.9217	0.9507	0.9464	0.9466	0.9574	0.9523	0.9503
		Min	0.9381	0.9371	0.9354	0.9423	0.9399	0.9396	0.9006	0.8964	0.9027	0.9106	0.8758	0.8955	0.9486	0.9460	0.9460	0.9565	0.9521	0.9497
	All data	Mean	0.9391	0.9381	0.9361	0.9408	0.9404	0.9398	0.9196	0.9116	0.9089	0.9198	0.9113	0.9098	0.9425	0.9452	0.9394	0.9510	0.9524	0.9482
		Std	0.0007	0.0006	0.0009	0.0005	0.0009	0.0006	0.0077	0.0056	0.0043	0.0037	0.0127	0.0083	0.0002	0.0008	0.0002	0.0	0.0004	0.0005
		Max	0.9404	0.9390	0.9375	0.9418	0.9426	0.9409	0.9309	0.9184	0.9185	0.9250	0.9213	0.9207	0.9430	0.9464	0.9398	0.9511	0.9532	0.9488
		Min	0.9378	0.9369	0.9341	0.9398	0.9388	0.9389	0.9004	0.8973	0.9029	0.9120	0.8772	0.8937	0.9421	0.9440	0.9391	0.9509	0.9517	0.9476
MSE		Mean	0.1189	0.1226	0.1274	0.1207	0.1221	0.1188	0.1579	0.1641	0.1690	0.1534	0.1657	0.1684	0.1265	0.0754	0.1245	0.0853	0.0895	0.1046
		Std	0.0040	0.0079	0.0039	0.0059	0.0047	0.0029	0.0169	0.0106	0.0115	0.0076	0.0249	0.0137	0.1143	0.0215	0.1013	0.0213	0.0213	0.0225
		Max	0.1250	0.1360	0.1329	0.1308	0.1301	0.1235	0.1953	0.1869	0.1902	0.1685	0.2322	0.1975	1.3878	0.1307	1.3878	0.1237	0.1239	0.1528
		Min	0.1116	0.1081	0.1158	0.1118	0.1127	0.1126	0.1281	0.1485	0.1557	0.1428	0.1443	0.1536	0.0013	0.0001	0.0007	0.0005	0.0011	0.0010
Rank			2						3						1					

Table 4
Monthly average solar radiation by city (kWh/m^2/day)

City	Data	January	February	March	April	May	Jun	July	August	September	October	November	December
Karaman	Measured	2.34	3.29	4.53	5.76	6.80	7.50	7.75	6.97	5.73	4.02	2.80	2.10
	Predicted	2.73	2.79	4.17	6.49	6.72	8.09	7.84	7.48	5.04	3.89	3.06	2.04
Konya	Measured	2.41	3.40	4.55	5.70	6.70	7.40	7.71	6.90	5.74	4.05	2.84	2.12
	Predicted	2.77	3.49	4.05	5.79	6.39	7.44	7.25	7.26	5.06	4.50	2.64	2.43
Aksaray	Measured	2.30	3.28	4.32	5.45	6.51	7.35	7.74	6.95	5.63	3.91	2.71	2.04
	Predicted	2.40	2.71	3.89	5.24	6.04	8.05	7.87	6.66	5.80	3.90	3.22	1.43
Nevşehir	Measured	2.30	3.28	4.32	5.45	6.51	7.35	7.74	6.95	5.63	3.91	2.71	2.04
	Predicted	2.24	2.69	4.64	5.55	6.77	7.22	7.89	6.49	5.65	4.32	2.90	1.77
Niğde	Measured	2.29	3.13	4.21	5.35	6.37	7.29	7.71	6.91	5.66	4.05	2.81	2.12
	Predicted	2.32	3.38	3.96	5.10	6.17	7.27	7.90	6.85	5.03	4.27	2.55	2.04
Kırşehir	Measured	2.12	3.07	4.21	5.34	6.40	7.18	7.59	6.79	5.43	3.73	2.55	1.85
	Predicted	2.08	2.94	4.90	5.45	6.06	7.70	7.39	7.30	4.74	3.91	2.40	1.83
Yozgat	Measured	2.12	3.07	4.21	5.34	6.40	7.18	7.59	6.79	5.43	3.73	2.55	1.85
	Predicted	1.86	2.62	4.13	4.72	6.65	7.68	7.73	6.83	4.82	3.52	2.06	2.39
Sums of the differences		1.24	2.58	2.59	2.09	1.88	2.48	1.32	2.22	3.47	1.56	1.99	1.87
Mean of the differences		0.18	0.37	0.37	0.30	0.27	0.35	0.19	0.32	0.50	0.22	0.28	0.27

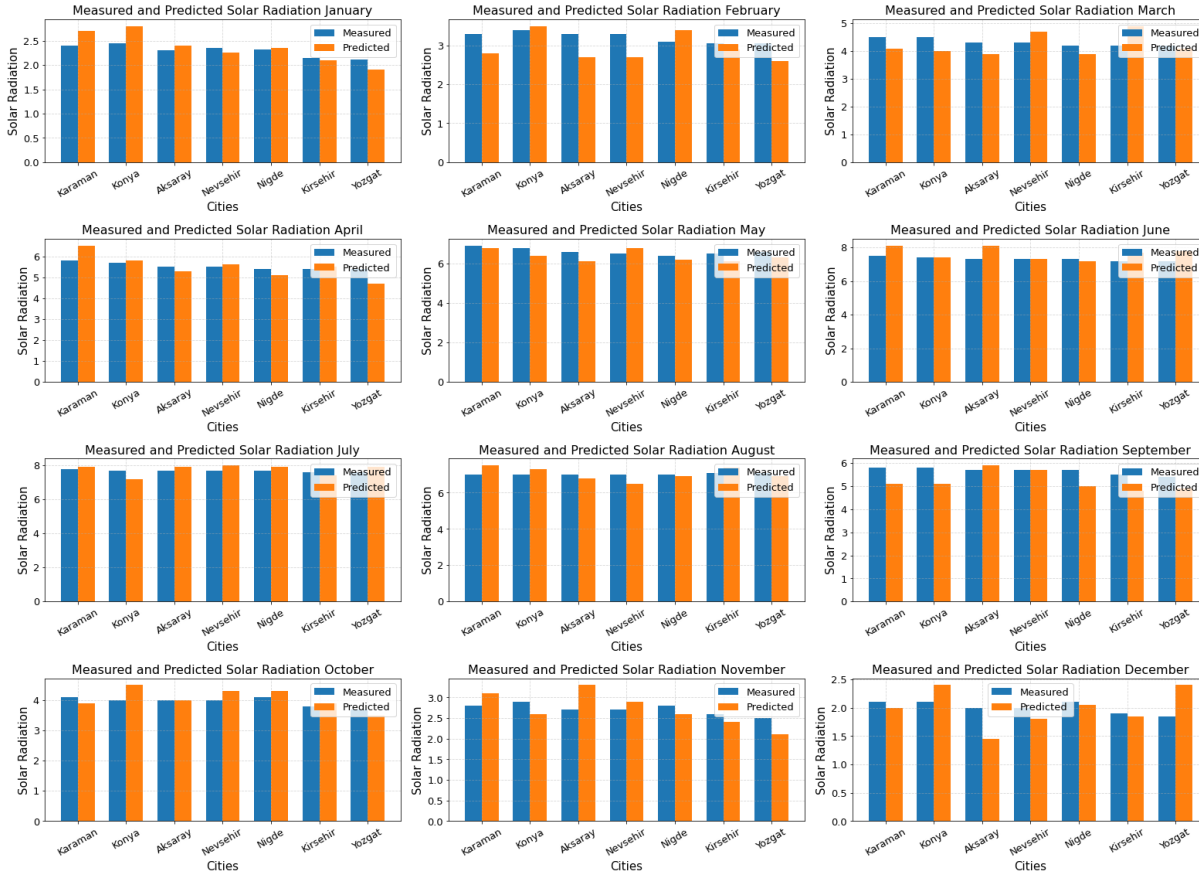


Figure 6
Monthly average solar radiation by city (kWh/m²/day)

DISCUSSION

The depth and width of an ANN strongly influence its fit: the universal approximation theorem implies that one sufficiently wide hidden layer can represent broad classes of continuous functions, yet deeper or wider stacks are often used in practice while excess capacity invites overfitting and very small nets may underfit. Read together, Table 3 and Figure 5 suggest that the proposed EVO-ANN navigates this trade-off favorably. The tight 95% confidence intervals for mean R and MSE across 10 runs indicate low run-to-run variability, and the Friedman and Wilcoxon outcomes ($p < 0.05$ for the 15×15 case and analogous comparisons elsewhere) support lower MSE and higher R for EVO-ANN than for both LM and SCG, so the gap is unlikely to reflect sampling noise alone. For the 15×15 configuration, test residuals were nearly centered, with standard deviation consistent with the reported MSE ($\sigma 2 \approx$ MSE), and no obvious systematic trend across the radiation range. Training diagnostics lie slightly above test performance, as usual when the loss is minimized on the training split, while held-out scores remain strong (Figure 5, Table 3), arguing against severe overfitting. Across trainers, EVO-ANN delivered the best mean all-data metrics; within each classical trainer a single layer of 20 neurons was preferred, whereas the 15×15 two-layer EVO layout maximized mean R and the single-layer 15-neuron EVO layout achieved the lowest mean MSE (Table 3). Collectively, these observations point to competitive bias–variance behavior for the metaheuristic training scheme under the architectures explored. For the KOP cities, Table 4 shows broadly close measured and predicted monthly means, yet February, March, and September exhibit larger gaps than other months. Continental climates often show pronounced diel temperature swings around the shoulder seasons: in spring and autumn, daytime insolation is weaker than in midsummer while nocturnal cooling can remain strong, which reshapes the daily mean that enters both NASA POWER and the learning target. If the training mix under-represents such regimes, the

model may retain residual seasonal error in those months. Figure 6 nevertheless follows the shared seasonal envelope—low values in January–March, a spring rise, summer maxima (notably July and August), and an autumn–winter decline—with measured and predicted curves nearly overlapping in midsummer and staying comparable elsewhere, which supports using the estimates for relative spatial–temporal comparisons even where absolute errors are larger. These outcomes are consistent with prior ANN studies of solar radiation in Türkiye, Fiji, and related GRNN formulations. Relative to the LM and SCG baselines in Table 3, EVO-ANN reaches the upper part of the reported correlation band and the lower part of the MSE band, which aligns with replacing pure gradient descent by population-based weight search augmented with Levy flights that encourage wider exploration. EVO-ANN's advantage also has a clear optimization interpretation. Gradient based methods (LM, SCG) perform local search and tend to converge to the nearest basin of the non-convex loss; quality depends on initialization. EVO maintains a population of weight vectors, iteratively favoring lower MSE, and Levy flights inject occasional large moves that help escape shallow minima. The systematic gains in R and MSE (Table 3) and the nonparametric test results match this global-versus-local perspective. The time complexity is derived as follows. Let N be the training set size, W the number of weights (and biases), P the EVO population size, T the number of EVO iterations, and E the epochs per fitness evaluation. One forward pass through the network uses each weight once per sample, so one sample costs $O(W)$ and one epoch over N samples costs $O(N.W)$; the backward pass is also $O(N.W)$, hence one epoch is $O(N.W)$. Each fitness evaluation runs E epochs, so it is $O(E.N.W)$. The EVO loop runs T iterations and evaluates P agents per iteration, giving total training time $O(P.T.E.N.W)$. At inference, one forward pass per sample yields $O(W)$ per sample. An important advantage of this complexity is that it is *linear* in both the training set size N and the number of weights W: doubling the data or the network size doubles the cost (up to constants). There are no quadratic or higher-order terms in N or W, which keeps the method scalable for larger datasets and deeper or wider networks.

CONCLUSIONS

This study proposed an EVO-optimized ANN (EVO-ANN) for shortwave downward solar radiation estimation in the KOP region of Türkiye. In summary, the EVO-ANN achieved a mean correlation coefficient (R) of up to 0.95 and a mean square error (MSE) as low as 0.0754 on the full dataset for the best configuration (Table 3), outperforming ANNs trained with Levenberg-Marquardt and Scaled Conjugate Gradient, which yielded mean R around 0.91–0.94 and MSE in the range 0.12–0.17. The superiority of the EVO-ANN was statistically significant (Friedman and Wilcoxon tests, $p<0.05$) over 10 independent runs. Monthly solar radiation estimates for the seven KOP cities showed good agreement with NASA POWER data (Table 4), supporting the use of the model for regional renewable energy planning.

While the results demonstrate promising performance and practical potential, several aspects provide opportunities for further refinement and broader evaluation. The current analysis focuses on the KOP region and relies on NASA POWER data; therefore, extending the assessment to other climatic regions and incorporating ground-based or alternative satellite datasets would help to further establish generalizability. In addition, the EVO and ANN hyperparameters (population size, number of iterations, epochs per fitness evaluation, and network architecture) were selected from a predefined set; exploring a wider search space or automated optimization strategies may reveal alternative performance–efficiency trade-offs.

Building on these observations, future work may explore applications across diverse climatic zones and countries, validate predictions using ground measurements where available, and compare EVO-ANN with alternative metaheuristic optimization strategies such as particle swarm optimization or genetic algorithms. Incorporating additional atmospheric inputs (e.g., cloud cover or aerosol optical

depth) and employing time-aware validation strategies, such as blocked cross-validation, could further strengthen temporal generalization. Finally, integrating the trained model into a practical decision-support framework for solar site selection or grid integration would help demonstrate its real-world applicability and operational value.

Data availability statement

Data available on request from the authors

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The Authors declare that there is no conflict of interest.

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Author Contributions

Ömer Özcan: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Visualization. Mehmet Çeçen: Conceptualization, Investigation, Resources, Funding acquisition, Writing – review & editing. Muhammed Karaaltun: Software, Data curation, Investigation, Visualization. Mehmet Hacıbeyoğlu: Methodology, Validation, Supervision, Writing – review & editing. All authors have read and approved the final version of the manuscript.

Sustainable Development Goals (SDG)

This study contributes to the United Nations Sustainable Development Goals, particularly SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action), by proposing an Energy Valley Optimization–based artificial neural network (EVO-ANN) for accurate solar radiation estimation to support renewable energy planning in the KOP region of Türkiye. The work also relates to SDG 9 (Industry, Innovation and Infrastructure) through the development of an optimization-based modeling approach for regional solar resource assessment.

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