POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)
URL: http://dergipark.org.tr/politeknik

Determining the optimum photovoltaic installation angle for provinces in turkey

Türkiye'deki iller için optimum fotovoltaik kurulum açısının belirlenmesi

***Yazar(lar) (Author(s))**: Sevda KAZEMZADEHMARAND[1], Adnan SÖZEN[2]*

ORCID[1]: 0000-0003-3301-1892

ORCID[2]: 0000-0002-8373-2674

To cite to this article: Kazemzadehmarand S., Sözen A., "Determining The Optimum Photovoltaic Installation Angle For Provinces In Turkey", ***Journal of Polytechnic***, 27(5): 1795-1804, (2024).

Bu makaleye şu şekilde atıfta bulunabilirsiniz: Kazemzadehmarand S., Sözen A., "Determining The Optimum Photovoltaic Installation Angle For Provinces In Turkey", ***Politeknik Dergisi***, 27(5): 1795-1804, (2024).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.1299063

Determining the Optimum Photovoltaic Installation Angle for Provinces in Turkey

Highlights

- *The optimal tilt angle for fixed solar panels has been determined*
- *Solar energy absorption has been optimized.*
- *Geographical quantities determine PV panel installation slope angle through an analytical relationship.*
- *A high prediction model was established.*
- *A multi-parameter prediction method has been developed using Artificial Neural Networks.*

Graphical Abstract

The network structure aims for the most accurate output using input parameters in the established model.

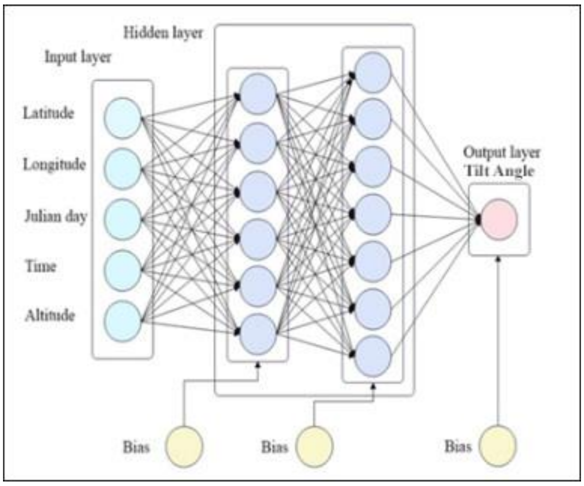

Figure. Network structure

Aim

Finding the best tilt angle for fixed solar panels for year-round maximum absorption.

Design & Methodology

Three different model network structures have been created using the Artificial Neural Networks.

Originality

An analytical relationship defines the slope angle for photovoltaic panel installation based on geographical factors.

Findings

Accurate predictions for optimal fixed solar panel angles in specific Turkish provinces were made to maximize year-round absorption.

Conclusion

The average annual optimum slope angles of the examined provinces are Ankara (35.18°), Antalya (34.29°), Ağrı (34.91°), Istanbul (34.50°), Sivas (34.96°), Izmir (35.19°), Sinop (35.06°) and Gaziantep (34.97°) were obtained.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Determining The Optimum Photovoltaic Installation Angle For Provinces In Turkey

Araştırma Makalesi / Research Article

Sevda KAZEMZADEHMARAND[1*], Adnan SÖZEN[1]

[1]Teknoloji Fakültesi, Enerji Sistemleri Mühendisliği Bölümü, Gazi Üniversitesi, Türkiye

(Geliş/Received : 18.05.2023 ; Kabul/Accepted : 12.09.2023 ; Erken Görünüm/Early View : 10.11.2023)

ABSTRACT

Solar trackers maximize solar radiation collection but are less commonly used due to their high cost, maintenance requirements, and the additional expenses associated with monthly angle adjustments. The main goal of this effort is proposing the optimization of solar energy absorption by determining the optimal tilt for fixed-site solar panels in Turkey. It introduces a mathematical equation that uses artificial neural networks to predict the ideal angle based on five specific features of the selected locations (latitude, longitude, Julian day, hour, and altitude) and cos θ, which are used for training and testing without requiring complicated calculations. Input variables, training procedures, and network design significantly impact the accuracy of Neural Network models' predictions. Using MATLAB, three distinct multilayer ANN models for this investigation were created, each employing unique training setups and procedures, MATLAB graphs are used to select algorithms and models based on the minimum MAE and RMSE, while the linear correlation coefficient (R) should be maximum. The RMSE value obtained according to the calculations of selected model which employs the feed forward Lunberg-Marquardt training algorithm, was $3.5881e^{-6}$, and the R value was 0.99998. The estimated data of the network were compared to the cosθ data, which were used for training and testing, yielding an RMSE error of 0.43% and an R2 value of 0.99978, indicating high accuracy. The average annual optimum inclination angles for the studied cities are as follows: Ankara (35.18°), Antalya (34.29°), Ağrı (34.91°), Istanbul (34.50°), Sivas (34.96°), Izmir (35.19°), Sinop (35.06°), and Gaziantep (34.97°).

Keywords: Solar energy, optimum tilt angle, solar panel, artificial neural network, solar radiation.

Türkiye'deki İller İçin Optimum Fotovoltaik Kurulum Açısının Belirlenmesi

ÖZ

Güneş takip cihazları, güneş ışınımının toplanmasını en üst düzeye çıkarır, ancak yüksek maliyetleri, bakım gereksinimleri ve aylık açı ayarlamalarıyla ilgili ek masraflar nedeniyle daha az kullanılmaktadır. Bu çalışmanın temel amacı, Türkiye'deki sabit güneş panelleri için en uygun eğimi belirleyerek güneş enerjisi emiliminin optimizasyonunu önermektir. Seçilen konumların beş spesifik özelliğine (enlem, boylam, Jülyen günü, saat ve yükseklik) ve eğim açısına (cos θ'ya) dayalı olarak ideal açıyı tahmin etmek için yapay zeka tekniklerinden Yapay Sinir Ağlarını (YSA) kullanan ve herhangi bir karmaşık hesaplamalara gereksinim duymadan eğitim ve test için kullanılan bir matematiksel denklem sunmaktadır. YSA için girdi değişkenleri, eğitim prosedürleri ve ağ tasarımı, Sinir Ağı modellerinin tahminlerinin doğruluğunu önemli ölçüde etkilemektedir. MATLAB kullanılarak, bu araştırma için üç farklı çok katmanlı YSA modeli oluşturularak, minimum hata değerlerine (MAE ve RMSE) dayalı algoritmaları ve modelleri seçmek için doğrusal korelasyon katsayısını (R) maksimum olması sağlayacak şekilde tasarlanmıştır. İleri beslemeli Lunberg-Marquardt eğitim algoritmasını kullanan seçilen modelin hesaplamalarına göre elde edilen RMSE değeri $3,5881*10^{-6}$, R değeri ise 0,99998 olarak bulunmuştur. Ağın tahmin edilen verileri, eğitim ve test için kullanılan cosθ verileriyle karşılaştırıldı ve %0,43'lük bir RMSE hatası ve 0,99978'lik bir R^2 değeri elde edilmiştir. İncelenen illerin ortalama yıllık optimum eğim açıları şu şekildedir: Ankara (35,18°), Antalya (34,29°), Ağrı (34, 91°), İstanbul (34,50°), Sivas (34,96°), İzmir (35,19°), Sinop (35,06°) ve Gaziantep (34,97°).

Anahtar Kelimeler: Güneş enerjisi , optimum açı, güneş paneli, yapay sinir ağ, güneş ışınım.

1. INTRODUCTION

One of the basic components of modern society is energy. Energy is needed to produce goods using natural resources and provide required services [1]. Methane, carbon dioxide, and nitrous oxide are among the various types of greenhouse gases that are emitted into the atmosphere when petroleum and other fossil fuels are burned for energy [2]. One of the recommended techniques for lowering greenhouse gas emissions is to switch to renewable energy [3]. Turkey has an enormous area of opportunity for generating electricity from the sun because of its geographical position. The Turkish Ministry of Energy and Natural Resource Development identified a yearly average of 1527.46 kWh/m2 according to their Solar Energy Potential Atlas. Turkey has a yearly solar electricity generation capacity of 189 GWh [4]. The amount of solar radiation solar devices get greatly affects how much energy is produced. It is essential to place the solar panels in a direction that absorbs the maximum amount of sunlight to obtain the most energy from the sun. Although solar tracking

*Corresponding Author
e-mail : kzm.sevda@gmail.com

devices are essential for maximizing the efficiency of solar radiation collection, their high cost prevents their widespread use [5]. Furthermore, monthly or yearly changes in the angle of the panels cause extra costs; the ideal tilt angle for stationary solar panels has to be determined in order to reduce these expenses. To maximize solar power output, the best angle of inclination for solar panels has been determined through numerous studies. At a given inclination angle, a module receives three types of radiation: direct, scattered, and reflected radiation. The solar zenith angles fluctuate throughout the day and year, affecting the amount of solar energy hitting the modules [6]. As "cosθ" on a surface rises, the overall quantity of solar energy that is absorbed on that surface will increase. When the angle of slope, θ, of the ray on a given surface is less, "cosθ" has its greatest value [7].

Naraghi M. obtained the optimal tilt angle using his numerical program. He estimated the global radiation components using the ASHRAE model and then determined the tilt angles for the desired locations [8].

The optimal monthly slope angles for different regions in India were estimated by Sharma A., Kallioğlub M., Awasthi A., Chauhan R., Fekete G., Singh T. using mathematical models and various statistical tools. For this purpose, different scenarios were presented for five-, four-, three-, and two-year compliance models, according to which the most profitable model can be used as a basic guide for the development of solar power plants [9].

In addition, Benghanem M. For optimal tilt angle determination, collector surfaces were assumed to face the equator. By estimating βopt for different months, the maximum energy was calculated in different months. Quadratic equations of the total radiation diagrams for different months were processed. These results show that the optimal tilting angle is almost exactly the same as the latitude of the Medina region [10].

The study conducted by Bakirci K. calculated the optimal slope angle using radiation formulas for eight major cities in Turkey. The estimation findings were confirmed to be correct based on the statistical error of the average deviation from the mean error (MBE), root-means-square error (RMSE), t-statistic, and Pearson's correlation coefficient (r). In summer, the optimal angle is at least 0°, whereas in winter, it is at its maximum [11].

The study by Baileka N., Bouchouichab K., Aounb N., EL-Shimyc M., Jamild B., Mostafaeipoure A.was conducted in the Adar Desert in Algeria, which lacks long-term meteorological data. To optimize solar energy, the slopes were changed regularly, seasonally, semi-annually, and yearly. When compared to horizontally placed modules, the solar energy received at monthly, seasonal, semi-annual, and yearly settings increased by 20.61%, 19.58%, 19.24%, and 13.78%, respectively. For hot months (April-September), 3.50 ° was the most appropriate tilt angle, and for cold months (October-March), it was 49.20 ° [12].

In Pune, Girnar J. and Gadhe P. investigated the most effective slope for constant solar power plants. Using a spreadsheet, they calculated the solar panel's inclination and the angle of the sun's azimuth. Monthly and annual radiation values for a surface at a certain angle have been calculated by calculating direct, scattered, and reflected radiation. Finally, the inclination angle of the solar panel was determined using a spreadsheet solver [13].

De Bernardeza L.S., Buitragob,c R.H. and García N.O. analyzed the energy production of PV modules in the Argentinian region using artificial neural networks. In this method, climate parameters collected over a year, as well as data from PV panels (energy falling on the PV panel, electrical energy produced by photovoltaic modules, and operating temperature of photovoltaic modules) were used. Despite a lack of data on solar radiation, artificial neural networks may be utilized to estimate the optimal angle for solar energy generation [14].

Gurlek C., Sahin M. estimated the global solar radiation of Sivas City using meteorological and geographical data and artificial neural networks. According to the results obtained, it is possible to estimate the global radiation amount in Sivas using artificial neural networks only for places where data such as the duration of sunshine and temperature are available. The consequences of network accuracy are as follows: mean deviation error (MBE) -1.264 MJ/m2 to 0.938MJ/m^2, root mean square error (RMSE) 0.710 MJ/m^2 to 1.598 MJ/m^2, and R^2 ranging from 0.984 to 0.994 [15].

To determine the exact amount of global radiation, Neelamegama P. and Arasu Amirtham V., created two neural network (ANN) models that used four distinct algorithms. These models have been evaluated using information gathered over the last years over different distinct places in India. Based on the lowest mean absolute error (MAE), root mean square error (RMSE), and maximum linear correlation coefficient (R), the optimal model and algorithm were selected. Where meteorological data are unavailable in different regions of India, the average monthly global radiation can be predicted [16].

Yadav A. K., Chandel S. S., in their research, they taught and assessed an artificial neural network to forecast the sun's radiation using data from 12 meteorological sites in India. The Levenberg–Marquard (LM) algorithm was the training algorithm used in this neural network. After comparing the results from the network with meteorological station data, the RMSE in this model was in the range of 0.0486-3.562 for different points [17].

Shaddel M., Seyed Javan D., Baghernia, P.Trained an artificial neural network using MATLAB software with data collected by pyrometers installed at the weather and solar station at Mashhad Ferdowsi University. Solar radiation data for 2013 were recorded at zero, 45, and 60-degree angles on inclined panels between 6 a.m. to 5 p.m., every 30 minutes. According to the findings, the neural network can be a dependable instrument for determining the quantity of solar energy in inclined photovoltaic panels in Mashhad [18].

Research was done on the effectiveness of solar power plants in Saudi Arabia by Al Garni H. Z., Awasthi A., and Wright D. They examined fixed solar modules in 18 areas using ground measurements. With a focus on various months, MATLAB was used to determine the best angles based on the azimuth and inclination angles. Due to the milder weather, energy efficiency maximized in March and October. With no expense, increasing the orientation five times a year enhanced productivity by 3.63%. Taking into account the weather, topography, and site attributes, six of the 18 regions were chosen for the best angles (slightly higher than latitude) and azimuth (20° to 53° west of south) [19].

To determine the ideal tilt angle and orientation of solar modules, Matius M. E., Ismail M. A., Farm Y. Y., Amaludin A. E., Radzali M. A., Fazlizan A., and Muzammil W. K. set out to make predictions. They evaluated the Liu and Jordan isotropic model using the GSA 2.3 simulator and compared it to three other models (Koronakis, Badescu, and Tian). The radiation approximation and software tilt angle agreed well with Tian's model. In comparison to GHQ 2.3, isotropic models were about 30% off [20].

Heibati S., Maref and Saber H. H. transformed the daily sun radiation parameters into a computer model. They identified the following control variables: ground reflection, tilt angles, and surface azimuth angles. They proposed three options for optimizing tilt angles using a flowchart and an objective function. Researchers looked at how control variables affected dynamic and ideal tilt angles for solar systems in Montreal. The best tilt angle for each scenario, based on the data, was 60–65° for winter, 20–22.5° for spring, 27.5–35° for summer, and °68–75° for fall [21].

For the purpose of calculating radiation on curved surfaces, Morcos V. H. created a mathematical model. He used it to locate the best solar collector inclinations in Egypt and discovered that rotating the collectors' inclination many times a year boosted radiation collection by 6.85% for flat-plate collectors and by 29.18% for concentrated collectors as compared to fixed placements [22].

Three models were created by Khoo Y. S., Nobre A., Malhotra R., Yang D., Rüther R., Reindl T., and Aberle A. G. to show the radiation on a solar module from various perspectives. Their work extends that of Liu, Jordan, Klucher, and Perez and is based on measurements of spherical GHI and DHI in Singapore. Perez's model was shown to be the most accurate when results from modeling were contrasted with sensor data from various inclinations. Additionally, a photovoltaic system's 10-degree eastward tilt demonstrated the best energy efficiency in Singapore's climate [23].

Artificial neural networks were utilized by Notton G., Paoli C., Vasileva S., Nivet M. L., Canaletti J. L., and Cristofari C. to quickly calculate global solar radiation. On the basis of optimal solar data gathered over a five-year period, the grid was assessed. According to estimates of the accuracy of the network, which was estimated to be around 6% (relative mean square error) for RRMSE and around 3.5% (relative mean absolute value) for RMAE, the ANN performs better than the experimental models [24].

Ideal tilt angles were established by Jafarkazemi F., Ali Saadabadi S., and Pasdarshahri H., using a mathematical model and meteorological data from 80 Iranian cities. They compared inclined panels to horizontal collectors and computed the solar radiation for various angles and durations. The results showed daily increases of 21.3 %, 21 %, 19.6 %, 19.3 %, and 13.3% in daily, monthly, seasonal, biennial, and yearly solar radiation, respectively. For the best tilt angles, researchers have suggested biannual changes that consider weather and latitude angles [25].

Using Liu and Jordan's approach, Khatib T., Mohamed A., Mahmoud M., and Sopian K. improved the tilt of solar panels. While monthly slope alterations are advantageous in the eastern regions, changing seasonal slopes is indicated for Peninsular Malaysia. The monthly changes produced a greater gain in energy than the seasonal changes [26].

The study conducted by Aksoy M. H., Ispir M., Yesil E., conducted in Konya, Turkey, researchers looked at PV system tilt angles in relation to row spacing. On a 3000 m^2 space, took into account spacings of 2, 2.5, 3, and 4 m were used while maintaining a 35° tilt. At optimum angles between 1° and 27°, the electricity output increased by 0.92% to 6.19%, ranging from 385.72 MWh to 622.77 MWh. The payback times were reduced by 0.91% to 5.83%, while the Performance Ratio increased by 1.44% to 20.61%. The most lucrative configuration produced an NPV/INV of 0.915, an IRR of 20.42%, and an ROI of 91.57% with a 3 m row spacing and a 21° tilt [27].

In Şanlıurfa, Beyazit N. I., Bulut H., Demirtaş Y., calculated horizontal diffuse radiation values using existing models due to limited measurements and expensive instruments. Measurements from a 7-year dataset with a solar tracker were employed to compare model results to actual measurements. Among the five models tested, Erbs et al. showed the least statistical error and was the most suitable. The commonly used Liu and Jordan model exhibited significant deviations from the measured data [28].

This study aims to help determine the PV installation angle for PV installations, which are becoming widespread day by day, by considering the geographical data of the installation location practically. The installation angle of PV systems that do not follow the sun is of great importance in order to ensure maximum solar energy absorption, taking into account the terrain conditions and the installation locations. With the determination of the optimum angle, it is seen that the annual average earnings increase by at least 5% compared to the normal production.

The present study is aimed to propose a method based on ANNs for creating an equation for predicting the optimum angle of tilt according to the five characteristics of any area in Turkey. The annual tilt angles of the modules for different locations were predicted using three multi-layer ANN models, each with different algorithms and structures. Five characters from eight selected locations in Turkey were used as inputs in ANN Models I, II, and III, respectively. Eventually, the annual average tilt angle was predicted. The latitude, longitude, Julian day, hour, and altitude data were used as inputs for the models. The cosθ function used to train and evaluate the algorithms was calculated for each hour from sunrise to sunset. All three designed models were trained and tested using the feed-forward Levenberg-Marquardt procedure (LM). The three ANN models were assessed based on the minimum mean absolute error (MAE), minimum root mean square error (RMSE), and maximum linear correlation coefficient (R). The errors reported in models using a multi-hidden layer architecture are within acceptable limits, clearly showing that artificial neural networks can be used for modeling in various fields of solar energy systems. In addition, the use of artificial neural saves time and avoids solving mathematical problems. The equation obtained from the ANN models is considered a suitable tool for estimating the slope angle in regions where long-term meteorological data are unavailable.

2. ARTIFICAL NEURAL NETWORK

Artificial Neural Networks were created from a collection of neurons to simulate information processing by the human brain during the learning process and performance [24]. Scientists have used ANNs to solve various problems. It can approximate any continuous nonlinear function with a desired degree of accuracy [1]. Neurons process the electrical signals that pass through them. The function of the neurons is based on flip-flop logic [20]. The input is connected to the neuron and to many levels of neurons by multiplying the input by a weight. Neurons employ a transfer function to acquire the results in the final step [16]. Figure 1 depicts the basic design of an ANN.

Several solar energy applications use ANN techniques as alternatives to conventional techniques [2]. Recently, neural network models have been used in solar energy applications to determine correlations among a variety of data [14]. For the current study, to determine the ideal inclination for solar panels at any location in Turkey, an Artificial Neural Network system was built. It was developed based on the geographical characteristics of eight cities in different Turkish provinces, under different climatic conditions. Gradient descent (GD), the Levenberg-Marquardt backpropagation algorithm, was employed in the current study for predicting the optimal inclination angle of the solar panel.

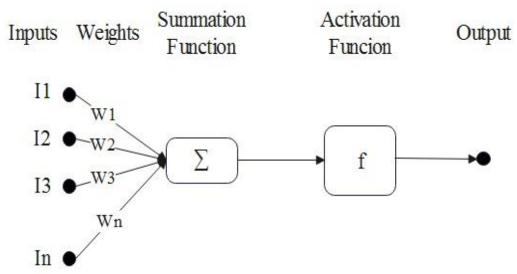

Figure 1. The Artificial Neural Network's general architecture.

3. METHODOLOGY

3.1. Data Collection

The numerical values for numerous factors, such as latitude, longitude, Julian day, decimal time, altitude, and cosθ, were gathered and computed for the eight locations studied. Values of latitude, longitude, and altitude parameters of the eight studied places are shown in table 1. The Julian day is a count of days in a year, and the time in decimal was calculated as Hour + minute/60. The cosθ was calculated for the hours between sunrise and sunset during the 365 days of a year for each selected city.

Table 1. Geographical attributes of eight studied places

City	Latitude	Longitude	Altitude (m)
Ağrı	39.7189	43.049	1640
Ankara	39.945	32.53	938
Antalya	36.892	30.69	30
İstanbul	41.01	28.58	40
İzmir	38.34	27.09	2
Gaziantep	37.05	37.22	850
Sinop	42.02	35.09	384
Sivas	39.747	37.011	1285

According to Equation (1), the angle among the rays of the sun and the line that is parallel to the surface is represented by the cosine of the solar impact angle, cosθ.

$$\cos\theta = (\sin\delta.\sin\varphi\,.\cos S) - (\sin H.\cos\varphi.\sin S) + (\cos\delta.\cos\varphi.\cos S.\cos H) + (\cos\delta.\sin\varphi.\sin S.\cos H) \quad (1)$$

δ: Declination Angle

φ: Latitude

S: $\varphi * 0.9$ (For Annually Optimum Yield)

H: Solar Hour Angle

The information is split into two groups after data collection: training and testing. To analyze the data provided, a neural network model is then employed.

3.2. ANNs Implementation

In the absence of a measuring instrument, the ANN model design could predict the optimal tilt angle. This ANN model will be invaluable for efficiently employing solar energy in many real-world uses and for free [16].

An artificial neural networks (ANN) architecture is made up of many layers, including an input layer for collecting data, a layer of output for sending out calculated data, and a number of concealed layers for connecting the input and output layers with neurons [24]. Artificial neural networks can predict output values after being trained on a collection of input-output data. To learn multilayer feed-forward networks, Gradient descent (GD), Levenberg-Marquardt back propagation (LM), robust back propagation (RP), and scaled conjugate gradient (SCG) are used [29]. In the current study a MATLAB version 2018 software package was used to perform the procedure. Using a feed-forward backpropagation network with four layers, a multilayer Artificial Neural Network (ANN) model was created, with the first hidden layer utilizing tangent sigmoid activation functions, the second concealed layer using logistic sigmoid activation functions, and the output layer using sigmoid activation functions. The input layer lacked an activation function. The tangent sigmoid function is one of the most frequently used functions and is quite similar to the sigmoid function. This nonlinear function is defined in the value range (-1, 1). Shown in the Equation (2)

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

Where “X” is the input for the transferring function.

The logistic sigmoid mathematical equation provides an output within the [0, 1] region regardless of the inputs of Equation (3).

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

Purelin is a helpful nonlinear regression or prediction transfer function. The output in Purelin is identical to the input and serves as a transferring function in the output layer as shown in Equation (4).

$$f(x) = x \tag{4}$$

The algorithm was trained using the Trainlm function, which is founded on the Levenberg-Marquardt algorithm. Latitude, longitude, Julian day, time in decimals, and altitude were chosen as input factors for each input layer neuron, and just the output cosθ was predicted. The performance factors that were employed in this study's algorithm training are listed in Table 2.

3.3. Normalization, Training, and Testing

An artificial neural network must be trained by changing the connections' weights so that it can identify and learn from patterns in the given training set. This means that the model should be capable of predicting new data with as minimum error as possible. For the current research, hourly statistics were gathered and calculated for days of the year between sunrise and sunset at eight survey sites. Before training, both the input and training datasets were normalized using the feature scaling method. This was performed to obtain all scaled data in the range between 0 and +1 to be more efficient. The following is the min-max method equation used to normalize the data in the desired interval. Equation (5)

$$X_n = \frac{x-\min(x)}{\max(x)-\min(x)} \tag{5}$$

Here, x is a variable that represents a parameter value within the dataset. The values max(x) and min(x) refer to the largest and smallest values of that parameter, respectively, within the dataset. 70% of the information was employed to train the model of the artificial neural network, 15% was used to test, and 15% was used to verify it. [16].

Table 2. Parameters that impact instruction effectiveness

Characteristic	Value
Maximum number of epoches to train	1000
Performance goal	0
Maximum validation failures	1000
Minimum performance gradient	$1e^{-12}$
Initial mu	0.001
Mu decrease factor	0.1
Mu increase factor	10
Maximum mu	$1e^{-10}$
Epoches between displays	25
Generate command-line output	FALSE
Show training GUI	true
Maximum time to train in secounds	inf

3.4. Selection of the Number of Neurons in The Hidden Layer

Choosing the right amount of neurons of hidden layers for a model is a difficult issue because there is no standardized method or approach to assist this process. Random initial weights are generally used to train ANN models. An issue with processing data is caused by a lack of hidden-layer neurons. A high number of hidden layer neurons causes unnecessary training time and makes it difficult to predict the appropriate connection weights. The trial-and-error procedure, which relies on evaluating the total error measure of the neural network, stands out as a prominent approach for determining the optimal number of neurons in the hidden layer [19]. The amount of neurons in the hidden layer was determined using the lowest mean square error (MSE) and the highest linear correlation coefficient (R). R-values greater than 0.9000 indicate that more predicted values agree with the measured values [16]. Therefore, three ANNs with different algorithms and training configurations were developed in this study and are shown in table 3.

The R-value for Model 1 was equal to 1, indicating that the network failed to test and train on different data. Based on the comparisons made above, Model 2 was found to be the best for foreseeing the inclination angle of solar panels with the lowest mean square error. Model 2 was the most appropriate model, according to the greatest R-values for training, testing, and confirmation. Model 2 is depicted in figure 2.

Table 3. The number of neurons used and the configuration of the ANNs

		Input Layer	Hidden Layer		Hidden Layer
Model 1	Number of neurons	5	15		1
	Activation Function	Purelin	Tansig		Purelin
	R^2-Value		1		
Model 2	Number of neurons	5	6	7	1
	Activation Function	Purelin	Tansig	Logsig	Tansig
	R^2-Value		0.99998		
Model 3	Number of neurons	5	5	8	1
	Activation Function	Purelin	Logsig	Tansig	Logsig

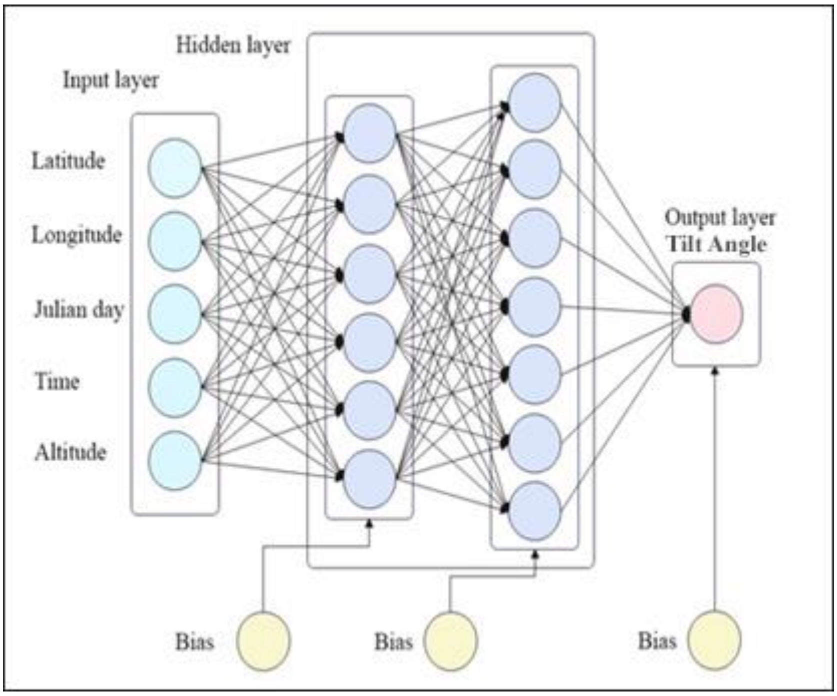

Figure 2. The number of neurons used and the configuration of the ANNs

3.5. Model Equations

A four-layered feed-forward backpropagation ANN with five input neurons, thirteen hidden neurons, six neurons in the first hidden layer and seven neurons in the second hidden layers, with sigmoid and Logsig transfer functions was trained using the Levenberg-Marquardt (LM). The Levenberg-Marquardt (LM) training algorithm, a popular optimization technique used in neural networks, was effectively utilized in this case to train the network; Moreover, the input layer's transfer function is linear, while the output layer's transfer function is sigmoid. The generated model is given by Equation (6).

$$Y(x) = \sum_{l=1}^{7}\Big\{\mathrm{tansig}(LW_l * \big[\sum_{j=1}^{6}\sum_{k=1}^{7}\mathrm{logsig}(LW_{j,k} * (\sum_{i=1}^{5}\sum_{j=1}^{6}\mathrm{tansig}(IW_{i,j} * x_i + b_j)\big) + b_k)\big] + b_l\Big\} \quad (6)$$

Where Y(x) is predicted response.

Equation (6) shows the trained feed-forward ANN model that predicts cosθ. "Tansig" and "Logsig" are functions used by MATLAB that calculate the output layer using the input. In this particular case, IW stands for the weights of the connections between the input layer with the layer that is concealed, while the weights of the connections between the concealed and layer of output are referred to as LWs. The symbols b_j, b_k, and b_l denote the weight values of the bias connections linking the layers that are concealed and the output layer. Equation (7) can be used to represent the model.

The weights of the layers as well as the biases for the proposed model obtained from the MATLAB software are given in a matrix format Equations (8) and (9).

Weights: $IW_{i,j}$ (6×5), $LW_{j,k}$ (7×6), $LW_{k,l}$ (7×1) (8)

Bias: b_j (6×1), b_k (7×1), b_l(1×1) (9)

Equation (10) provides a prediction model for determining the optimum inclination angle.

$$Y_n = \mathrm{tansig}\Big(B_l + LW_{k,l} * \mathrm{logsig}\Big(B_k + LW_{j,k} * \mathrm{tansig}\big(B_j + LW_{i,j} * x_n\big)\Big)\Big) \quad (10)$$

Where Y_n represents the normalized output.

$$f_3\left(W_l, f_2\left(W_k, f_1\left(W_j, X_i\right)\right)\right) = \frac{2}{1+e^{\left(-2\left[\sum_{l=1}^{l} W_l \frac{1}{1+e^{\left(-\left[\sum_{k=1}^{k} W_k\left(\frac{2}{1+e^{-2\left(\sum_{j=1}^{j} W_j X_i + b_j\right)}}-1\right)+b_k\right]\right)}}+b_l\right]\right)}} - 1 \quad (7)$$

4. OUTCOMES AND DISCUSS

4.1. Data Selection for Models

Developing an efficient model that can accurately forecast the tilt angle of solar panels in Turkey using easily accessible data is the main goal of current research. The model aims to utilize readily available data sources for this purpose. The input and output target datasets of eight selected locations in different provinces of Turkey were collected and calculated. Subsets for training and testing were developed from the input and output target databases. The five input parameters of latitude, longitude, Julian day, hour, altitude, and declination angle were used as the sole output parameter predicted using the Levenberg-Marquardt (LM) back-propagation method to create and develop three different ANN models in MATLAB version 2018. 70% of the gathered data were used as training data, 15% were used for testing, and the remaining 15% were used to verify data that had not been previously used for training.

4.2. ANN Model Performance

Each artificial neural network model's efficiency was assessed using the R and RMSE. Equation (11) and Equation (12) were used to explain the root mean square error (RMSE):

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(X_i - \hat{X}_i)^2}{N}} \quad (11)$$

Where, N: total number of data points being analyzed,

X_i: the actual calculated hourly tilt angle panel,

$\hat{X}_i$: the predicted hourly tilt angle of the panel as generated by the artificial neural network (ANN) model.

$$R^2 = 1 - \frac{\sum_i^N (y_i - \hat{y}_i)^2}{\sum_i^N (y_i - \bar{y})^2} \quad (12)$$

Where, $\hat{x}_i$: ANN predicted hourly tilt angle of a panel

x_i: Actual calculated hourly tilt angle of a panel,

$\bar{x}_i$: Average of x_i

The amount of dispersion the ANN model generated is displayed by the root mean square error (RMSE). The prediction accuracy of an ANN model with a lower RMSE is outstanding. Linear correlation coefficients (R) were used to establish the link between observed and predicted values. The best models were determined to be the ANN models with lower RMSE and higher R values.

Table 4. Statistical indicators of the models

		R-Value	RMES- Value
Model 1	Training	1	5.30E-07
	Validation	1	
	Test	1	
	All	1	
Model 2	Training	0.99998	3.59E-06
	Validation	0.99973	
	Test R	0.99998	
	All	0.99998	
Model 3	Training	0.92467	2.88E-02
	Validation	0.92431	
	Test	0.92273	
	All	0.92433	

Table 4 shows the effectiveness of the developed models in terms of the linear correlation coefficient between the anticipated output of an artificial neural network and the observed target as well as the root mean square error.

The finest outcomes for Model (II) training and testing were obtained with lowest RMSE values as $3.5881e^{-6}$, according to the chart. The highest R values of 0.99998 were found for both the testing and training data sets. The data analysis demonstrates that the Levenberg-Marquardt back propagation (LM) approach used in ANN model (II) is appropriate for producing an accurate hourly tilt angle forecast for solar panels. The data were contrasted with the data computed using the RMES and R2 formulas in order to assess the precision of the data received from the estimation of model 2. The final results were 0.43 and 0.99978 for RMSE and R, respectively.

The results showed that a multilayer perceptron with double hidden layers, a mix of seven and six neurons, Tansig and Logsig transfer functions, and Tansig function on the output layer produced the best results for the given research.

4.3. Optimum Angle for Provinces

The annual optimum inclination angle was obtained by averaging the scatter angles predicted for the studied cities. As shown in the figure 3, the accuracy of the results was evaluated by determining the correlation coefficient (R^2) and the results are shown in table 5.

Figure 3. Average yearly optimum tilt angle for eight studied cities.

Table 5. Statistical test results of determining the correlation coefficient.

City	Ağrı	Ankara	Antalya	Gaziantep	İstanbul	İzmir	Sinop	Sivas
Optimum Angle	34.91	35.18	34.29	34.97	34.50	35.19	35.06	34.96
R-Square	0.9989	0.9973	0.9973	0.9973	0.9973	0.9973	0.9973	0.9973

Comparison of the research results with the literature is given in Table 6. When the statistical approximation value (R^2) values given for the prediction models of PV installation angles obtained with similar parameters but different training algorithms are examined, the prediction accuracy of the model applied in this study was found to be higher.

Table 6. Statistical indicators of the models

Research		R-Value
Sharma et al [9]		0.9986
Gurlek et al [15]		0.987
Neelamegam et al [16]		0.9272
Shaddel et al [18]	Model 1	0.9242
	Model 2	0.9302
Notton et al [24]	Model 1	0.998
	Model 2	0.997
	Model 3	0.997
Present study		0.99998

5. CONCLUSION

One of the most important parameters in the installation of photovoltaic solar panels is to determine the installation angle according to the location. This study has practically developed an expression that gives the optimum installation angle according to the location data of the PV installation. For this, artificial neural networks method, which is one of the artificial intelligence techniques, was used. The difference from the studies in the literature is that the optimum angle that will provide high PV performance is determined based on the position data. The optimum placement and orientation of solar panels is critical for effective solar energy use, particularly in areas without access to meteorological data. Developing an artificial neural network (ANN) model that can forecast the yearly ideal angle of stationary solar arrays in Turkey was the aim of this study. Three independent artificial neural network models were created and assessed using the Levenberg-Marquardt (LM) approach; each model had a unique layout and number of neurons. For the purpose of training and evaluating the network, spatial data from eight distinct Turkish cities were gathered. The second model, which employs the Lunberg-Marquardt training algorithm and has five neurons in the data input, six connections in the first layer, and seven neurons in the corresponding second layer, which is the hidden layer, was chosen as the most effective model according to the three designed models' highest R values and lowest RMSE principles. The coefficient of determination statistical error analysis revealed that there was a high level of similarity between the predicted values and computed values for the solar panel's yearly ideal angle.

The findings indicate that the artificial neural network (ANN) is able to accurately forecast the typical annual ideal tilt angle for solar panels without the need for time-consuming quantitative computations.

SYMBOLS AND ABBREVIATIONS

kWh/m	Kilowatt hour/ square meter
GWh	Gigawatt hour
ANN	Artificial Neural Network
GD	Gradient descent
IW	Input Weight
LM	Levenberg-Marquard
LW	Line Weight
MAE	Mean Absolute Error
MBE	Mean Bias Error
R	Correlation coefficient
RMSE	Root Mean Square Error
RP	Resilient back propagation
SCG	Scaled conjugate gradient

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in their studies do not require ethics committee approval and/or legal-specific permission.

AUTHORS' CONTRIBUTIONS

SEVDA KAZEMZADEHMARAND: Performed the experiments and analyse the results.

ADNAN SÖZEN: Performed the experiments and analyse the results.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

REFERENCES

[1] Hinrichs R. A., and Kleinbach M. H., "Energy: Its Use and The Environment", Fifth Edition, Boston, *MA: Cengage Learning*, (2018).

[2] Chichilnisky G., "What is sustainable development?", ***Land Economics***, (1997).

[3] Hussain A., Arif S. M., and Aslam M., "Emerging renewable and sustainable energy technologies: State of the art", ***Renewable and Sustainable Energy Reviews***, 71: 12-28, (2017).

[4] https://enerji.gov.tr/eigm-yenilenebilir-enerji-kaynaklar-gunes, (2022).

[5] Sharma A., Kallioğlu M. A., Awasthi A., Chauhan R., Fekete G., and Singh T., "Correlation formulation for optimum tilt angle for maximizing the solar radiation on solar collector in the Western Himalayan region", ***Case Studies in Thermal Engineering***, 26, 101185, (2021).

[6] De Bernardez L. S., Buitrago R. H., and Garcia N. O. "Photovoltaic generated energy and module optimum tilt angle from weather data", ***International Journal of Sustainable Energy***, 30(5): 311-320, (2011).

[7] Goldemberg J., "Energy: What everyone needs to know?" *Oxford: Oxford University Press*, (2012).

[8] Naraghi M. H., "Optimum solar panel tilt angle for maximum annual irradiation", ***In Asme International Mechanical Engineering Congress and Exposition***, New York, ABD, 211-220, (2009).

[9] Sharma A., Kallioğlu M. A., Awasthi A., Chauha, R., Fekete G., and Singh T. ,"Correlation formulation for optimum tilt angle for maximizing the solar radiation on solar collector in the Western Himalayan region", ***Case Studies in Thermal Engineering***, 26, 101185, (2021).

[10] Benghanem M., "Optimization of tilt angle for solar panel: Case study for Madinah, Saudi Arabia" ***Applied Energy***, 88(4): 1427-1433, (2011).

[11] Bakirci K. "General models for optimum tilt angles of solar panels: Turkey case study", ***Renewable and Sustainable Energy Reviews***, 16(8): 6149-6159, (2012).

[12] Bailek N., Bouchouicha K., Aoun N., Mohamed E. S., Jamil B., and Mostafaeipour, A., "Optimized fixed tilt for incident solar energy maximization on flat surfaces located in the Algerian Big South", ***Sustainable Energy Technologies and Assessments***, 28: 96-102. (2018).

[13] Ginar J., Gadhe P.,"Optimized Tilt Ange for Solar Panel in pune", ***International journal for Reaserch in Engineering & Application Management***. https://www.ijream.org/papers/AMET201944.pdf. (2018).

[14] De Bernardez L. S., Buitrago R. H., and Garcia N. O., "Photovoltaic generated energy and module optimum tilt angle from weather data", ***International Journal of Sustainable Energy***, 30(5): 311-320, (2011).

[15] Gurlek C., and Sahin M., "Estimation of the global solar radiation with the artificial neural networks for the City of Sivas", ***European Mechanical Science***, 2(2): 46-51, (2018).

[16] Neelamegam P., and Amirtham V. A., "Prediction of solar radiation for solar systems by using ANN models with different back propagation algorithms" ***Journal of Applied Research and Technology***, 14(3): 206-214, (2016).

[17] Yadav A. K., and Chandel S. S., "Artificial neural network based prediction of solar radiation for Indian stations", ***International Journal of Computer Applications** (0975 – 8887)*, 50(9): 1-4, (2012).

[18] Shaddel M., Javan D. S., and Baghernia P., "Estimation of hourly global solar irradiation on tilted absorbers from horizontal one using Artificial Neural Network for case study of Mashhad", ***Renewable and Sustainable Energy Reviews***, 53: 59-67, (2016).

[19] Al Garni H. Z., Awasthi A., and Wright D. (2019). "Optimal orientation angles for maximizing energy yield for solar PV in Saudi Arabia". ***Renewable Energy***, 133, 538-550.

[20] [20] Matius M. E., Ismail M. A., Farm Y. Y., Amaludin A. E., Radzali M. A., Fazlizan A., and Muzammil W. K. (2021). "On the optimal tilt angle and orientation of an on-site solar photovoltaic energy generation system for Sabah's rural electrification". ***Sustainability***, 13(10), 5730.

[21] Heibati S., Maref W., and Saber H. H. (2021). "Developing a model for predicting optimum daily tilt angle of a PV solar system at different geometric, physical and dynamic parameters". ***Advances in Building Energy Research,*** 15(2), 179-198.

[22] Morcos V. H. (1993). "Optimum tilt angle and orientation for solar collectors in Assiut, Egypt". ***International Journal of Renewable Energy***, 4(3), 291-298.

[23] Khoo Y. S., Nobre A., Malhotra R., Yang D., Rüther R., Reindl T., and Aberle A. G.(2014). "Optimal orientation and tilt angle for maximizing in-plane solar irradiation for PV applications in Singapore". ***The Institute of Electrical and Electronics Engineers Journal of Photovoltaics***, 4(2), 647-653.

[24] Notton G., Paoli C., Vasileva S., Nivet M. L., Canaletti J. L., and Cristofari C.,"Estimation of hourly global solar irradiation on tilted planes from horizontal one using artificial neural networks", ***Energy***, 39(1): 166-179, (2012).

[25] Jafarkazemi F., Ali Saadabadi S., and Pasdarshahri H. (2012). "The optimum tilt angle for flat-plate solar collectors in Iran". ***Journal of Renewable and Sustainable Energy***, 4(1), 13118.

[26] Khatib T., Mohamed A., Mahmoud M., and Sopian K. (2015). "Optimization of the tilt angle of solar panels for Malaysia". ***Energy sources, part A: Recovery, Utilization, and Environmental Effects***, 37(6), 606-613.

[27] Aksoy M. H., Ispir M., Yesil E., (2023). "Impact of Tilt Angle on The Performance of The Photovoltaic Systems for Different Row Spacing". ***Journal Of Polytechnıc***, 2023, 1 – 1.

[28] Beyazit N. I., Bulut H., Demirtaş Y., (2017). "Analysis of Diffuse Radiation Models for Horizontal Surface According to Measurement Results". ***Journal Of Polytechnıc***. 557 – 563.

[29] Cömert Z., and Kocamaz A. (2017). "A study of artificial neural network training algorithms for classification of cardiotocography signals". *Bitlis Eren University **Journal of Science and Technology***, 7(2), 93-103.