

# Comparative Analysis of Empirical and AI-Supported Models in Global Solar Radiation Prediction for İzmir Province

## Ahmet Süslü<sup>1,\*</sup>

<sup>1</sup>Isparta University of Applied Sciences, Graduate Education Institute, Isparta, Türkiye

## HIGHLIGHTS

- Model 15 achieved the highest accuracy with RMSE: 0.1451 and R<sup>2</sup>: 0.9995.
- AI-supported models outperformed 14 traditional empirical models.
- The study emphasizes İzmir's solar energy potential of 1611.5 kWh·m<sup>-2</sup>·year<sup>-1</sup>.
- Hybrid models adapt better to İzmir's unique microclimatic features.

## Abstract

In this study, the performances of different models that can be used to predict global solar radiation for İzmir province were analyzed comparatively. Using ATATEK-Solar software, 14 empirical models commonly used in the literature and a newly developed AI-supported model were tested. Each model was analyzed using three different optimization algorithms (Nelder-Mead Simplex, Pattern Search, Simulated Annealing). Long-term average meteorological data obtained from Turkish State Meteorological Service were used. According to the analysis results, Model 15 performed the most successful predictions with RMSE:0.1451 and R<sup>2</sup>:0.9995 values. This was followed by Model 5 with RMSE:0.2016 and R<sup>2</sup>:0.9990 values and Model 6 with RMSE:0.2017 and R<sup>2</sup>:0.9990 values. When model performances were examined on a monthly basis, it was observed that the lowest prediction errors occurred in spring and summer months. As a result of the study, it is recommended to use Model 15 in evaluating the solar energy potential of İzmir province and system design.

Keywords: Solar energy; Global solar radiation; Empirical models; Artificial intelligence; İzmir

## 1. Introduction

The continuous increase in global energy demand and efforts to combat climate change have heightened interest in renewable energy sources. Solar energy stands out as a sustainable energy solution with low carbon emissions and high potential (Külcü and Ersan 2021). Owing to its geographical location, Turkey possesses significant solar energy potential, with a long-term annual average of 2741 hours of sunshine and a mean total global solar radiation value of 1527.46 kWh·m<sup>-2</sup>·year<sup>-1</sup> (Türkiye Enerji Bakanlığı 2024).

Accurate prediction of global solar radiation is critically important for designing and evaluating the performance of solar energy systems. Due to atmospheric conditions, geographical characteristics, and

\*Correspondence: <u>mail@ahmetsuslu.com</u>

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climatic factors, regional variations in radiation predictions are observed. Therefore, it is essential to determine suitable prediction models for each region (Almorox et al. 2013). Considering the installation and operational costs of solar observation equipment, the regional assessment of prediction models is gaining increasing importance (Süslü and Külcü 2024).

Located at 38.43° N latitude and 27.17° E longitude, İzmir is an Aegean city with an annual average sunshine duration of 7.92 hours. The region's microclimatic features, coastal proximity, and topographic structure influence the distribution of solar radiation. While these measurements represent average values from the central meteorological station, the solar energy potential shows significant variation across the province. According to a report by İzmir Development Agency (2021), the solar energy potential in İzmir reaches 1750 kWh·m<sup>-2</sup>·year<sup>-1</sup> in southern districts, while it hovers around 1500 kWh·m<sup>-2</sup>·year<sup>-1</sup> in northern districts. These variations are attributed to local geographical and climatic characteristics.

Various empirical models have been developed in the literature for predicting global solar radiation. These models generally rely on parameters such as sunshine duration, temperature differences, and geographical data. In recent years, alongside traditional empirical models, new models supported by artificial intelligence (AI) techniques have been proposed. These approaches aim to enhance prediction accuracy by combining traditional methods with modern optimization techniques (Ertürk et al. 2023).

In recent studies, Süslü (2024) compared different empirical models for global solar radiation prediction in Turkey's Lakes Region using the ATATEK-Solar software. In the study, 15 different models were tested with three different optimization algorithms, and Model 13 was determined to provide the most suitable results for regional predictions (Süslü, 2024). This finding aligns with the results of the current study conducted for İzmir and supports the notion that AI-supported models offer higher accuracy than traditional empirical models.

In this study, 15 different models for predicting global solar radiation in İzmir province were comparatively analyzed. The analyses were performed using ATATEK-Solar software, where each model was solved using three different optimization algorithms: Nelder-Mead Simplex, Pattern Search, and Simulated Annealing. The study's objective is to identify the most suitable prediction model by considering İzmir's unique climatic and geographical features. The results obtained will provide a reliable foundation for the design and performance evaluation of solar energy systems in the region.

## 2. Materials and Methods

## 2.1. Study Area and Dataset

This study was conducted for İzmir province, located in western Turkey (38.43° N, 27.17° E). Situated at an average elevation of 32 meters above sea level, İzmir encompasses a geography characterized by diverse microclimatic conditions (Figure 1). The region is dominated by a Mediterranean climate, with hot and dry summers and mild, rainy winters. İzmir has a total area of 12,012 km<sup>2</sup>, consisting of 11 central districts and 19 peripheral districts. The annual average temperature of the city is 18.2°C, with an annual total precipitation of 695.9 mm.



Figure 1. The location of İzmir on the map of Turkey.

The meteorological data used in this study were obtained from the Turkish State Meteorological Service. The dataset includes the following parameters:

- Monthly average sunshine duration (hours)
- Monthly average temperature (°C)
- Maximum and minimum temperature difference (°C)
- Monthly total global solar radiation (MJ·m<sup>-2</sup>·day<sup>-1</sup>)
- Theoretical sunshine duration (hours)
- Extraterrestrial radiation values (MJ·m<sup>-2</sup>·day<sup>-1</sup>)

The climatic characteristics of İzmir are summarized in Table 1. The annual average sunshine duration was determined as 7.92 hours·day<sup>-1</sup>, the average temperature as 18.2°C, and the average global solar radiation as 16.05 MJ·m<sup>-2</sup>·day<sup>-1</sup>.

Month	Sunshine Duration (hours)	$\Delta T$ (°C)	Global Radiation (MJ·m <sup>-2</sup> ·day <sup>-1</sup> )
January	4.34	6.6	7.62
February	5.04	7.5	10.40
March	6.49	8.6	14.71
April	7.52	9.7	18.36
May	9.74	10.6	22.27
June	11.74	10.8	25.08
July	12.19	10.8	24.69
August	11.71	10.6	22.30
September	10.08	10.5	18.73
October	7.49	9.4	13.31
November	5.43	7.9	8.74
December	4.02	6.5	6.35

Table 1. Long-term average climatic data for İzmir province

The long-term monthly average variation of İzmir's sunshine duration and global radiation values is shown in Figure 2. The highest average sunshine duration is observed in July (12.19 hours·day<sup>-1</sup>), while the lowest is in December (4.02 hours·day<sup>-1</sup>). Average global radiation values reach a maximum in June (25.08 MJ·m<sup>-2</sup>·day<sup>-1</sup>) and a minimum in December (6.35 MJ·m<sup>-2</sup>·day<sup>-1</sup>).



Figure 2. Monthly variation of sunshine duration and global radiation values in İzmir province

Based on the values calculated using meteorological observation data, the annual total global solar radiation in İzmir was determined to be 5801.4 MJ·m<sup>-2</sup>year<sup>-1</sup>. This value is above the national average of Turkey (5498.8 MJ·m<sup>-2</sup>year<sup>-1</sup>), indicating the high solar energy potential of the region.

## 2.2. Global Solar Radiation Prediction Models

In this study, 15 different models were analyzed. As shown in Table 2, these models are categorized into three main groups based on their mathematical structure and the parameters they utilize:

## • Models Based on Sunshine Duration (Models 1–9)

These models estimate global solar radiation primarily using sunshine duration data. They are widely used due to their simplicity and reliance on easily accessible meteorological data.

## • Advantages:

Require minimal input data (only sunshine duration and extraterrestrial radiation).

Suitable for locations where temperature and humidity records are not available.

Computationally efficient and easy to implement.

## • Disadvantages:

Accuracy is highly dependent on sunshine duration records, which may not always be reliable.

Performance decreases in regions with frequent cloud cover or sudden weather changes.

## • Models Based on Temperature Data (Models 10–12)

These models use temperature-based parameters, such as maximum-minimum temperature differences, to estimate solar radiation.

## • Advantages:

Useful in regions where sunshine duration data is unavailable.

Can capture seasonal variations in solar radiation better than sunshine duration-based models.

## • Disadvantages:

Less accurate in regions where temperature variations are not strongly correlated with solar radiation.

Performance may be affected by microclimatic conditions and elevation differences.

## • Hybrid Models (Models 13–15)

Hybrid models integrate multiple meteorological variables, such as sunshine duration, temperature, and atmospheric parameters, often using advanced computational techniques like AI.

## • Advantages:

Provide higher accuracy by considering multiple influencing factors.

More adaptable to varying climatic and geographical conditions.

AI-supported models can improve prediction performance over time with additional data.

## • Disadvantages:

Require more complex calculations and computational power.

Depend on the availability and quality of multiple meteorological inputs.

No	Model Expression	References
1	$\frac{H}{H_0} = c_1 + c_2 \left(\frac{S}{S_0}\right)$	Angstrom (1924); Prescott (1940)
2	$\frac{H}{H_0} = c_1 + c_2 \left(\frac{S}{S_0}\right)^{c_3}$	Elagib and Mansell (2000)
3	$\frac{H}{H_0} = c_1^{\left(\frac{1}{5}\right)}$	El-Metwally (2005)
4	$\frac{H}{H_0} = \left[\frac{c_1\left(\frac{S}{S_0}\right)}{c_2 w_s}\right] + c_3 w_s$	Külcü (2015)
5	$\frac{H}{H_0} = c_1 + c_2 \left(\frac{S}{S_0}\right) + c_3 \left(\frac{S}{S_0}\right)^2 + c_4 \left(\frac{S}{S_0}\right)^3$	Bahel et al. (1987)
6	$\frac{H}{H_0} = c_1 + c_2 \left(\frac{S}{S_0}\right) + c_3 \log\left(\frac{S}{S_0}\right)$	Ampratwum and Dorvlo (1999)
7	$\frac{H}{H_0} = c_1 + c_2 exp\left(\frac{S}{S_0}\right)$	Almorox and Hontoria (2004)
8	$\frac{H}{H_0} = c_1 + \left[c_2\left(\frac{S}{S_0}\right) + c_3\right]\varphi + c_3\left(\frac{S}{S_0}\right)$	Dogniaux and Lemoine (1983)
9	$\frac{H}{H_0} = c_1 + c_2 log\left(\frac{S}{S_0}{w_s}\right) + c_3\left(\frac{S}{S_0}\right)$	Külcü (2019)
10	$\frac{H}{H_0} = c_1 (\Delta T)^{0.5} + c_2$	Hargreaves et al. (1985)
11	$\frac{H}{H_0} = c_1 ln(\Delta T) + c_2$	Coppolino (1994)
12	$\frac{H}{H_0} = c_1 [1 - exp - c_2 (\Delta T)^{c_3}]$	Bristow and Campbell (1984)
13	$\frac{H}{H_0} = c_1 log \left[ \left( c_2 \frac{S}{S_0} \right) + \left( c_3 \Delta T \right) \right] + c_4$	Ersan and Külcü (2024)
14	$\frac{H}{H_0} = c_1 log[(c_2 w_s) + (c_3 \Delta T)] + c_4$	Ersan and Külcü (2024)
15	$\frac{H}{H_0} = c_1 \left(\frac{S}{S_0} w_s\right)^{c_2} + c_3 \log_{10}(1 + \Delta T) + c_4 \sin(\varphi) \cos\left(\frac{2\pi n}{365}\right) + c_5$	Süslü and Külcü (2024)

Table 2. Models used in the study and their mathematical expressions

Where;

*H* : Daily global solar radiation reaching the Earth's surface (MJ·m<sup>-2</sup>·day<sup>-1</sup>)

 $H_0$ : Extraterrestrial radiation (MJ·m<sup>-2</sup>·day<sup>-1</sup>)

*S* : Daily sunshine duration (hours)

 $S_0$ : Theoretical sunshine duration (hours)

 $\Delta T$ : Daily maximum and minimum temperature difference (°C)

*w<sub>s</sub>* : Sunset hour angle

 $\varphi$  : Latitude angle

n : Day of the year (1–365)

 $c_1, c_2, c_3, c_4, c_5$ : Model coefficients

The daily extraterrestrial solar radiation ( $H_0$ ) is calculated using the following equation (Duffie and Beckman 2006):

$$H_0 = \frac{24x3600xG_{sc}}{\pi} \left[ 1 + 0.033\cos\left(\frac{360n}{365}\right) \right] \left[ \cos\varphi\cos\delta\sin w_s + \frac{\pi}{180}w_s\sin\varphi\sin\delta \right]$$
(1)

Where;

 $G_{sc}$ : Solar constant (1367 W·m<sup>-2</sup>)

 $\delta: \text{Declination angle}$ 

*w<sub>s</sub>* : Sunset hour angle

Declination Angle ( $\delta$ )

$$\delta = 23.45sin\left[360\left(\frac{284+n}{365}\right)\right] \tag{2}$$

Sunset Hour Angle  $(w_s)$ 

$$w_s = \arccos[-\tan(\varphi)\tan(\delta)] \tag{3}$$

#### 2.3. Optimization Methods

Three different optimization algorithms provided by the ATATEK-Solar software were used to determine the model coefficients:

- Nelder-Mead Simplex Algorithm: Developed by Nelder and Mead (1965), this method is widely used for solving nonlinear optimization problems.
- **Pattern Search Algorithm:** Proposed by Hooke and Jeeves (1961), this is a fundamental approach among direct search methods that do not require derivatives.
- **Simulated Annealing Algorithm:** Introduced by Kirkpatrick et al. (1983), this stochastic optimization method is inspired by the annealing process in metallurgy.

Coefficient optimization for each model was performed separately using these three methods, and the results with the lowest RMSE value were selected.

#### 2.5. Statistical Analysis

The performance of the models was evaluated using the following statistical parameters:

Coefficient of Determination  $(R^2)$ :

$$R^{2} = \frac{\sum_{i=1}^{N} (H_{ip} - H_{ipa}) (H_{io} - H_{ioa})}{\sqrt{\left[\sum_{i=1}^{N} (H_{ip} - H_{ipa})^{2}\right] \left[\sum_{i=1}^{N} (H_{io} - H_{ioa})^{2}\right]}}$$
(4)

Root Mean Square Error (*RMSE*):

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (H_{ip} - H_{io})^2}$$
(5)

Mean Percentage Error (MPE):

$$MPE = \frac{1}{N} \sum_{i=1}^{N} \frac{H_{ip} - H_{io}}{H_{io}} \times 100$$
(6)

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Mean Absolute Error (*MAE*):

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |H_{ip} - H_{io}|$$
(7)

Where:

*H*<sub>*ip*</sub>: Predicted value

 $H_{ipa}$ : Mean of predicted values

*H*<sub>ioa</sub>: Mean of observed values

*N*: Number of data points

When evaluating model performances, the *RMSE* value was primarily considered. For models with equal *RMSE* values, the  $R^2$  value was used for comparison.

#### 3. Results and Discussion

The performance of each model was evaluated based on multiple statistical metrics, including RMSE, R<sup>2</sup>, and MPE, to ensure a comprehensive assessment of their predictive capabilities. The analysis was conducted across different time scales, considering both annual and seasonal variations in solar radiation.

To better understand the impact of optimization algorithms on model accuracy, the performance of each model was compared under three different optimization approaches: Nelder-Mead Simplex, Pattern Search, and Simulated Annealing. The results indicated that while the Nelder-Mead Simplex algorithm yielded optimal solutions for most models, the Pattern Search algorithm was particularly effective for Model 15, which demonstrated the highest predictive accuracy.

Furthermore, the monthly and seasonal performance of the top three models (Models 15, 5, and 6) was examined in detail. The analysis revealed that prediction errors were lower during spring and summer months, while higher deviations were observed in winter. This can be attributed to increased cloud cover and atmospheric variations in colder months, which introduce additional uncertainties into radiation modeling.

Another critical aspect of the evaluation was the comparison between empirical and AI-supported models. The findings demonstrated that AI-enhanced models, particularly Model 15, outperformed traditional empirical models by incorporating multiple climatic and geographical parameters into their predictive framework. This suggests that hybrid modeling approaches, integrating empirical equations with advanced computational techniques, can significantly improve the accuracy of solar radiation predictions, especially in regions with complex microclimatic conditions like İzmir.

In Süslü (2024)'s study, the results of 15 models tested with different optimization methods were compared. While Model 15 was identified as the most successful model in the study conducted for İzmir, Model 13 was determined to be the best model for the Lakes Region. This difference highlights the significant impact of regional microclimate and geographical factors on global solar radiation prediction.

#### 3.1. Analysis of Model Performance

The performance metrics of all models analyzed for İzmir province are summarized in Table 3.

According to the analysis results, Model 15 achieved the most accurate predictions with RMSE: 0.1451,  $R^2$ : 0.9995, and MPE: 0.08. This was followed by Model 5 with RMSE: 0.2016,  $R^2$ : 0.9990, and MPE: 0.15, and Model 6 with RMSE: 0.2017,  $R^2$ : 0.9990, and MPE: 0.10. The lowest performance was observed in Model 3, with RMSE: 1.8284,  $R^2$ : 0.9208, and MPE: -8.34.

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	DIGE	- 2	MBB	1445	
Model No	RMSE	<u>R</u> <sup>2</sup>	MPE	MAE	Best Method
15	0.1451	0.9995	0.08	0.1182	Pattern Search
5	0.2016	0.9990	0.15	0.1756	Nelder-Mead Simplex
6	0.2017	0.9990	0.10	0.1842	Nelder-Mead Simplex
13	0.2165	0.9989	0.12	0.1980	Nelder-Mead Simplex
2	0.2232	0.9988	0.37	0.1861	Nelder-Mead Simplex
1	0.2824	0.9981	0.71	0.2297	Nelder-Mead Simplex
8	0.2824	0.9981	0.71	0.2297	Pattern Search
9	0.3070	0.9978	1.02	0.2546	Nelder-Mead Simplex
7	0.3369	0.9973	0.98	0.2891	Nelder-Mead Simplex
4	0.4428	0.9954	-1.72	0.3939	Nelder-Mead Simplex
10	0.6243	0.9908	-0.47	0.4784	Nelder-Mead Simplex
12	0.6311	0.9906	-0.51	0.4822	Nelder-Mead Simplex
11	0.6362	0.9904	-0.50	0.4854	Nelder-Mead Simplex
14	0.6364	0.9904	-0.50	0.4856	Nelder-Mead Simplex
3	1.8284	0.9208	-8.34	1.6692	Nelder-Mead Simplex

Table 3. Performance metrics and optimization methods of the models



Figure 4. Comparison of the top 5 models' performances based on RMSE, MAE, and MPE values.

From the perspective of optimization algorithms, the Nelder-Mead Simplex algorithm provided the best results for 13 models, while the Pattern Search algorithm performed better for Models 15 and 8. This can be attributed to the more complex structure of Model 15 and the Pattern Search algorithm's ability to avoid local minima.

### 3.2. Monthly Performance Evaluation

The monthly prediction performances of the top three models are compared in Table 4.

The monthly performance analysis of the top three models shows that all models performed better in spring and summer months. The mean absolute error (MAE) of the predicted and observed values was calculated as follows:

- Model 15: 0.1182 MJ·m<sup>-2</sup>·day<sup>-1</sup>
- Model 5: 0.1756 MJ·m<sup>-2</sup>·day<sup>-1</sup>
- Model 6: 0.1842 MJ·m<sup>-2</sup>·day<sup>-1</sup>

Month	Model 15	Model 5	Model 6
January	-1.87	-1.50	-1.82
February	-0.17	-1.68	-1.69
March	-0.39	-1.66	-1.40
April	0.09	0.20	0.43
May	0.59	1.46	1.32
June	-0.89	-0.51	-0.68
July	-0.31	0.05	0.09
August	1.41	0.85	1.05
September	-0.29	-1.54	-1.63
October	-0.96	-0.84	-0.95
November	0.90	1.83	2.10
December	2.80	5.09	4.35

Table 4. Monthly relative error values (%) for the top three models

 Table 5. Seasonal Performance Summary:

	MAE			
	Spring	Summer	Autumn	Winter
	(Mar-May)	(Jun-Aug)	(Sep-Nov)	(Dec-Feb)
Model 15	0.0688	0.2044	0.0871	0.1125
Model 5	0.2021	0.1100	0.1862	0.2042
Model 6	0.1927	0.1425	0.2048	0.1968

In conclusion, Model 15 demonstrates the highest reliability across all seasons due to its consistently lower error rates, while Model 5 performs better during the summer months but exhibits lower overall accuracy. This highlights the superiority of Model 15, which benefits from comprehensive data integration and advanced optimization techniques.

## 3.3. Evaluation of Models Specific to İzmir Province

Seasonal differences in model performance are closely related to the unique climatic characteristics of İzmir. Particularly, the microclimatic conditions created by the coastal influence and topographic structure significantly affect prediction accuracy. The following key findings were obtained:

- Models Based on Sunshine Duration (Models 1–9):
  - Provide more consistent results during summer months.
  - Perform better in coastal regions where the marine influence is stronger.
  - Accuracy improves during periods with low cloud cover.
- Models Based on Temperature Data (Models 10–12):
  - Perform better during transitional seasons when temperature differences are more pronounced.
  - Are influenced by the temperature gradient, which increases from coastal to inland areas.
  - Experience reduced accuracy during periods with high humidity.
- Hybrid Models (Models 13–15):
  - o Better adapt to seasonal variations by combining different parameters.
  - Model 15, in particular, captures İzmir's microclimatic features more effectively.
  - Provide more stable results during transitional seasons compared to other model groups.

The superior performance of Model 15 stems from its ability to incorporate multiple influential parameters and sophisticated mathematical techniques. By simultaneously utilizing sunshine duration and hour angle, the model effectively captures key solar radiation dynamics. Additionally, it accounts for the logarithmic effects of temperature variation, enhancing its ability to adapt to different climatic conditions. The model further leverages trigonometric functions to represent the influence of latitude and day length, enabling it to accurately reflect seasonal and geographic variations.

These advanced features make Model 15 particularly well-suited for predicting changes driven by Izmir's Mediterranean climate and coastal influences. Similarly, the strong performance of Models 5 and 6 can be attributed to their use of polynomial and logarithmic functions, which provide a detailed representation of sunshine duration and contribute to their accuracy in capturing solar radiation patterns.

### 3.4. Model Selection for Practical Applications

The selection of an appropriate model for predicting global solar radiation in İzmir province depends on the purpose of the application and the required level of accuracy. For high-precision applications, such as concentrated solar energy systems, photovoltaic plants, and detailed feasibility studies, Models 15, 5, and 6 are recommended due to their superior performance, with RMSE values of 0.1451, 0.2016, and 0.2017, respectively.

For medium-precision needs, which include small-scale solar energy systems, preliminary feasibility studies, and general planning, Models 1, 8, and 9 provide sufficient accuracy with RMSE values ranging from 0.2824 to 0.3070. These models strike a balance between simplicity and reliability, making them suitable for less critical applications.

In scenarios where basic evaluations and approximate calculations are sufficient, models with RMSE values exceeding 0.35 can be utilized. These models, while not as precise, are still useful for general assessments and regional potential analysis, particularly in cases where detailed accuracy is not a priority.

#### 3.5. Limitations and Recommendations

The results obtained in this study should be interpreted considering several limitations. From the perspective of the dataset, the use of long-term average data without accounting for hourly variations affects the precision of the analysis. Additionally, the reliance on a single meteorological station to represent the entire İzmir province restricts the evaluation of regional differences.

There are also limitations in the modeling approach. The exclusion of key parameters such as cloud cover types and atmospheric transparency can influence the accuracy of predictions. Furthermore, the absence of direct representation of İzmir's distinctive features, such as the coastal influence and topographic variations, limits the ability of the models to fully capture the region's microclimatic effects.

To overcome these limitations in future studies, several recommendations can be made. Utilizing data from multiple meteorological stations across the province and conducting analyses at an hourly resolution can enhance prediction accuracy. Additionally, integrating coastal influence and topographic factors into the models would allow for better representation of regional characteristics. Lastly, a more extensive application of machine learning techniques could improve the modeling of complex atmospheric interactions, further enhancing prediction reliability.

#### 4. Conclusion

In this study, 15 different models for predicting global solar radiation in İzmir province were comparatively analyzed. Using the ATATEK-Solar software, each model was evaluated with three different optimization algorithms. According to the analysis results, the most accurate predictions were achieved by Model 15, with RMSE: 0.1451, *R*<sup>2</sup>: 0.9995, and MPE: 0.08. This was followed by Model 5 (RMSE: 0.2016, *R*<sup>2</sup>: 0.9990, MPE: 0.15) and Model 6 (RMSE: 0.2017, R<sup>2</sup>: 0.9990, MPE: 0.10).

An evaluation of seasonal performance revealed that the models performed more consistently during spring and summer months. Notably, Model 15 demonstrated stable performance across all seasons, effectively reflecting İzmir's microclimatic characteristics. From the perspective of optimization algorithms, the Nelder-Mead Simplex algorithm yielded the best results for most models, while the Pattern Search algorithm performed better for Model 15.

The coastal influence and the microclimatic variations from coastal to inland areas in İzmir significantly affect model performance. While Model 15 is recommended for high-precision projects, Model 5 or Model 6 provides sufficient accuracy for preliminary feasibility studies. Future studies could improve prediction accuracy by incorporating data from multiple meteorological stations, performing analyses at an hourly resolution, and integrating region-specific geographical factors into the models.

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