



Research Article

Fuzzy logic approaches for forecasting daily global solar radiation: A comparative analysis of climatic variables

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ABSTRACT

Accurate prediction of solar radiation is important for the design and optimization of photo-voltaic systems and for efficient energy management and sustainability planning. However, in many regions direct solar radiation measurements are scarce or not available, which makes the forecasting from available climatic variables more and more important. This study addresses this challenge by developing three simple-structured fuzzy logic models to predict daily global solar radiation using three different combinations of commonly recorded weather inputs: temperature and relative humidity, temperature and wind speed, and relative humidity and wind speed. The models were trained with data from Ankara, Türkiye and evaluated using mean absolute percentage error and root mean square error metrics. Comparing the models tested, the relative humidity and wind speed model resulted in the best forecasting performance with a mean absolute percentage error of 9.07% and a root mean square error of 0.85 kWh/m²-day. It also outperformed the feedforward artificial neural network model used for comparison, which produced an error of 14.38%. Results indicate that wind speed has more direct effects on estimation of solar radiation while the effect of temperature appears more indirect. A major contribution of the present study is that reasonably simple fuzzy logic models can provide good prediction performance if the right input variables are selected. This is particularly important when compared to more complex artificial intelligence methods, which usually require larger data sets and a larger number of input parameters. In this sense, the proposed approach also helps to overcome limitations reported in previous studies, such as the use of high-dimensional input sets and models developed mainly for short-term forecasting. Overall, the results show that fuzzy logic can be an accurate and computationally efficient alternative for solar radiation forecasting, especially when the available data are limited.

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INTRODUCTION

Renewable energy sources are gaining more and more importance due to their environmentally friendly features

[1], use of naturally available resources [2], and potential to reduce greenhouse gas emissions [3]. Wind, solar, hydro, biomass and geothermal power can also enhance energy security by reducing dependence on fossil fuels [4, 5]. Of

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these alternatives, solar energy has become particularly attractive due to low operating costs, wide range of applications and decreasing installation costs driven by technological advances [6–8]. Consequently, the share of solar energy in the global energy production has increased rapidly in recent years. For example, in 2023 solar photovoltaic accounted for three-quarters of all added renewable energy capacity worldwide [9]. As this growth has occurred, so too has the number of solar energy facilities in various regions increased. However, the efficient planning and operation of such facilities rely to a large extent on a correct assessment of the available solar radiation potential. Accurate information of regional solar radiation can contribute to better system design, increase energy yield and reduce payback period of the investment [10]. Hence, accurate determination of solar radiation potential is an important step in planning of sustainable solar energy projects.

Total solar radiation on a given surface can be measured directly with instruments like pyranometers [11]. However, the density of meteorological stations is not uniform across the globe, and many regions still do not have adequate ground-based measurement infrastructure. As a result, reliable solar radiation measurements are unavailable for numerous locations. This limitation makes it difficult to assess regional solar energy potential accurately and may lead to less reliable system design, higher investment costs, and lower energy production efficiency. For this reason, estimating solar radiation from commonly available climatic variables has become an important alternative in regions where direct measurements are limited or unavailable [12]. Against this background, the present study focuses on developing a practical and accurate forecasting approach that relies on a small number of widely available climatic variables and can therefore be applied in data-scarce regions.

In the literature, methods used for forecasting solar radiation are generally based on linear [13] and nonlinear modeling [14], artificial intelligence (AI)-based modeling [15], and fuzzy logic-based modeling techniques [16]. Although regression-based models are frequently used to forecast meteorological parameters [17], in the context of solar radiation forecasting AI models incorporating artificial neural network (ANN) algorithms are widely employed, whereas fuzzy logic approaches remain comparatively less prevalent [18]. This prevalence may be due to the ANN model's relative ability to model complex and nonlinear relationships in meteorological data, which can be advantageous in solar radiation forecasting. Girdhani and Agrawal [19] investigated the performance of different prediction methods such as ANN, long short-term memory, convolutional neural networks, Prophet, and SARIMAX for predicting daily global horizontal solar radiation in Bhopal, India. The models were developed with a variety of meteorological input variables. Among the methods evaluated, the ANN showed the best performance with a mean absolute percentage error (MAPE) of 2.5466%. Meanwhile, the

MAPE of long short-term memory, convolutional neural networks, SARIMAX, and Prophet were 4.2124%, 4.8266%, 8.109%, and 13.45%, respectively. Bilgili and Ozgoren [20] modeled the daily global solar radiation for Adana, Türkiye, by using multiple linear regression, multiple nonlinear regression and feedforward ANN methods. Sunshine duration, air temperature, wind speed, and the day of the year were used as input parameters. The MAPE of the forecast was calculated as 9.23%. Behrang et al. [21] applied multilayer perceptron and radial basis function neural networks to model daily global solar radiation for Dezful, Iran. The input parameters were day of the year, mean daily air temperature, relative humidity, sunshine hours, evaporation and wind speed. The best performance of multilayer perceptron network was obtained with wind speed, day of the year, daily average air temperature, relative humidity and sunshine hours with a MAPE of 5.21%. The combination of daily average air temperature, day of year and sunshine hours in the radial basis function network also provided a satisfactory accuracy with a MAPE of 6.53%. Asl et al. [22] predicted daily global solar radiation in Dezful, Iran, by multilayer perceptron neural networks. Input parameters were day of year, daily mean air temperature, relative humidity, sunshine hours, evaporation, wind speed and soil temperature. The MAPE of the forecast was found to be 6.08%. Almasoud et al. [23] used ANN for estimating the monthly mean daily solar radiation on horizontal surface for nine meteorological stations in Saudi Arabia. The input parameters were altitude, latitude, longitude, month, maximum and minimum air temperature, maximum and minimum relative humidity and sunshine duration. The resulting forecast had a MAPE of 6.86%. Besides single ANN-based models, hybrid methods have been studied in several papers for improving the forecasting performance. For example, Khalfa et al. [24] proposed a hybrid model by integrating multiple learning algorithms and achieved a MAPE of 1.58%, which demonstrated a better accuracy compared to the traditional methods. Hybrid deep learning approaches have also shown good performance for solar radiation forecasting. Mariappan et al. [25] proposed a hybrid convolutional neural network and stacked long short-term memory model with feature selection and metaheuristic-based hyper-parameter tuning. The model reached a MAPE of 3.63% and outperformed some traditional and deep learning approaches.

In general, AI-based models reported in the literature have shown good performance for solar radiation forecasting. However, the dependence on large datasets and the fairly high computational requirements might limit their practical use [26]. Since it can handle uncertainty and incomplete information, fuzzy logic provides a potentially useful alternative [27]. But, fuzzy logic-based approaches have received relatively little attention in the literature despite these advantages. Boata [28] designed a fuzzy logic model based on Takagi–Sugeno for hourly prediction of global solar radiation at Timisoara, Romania. The model

was fed with loss components as input parameters, defined as the difference between the measured and forecasted hourly global solar radiation under clear-sky conditions. The model gave a reasonable accuracy; however, the performance was degraded in cloudy conditions and the forecasting horizon was limited to one hour. Chugh et al. [29] presented a Mamdani-based fuzzy logic model for hourly global solar radiation forecasting in New Delhi, India. The model predicted the radiation in the fifth hour with the solar radiation measured in the previous four hours. The model is designed for short-term forecasting and has a reported MAPE of 1.052%. How the model performs for longer forecasting horizons is unclear. Boata and Pop [30] used a Takagi-Sugeno based fuzzy logic model to predict the daily global solar radiation at Timisoara, Romania. The model was using only air temperature without considering other relevant meteorological variables, but gave almost reasonable results. Rizwan et al. [31] suggested a Mamdani based fuzzy logic model for the prediction of global solar energy for four Indian cities. The input parameters for the model were latitude, longitude, altitude, the month of the year, duration of sunshine and temperature. It achieved a MAPE of 5.56% for the four stations. However, the use of six input parameters increased the complexity of the model and its computational requirements during training and implementation. Mehta and Basak [32] in Patiala, India, proposed a similar fuzzy logic model for solar radiation prediction. Input parameters included temperature, humidity, wind speed, time of day and atmospheric pressure. The model obtained a MAPE of 1.703% in relation to the actual measured solar radiation data in real time. But the high dimensional structure and the rule base of 1,200 rules lead to high computational complexity and processing requirements.

Previous studies show that fuzzy logic-based models have great potential in solar radiation forecasting, but there are still some limitations. These include models developed for specific weather conditions, limited consideration of relevant input variables and increasing system complexity as the number of inputs increases. Some techniques are limited to short-term forecasting, while the performance of others on longer forecasting horizons is still not clear. Moreover, although more input variables can improve the accuracy of predictions, they may also increase the computational load and processing time, limiting the practicality of such models in data-limited applications. In an effort to overcome these limitations, the present study developed three Mamdani-type fuzzy logic models for forecasting daily solar radiation in Ankara, Türkiye, using three different input variable pairs: temperature and relative humidity (TH), temperature and wind speed (TW), and relative humidity and wind speed (HW). Each model had 16 fuzzy rules. The input and output variables were fuzzified using four triangular membership functions. The defuzzification was performed using the largest of maximum method (LoM). Performance of the forecasting was evaluated by

the MAPE and root mean square error (RMSE). Then the effects of different combinations of inputs on the forecasting accuracy were investigated, and the best fuzzy logic model was compared with a feedforward ANN model to assess the performance of the two approaches on the same forecasting problem. To summarize, the study suggests a straightforward forecasting framework, aiming to reach high accuracy with a small number of easily accessible climatic variables. The main contributions of this study are summarized as follows:

- First, the literature review was carried out to find the climatic variables that are most frequently used for solar radiation forecasting. According to this assessment, ambient temperature, relative humidity and wind speed were selected and grouped into three different input pairs. These combinations were then used to build three relatively simple fuzzy logic models for the selected region of study.
- Secondly, the effect of various input combinations on forecasting performance was investigated by comparing the three proposed models. This comparison allowed us to assess the contribution of each pair of climatic variables to the model accuracy and gain insight on whether an appropriate selection of inputs could improve performance without increasing model complexity or computational requirements.
- Finally, the performance of fuzzy logic models was further evaluated by comparing the best performing model with a feedforward ANN model developed for the same region and forecast period. The comparison also gave another criterion to assess the applicability of the proposed fuzzy logic approach, especially in cases where data and computational resources are limited.

The remainder of the paper is organized as follows. Section 2 describes the methodology including the dataset, the fuzzy logic models developed, the ANN model used for comparison and the performance evaluation metrics. The results obtained from the fuzzy logic and ANN models are presented and discussed in Section 3. Finally, Section 4 presents a summary of the main findings and conclusions of the study.

MATERIALS AND METHODS

Dataset

This study aims to forecast daily solar radiation using various climatic variables. The climatic variables considered include sunshine duration, maximum ambient temperature, relative humidity, latitude, longitude, day of the year, daily clear-sky global radiation, total cloud cover, temperature, clearness index, altitude, months, average temperature, average cloudiness, average wind speed, atmospheric pressure, reference clearness index, average diffuse radiation, evaporation, and soil temperature [12]. Among these variables, relative humidity, ambient temperature, and wind

speed are comparatively easier to measure and access [33]. The primary reasons for this are that these data are mostly recorded directly by meteorological stations, and the measurement devices are widely available. Additionally, these variables can often be measured using economical equipment, and their results are quickly accessible. Therefore, relative humidity, ambient temperature, and wind speed were selected as input variables for modeling within the scope of this study.

The study area was selected as Ankara, the capital of Türkiye, located at 39.92° latitude and 32.84° longitude at an elevation of approximately 893 m above sea level. The dataset includes relative humidity, ambient temperature, wind speed, and daily solar radiation data covering the seven-month period from January to July 2024. These data were obtained from the Prediction of Worldwide Energy Resources database provided by the National Aeronautics and Space Administration. In this study, daily solar radiation for July was forecasted using both the fuzzy logic model and the ANN model. The corresponding data are presented in Figure 1.

Fuzzy Logic Models

Fuzzy logic, developed by Zadeh in 1965 [34], extends beyond the binary true-or-false framework of classical logic, allowing the evaluation of uncertainty and intermediate values. Fuzzy logic systems operate through a process consisting of four fundamental steps: fuzzification, rule base, inference system, and defuzzification. Figure

2 illustrates the functioning of these steps for forecasting daily solar radiation.

Fuzzification is the process of converting input variables into fuzzy sets using membership functions defined over appropriate ranges [35]. Membership functions define the degree to which a given value belongs to a fuzzy set, with membership values ranging from 0 to 1. Different types of membership functions, including triangular, Gaussian, and trapezoidal functions, have been widely used in the literature. In this study, the triangular membership function was selected because of its simple structure, low computational requirements, and ease of implementation [36]. The mathematical expression of the triangular membership function is given as follows:

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x \leq b \\ \frac{c-x}{c-b}, & b < x < c \\ 0, & x \geq c \end{cases} \quad (1)$$

where $\mu(x)$ represents the membership degree of the value x , a denotes the left vertex of the triangle, b represents the top vertex of the triangle, and c is the right vertex of the triangle. Within the scope of this study, each input and output variable was fuzzified using four triangular membership functions defined over appropriate ranges. These membership functions use the linguistic terms very low (VL), low (L), medium (M), and high (H) to describe the input and output variables. Figure 3 provides a detailed illustration

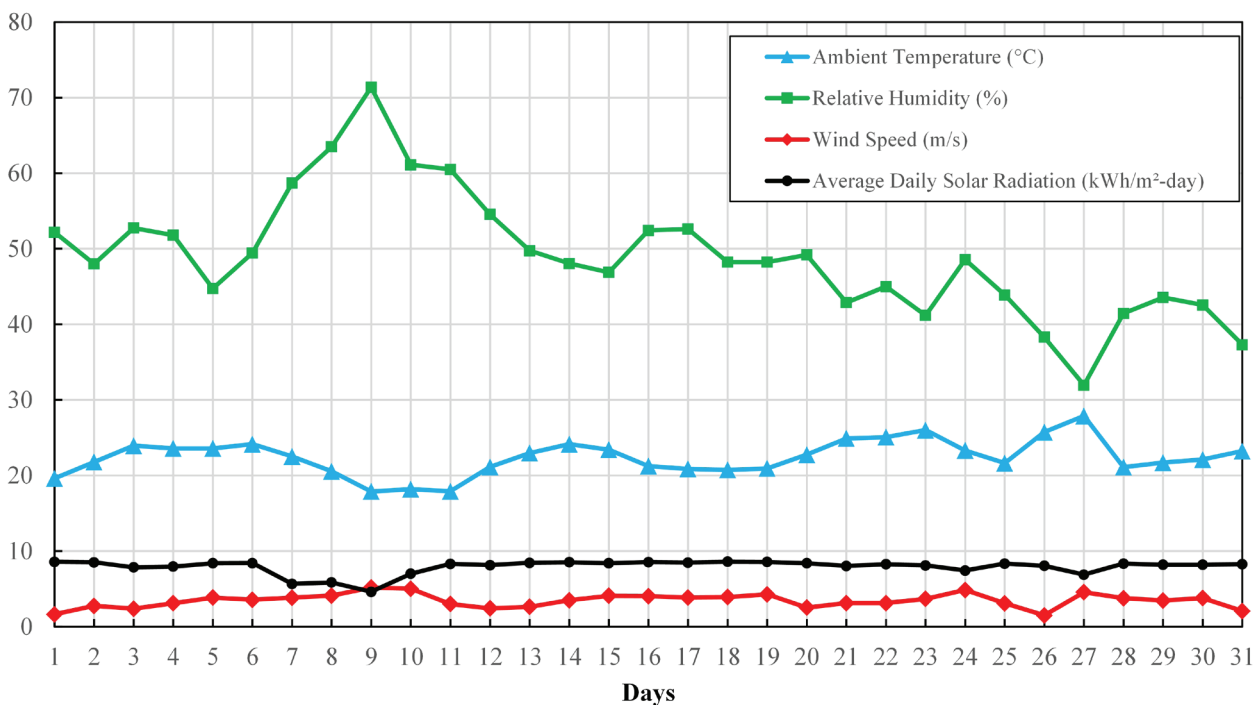


Figure 1. Climatic variables for July.

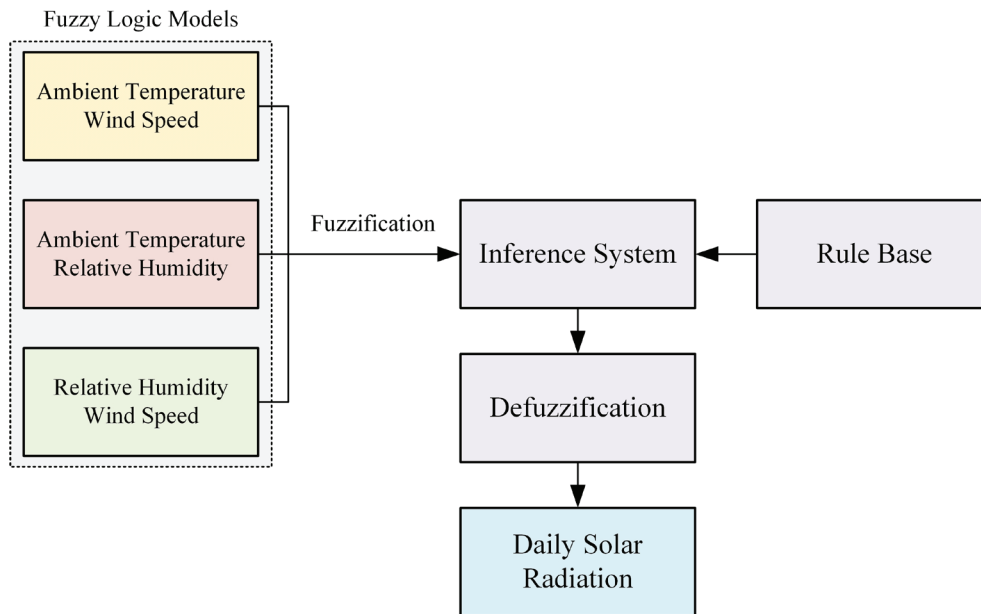


Figure 2. The operation of the fuzzy logic model for forecasting daily solar radiation.

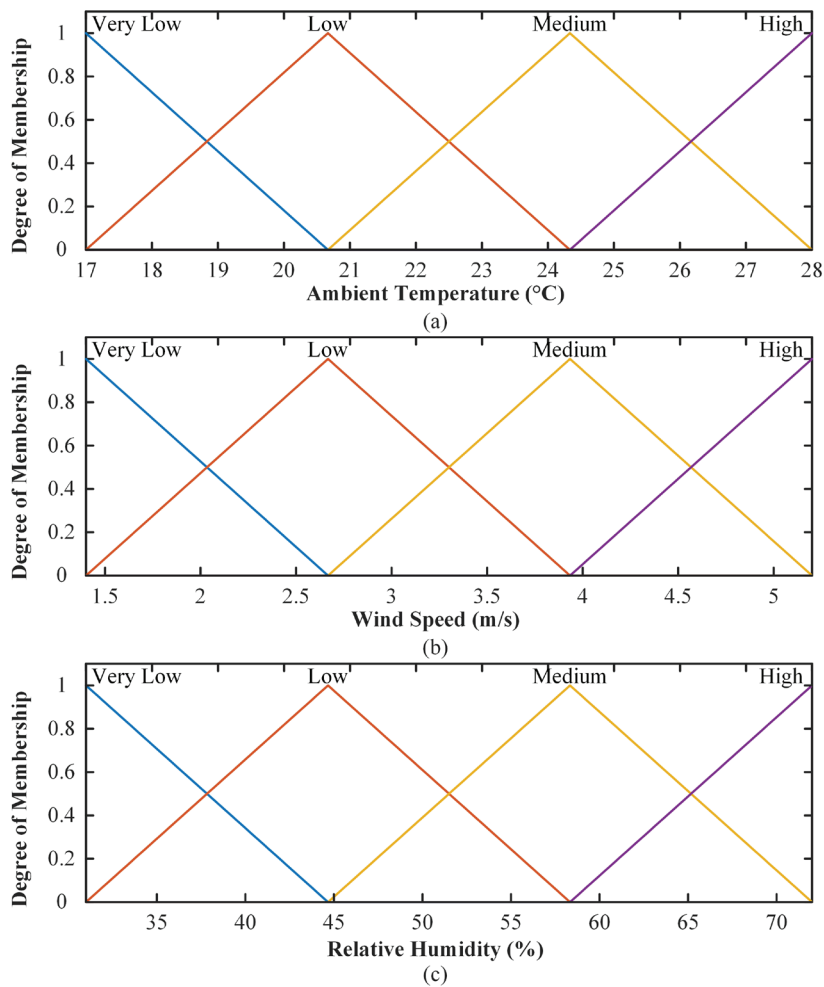


Figure 3. Membership functions created for the input variables. (a) Ambient temperature. (b) Wind speed. (c) Relative humidity.

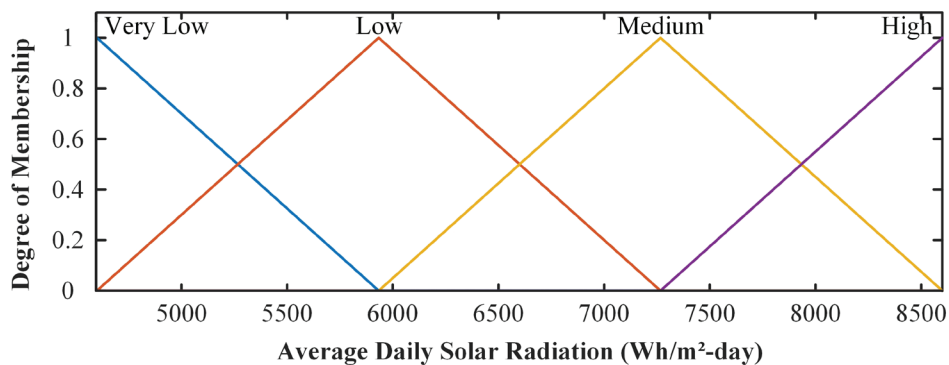


Figure 4. Membership functions created for the output variable.

of the membership functions created for the input variables, while Figure 4 presents those designed for the output variable.

The fuzzification stage is then followed by the rule base in the fuzzy logic system. At this stage, the fuzzy sets obtained from the input variables are associated with the output variables through a set of logical rules. The rule base is a set of “IF-THEN” statements that defines the relationship between inputs and outputs [37]. These rules define the system’s response to various input conditions. They are normally defined based on expert knowledge, historical data or a combination of both. They can also include logical operators such as ‘and’ and ‘or’. When the conditions in the rule are true, the corresponding output is fired. A simple fuzzy rule might read as follows:

$$\text{IF } i_1 \text{ is } A \text{ AND } i_2 \text{ is } B, \text{ THEN } o_1 \text{ is } C. \quad (2)$$

where i_1 and i_2 represent the input variables, A and B are the linguistic terms associated with these variables, o_1 denotes the output variable, and C is the linguistic term for the output variable. In this study, rule matrices have been designed for three different fuzzy logic models. Each model contains customized rules to determine the outputs corresponding to different combinations of the input variables. The designed rule matrices associate the linguistic expressions of the input variables (VL, L, M, H) with the appropriate fuzzy sets of the output variable. Tables 1-3 present the rule matrices created for the three different fuzzy logic models. The triggering of each rule in the rule matrix depends on the membership degrees of the input variables. If multiple rules are triggered simultaneously, the inference system combines the information from these rules and proceeds to the defuzzification stage of the system.

The output values obtained by the inference system are expressed as fuzzy sets and are not used directly without undergoing defuzzification. Defuzzification is the process of converting these fuzzy outputs into a crisp value [38]. In the literature, various methods for defuzzification exist. Among the most commonly used methods are centroid,

Table 1. Rule matrix of the fuzzy model with input variables relative humidity (i_1) and wind speed (i_2)

i_1 / i_2	VL	L	M	H
VL	H	H	M	L
L	H	M	M	L
M	M	M	L	L
H	L	L	VL	VL

Table 2. Rule matrix of the fuzzy model with input variables ambient temperature (i_3) and relative humidity (i_1)

i_3 / i_1	VL	L	M	H
VL	L	L	VL	VL
L	M	M	L	VL
M	H	H	M	L
H	H	H	M	L

Table 3. Rule matrix of the fuzzy model with input variables ambient temperature (i_3) and wind speed (i_2).

i_3 / i_2	VL	L	M	H
VL	H	M	L	VL
L	H	H	M	L
M	H	H	M	M
H	H	H	M	L

bisector, mean of maximum, smallest of maximum, and LoM methods [39]. In this study, the LoM method was preferred for the defuzzification of the fuzzy output. In the LoM method, if more than one output value has the maximum membership degree, the largest of these values is selected as the crisp output. The LoM process can be mathematically expressed as follows:

$$\mu_{LoM}(x) = \max(\mu_1(x), \mu_2(x), \dots, \mu_n(x)) \quad (3)$$

where $\mu_1(x)$, $\mu_2(x)$, ..., $\mu_n(x)$ represents the membership degrees of the fuzzy output functions, and through the max function, the highest value among these functions is selected, i.e., $\mu_{LoM}(x)$.

Finally, fuzzy systems can be classified into three main categories: Sugeno-type, Mamdani-type, and Tsukamoto-type. Sugeno-type expresses the outputs as either a constant number or a linear function [40], while Mamdani-type is typically preferred in more intuitive, rule-based systems [41], where the outputs are expressed through more complex functions. Conversely, the Tsukamoto-type is a method in which the outputs are based on ordered membership functions [42]. Mamdani-type is good for its intuitive structure and ease of implementation. Therefore, Mamdani type fuzzy logic system has been preferred in this study.

Artificial Neural Network Model

ANNs are mathematical models, which are based on the biological nervous system, and designed to learn from data [43]. They are usually composed of interconnected artificial neurons with many layers. The ability of ANNs to learn complex relationships from data and generalize to unseen cases has led to their widespread use to solve a variety of complex problems [44]. Different network architectures can

be used depending on the problem, such as feedforward, feedback and convolutional neural networks. Among them, feed forward neural networks are popular due to their relatively simple structure and efficient training process [45]. In this architecture, information flows in one direction, the output of each layer being the input of the next. In the present work, the feedforward network was trained by using data for six months of the study area, and then it was used to predict the daily solar radiation for the seventh month. The network architecture used is shown in Figure 5.

The feedforward neural network used in this study consists of three layers: input layer, hidden layer, and output layer. The input layer has three neurons for the three input variables: relative humidity, ambient temperature, and wind speed. The hidden layer has ten neurons and uses the rectified linear unit (ReLU) activation function. Mathematically, the ReLU function can be written as:

$$f(X) = \max(0, X) \quad (4)$$

where $f(X)$ represents the output of the activation function, and X denotes the total input received by the neuron. In the output layer, there is a single neuron, and this neuron is used to forecast the daily solar radiation. A linear activation function is applied in the output layer. The linear activation function is expressed as follows:

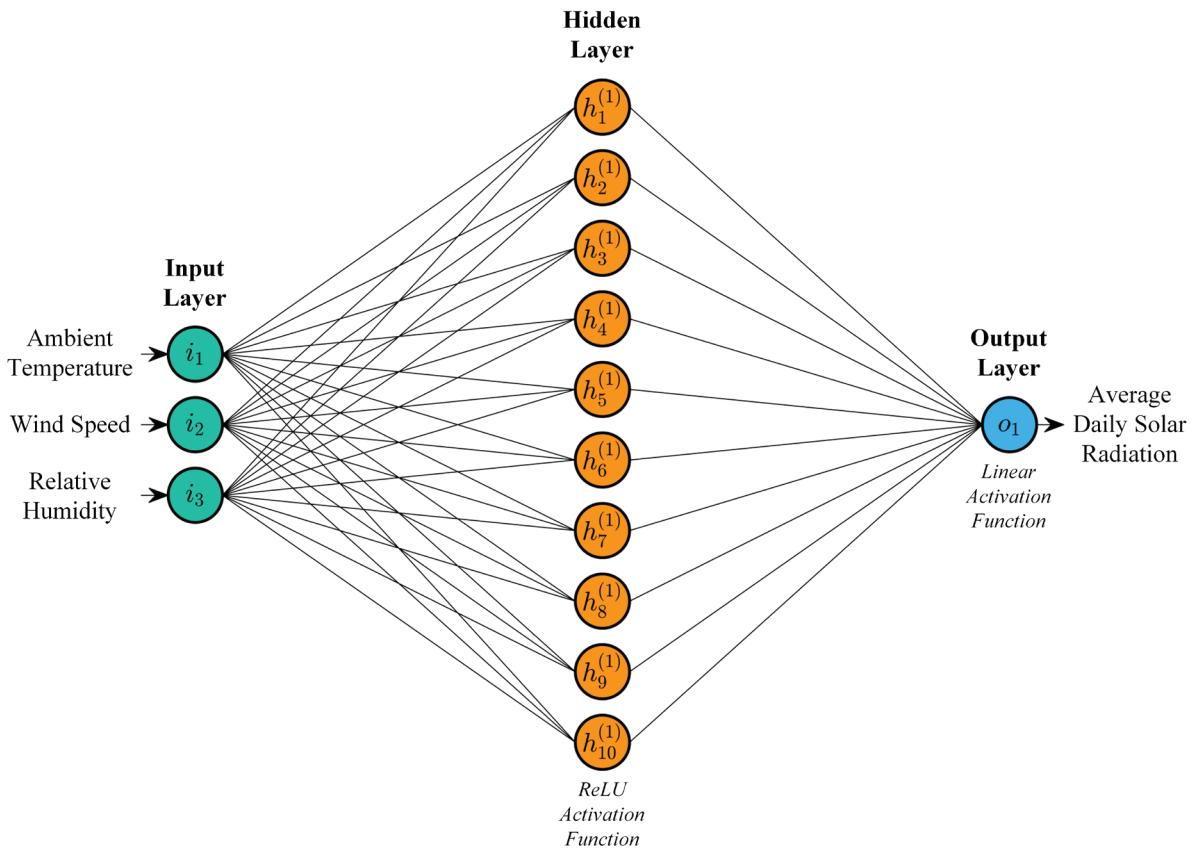


Figure 5. Three-layer feedforward ANN structure.

$$f(X) = X \quad (5)$$

As shown in Figure 5, the output of the hidden layer neurons can be calculated through the weighted sum of the values received from the neurons in the input layer and the activation function. The values of the hidden layer neurons are expressed as follows:

$$h_j = f_1 \left(\sum_i w_{ij} k_i \right) \quad (6)$$

where h_j represents the values of the hidden layer neurons, $f_1(\cdot)$ denotes the ReLU activation function, w_{ij} is the adjustable weight between the input and hidden layers, and k_i is the value of the input layer neuron. The hidden layer is considered as the input to the output layer. Therefore, the value of the output layer neuron can be expressed as follows:

$$o_j = f_2 \left(\sum_i v_{ij} h_i \right) \quad (7)$$

where o_j represents the value of the output layer neuron, $f_2(\cdot)$ denotes the linear activation function, and v_{ij} is the adjustable weight between the hidden and output layers.

Finally, the backpropagation algorithm was used to train the network. Backpropagation is a supervised learning method in which input samples are provided together with their corresponding target outputs [46]. During training, the error is propagated backward through the network to update the connection weights, and this process is repeated until the error is sufficiently reduced. In this study, model performance during training was evaluated using the mean squared error (MSE), and the variation in the error was monitored throughout the training process. Training was terminated when the MSE reached 10^{-2} , which was taken as the criterion for sufficient learning. The corresponding error metric is calculated using the following expression:

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (8)$$

where N represents the total number of samples in the training dataset, y_i is the actual value, and $\hat{y}_i$ is the value forecasted by the model.

Performance Evaluation Metrics

The performance of forecasting models is typically measured using error metrics. Among these metrics, the most common are MSE, mean absolute error, R-squared, MAPE, and RMSE [47]. Within the scope of the study, MAPE and RMSE, which are the most common metrics [12] in evaluating the solar radiation forecasting performance, were used. The MAPE can be expressed as Equation 9 [48], and the RMSE as Equation 10 [49].

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100 \quad (9)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (10)$$

It should be noted that the MSE defined in Equation 8 is only used during the training process of the ANN model. In this study, the evaluation of the forecasting performance of both the fuzzy logic and ANN models was conducted through the metrics presented in Equation 9 and Equation 10.

RESULTS AND DISCUSSION

This study compared three different fuzzy logic models to evaluate the impact of various climatic variables on the forecast of daily average solar radiation. The daily radiation forecasts for a one-month period are presented in Figure 6,

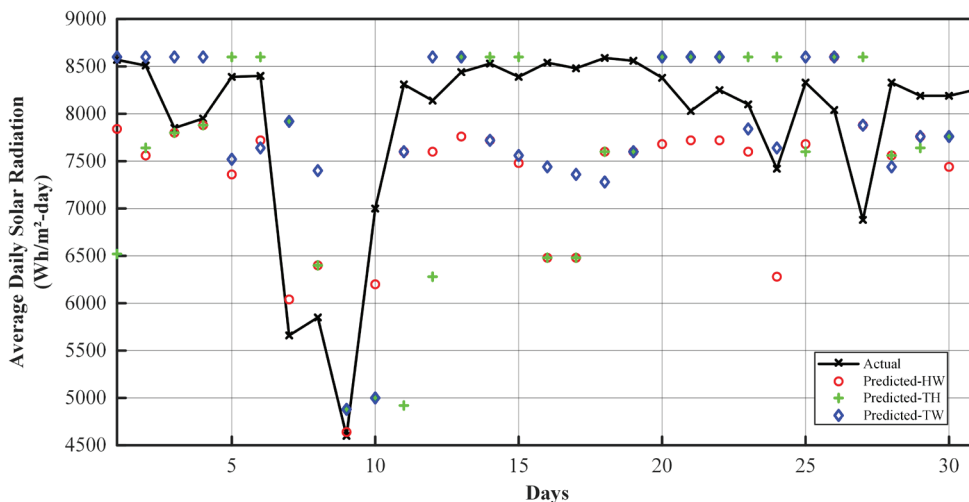


Figure 6. Average daily solar radiation forecasts of fuzzy logic models for a one-month period.

Table 4. Comparison of solar radiation forecasting performance of fuzzy logic models developed with different input pairs

Input Pair	RMSE (kWh/m ² -day)	MAPE (%)
HW	0.85	9.07
TW	0.89	9.61
TH	1.23	11.80

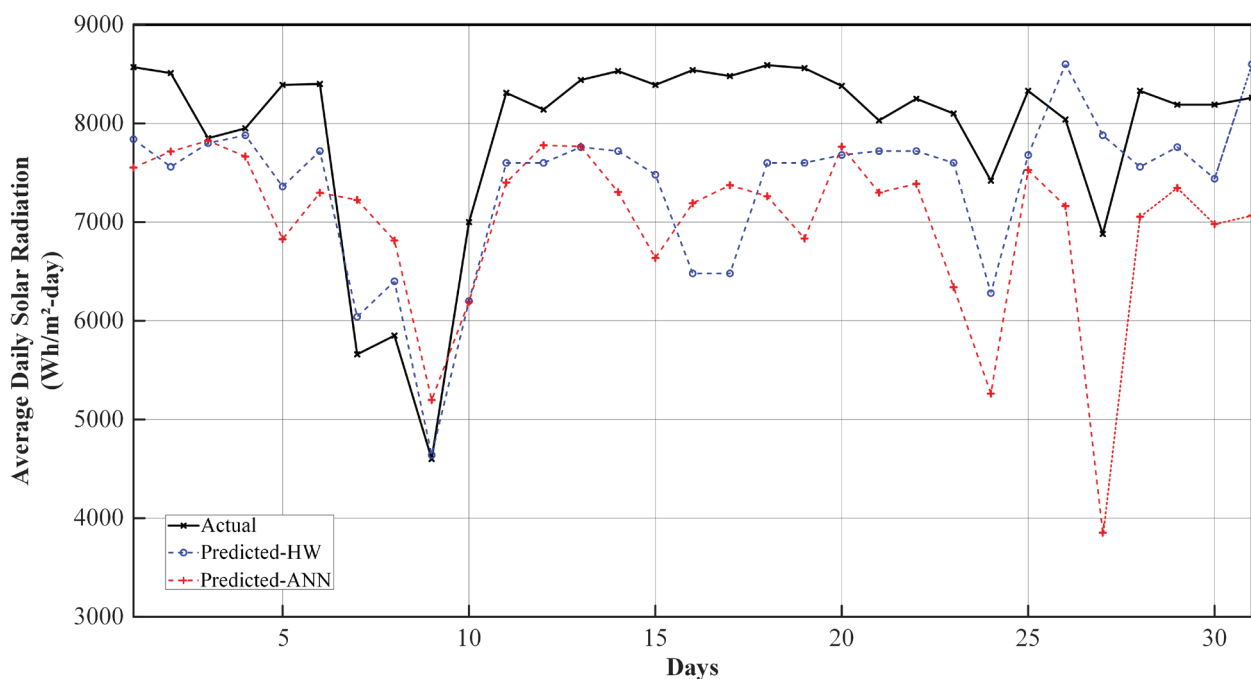
while the performance comparison of the models is provided in Table 4. According to the results, the model developed with HW as inputs demonstrated the best forecasting performance, with a MAPE of 9.07%. This was followed by the model using TW inputs, which achieved a MAPE of 9.61%. The model developed with TH inputs, however, exhibited lower performance compared to the others, with a MAPE of 11.80%.

The evaluation of the importance of climatic variables in solar radiation forecasting, based on the results of fuzzy logic-based models, indicates that wind speed is one of the most influential factors. The wind speed is present in the model with the best forecast performance and in the second ranked model, showing that it has a significant impact on the forecasting of solar radiation. Relative humidity is an important factor of radiation attenuation as it influences the amount of water vapor in the atmosphere [50]. However, it is only present in the first and third ranked combinations

in terms of forecast performance. The temperature is generally considered a product of solar radiation. So, the temperature does not directly improve forecasts, but plays an indirect role. The results indicate that wind speed is more influential than relative humidity in the fuzzy logic-based solar radiation forecasting and temperature can be taken as a secondary parameter.

In addition to evaluating the impact of climatic variables on solar radiation forecasting, this study also assesses the effectiveness of forecasting solar radiation using fuzzy logic models. For this purpose, the best-performing fuzzy logic model (built with the HW input pair) was compared with a feedforward ANN trained with six months of data from the analysis region. Figure 7 presents the daily radiation forecasts for a one-month period from both approaches. The comparison results revealed that the ANN forecasting model had an MAPE of 14.38%, compared with 9.07% for the HW fuzzy logic model. In fact, the forecasting performance of the ANN was lower than that of all three fuzzy logic models. This demonstrates that fuzzy logic approaches are an effective tool for daily solar radiation forecasting and can provide more accurate results compared to more complex forecasting methods.

Finally, Figure 8 compares the performance of all forecasting models considered in this study based on RMSE and MAPE criteria. The literature indicates that in the classification, a MAPE of less than 10% indicates excellent forecasting accuracy, between 10% and 20% indicates good accuracy, between 20% and 50% is acceptable and above

**Figure 7.** Average daily solar radiation forecasts for the fuzzy logic model (built with the HW input pair) and the ANN model for a one-month period.

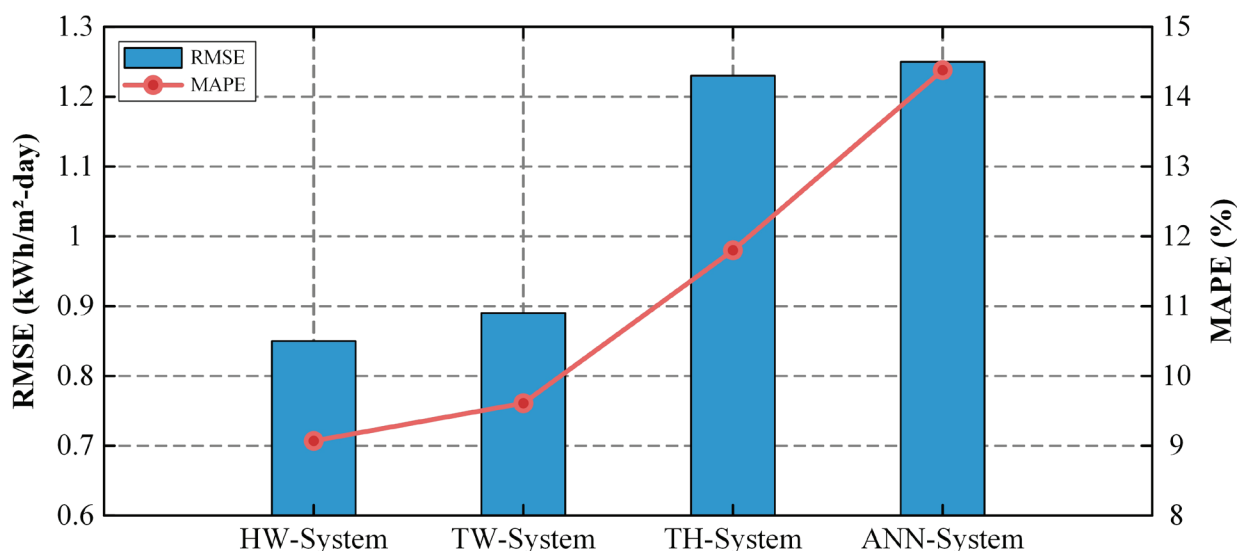


Figure 8. Performance comparison of all forecasting models presented in the study.

50% indicates poor forecasting performance [51]. Based on this classification, several of the fuzzy logic models developed with different combinations of inputs achieved excellent forecasting accuracy with MAPE values less than 10%. The results also suggest that the forecasting performance can be improved by appropriate selection of climatic variables without increasing the model complexity. The results show the potential of fuzzy logic-based approaches for solar radiation forecasting, and more generally for solar energy systems planning and optimization.

The fuzzy logic model developed in this work has several advantages in terms of model simplicity, data availability and forecasting performance compared to previous studies. However, there were some methodological limitations in the earlier studies. Refs. [28] and [29] presented a short-term or hourly forecast, and Ref. [28] also demonstrated limited performance under cloudy conditions. Conversely, Ref. [30] used only air temperature as an input and did not include any other potentially relevant climatic variables. The current study focuses on daily forecasting and examines different combinations of multiple meteorological inputs, thereby addressing these limitations. Other studies, e.g., Refs. [31, 32] used five or more input parameters which led to more complex model structure and higher computational requirements. For example, in Ref. [32] a fuzzy system with around 1,200 rules was developed. Additional inputs can improve the accuracy of the forecasts, but the increased complexity of the model can increase the computational requirements and reduce the ease of implementation. Moreover, it is observed that the MAPE is a function of the study region, forecasting time horizon, and the variability of solar radiation and should not be treated in isolation when comparing different studies. However, the best fuzzy model in this study with MAPE below 10%, which is

equivalent to the classification of the forecasting accuracy in Ref. [51] as excellent, was obtained with only two inputs, HW, and a small rule base of 16 rules. Both variables are readily available from meteorological datasets which may facilitate the application of the model in different regions. Furthermore, the comparison of the various input combinations revealed that among the climatic variables considered in this study, wind speed had the highest impact on the forecasting performance. In general, the results indicate that careful selection of input variables can lead to high forecasting accuracy without the need for high-dimensional input sets or highly complex model structures, which may be especially useful for data-scarce applications.

CONCLUSION

The forecasting of solar radiation is an important topic because of its broad application from photovoltaic energy production, agricultural planning, to building energy efficiency and climate change research for energy management and sustainable development goals. Linear and nonlinear modeling techniques, AI based approaches and fuzzy logic-based models are used for solar radiation forecasting. However, these methods pose several challenges and fuzzy logic-based models in particular, have gained less prominence in the literature as compared to other approaches. However, their ability to deal with uncertainties and flexibility in the interpretation of complex relationships can lead to substantial benefits for solar radiation forecasting. In this sense, the correct selection of the input parameters in the construction of a fuzzy logic system is important for improving the accuracy of the forecasts. Three different fuzzy logic models were developed in this study to analyze the key climatic variables that influence solar radiation

using pairs of input variables: TH, TW and HW. In addition, the fuzzy logic models were compared with an ANN model for the evaluation of their performance in solar radiation forecasting.

The main novelty of this study is to demonstrate that low-complexity fuzzy logic models, designed with meteorologically relevant and easily accessible inputs, can outperform more sophisticated AI models in terms of accuracy and computational efficiency. To the best of our knowledge, this study is the first to systematically compare the performance of fuzzy logic models and ANN models under the same conditions and to rank the contribution of individual climatic variables in fuzzy logic based solar radiation forecasting. The results of daily average solar radiation forecasting for a one-month period in Ankara, Türkiye based on error percentages obtained from three different fuzzy logic models show that the model using HW as inputs obtained the lowest error with a MAPE of 9.07%. The TW model followed with a MAPE of 9.61%, while the model with TH inputs showed the lowest performance with MAPE 11.80%. The results show that the most important parameter for solar radiation forecasting is wind speed, followed by relative humidity, and temperature plays a secondary role. Furthermore, the ANN model that was used to test the effectiveness of fuzzy logic systems, exhibited a lower forecasting accuracy with a MAPE of 14.38% compared to all fuzzy logic models. Accordingly, in the solar radiation forecasting field, fuzzy logic models with simple structures can provide more effective and reliable results than more complicated AI methods, by only detecting accurate climatic inputs, without increasing the complexity or the computational cost of the model. Fuzzy logic models have a great potential in the planning and optimization of solar energy systems because of their excellent accuracy rates and flexible structures. These models could therefore play a crucial role in achieving sustainability goals, including improving the efficiency of use of renewable energy sources, reducing carbon footprints and enhancing security of energy supply.

In future work, it would be advantageous to increase the number of climatic variables used to forecast solar radiation so as to improve the accuracy and scope of the models. For instance, the inclusion of variables such as atmospheric pressure, sunshine duration and cloud cover ratio in the model may further improve the forecasting performance. Furthermore, the results could be generalized better by performing studies on larger datasets and considering different geographical regions and seasonal variations. From an application point of view, the proposed fuzzy logic models are a practical tool for energy planners, policy makers and engineers to forecast solar radiation in data scarce regions. Their low computational requirements and dependence on easily measurable climatic inputs make them suitable for real-time applications in solar energy project planning, agricultural scheduling and grid load balancing. Moreover, these models are scalable and interpretable, can be adapted to different geographical and socioeconomic contexts, and

do not require high-dimensional datasets or complex AI architectures. Such long-term research and deployment of simplified fuzzy models would be of great help for better planning of solar energy systems, optimization of energy production forecasts and sustainable energy management, especially in developing regions with limited infrastructure.

NOMENCLATURE

AI	Artificial Intelligence
ANN	Artificial Neural Network
H	High
HW	Relative Humidity and Wind Speed
L	Low
LoM	Largest of Maximum
M	Medium
MAPE	Mean Absolute Percentage Error
MSE	Mean Squared Error
ReLU	Rectified Linear Unit
RMSE	Root Mean Square Error
TH	Temperature and Relative Humidity
TW	Temperature and Wind Speed
VL	Very Low

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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