Green Energy, Environment and Sustainable Development 275
C. Wang et al. (Eds.)

doi:10.3233/ATDE230300

Global Solar Radiation Forecasting with Artificial Neural Networks

Mihriban SARI and Muslum ARICI[1]
Mechanical Engineering Department, Engineering Faculty, Kocaeli University (Umuttepe Campus), Kocaeli 41001, Turkey

Abstract. This study presents a detailed examination of using artificial neural networks for predicting global solar radiation. The research aims to develop an artificial neural network model using five years of solar radiation and meteorological variables (precipitation, wind speed, relative humidity, vapor pressure, cloudiness, current pressure, average temperature, number of sunny days, solar radiation, and daily average solar intensity) obtained from the central meteorological observation station of Kocaeli province between 2017 and 2021. The model aims to address the complexity of solar radiation as a phenomenon and the challenges associated with direct measurement. Artificial neural networks are considered an ideal tool for this purpose due to their ability to analyze complex data structures and identify relationships. The dataset used in this study includes detailed measurements of five years of solar radiation and meteorological variables collected from the meteorological observation station. These data encompass factors crucial for solar radiation prediction and provide information to enhance the accuracy of the model. The dataset is divided into training, validation, and testing phases, and relevant metrics are used to evaluate the performance of the artificial neural network model. The results demonstrate the successful prediction of global solar radiation by the developed artificial neural network model. The model undergoes a learning process to comprehend the complexity of solar radiation and make predictions by utilizing the relationships between various meteorological variables. This study emphasizes the importance of solar radiation prediction in areas such as solar energy projects, energy planning, and climate change research.

Keywords. Empirical modeling, global solar radiation, machine learning, artificial neural networks

1. Introduction

Solar radiation is defined as the power emitted per unit area of the sun and the power transmitted in the form of electromagnetic radiation [1]. Solar radiation quantity is a crucial factor in the energy sector, playing a significant role in applications like meteorological studies and the design of solar energy-dependent projects. It is particularly important for determining the performance of systems such as photovoltaic systems and optimizing natural lighting systems in buildings.

It has been observed from satellite measurements that the absolute value of the amount of solar radiation coming from outside the earth is 1361 W/m^2 and that the

[1] Corresponding Author, Muslum ARICI, Mechanical Engineering Department, Engineering Faculty, Kocaeli University (Umuttepe Campus), Kocaeli 41001, Turkey; Email: muslumarici@gmail.com

solar radiation value should be significantly lower than the value of 1365 W/m^2 observed in conventional radiometers [2]. But when solar radiation from the outer planets encounters the atmosphere, it weakens and ceases to be constant. This attenuation is due to the scattering or absorption of photons interacting with the shielding material in the atmosphere.

One of the main negative impacts of the increasing population is the ever-increasing need for energy. For this reason, fossil fuel reducing energy consumption and creating more sustainable energy resources are needed. Among renewable energy sources, the sun has a serious advantage as it is an infinite energy source [3]. Measurement of the amount of solar radiation, such as pyranometers, pyheliometers and solar meters can be measured with the help of devices. Due to the high cost of these instruments, it is not possible to experimentally measure solar radiation at all points on the globe. To overcome this challenge, the relationship between meteorological variables and solar radiation models that mathematically describe the relationship has been proposed [4]. The approaches presented are designed based on the principles of astronomy and geometry in relation to the motion of the Earth around the sun. Nowadays, there is a need for a reliable estimation methodology considering these mathematical approaches describing solar radiation and environmental factors in evaluating the economic analysis of PV plants planned to be established. The artificial neural networks (ANN) technique is very popular in forecasting applications due to its high processing speed, simple applicability and low cost, and ANN applications have been used to predict many different parameters in solar radiation measurements [5].

In this study, an ANN model was developed using 5-year solar radiation and meteorological variables (precipitation, wind speed, relative humidity, vapor pressure, cloudiness, current pressure, average temperature, number of sunny days, solar radiation, and daily average solar intensity) obtained from the central meteorological observation station of Kocaeli province for the limited period between 2017 and 2021. The ANN structure was modeled in Python (Kaggle) using feed-forward ANN modeling topology. The solar radiation estimation values obtained with the presented approach are compared with the actual measurement results and statistically evaluated. As a result of the model comparisons, it was determined that artificial neural networks gave the best prediction results with the available data. As a result of ANN modeling, whether the models work well or not depends on the amount of deviation between the measured real values and the output values generated by the ANN model. As mentioned above, four different statistical methods such as R^2, RMSE, MSE and MAPE were used to determine the optimal ANN architecture and the errors were compared to find the optimal model. In order to make more use of solar radiation and to obtain a larger amount of radiation, many scientists have been researching since time immemorial and have proposed numerous statistical models based on different meteorological, geographical and climatological parameters. Wong and Chow conducted research on solar energy models and as a result of this research, they divided the models into parametric and component models. They classified the models they obtained and compared them. They found that detailed information on atmospheric conditions is needed for parametric models and one of the most widely used parametric models is the Ashre model [6]. The calculation of the average daily global radiation in relation to the sunshine duration was made with the Angström model. This model was developed by Prescot in 1940 and transformed into the Angström-Prescot model. Diagne et al. [7] continued their studies by taking 4-year data from 5 stations in the USA.

Similarly, Reindl et al. conducted research on diffuse radiation at 5 stations in the USA. Lam and Lee developed direct and diffuse radiation models with their studies in Hong Kong.

Skarweit and Olseth [8] suggested that diffuse radiation depends on other parameters such as relative humidity and temperature and developed a model for direct radiation.

In 1987, Maxwell developed a model for the estimation of direct normal radiation based on the global radiation in the horizontal plane as previously interpreted by Batlles et al. [9]. Various empirical models are used to calculate the solar radiation reaching any surface area. Climatological, meteorological and geographical parameters such as sunshine duration, air temperature, latitude, longitude, precipitation, relative humidity and cloudiness are also commonly used to estimate global solar radiation. The most widely used parameter for estimating global solar radiation is the sunshine duration, which can be measured easily and reliably. Most of the global solar radiation estimation models are used to estimate solar radiation amounts [10]. Bora et al. [11] showed that ANN methodology can be used to predict the output power of PV modules. In the study, Ceylan suggested that module temperature in photovoltaic panels can be predicted by ANN. Various methods based on ANN applications in the estimation of solar radiation have been the subject of investigation by many researchers and the estimation of global solar radiation (GSR) using ANN has been examined and discussed. It has been shown that ANN can be used to predict daily solar radiation when daily maximum and minimum air temperature and precipitation measurements are available. Using data from 41 radiation collection stations with known locations in Saudi Arabia, it was determined that the solar radiation of unknown locations can be determined by ANN, and ANN applications were used in solar radiation modeling for regions with different latitudes and climates [12].

This study provides a detailed examination of the use of artificial neural networks for predicting solar radiation. It aims to develop an artificial neural network model using five years of solar radiation and meteorological variables obtained from the central meteorological observation station in Kocaeli province. The primary objective of this study is to create a prediction model using current meteorological data to estimate solar radiation. Solar radiation is an essential parameter in the energy sector, and accurate predictions are crucial for sizing solar energy-dependent projects and determining their performance. The study addresses the complexity of solar radiation as a phenomenon and the challenges associated with direct measurement by employing analytical tools such as artificial neural networks. The dataset used in this study includes detailed measurements of solar radiation and meteorological variables collected over a five-year period from the meteorological observation station. These data encompass factors that are critical for predicting solar radiation and provide valuable information to enhance the accuracy of the model. The dataset is divided into training, validation, and testing phases, and the performance of the artificial neural network model is evaluated using relevant metrics. The results demonstrate the successful prediction of global solar radiation by the developed artificial neural network model. The model has the ability to understand the complexity of solar radiation and make predictions by utilizing the relationships between various meteorological variables.

This study emphasizes the importance of predicting solar radiation in areas such as solar energy projects, energy planning, and climate change research.

2. Methodology

In this study, an artificial neural network model was developed using 5 years of data obtained from the central meteorological observation station of Kocaeli province. The data included solar radiation and various meteorological variables. The aim was to create a model that can predict solar radiation using these variables.

Since Kocaeli has a transitional climate between the Mediterranean and Black Sea climates, it can exhibit significant variability. Therefore, the hypothesis was that meteorological variables influence solar radiation, and these variables can be used to predict solar radiation. The artificial neural network model was developed using Python programming language and the Kaggle environment. The structure of the model was created using a feedforward artificial neural network topology. This topology is used for feeding the data, transmitting information between layers, and obtaining results. The trained artificial neural network model with the collected data was used to predict solar radiation. The model analyzes the relationships between the data and makes predictions on new data. This allows for utilizing the model to predict solar radiation without the need for direct measurements [13].

The success criterion of the model was determined by comparing the predicted values with the actual measurement results. Statistical evaluation methods were used to assess the accuracy of the model's predictions. According to the comparison results, it was determined that the artificial neural network model provides the best prediction results with the available data. This study demonstrates that artificial neural networks are a successful method for predicting solar radiation. The detailed analysis of the model and the results of statistical evaluation provide information about the reliability and usability of the model. Such models can be significant tools in meteorological forecasts and climate analyses [14].

Firstly, the meteorological data mentioned above was obtained from the General Directorate of Meteorology through the Kocaeli University Faculty of Engineering. The existing data was provided in Excel format and subsequently organized and made processable. These editing procedures have made the data more accessible and suitable for analysis and processing [15]. The studies were conducted on the Kaggle platform. The data was uploaded to Kaggle and a dataset was created. This enabled easier access to the data and allowed it to be stored in a shareable format. The required libraries have been installed in advance. The NumPy library was used for fast scientific calculations. It is particularly preferred for mathematical and statistical calculations and plays an important role in data analysis [16].

The Seaborn Library was used for data visualization. Seaborn is a plotting library that enables the visual presentation of data in a more understandable way. This library allows for the visual exploration of relationships, distributions, and patterns in the dataset [17]. Furthermore, the Pandas library was used for data processing and analysis. Pandas is a commonly used library for data manipulation and analysis. Operations such as reading, filtering, transforming, and summarizing the dataset were performed using the Pandas library.

In this way, the process from the data source to the preparation of the dataset, conducting the work on the Kaggle platform, and utilizing the necessary libraries have been explained in detail [18]. A small portion of the meteorological data for the province of Kocaeli is shown in Table 1.

Table 1. Meteorology data.

Station number	Year	Month	Day	Rains	Wind speed	Relative humidity	Vapor pressure	Cloudiness
0 17066	2017	1	1	4.8	2.7	90.0	6.6	2.8
1 17066	2017	1	2	1.0	1.1	80.8	5.7	0.0
2 17066	2017	1	3	0.0	1.0	69.9	5.4	2.0
3 17066	2017	1	4	0.2	1.1	66.2	6.3	4.6
4 17066	2017	1	5	0.0	1.9	66.3	8.1	5.5

Examining the variable types and memory usage in the data frame is important for data analysis and memory management. Properly defining variable types ensures accurate interpretation of the data and prevents incorrect analysis results. Additionally, memory usage needs to be efficiently managed as large data sets can occupy a significant amount of memory space. Monitoring memory usage is important to determine the memory requirements of the data frame and prevent unnecessary memory consumption. Therefore, looking at variable types and memory usage is a crucial step in performing accurate data analysis and optimizing memory management [19]. The variable types and memory usage are shown in Table 2.

Table 2. Variable types and memory usage.

<class ‘pandas.frame.DataFrame ‘>
RangeIndex: 1826 entries, 0 to 1825
Data columns (total 16 columns):

#	Column	Non-null count	Dtype
0	Station number	1826 non-null	Int64
1	Year	1826 non-null	Int64
2	Month	1826 non-null	Int64
3	Day	1826 non-null	Int64
4	Rains	1826 non-null	float64
5	Wind speed	1826 non-null	float64
6	Relative humidity	1826 non-null	float64
7	Vapor pressure	1826 non-null	float64
8	Cloudiness	1826 non-null	float64
9	Actual pressure	1826 non-null	float64
10	Average temperature	1826 non-null	float64
11	Sunshine duration (h)	1826 non-null	float64
12	Latitude	1826 non-null	float64
13	Longitude	1826 non-null	float64
14	Solar radiation	1826 non-null	float64
15	Total global insolation intensity	1826 non-null	float64

The basic statistical values in the data frame provide information about the distribution of the data. The describe function summarizes the data by displaying the mean, standard deviation, minimum and maximum values, quartiles, and other statistics. This makes the data set more meaningful and allows for interpretation. The standard deviation in the average temperature data is a measure of how spread out the data is. A higher standard deviation indicates that the data points are more spread out from the mean [20]. Therefore, the distribution of temperature values is wider in relation to the mean. Variance, on the other hand, is defined as the square of the standard deviation and is unitless. Variance is a measure of the overall spread of the data. It represents the average of the squared differences between each data point and the mean. Like the standard deviation, variance is a measure of how spread out the data is [21]. Based on this information, we can say that the temperature values have the largest variance in relation to the mean. This means that the temperature values can deviate more from the mean and have a wider distribution. The statistical values of the utilized data are shown in Table 3.

Table 3. Statistics values.

	Count	Mean	Std.	Min	25%	50%	75%	Max
Station number	1826.0	17066.0	0.000000e+00	17066.0	17066.0	17066.0	17066.0	17066.0
Year	1826.0	2019.000548	1.414407e+00	2017	2018	2019	2020	2021
Month	1826.0	6.523549	3.449478e+00	1	4	7	10	12
Day	1826.0	15.727820	8.801735e+00	1	8	16	23	31
Rains	1826.0	2.174699	5.595023e+00	0	0	0	1.4	76.4
Wind speed	1826.0	1.549343	4.604133e-01	0.4	1.3	1.5	1.8	4.5
Relative humidity	1826.0	74.118839	1.248663e+01	33.5	65.5	73.9	83.175	98.9
Vapor pressure	1826.0	13.608379	5.614692e+00	2.9	8.8	12.6	18.2	28.8
Cloudiness	1826.0	3.676123	2.179134e+00	0.0	1.9	3.8	5.6	7.0
Actual pressure	1826.0	1006.855696	5.946523e+00	988.3	1002.725	1006.3	1010.7	1029.1
Average temperature	1826.0	16.442223	7.040671e+00	-2.8	10.7	16.550	22.8	30.5
Sunshine duration (h)	1826.0	5.412432	4.22446e+00	0.0	1.1	6.0	8.9	12.8
Latitude	1826.0	40.717700	7.107374e-15	40.7177	40.7177	40.7177	40.7177	40.7177
Longitude	1826.0	29.819300	0.000000e+00	29.82	29.82	29.82	29.82	29.82
Solar radiation	1058.0	5.001040	3.986736e+00	0.1	0.7	4.1	7.2	14.9
Total global insolation intensity	1027.0	304634.638656	2.427725e+05	4200.00	102600.0	250800.0	435531.9	898872.3

Correlation analysis is a statistical method used to examine the relationship between two or more variables and determine the direction and strength of this relationship. The correlation coefficient takes values between -1 and 1, representing different types of relationships. A correlation coefficient (r) value of -1 indicates a negative perfect relationship, where one variable decreases as the other variable increases. r=0 indicates no relationship, meaning there is no association between the variables. r=1 indicates a perfect positive relationship, where both variables increase or decrease together. A high value like r=0.7 indicates a good positive relationship, where the variables show a similar trend of increase or decrease.

A lower value like r=-0.3 indicates a moderate negative relationship, where one variable increases as the other variable decreases, but the relationship is weaker [22]. According to the data, the strongest positive relationship (0.895437) is found between solar radiation and daily insolation intensity. This indicates that as solar radiation increases, daily insolation intensity also increases. The two variables show a simultaneous increase. Additionally, there is a positive relationship (0.894275) between mean temperature and vapor pressure. In this case, as the mean temperature increases, vapor pressure also increases. The two variables show a simultaneous increase. These correlation analysis results demonstrate the presence of positive relationships between solar radiation and daily insolation intensity, as well as between mean temperature and vapor pressure.

By examining the distribution of the relationship between the data, we observed how this relationship is distributed. The correlation coefficients obtained through correlation analysis indicate the direction (positive or negative) and strength of the relationship. According to the relevant data, we observed that there is a strong positive relationship between solar radiation and daily insolation intensity. This relationship indicates that as solar radiation increases, daily insolation intensity also increases. The relationship between these two variables is expressed by a high correlation coefficient [23]. Additionally, we observed a positive relationship between mean temperature and vapor pressure. It was observed that as the mean temperature increases, the vapor pressure also increases. This indicates that the two variables show an increase together. These distribution observations help us understand how the relationship between the data is distributed and how it changes. It is also important to mention that heat maps are used to visualize these relationships. Heat maps represent different values of the data with colors, allowing us to easily perceive the distribution of relationships. This enables us to better understand and visually observe the distribution of the relationship between the data. The heat map illustrating the data distribution is depicted in Figure 1. The relationship distribution between the data is shown in Figure 2.

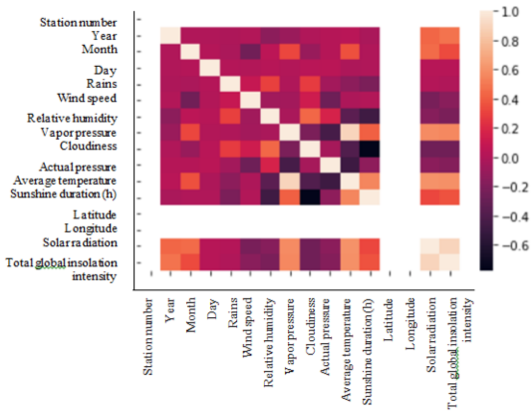

Figure 1. Heat map.

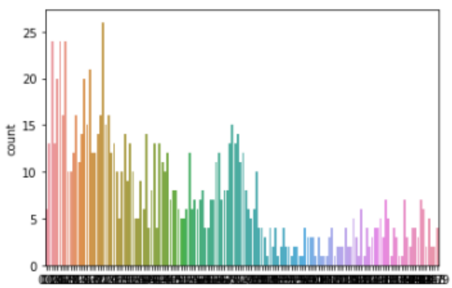

Figure 2. Distribution of relationship between data.

A relationship between solar radiation and total insolation intensity data has been identified. After the completion of the examinations, 20% of the available data was used as training data, and the remaining 80% was set aside as test data. The prediction-test data is shown in Figure 3. After the training process was completed, four different statistical methods, namely R2 (Coefficient of Determination), RMSE (Root Mean Square Error), MSE (Mean Square Error), and MAPE (Mean Absolute Percentage Error) were used to evaluate the errors and determine the most appropriate model. The graph shown in Figure 3 illustrates the relationship between the prediction results and the test data. This graph is used to assess the performance of the model and how closely the predictions align with the actual data. A higher R2 value indicates that the predictions are closer to the actual data and that the model exhibits a better fit. Error metrics such as RMSE, MSE, and MAPE are used to measure the accuracy of the predictions and the performance of the model. Evaluating these metrics helps determine which model is the most suitable.

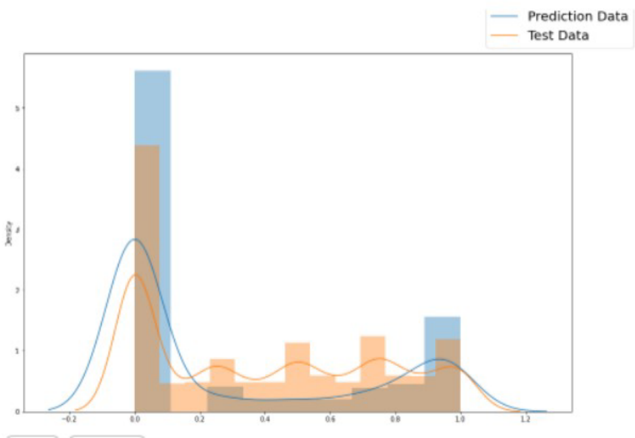

Figure 3. Prediction-test data.

In this way, it is explained that the relationship between solar radiation and total insolation intensity was analyzed using statistical methods, and the most appropriate model was determined. These analyses contribute to a better understanding of the data and the development of an effective model for predicting solar radiation.

3. Results and Discussion

The study's main goals were to identify the best model for forecasting solar radiation and to comprehend the relationship between solar radiation and total solar irradiance. Initial research found a substantial positive link between solar radiation and total solar irradiance, demonstrating that when solar radiation rises, daily solar irradiance also rises. Using four distinct statistical metrics R^2, RMSE, MSE, and MAPE the performance of the chosen model for forecasting solar radiation was assessed following the training procedure. These metrics are frequently used to assess the model's overall performance and prediction accuracy. The chosen model does a good job of forecasting solar radiation, as seen by the high R^2 value and low error metrics.

The results show that a useful model can be created to comprehend the connection between solar radiation and total solar irradiance as well as forecast solar radiation. This can contribute to better utilization of solar energy and assist in the planning and decision-making processes in the energy sector. Additionally, in the agricultural sector, estimating solar irradiance plays a key role in the planning of agricultural activities and improving plant development. The management of agricultural practices like irrigation and fertilization can be made more effective and sustainable with the help of accurate solar irradiance predictions. It's crucial to take into account the limitations of this study, though. Firstly, the utilization of a narrow period and data from a specific geographical location may impede the generalizability of the findings. In order to better understand the link between solar radiation and solar irradiance in various geographical locations, future research should include bigger and more varied datasets.

The choice of statistical metrics for assessing model performance and prediction precision is also very important. Results might vary depending on the metrics used or how various datasets are evaluated. Therefore, future research might examine the use of various measures and evaluate the outcomes. The goal of this study was to identify the best effective model for forecasting solar radiation by studying the link between solar radiation and total solar irradiance. The results show that as solar radiation increases, daily solar irradiance also rises.

The results of this study can aid in improving our comprehension of solar energy potential and the creation of more dependable and precise solar radiation prediction models. This can support more efficient use of renewable energy sources and optimize the use of solar energy in the energy industry. Additionally, the results acquired might also play a vital role in the agriculture sector. The prediction of solar irradiance holds great importance in the planning of agricultural activities and optimizing plant growth and productivity. An accurate forecast of solar irradiance can give a more effective and sustainable approach to the control of agricultural techniques such as irrigation and fertilization.

It is crucial to take into account this study's constraints. The conclusions' generalizability can be constrained by the use of data from a restricted geographic area and a constrained period. Future research can use a larger and more varied dataset to examine the relationship between solar radiation and solar irradiance in more detail for various geographical regions. Finally, this work focused on creating an appropriate model for forecasting solar radiation and examining the link between solar radiation and total solar irradiance. The obtained data show that with an increase in solar radiation, there is an increase in daily solar irradiance. This work contributes significantly to a better understanding and utilization of solar energy potential.

4. Conclusion

This study aimed to examine the relationship between solar radiation and total insolation intensity data and determine the most appropriate model for predicting solar radiation. Firstly, the distribution and relationship of the data were analyzed, revealing a strong positive relationship between solar radiation and total insolation intensity. This relationship indicates that daily insolation intensity increases with an increase in solar radiation. Subsequently, the data were divided into training and test sets, and model training was conducted. After completing the training process, various statistical methods such as R2 (Coefficient of Determination), RMSE (Root Mean Square Error), MSE (Mean Square Error), and MAPE (Mean Absolute Percentage Error) were used to evaluate the errors and identify the most suitable model. These evaluations aimed to assess how well the predictions align with the test data. A higher R2 value indicates that the predictions are closer to the actual data, indicating a better fit of the model. Error metrics such as RMSE, MSE, and MAPE were used to measure the accuracy of the predictions and the performance of the model. Evaluating these metrics helps determine the most appropriate model. The results demonstrate that a strong relationship exists between solar radiation and total insolation intensity, and an effective model can be developed to predict solar radiation. The selected model exhibits a good fit and low error value, making it suitable for predicting solar radiation and offering utility in the energy sector, agriculture, and environmental studies. However, this study has some limitations.

Firstly, the dataset used covers a limited time range and pertains to a specific geographic region, making generalization challenging. Additionally, the performance of the model and the accuracy of the predictions were evaluated using the employed statistical metrics. Using different metrics or examining different datasets could yield different results. For future studies, it is recommended to employ a broader dataset and consider data from different geographical regions. Additionally, conducting a comprehensive analysis by comparing different models and utilizing a wider range of statistical metrics would be beneficial. In conclusion, this study reveals a strong relationship between solar radiation and total insolation intensity and demonstrates that an effective model can be developed to predict solar radiation. The findings of this study can contribute to better utilization of solar energy resources, improved agricultural planning, and environmental impact assessment. Ultimately, understanding the relationship between solar radiation and total insolation intensity and determining an appropriate model for predicting solar radiation were the main objectives of this study. The obtained results indicate that daily insolation intensity increases with an increase in solar radiation. This information can contribute to the better understanding and utilization of solar energy potential, as well as inform decision-making in various sectors such as energy, agriculture, and environmental studies. In this way, more reliable and accurate predictions can be obtained to better understand and harness solar energy potential.

References

[1] Alzahrani A, Shamsi P, Dagli C, Ferdowsi M. Solar irradiance forecasting using deep neural networks. Procedia Computer Science. 2017;114:304 313.

[2] Arya JS, Singh O, Aggarwal SK. Solar energy radiation forecasting methods in the current scenario. 2016.

[3] Atkinson PM, Tatnall AR. Introduction neural networks in remote sensing. International Journal of Remote Sensing. 1997;18(4):699 709.

[4] Boland J. Time-series analysis of climatic variables. Solar Energy. 1995;55(5):377388.

[5] Box GE, Jenkins GM, Reinsel GC, Ljung GM. Time Series Analysis: Forecasting and Control. John Wiley and Sons. 2015.

[6] Cao S, Cao J. Forecast of solar irradiance using recurrent neural networks combined with wavelet analysis. Applied Thermal Engineering. 2005;25(2):161-172.

[7] Diagne M, David M, Lauret P, Boland J, Schmutz N. Review of solar irradiance forecasting methods and a proposition for small-scale insular grids. Renewable and Sustainable Energy Reviews. 2013;27:65-76.
[8] Skartveit A, Olseth JA. A model for the diffuse fraction of hourly global radiation. Solar Energy. 1987;38(4):271-274.
[9] Batlles FJ, Rubio MA, Tovar JJ. Empirical modeling of hourly direct irradiance by means of hourly global irradiance. Proceedings of the ICE - Energy. 2020;25(7):675-688.
[10] Ko CN, Lee CM. Short-term load forecasting using SVR (support vector regression)-based radial basis function neural network with dual extended Kalman filter. Energy. 2013;49:413-422.
[11] Mittal M., Bora B., Saxena S., Gaur A.M. Performance prediction of PV module using electrical equivalent model and artificial neural network. Sol. Energy. 2018;176:104-117. doi:10.1016/j.solener.2018.10.018.
[12] Soubdhan T, Voyant C, Lauret P. Influence of global solar radiation typical days on forecasting models error. Third Southern African Solar Energy Conference (SASEC2015). 2015. Retrieved from https://hal.archives-ouvertes.fr/hal-01099487.
[13] David M, Ramahatana F, Trombe PJ, Lauret P. Probabilistic forecasting of the solar irradiance with recursive ARMA and GARCH models. Solar Energy. 2016;133:55-72.
[14] Duffie JA, William AB. Solar Engineering of Thermal Processes. 1980.
[15] Hinton G, et al. Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. IEEE Signal Processing Magazine. 2012;29(6):82-97. doi:10.1109/MSP.2012.2205597.
[16] Winkler WE. Data cleaning methods. Proc ACM SIGKDD Workshop on Data Cleaning, Record Linkage, and Object Consolidation. 2003.
[17] Cyril V, Gilles N, Soteris K, Marie-Laure N, Christophe P, Fabrice M, Alexis F. Machine learning methods for solar radiation forecasting: A review. Renewable Energy. 2017;105:569-582.
[18] Alzahrani A, Shamsi P, Ferdowsi M. A novel non-isolated high-gain Dc-dc boost converter. 2017 North American Power Symposium (NAPS), Morgantown, WV. 2017;1-6.
[19] Ssekulima EB, Anwar MB, Al Hinai A, El Moursi MS. Wind speed and solar irradiance forecasting techniques for enhanced renewable energy integration with the grid: A review. IET Renewable Power Generation. 2016;10(7):885-989. doi:10.1049/iet-rpg.2015.0477.
[20] Alberto D, Sonia L, Giampaolo M. Comparison of different physical models for PV power output prediction. Solar Energy. 2015;119:83-99.
[21] Phinikarides A, Makrides G, Kindyni N, Kyprianou A, Georghiou GE. ARIMA modeling of the performance of different photovoltaic technologies. 2013 IEEE 39th Photovoltaic Specialists Conference (PVSC), Tampa, FL. 2013;0797-0801.
[22] Gana NN, Akpootu DO. Angstrom type empirical correlation for estimating global solar radiation in North-Eastern Nigeria. The International Journal of Engineering and Science. 2013;2:58-78.
[23] Bishal MM, Mohd. S, Abhik KD. An empirical model for ramp analysis of utility-scale solar PV power. Solar Energy. 2014;107:44-49. https