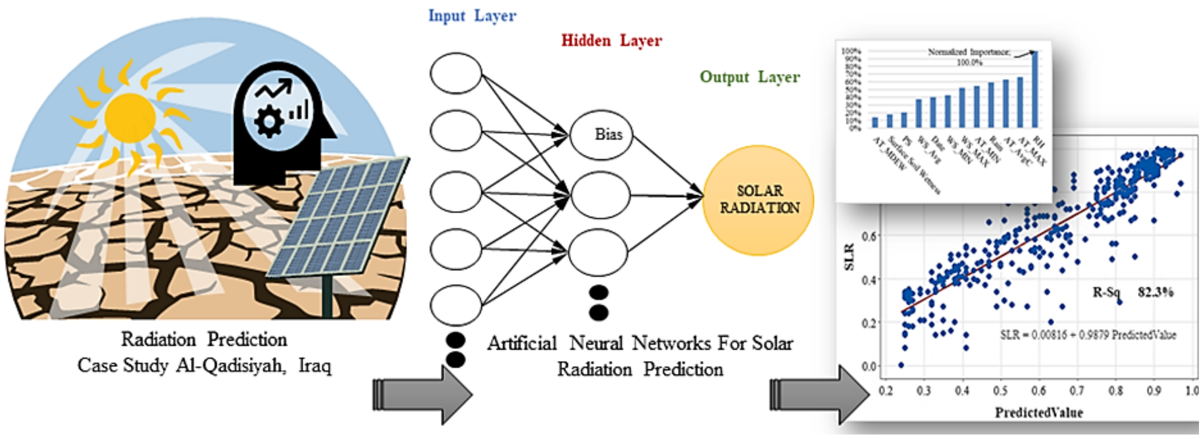
Artificial Neural Networks for Solar Radiation Prediction: Case Study, Al-Qadisiyah, Iraq

Ahmed Al-Rubaye [1*], Marwah M. Al-Khuzaie [2]

[1] *Mechanical Engineering Department University of Al-Qadisiyah, Al-Qadisiyah, Iraq*

[2] *Civil Engineering Department University of Al-Qadisiyah, Al-Qadisiyah, Iraq*



ABSTRACT: For solar energy to develop a clean, renewable alternative to fossil fuels, it is important to be able to correctly predict surface longwave radiation. To improve cost-efficiency and accuracy in surface longwave radiation (SLR) predictions, forecast systems are increasingly utilizing artificial neural networks (ANNs). This study uses two different procedures for predicting solar radiation in great detail. The first model uses weather statistics from a station in Al-Qadisiyah, Iraq. The second model, on the other hand, uses daily statistics from 2022 from NASA's Prediction of Worldwide Energy dataset for the same site. The scaled conjugate gradient technique was used in both models. The goal is to find the best mix of meteorological factors that can be used with an ANN model to achieve accurate predictions. Based on the findings of this study, temperature, relative humidity, and Rainfall all seem to have a big effect on SLR. On the other hand, windy weather doesn't have much of an effect on SLR. ANN models also did very well when trained with data from NASA's Prediction of Worldwide Energy, with an R^2-value of 0.823 and an RMSE value of 0.0106. The results show that this mix does better than other models in terms of performance score.

الملخص: يعد التنبؤ الدقيق للإشعاع السطحي طويل الموجة أمرًا ضروريًا لتطوير الطاقة الشمسية كبديل نظيف ومتجدد للوقود الأحفوري. لتقليل التكاليف وتحسين الكفاءة، تم استخدام أنظمة التنبؤ مثل الشبكات العصبية الاصطناعية (ANN) للتنبؤات بإشعاع الموجات الطويلة السطحية (SLR). تقدم هذه الدراسة تحليلا شاملا لنموذجين مختلفين للتنبؤ بالإشعاع الشمسي. يستخدم النموذج الأول بيانات الأرصاد الجوية التي تم جمعها من محطة في القادسية، العراق، بينما يعتمد النموذج الثاني على مجموعة بيانات التنبؤ بالطاقة العالمية التابعة لوكالة ناسا لنفس الموقع ويغطي البيانات اليومية لعام 2022. وتم استخدام The scaled conjugate gradient algorithm في كلا النموذجين. الهدف هو تحديد المزيج الأمثل لمتغيرات الأرصاد الجوية التي يمكن استخدامها مع نموذج (ANN)لتحقيق تنبؤات دقيقة. تشير نتائج هذا البحث إلى أن درجة الحرارة والرطوبة النسبية وهطول الأمطار لها علاقة كبيرة مع SLR. ومن ناحية أخرى، فإن درجة حرارة الرياح لها تأثير ضئيل على SLR. علاوة على ذلك، عندما يتم تدريب نماذج الشبكات العصبية الاصطناعية باستخدام بيانات من توقعات ناسا للطاقة العالمية، فقد حققت قيمة R^2 تبلغ 0.823 وقيمة RMSE منخفضة تبلغ 0.0106. تشير هذه النتائج إلى أن هذا المزيج يتفوق على النماذج الأخرى من حيث درجة الأداء.

Keywords: Solar radiation, Surface Longwave Radiation, Artificial Neural Network.

الكلمات المفتاحية: الإشعاع الشمسي، إشعاع الموجات الطويلة السطحية، الشبكة العصبية الاصطناعية.

Corresponding author's e-mail: ahmed.alrubaye@qu.edu.iq

DOI:10.53540/tjer.vol.20iss2pp106-112

1. INTRODUCTION

It is widely accepted that solar radiation is the primary source of energy for our planet, accounting for nearly 99.97% of the heat energy required for a variety of chemical and physical processes in the atmosphere, oceans, land, and other bodies of water (Yousif et al., 2019)and(A. Al-Rubaye, 2019). This makes it a crucial component of renewable energy sources. In fact, global solar radiation is considered the most critical parameter in meteorology, renewable energy, and solar energy conversion applications, particularly when it comes to sizing standalone photovoltaic systems(Ojeda et al., 2021). Solar radiation measurements are used to figure out how much power we can get from the sun. This helps us design things like solar water heaters, study agriculture, dry wood, and create solar panels(Benghanem, 2012). The measurements can be used to identify the required energy for a building and investigate the climate conditions (R. T. A. Al-Rubaye et al., 2018).
Different fields, such as agricultural studies, renewable energy detections, and weather conditions, need solar radiation prediction (Emmanuel Ogwuche, 2017). To limit the solar radiation levels, these areas require an accurate method to be followed (Yeom et al., 2016). Several investigations are concerned with the development of different methods, like artificial neural networks, for estimating solar radiation levels (Berrizbeitia et al., 2020). The performance of the artificial neural networks model is significant in solar-level detection(Boutahir et al., 2022). These models are required to display the hard correlation between weather conditions and solar radiation, which results in exact prediction compared to the conventional models, similar linear regression or fuzzy logic models (Wang et al., 2018). Different investigations are interested in studying the performance of the artificial neural network approach, as the investigation conducted by Gueymard et al. (Gurlek & Sahin, 2018).
The researchers confirmed the importance of employing efficient models for accurately predicting solar radiation in the globe. Since the cost of fixing the measuring instruments is high, this coefficient can only be found in a few places. Thus, it is commonly employed for such calculations. This ratio is measured by determining the relationships between data received from several sources (Lee et al., 2020). Employing different familiar meteorological factors, including temperature, sunshine hours, relative humidity, latitude, and longitude, many scholars succeeded in developing empirical models for estimating the global radiance value. Nevertheless, applying artificial neural networks to predict solar radiation at particular positions is the subject of interest in a few investigations (E. et al., 2016). The current investigation revealed the artificial neural network's ability to predict the exact amount of sunlight according to different factors, including temperature, humidity, wind speed, and sunlight duration (Berrizbeitia et al., 2020). An evolutionary artificial neural network with excellent accuracy was suggested for solar radiation prediction (Aldhshan et al., 2021). In another investigation, ANN models with various surface expansion schemes were employed in solar radiation forecasting for solar systems. The researchers emphasised that employing ANN models in predicting solar light levels is accurate (Premalatha & Valan Arasu, 2016). The study developed two ANN models with four different algorithms based on their minimum mean absolute error (MAE), mean square error (RMSE), and maximum linear correlation coefficient (R). Four surface diffusion methods had to be compared: gradient descent (GD), Levenberg–Marquart (LM), flexible diffusion (RP), and scaled conjugate gradient (SCG) at the input parameters latitude, longitude, elevation, year, and They include month, average ambient air temperature, stationary pressure, wind speed, and monthly global temperature.
Another investigation was done by Kayri (2016) to compare the prediction ability of Bayesian regularisation and the Levenberg-Marquart algorithm employing artificial neural networks (ANN) against social information. MATLAB was employed to test the ANN model with 1 to 5-neuron architectures. It is revealed that the BR approach is more accurate and has a high ability to predict solar radiation. It is approved through the decreased SSE and enhanced correlation value. Okut et al. clarified that if the Mean Squared Error (MSE) is low, the LM model concentrates rapidly. In addition to that, the predicted performance of the BR and SCG models was measured to exceed the BRANN performance. According to the findings, despite the accurate performance of the BR approach among the ANN models, the LM algorithm is more suitable for converging rapidly. A new model was taken into consideration by (Ghazvinian et al., 2019). A support vector regression model, in combination with an improved model based on particle swarm optimisation, designed a new model for further solar radiation prediction. For this purpose, the scholars used several approaches, such as M5T, GP, SVR, SVR-PSO, SVR-IPSO, SVRGA, SVR-FFA, and MARS. As a result, the performance of the SVR-IPSO model is better than that of others. The researchers proposed that the performance of the models could be progressed by integrating different inputs within direct sunlight. For imitating the function of the human brain, ANNs are a main element of computing that is necessary for data collection and analysis. These methods are able to solve the important problems that the conventional methods encounter in their performance. They are able to comprehend, learn, and ask questions that are needless to reprogram, making it simple to manage. Additionally, the ANN models perform with high accuracy that can be applied in parallel technology, and they solve Neural network-based algorithms, stochastic approaches, and computer science, engineering, and ANN research have received substantial attention because of their flexibility and efficacy. ANNs have been widely used in research to solve complex problems. For example, Bayesian regularisation methods based on neural networks have been able to calculate physical parameters such as thermal relaxation parameter, Prandtl number, water suction/injection, and stretch/shrink paper, such as(Yazdani et al., 2016) (Raja Shoaib, et al., 2022) and (Raja, Awan, et al., 2022).

The objective of this research project was to develop a model that could accurately predict daily average longwave surface radiation levels in Iraq. Furthermore, the study aimed to identify the main factors affecting solar radiation by analysing data to identify the most important factors affecting sunlight in Iraq. Using this information can improve the accuracy of future forecasts and help design more efficient solar energy systems. To achieve this, we used weather data from local stations and NASA global energy resource forecasts for one year at Al-Qadisiyah using ANN.

2. MATERIALS AND METHODS

2.1 Collection of the data

Proper data collection is essential for conducting effective research and analysis. Without accurate and comprehensive data, the value of any project can be compromised or rendered ineffective. (Pandu et al., 2022). One area where the collection of data is crucial for making informed decisions is meteorology. (AYKO & BOZKURT KESER, 2021). In Iraq, a minimum number of meteorological data collection points is needed to improve accuracy in Surface longwave radiation (SLR) predicting. The first source of data from the Iraq Meteorological Centre, AL-Qadisiyah, daily data for ten variables(Alnawas et al., 2022): Date, Rain mm, Relative Humidity % RH; RH Max %; RH Min %, Wind Speed WS m/s; WS Avg m/s; WS Max m/s, Average Temperature AT; °C, AT Max °C; AT Min °C, AT Avg °C, SLR Total Mj/m^2 and Evaporation Transpiration Et were accumulated from January 1, 2022 to December 31, 2022.

Information about these ten elements will help meteorologists in Iraq recognise the local weather styles and make more accurate predictions about surface longwave radiation (SLR). SLR is a vital aspect in many regions, including weather studies, power manufacturing, and farming. Meteorologists can study the modern climate and find any tendencies or oddities by amassing daily information on things like Rain mm, Relative Humidity% RH, Wind Speed WS m/s, and Average Temperature AT °C. This consideration is essential for making exact predictions of SLR. Meteorologists can find out how much Rain falls in a favourable location, for example, by watching rain mm information. They can use this data to determine how Rain modifies SLR levels. Similarly, Relative Humidity% RH facts tell us approximately how much water is within the air, which adjusts SLR forecasts. Wind Speed WS m/s measurements are essential for understanding air movement patterns that can impact SLR. By analysing wind speed data at different points throughout, Table 1 shows the statistical values, including the range of daily Surface longwave radiation values station, for latitude 32.01°N and longitude 44.89°E.

The second type of source of data affecting the intensity of solar radiation can be studied by analysing the data recorded by NASA's Prediction of Worldwide Energy Resource for Qadisiyah (*Prediction of Worldwide Energy Resource*, n.d.), specifically the daily data. This dataset provides valuable information on various variables that can influence solar radiation intensity. These twelve variables include Rainfall (mm): Rainfall can have a significant impact on solar radiation as clouds and precipitation can block or scatter sunlight, reducing the amount of radiation reaching the Earth's surface. Relative humidity (% RH): High humidity levels can also affect solar radiation by increasing atmospheric moisture content, which can absorb and scatter sunlight. Wind Speed (WS) and Wind Speed Averages (WS Avg): Wind speed can influence solar radiation by affecting the movement and dispersion of clouds. Higher wind speeds may result in more cloud cover, reducing the amount of direct sunlight reaching the surface. Wind Speed Maximum (WS Max) and Wind Speed Minimum (WS Min): The range of wind speeds experienced throughout a day can provide insights into how variations in wind patterns affect solar radiation. Average Temperature (AT), Maximum. Dew/Frost Point °C, Surface Pressure (kPa) Surface Soil Wetness and SLR Total Mj/m^2 were accumulated at the same location and at the same time for the year 2022 shown in Table 2 the statistical values, including the range of daily Surface longwave radiation values station. The entire dataset is split into two categories, such as the training set and the testing set after the data has been collected. With the ANN model's aid, it is processed further.

Table 1. The basic statistical values of the Local Iraq data

Variable	Mean	StDev	Min.	Med.	Max.
Date					
Rain mm	0.13	1.36	0.00	0.00	20.20
AT Max °C	33.08	9.99	11.61	34.07	48.80
AT Min °C	17.48	8.02	-1.71	18.22	35.12
AT Avg °C	25.28	8.82	5.51	26.23	40.11
RH Max %	54.83	23.66	22.10	48.72	100.00
RH Min %	18.84	13.16	4.80	11.84	60.07
WS Avg m/s	1.93	0.60	0.81	1.82	3.87
WS Max m/s	7.52	2.25	3.09	7.48	14.83
ET mm	5.27	3.27	0.24	4.55	17.38
SLR Total Mj/m^2	15.12	5.58	6.78	14.30	26.82

Table 2. The basic statistical values of the NASA data

Variable	Mean	StDev	Min.	Med.	Max.
Date					
Rain mm	0.17	1.61	0.00	0.00	24.83
AT Max °C	34.01	11.35	0.00	35.56	51.36
AT Min °C	18.91	9.85	-3.53	20.08	36.14
AT Avg °C	26.08	10.83	0.00	27.78	43.67
Dew/Frost Point °C	3.12	4.81	-11.74	3.49	14.11
RH Avg %	29.11	18.14	0.00	21.44	87.12
WS Avg m/s	1.42	0.84	0.00	1.24	4.41
WS Max m/s	4.67	1.68	0.00	4.66	8.89
WS Min m/s	2.91	1.21	0.00	2.73	6.55
Surface Pressure (kPa)	99.92	9.14	0.00	100.78	102.66
Surface Soil Wetness	0.07	0.12	0.00	0.00	0.42
SLR_Mj/m^2	18.96	6.33	2.60	20.00	28.41

2.2 Normalisation of data

Normalisation is an essential technique used in Artificial Neural Networks to scale and transform input data so that it becomes suitable for processing. It involves minimising the impact of data variability and noise, making it easier for the network to identify significant patterns from the input data. The study applies min-max normalisation to all variables to ensure their values are always between 0 and 1. This is done before and after the variables are inserted into the neural network of the ANNs; this process aims to improve speed and accuracy. (Singh & Singh, 2020) is as follows:

$$X_{\text{normalised}} = \frac{X - X_{min}}{X_{\max} - X_{\min}} \qquad (1)$$

2.3 Utilisation of artificial neural networks

The tissue synthesis used to predict solar radiation and surface wavelength radiation is largely dependent on meteorological data input. This method has been widely used in experiments and has proved effective in solar radiation calculations. Vakili, M. developed a solar radiation forecasting model using ANN and specialised modelling techniques. Where meteorological data for the predicted area were not available, solar radiation was estimated from meteorological data. This phenomenon emphasises the significance of precise morphological samples for precise solar radiation forecasting (Vakili et al., 2017). Artificial tissues with several layers, including input, one or more storage layers, and output, are used to get a precise estimation of input data. Different input values and training data were used to develop the two ANN models. The first model contained ten objects and was trained on weather data from a station in Al-Qadisiyah, Iraq. In the second model, twelve features were used as input, and the NASA global energy forecast dataset was used to train the ANN. The study used various atmospheric variables to predict daily average surface longwave radiation. Performance metrics for training the algorithms can be found in Tables 1 and 2. The artificial neural network model employed in this study is depicted in Figure 1. and Figure 2. The steps in the workflow could be accomplished using modules such as data loading, neural network configuration, and network training.

Partition Dataset. This group outlines the process for dividing the active data as training 70%, testing 30%, and holdout as null samples. The network's structure is specified using the Architecture tab. They used two Hidden Layers. The Sigmoid Real-valued arguments are taken and transformed to the range (0, 1). The Training section is used to describe how its network should be learned. Which training choices are accessible depends on the type of training and the optimisation method. The type of training used is batch with a scaled conjugate gradient. A method for optimisation. This approach is used to calculate the synaptic weights. The Scaled Conjugate Gradient. Online or mini-batch training cannot use conjugate gradient methods because the justifications for their use only apply to batch training types. Descent in Gradient. This technique must be used in conjunction with online or mini-batch training, though batch training is also an option.

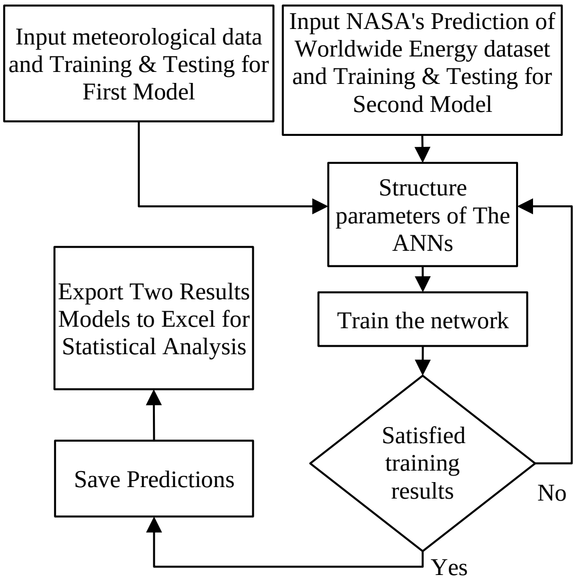


Figure 1. Methodology of the ANNs for SLR prediction system.

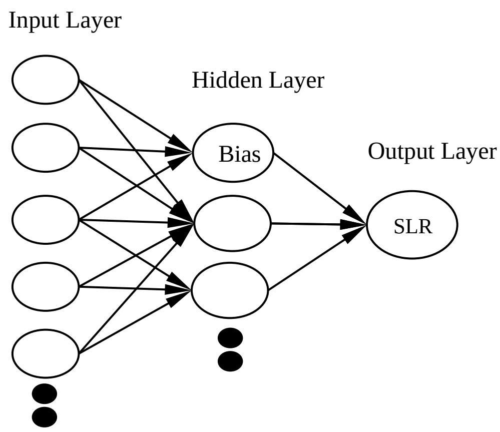


Figure 2. Architecture of the ANNs models utilised in the present study.

2.4 Statistical investigation

The sum of Squares Error (SSE) is important in statistical analysis and machine learning. An indicator of how well a statistical model or machine learning algorithm fits the data. In other words, SSE can differentiate between observed and predicted values. According to the squared differences between each observation in the data set and its corresponding predicted value, the SSE is measured. The mathematical representation of SSE is as follows:

$$SSE = \Sigma (y_i - \bar{y})^2 \qquad (2)$$

where y_i refers to the observed value, $\bar{y}$ the predicted value represents a product of all the observations included inside the data set.

Thus, SSE has a crucial role in determining the accuracy of data. If the SSE value is smaller, the model suits the data accurately. In contrast, if the SSE is high, the model poorly fits the data. The distinction between the estimated and absolute value points out the relative error of a quantity. They are often explained by percentages, units, or decimals. Unlike absolute error, relative error takes into account the size of the numbers being compared, resulting in a more accurate indication of how near the estimate is to the real value.

The following formula is the relative error equation:

Relative error (RE) = (Exact Value - Approximate Value) / Exact Value

The results obtained from the current model are not enough to assess the performance via only MSE and R. Thus, the process of analysis should be improved by additional statistics and modifications like the root mean square error (RMSE)(Abiodun et al., 2019).

$$RSME = \frac{1}{n}\sqrt{\sum_{i=n}^{n}(X_i - Y_i)^2} \tag{3}$$

3. RESULTS AND DISCUSSION

The current investigation aimed to develop an accurate ANN method to evaluate the levels of the surface ling-waves in Iraq by employing traditional methods. To achieve this purpose, the data were gathered from two sources: common Iraqi samples and NASA samples of the Energy Resource in 2022. To ensure the reliability of results, randomly divided the input and target datasets into two subsets: training and testing datasets. Took great care to avoid any data repetition at any stage of the process. Designed and developed two ANN models depending on the type of source data; the first model used ten input parameters for local data, and the second model used 12 for NASA data and only one output parameter, daily average surface longwave radiation. They used the scaled conjugate gradient (SCG) algorithm for both models. Table 2 data were used for training, and data from only one station were analysed. 70% of the collected data was used for training and 30% for testing. Several metrics, including linear correlation coefficient (R), R squared linear, sum of squares, and relative error, were used to evaluate the performance of each ANN model. This study aimed to develop an accurate ANN model for daily presentation wavelengths in Iraq using commonly available meteorological parameters. Researchers and policymakers in the energy sector will benefit from the findings they provide. A comparative investigation, in which two synthetic neural network methods are compared, revealed that when spatially integrated data are provided, these models are able to provide precise estimation of daily solar gradation in the globe. They were tested. Thus, the result is significant since it displays that these models can be employed to predict different levels of solar radiation with high accuracy levels, which is fundamental for several uses in producing solar energy and weather forecasting. Moreover, it adds useful findings to the capability of artificial neural network models for determining the levels of solar radiation and emphasises the significance of performing different investigations in this field (Abed et al., 2021).

Consequently, the existence of an ideal ANN model is regarded as fundamental for getting a logical estimation of the daily peak wavelength intensity. The efficiency of the first and second models of artificial neural networks through employing the framework is demonstrated in Figures (3 and 4). Given the minimum relative error, minimum sum squared error, and maximum linear regression coefficient, an optimal model of ANNs is obtained. The projected values for the ANN second model are in good agreement with the measured values, according to the examination of the data. The quantity and number of variables used during the training session allow ANN model 2 to predict accurately.

Table 3. Function Error and R^2 with algorithms for training SCG

Regression Analysis: SLR versus Predicted Value	Function	Local Data	NASA Data
	SSE	5.4797	3.8799
	RSME	0.0150	0.0106
	R Squares Linear	0.823	0.805
Training	The sum of Squares Error SSE	1.479	1.030
	Relative Error RE	0.209	0.171
Testing	The sum of Squares Error SSE	0.517	0.431
	Relative Error RE	0.193	0.158

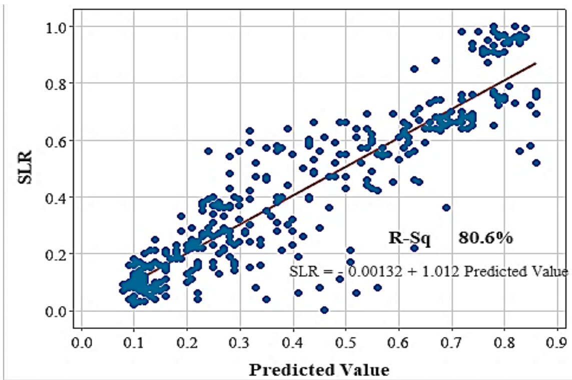


Figure 3. SLR predicted by the Neural Networks versus SLR Measured values and R Squares Linear for Data Local Iraq and SCG.

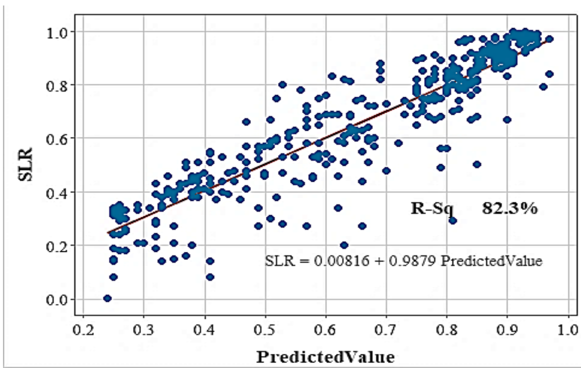


Figure 4. SLR predicted by the Neural Networks versus SLR Measured values and R Squares Linear for Data NASA and SCG.

To simplify which variables have a greater impact on the predicted solar radiation value, values were calculated as Normalised Importance. It is a metric used to assess the percentage improvement in comparison to the most influential predictor. To determine the normalised importance, we divide the importance score of each variable by the highest score among all variables and subsequently multiply the quotient by 100%, as shown in Figure 5. The results of this study suggest that temperature, relative humidity, and Rainfall are strongly correlated with SLR, as depicted in Figure 4. Conversely, wind speed appears to have minimal impact on SLR.

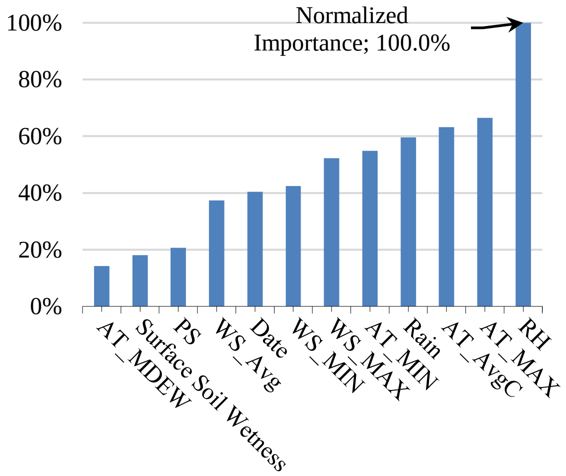


Figure 5. Calculation of Normalised Importance Data from the ANNs Model of the NASA Prediction of Worldwide Energy Resource.

CONCLUSION

Solar radiation prediction using artificial neural networks looks promising worldwide. More studies on its use in Al-Qadisiyah, Iraq, are needed. Advanced algorithms and local meteorological data can improve sun radiation estimates in this region. This study uses an artificial neural network model using weather monitoring network data and time series records to estimate sun radiation in Al-Qadisiyah, Iraq, accurately.

An artificial neural network predicted Iraq's daily average global sun radiation. Scaled conjugate gradient methods were used to train and test the models using meteorological data from a single station over a year.

The first model used the Iraq Meteorological Center's AL-Qadisiyah dataset with ten covariates for training and testing. Instead, the second model used NASA's Prediction of Worldwide Energy Resource database to analyse Qadisiyah data and 12 variables to estimate solar radiation intensity.

The most accurate models and artificial neural networks have low sum square error relative to measured values and high linear regression coefficients. Our results showed that the second model utilising ANNs predicted values that matched accurate measurements better than the first model. This second model was trained and tested on a larger dataset. Additionally, while examining calculation errors for surface longwave radiation, They found a substantial R-value of 0.823 and a low RMSE of 0.0106 between projected values from ANNs in the second model and actual observations.

Two artificial neural network models were tested to estimate sun radiation in Al-Qadisiyah, Iraq. The second model employed NASA's Prediction of Worldwide Energy Resource database and was more accurate than the first, which used Iraq Meteorological Centre data. Both models accurately calculated solar radiation. Temperature, relative humidity, Rainfall, and temperature strongly correlated with surface longwave radiation, but wind had little influence.

CONFLICT OF INTEREST

The authors declare no conflicts of interest regarding this article.

FUNDING

The research for this publication was conducted independently and without relying on any external financial support.

ACKNOWLEDGMENT

The authors appreciate the support and collaboration of the Department of Mechanical Engineering, Al-Qadisiyah University, Iraq, in conducting the research for this study.

REFERENCES

Abed, M., Imtiaz, M. A., Ahmed, A. N., & Huang, Y. F. (2021). The long short-term memory neural network technique is used to predict monthly pan evaporation. Scientific Reports, 11, 1, 20742.

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Umar, A. M., Linus, O. U., Arshad, H., Kazaure, A. A., Gana, U., & Kiru, M. U. (2019). Comprehensive Review of Artificial Neural Network Applications to Pattern Recognition. In *IEEE Access*, 7, 158820–158846.

Al-Rubaye, A. (2019). Experimental investigation for solar thermal hybrid installs to inverter air conditioning vapour-compression cycle system. IOP Conference Series: Materials Science and Engineering, 557, 1, 012079.

Al-Rubaye, R. T. A., Al-Rubaye, A. T. A., & Al-Khuzaie, M. M. (2018). Optimal Design of Hybrid Renewable Energy System off the Grid in Al-Diwaniyah, Iraq. IOP Conference Series: Materials Science and Engineering,

Aldhshan, S. R. S., Abdul Maulud, K. N., Wan Mohd Jaafar, W. S., Karim, O. A., & Pradhan, B. (2021). Energy consumption and spatial assessment of renewable energy penetration and building energy efficiency in Malaysia: A review. In *Sustainability (Switzerland)* 13, 16, 9244).

Alnawas, A., Al-Khafaji, N., & Azeez, H. (2022). Precipitation Forecast for Thi-Qar Province of Iraq Utilizing Machine Learning Approaches. Proceedings of 2nd International Multi-Disciplinary Conference Theme: Integrated

Sciences and Technologies, IMDC-IST 2021, 7-9 September 2021, Sakarya, Turkey.

Ayko, O., & Bozkurt Keser, S. (2021). A comparison of machine learning algorithms for forecasting solar irradiance in Eskişehir, Turkey. International Journal of Applied Mathematics Electronics and Computers, 9, 4, 103–109.

Benghanem, M. (2012). Artificial intelligence techniques for prediction of solar radiation data: a review. International Journal of Renewable Energy Technology, 3, 2, 189.

Berrizbeitia, S. E., Gago, E. J., & Muneer, T. (2020). Empirical models for the estimation of solar sky-diffuse radiation. A review and experimental analysis. In *Energies*, 13, 3,701).

Boutahir, M. K., Farhaoui, Y., Azrour, M., Zeroual, I., & El Allaoui, A. (2022). Effect of Feature Selection on the Prediction of Direct Normal Irradiance. Big Data Mining and Analytics, 5, 4, 309–317.

E., N.-A., V., S.-S., M., Q.-D., & C., G.-A. (2016). Solar Radiation Prediction for Dimensioning Photovoltaic Systems Using Artificial Neural Networks. International Journal of Engineering and Technology, 8, 4, 1817–1825.

Emmanuel Ogwuche, I. (2017). Investigation of the Dependence of Global Solar Radiation on Some Atmospheric Parameters Over Kano and Oyo-Nigeria. Radiation Science and Technology, 3,1, 1.

Ghazvinian, H., Mousavi, S. F., Karami, H., Farzin, S., Ehteram, M., Hossain, M. S., Fai, C. M., Hashim, H. Bin, Singh, V. P., Ros, F. C., Ahmed, A. N., Afan, H. A., Lai, S. H., & El-Shafie, A. (2019). Integrated support vector regression and an improved particle swarm optimisation-based model for solar radiation prediction. PLoS ONE, 14, 5, e0217634.

Gurlek, C., & Sahin, M. (2018). Estimation of the Global Solar Radiation with the Artificial Neural Networks for the City of Sivas. European Mechanical Science, 2, 2, 46–51.

Lee, D., Lee, S. J., & Seo, Y. J. (2020). Application of recent developments in deep learning to ANN-based automatic berthing systems. International Journal of Engineering and Technology Innovation, 10, 1, 75–90.

Ojeda, J. M. P., Bocanegra, S. R., & Huatangari, L. Q. (2021). Determination of the Compressive Strength of Concrete Using Artificial Neural Network. International Journal of Engineering and Technology Innovation, 11, 3, 204–215.

Pandu, S. B., Sagai Francis Britto, A., Sekhar, P., Vijayarajan, P., Albraikan, A. A., Al-Wesabi, F. N., & Al Duhayyim, M. (2022). Artificial intelligence-based solar radiation predictive model using weather forecasts. Computers, Materials and Continua, 71, 1, 109–124.

Prediction of Worldwide Energy Resource. (n.d.). https://power.larc.nasa.gov/data-access-viewer/

Premalatha, N., & Valan Arasu, A. (2016). Prediction of solar radiation for solar systems by using ANN models with different backpropagation algorithms. Journal of Applied Research and Technology, 14, 3, 206–214.

Raja, M. A. Z., Awan, S. E., Shoaib, M., & Awais, M. (2022). Backpropagated Intelligent Networks for the Entropy Generation and Joule Heating in Hydromagnetic Nanomaterial Rheology Over Surface with Variable Thickness. Arabian Journal for Science and Engineering, 47, 6, 7753–7777.

Raja, M. A. Z., Shoaib, M., Khan, Z., Zuhra, S., Saleel, C. A., Nisar, K. S., Islam, S., & Khan, I. (2022). Supervised neural network learning algorithm for three-dimensional hybrid nanofluid flow with radiative heat and mass fluxes. Ain Shams Engineering Journal, 13, 2, 101573.

Singh, D., & Singh, B. (2020). Investigating the impact of data normalisation on classification performance. Applied Soft Computing, 97, 105524.

Vakili, M., Sabbagh-Yazdi, S. R., Khosrojerdi, S., & Kalhor, K. (2017). Evaluating the effect of particulate matter pollution on estimation of daily global solar radiation using artificial neural network modeling based on meteorological data. Journal of Cleaner Production, 141, 1275–1285.

Yazdani, M. G., Salam, M. A., & Rahman, Q. M. (2016). Investigation of the effect of weather conditions on solar radiation in Brunei Darussalam. International Journal of Sustainable Energy, 35, 10, 982–995.

Yeom, J. M., Seo, Y. K., Kim, D. S., & Han, K. S. (2016). Solar radiation received by slopes using COMS imagery, a physically based radiation model, and GLOBE. Journal of Sensors, 2016, 1–15.

Yousif, J. H., Kazem, H. A., Alattar, N. N., & Elhassan, I. I. (2019). A comparison study based on artificial neural network for assessing PV/T solar energy production. Case Studies in Thermal Engineering, 13, 100407.