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Artificial neural network modeling of solar photovoltaic panel energy output

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C H R O N I C L E

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A B S T R A C T

Solar panel energy output is an essential parameter for the design and operation of renewable energy systems. Previously, little was known about the precise relationship between the energy outputs of solar panels with various meteorological, radiometric, and weather conditions in the southern California region. Without precise modeling or prediction systems, solar energy can potentially be wasted due to grid energy fluctuation. Thus, it is intended to use an artificial neural network (ANN) to develop solar panel energy output prediction model with a high degree of accuracy. A self-developed feedforward ANN model utilizing the Rectified linear unit (ReLu) activation function was used in the present study. Meteorological, weather, and sun irradiation data collected throughout the last year from a residential location have been used to train the models. The model's performance was identified based on the minimum mean absolute error (MAE) and root mean square error (RMSE) and maximum linear correlation coefficient (R^2). Further, the present self-developed ANN model was consistent with other solar energy experimental results and theoretical analysis. The developed ANN model using the Python programming language achieved a high R^2 of more than 85% which ascertains the accuracy and suitability of the model to predict the daily solar energy output in local southern California area. This ANN modeling approach can be extended to many other applications such as SCORE, commercial, and residential building design.

1. Introduction

Much of the present day's infrastructure and technology are extremely dependent on electricity, mainly produced through fossil fuels such as petroleum, natural gas, or coal. Moreover, the world primary energy demand is projected to expand by almost 60% from 2002 to 2030, with an average increase of 1.7% per year (Solangi et al., 2011). However, the high environmental impact of current energy resources, along with the need for addressing the impact of climate change, led to the important development of renewable energy sources, including solar energy (Owusu & AsuMAEusarkodie, 2016). The International Energy Agency (IEA) has stated that electricity generation from renewable energy is expected to reach 90% by 2050, with solar photovoltaic and wind together accounting for nearly 70% (*IEA*). Moreover, the amount of available solar energy on our planet has been found to be 516 times more than that of currently present oil reserves and 157 times more than that of coal reserves (Nordell, 2003). Thus, renewable solar energy has experienced a huge growth in the last two decades, and they are today regarded as the resources which will erase fossil fuels from society within the next fifty years (*IEA*). For example, in the state of California, with more than 11 million homes installed solar photovoltaic panels, more than 26% of electricity is coming from renewable solar energy (California Solar).

Although solar energy is paving the way for clean energy, the power output of solar systems is intermittent by nature and largely dependent on weather and climate conditions (Meer & Shepero, 2018). This dependency creates new challenges, especially locations where weather is notably volatile. These fluctuations affect the quality of the energy generated and injected into the grid, resulting in a form of short-term frequency and voltage instabilities (Lave & Kleissl, 2013). Thus, to balance the supply and demand of the electricity system, power grid systems need to take more action to curtail renewable

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solar energy generation. Correspondingly, despite many countries struggling to meet renewable solar energy generation and carbon emission targets, electricity generated from renewables is still being wasted (Cornelia et al., 2022). The best mitigation strategy would be the use of forecasting techniques to anticipate the variations in the solar energy inputs (Caldas et al., 2019). Therefore, there is now a strong imperative to develop innovative approaches to forecasting solar energy generation (Guijo et al., 2020 and Renno et al., 2016). Furthermore, there are many other reasons or benefits associated with precisely predicating solar energy output. First, forecasting the solar panel energy outputs in a specific region can assist investors in properly building and installing solar plants with an accurate capacity to enable optimal management of the energy system (Geetha et al., 2022). In addition, with the development of solar energy, enhanced cars, drones, and various vehicles, the solar car optimized router estimation (SCORE) that utilizes solar energy to pick up the route with the maximum solar energy absorption route is under intensive evaluations (Hasicic et al., 2017). The SCORE requires forecasting solar energy in real time based on all available solar irradiance, weather, and public transportation data into the model (Hasicic et al., 2017).

Various models have been used for solar photovoltaic energy output forecasting (Cornelia et al., 2022). The models are commonly divided into empirical methods, physical models, and statistical approaches (Ahmed et al., 2020). Empirical methods adopt the idea that the current day's climate is equivalent to the prevailing conditions of the previous day and is used for short-term and very-short-term forecasting. Physical models commonly use numerical atmospheric data to forecast weather. Statistical models utilize mathematical equations to extract patterns from input data. Statistical techniques can be divided into two groups: time-series and machine learning (ML) based models (Ahmed et al., 2020). All of these models that require transforming meteorological and weather data into power generation are the solar panel energy forecasts. Thus, the solar industry has to rely on this photovoltaic theory to predict a photovoltaic panels' effectiveness in various meteorological conditions, including radiance, wind speed, temperature, relative humidity, etc. As expected, precise weather and environmental data are required for accurate and useful solar energy prediction. Therefore, physical and empirical models function best on the expected and ideal performance of various weather conditions. The time-series based statistical approach relating solar panel activity to irradiance could potentially fail either because of the nonlinearity present or other unpredictable weather variables (Chang et al., 2021). Recently, more ML models based on artificial intelligence (AI) have received great attention. The AI models utilize AI's ability to learn from historical data patterns and improve predictions with further training runs. So far, Artificial Neural Networks (ANN) are considered the most successful method for solar panel power forecasting and are starting to be used more due to their ability to model non-linear, complex, and dynamic processes (Ahmed et al., 2020).

Unfortunately, predictions regarding solar photovoltaic power are not a simple process because it depends mainly on climate and environmental conditions that change over time. It is well known that solar energy performance relied on dust, humility, temperature, duration of sunshine, precipitation, wind speed, latitude, longitude, declination angles, in addition to panel types, and more (Renno et al., 2016; Touati & Al-Hitmi, 2013). Little research was conducted on the correlation between solar energy's performance with many important meteorological variables. In addition, most manufacturers of solar panels design their systems against standard conditions that are assumed at 25°C temperature, 1000 W/m^2 solar irradiance and mass of air at 1.5. These assumptions are most likely invalid against varying weather conditions. For example, it is generally required to align solar panels with an orientation towards the Equator with a minimum tilt angle of 15° and 20° for maximum annual solar energy output. However, an experimental study confirmed that up to 20° of deviation from the optimal orientation and inclination does not influence solar production. For some locations, the optimal orientation is east or west, rather than the commonly expected north or south (Tsoukpoe, 2022). This is consistent with many research results due to highly dynamic and specific climates and environmental conditions where it would be ideal to develop location specific solar panels and prediction models (Renno et al., 2016; Zazoum, 2022). The development of global solar energy prediction would be rather complex since all input variables are site specific. Thus, there is a need to develop accurate evaluation of solar panel energy potential for each specific location to configure a local solar power system. This gives support to the evaluation of a cleaner production for different locations, taking into account different components of the solar source, such as meteorological, climatic and radiometric conditions. To our knowledge, little is known about the exact relationships between solar panels energy output and meteorological, climatic and radiometric conditions for the southern California area where solar irradiance energy is abundant. In addition, no accurate statistical model is available to predict the effects of various meteorological conditions on local solar panel energy output.

Therefore, this evaluation attempted to develop a reliable prediction model with a high linear correlation coefficient (R^2) between predictions and measured data which exceeded 80% using an artificial neural network (ANN). In the present work, the modeling of daily local residential solar photovoltaic panel energy outputs was made with an ANN model. Multiple inputs were used in the ANN model. The inputs are all available meteorological, climatic, and radiometric conditions, including wind speed and relative humidity. Only one output, the local solar panel energy outputs, was predicted as the output of the model. The ANN was trained and tested by using the activation function: Rectified linear unit (ReLu). The Adam optimizer and dropout regularization were adopted to improve the model. We conducted a detailed ANN model analysis with a reported minimum mean absolute error (MAE), root average square error (RMSE), and a maximum linear correlation coefficient (R^2). The present work attempts to establish the specific relationship between the solar output, meteorological, climatic, and radiometric conditions of local specific residential areas using a self-developed ANN model. Overall, the self-developed ANN was developed for a specific location to ensure an accurate solar panel energy prediction. The rest of the paper is organized with the next section introducing the ANN architecture and methodology in developing the ANN in addition to the algorithm used in this paper which is followed by the model results, analysis and discussion, and finally main conclusions drawn from this work.

2. Materials and Method

2.1 Artificial neural network

Artificial neural networks (ANN) can be used for numerous functions such as curve fitting, logistic regression, and linear regression. In this work, artificial neural networks are used to formulate the solar panel energy prediction model for residential houses through linear regression. During the training, neural networks were adopted with a series of algorithms to recognize relationships between data that are non-linear. The fundamental unit of an artificial neural network is a neuron or node that uses a transfer function to formulate the output. Each neuron is activated by an electrical signal performs calculations on its given data before sending it to the next layer (Geetha et al., 2022; Geethaa & Santhakumar, 2022). In the final stage, the neurons apply a transfer function to obtain the result. The general architecture of the ANN model used in this study was shown (Fig. 1). The advantage of ANN techniques is that they do not need to know the mathematical calculations between the parameters, rather they involve lesser computational effort and provide a compact solution for multi-variable issues (Geetha et al., 2022). This system allowed the network to adjust all adjustable coefficients by learning how to adjust them in a way that made the prediction the most accurate. This would maximize the linear correlation coefficient which is the R^2 value that provides information about the goodness of fit of a model.

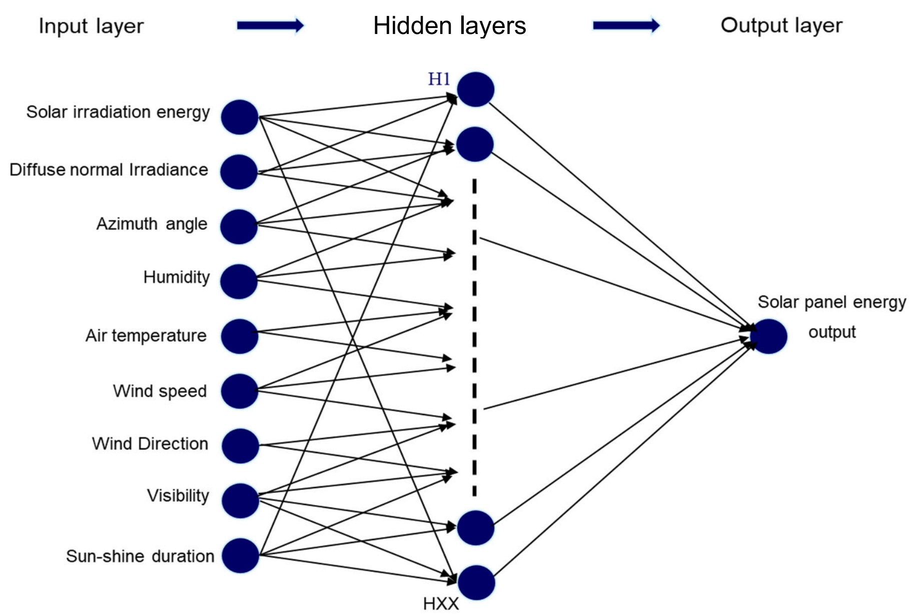


Fig. 1. Artificial neural network used in this evaluation. A standard feed-forward network with multiple hidden layers was employed to develop the model. The hidden layers are located between the input and output layers. They perform the activation function transformations on the inputs entered into the network.

In an ANN, the activation function within the hidden layers is responsible for transforming the weighted inputs from the nodes into the activation of the nodes. Traditionally, two widely used activation functions are the hyperbolic tangent (TanH) and Rectified linear activation function (ReLu) (Agarap 2023). ReLu is linear for all positive values, and zero for all negative values. It is widely used among the deep learning community for many applications. TanH, on the other hand, adopted a logistic non-linear activation function that outputs values between -1.0 and 1.0. For ReLu and TanH, they are mathematically defined as Eq. (1) and Eq. (2). The plots of inputs with outputs for the ReLu and TanH activation functions clearly demonstrated their linear and non-linear graphic features, respectively (Figure 2). It is generally preferred to use ReLu over the TanH function due to the benefits of its simpler calculations and faster convergence. To improve the activation function accuracy and speed of ANN model, the Adam Optimizer was used (Kingma, 2023). By analyzing the historical gradients and adjusting the learning rate for each parameter in real-time, the Adam Optimizer can help the model converge faster and more accurately during training, especially when it has to handle noisy and sparse datasets, which are common in real-world applications like solar panel outputs that highly depends on weather and climate information (Eq. (3)).

$$y = \max(0, x) \tag{1}$$

$$\mathrm{TanH}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\left[\frac{\delta L}{\delta w_t}\right] \mu_t = \beta_2 \mu_{t-1} + (1-\beta_2)[\frac{\delta L}{\delta w_t}]^2 \tag{3}$$

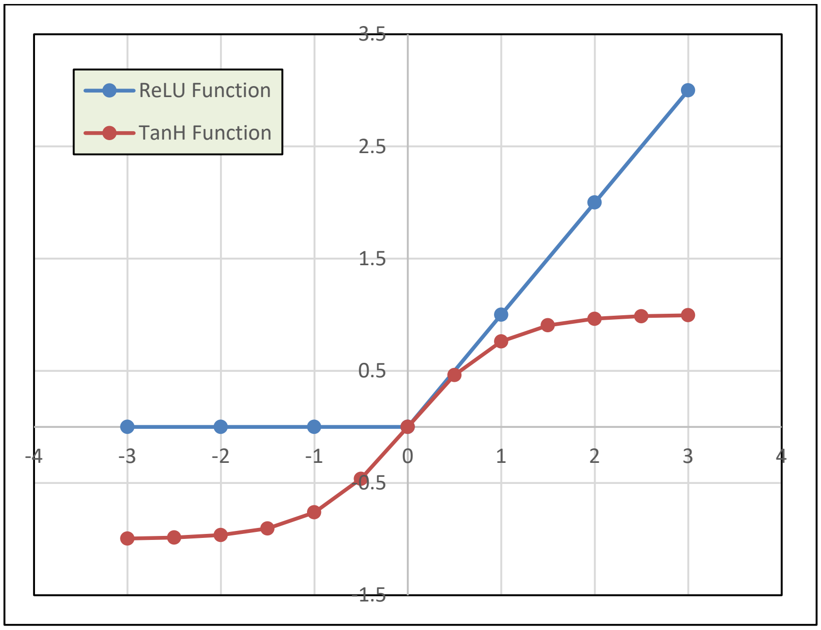


Fig. 2. Activation function of both ReLu and TanH. The TanH has range from -1 to 1 with sigmoidal shape. The ReLu function returns 0 if it receives any negative input, but for any positive value x, it returns that value back. ReLu is considered the best activation function since it eliminates the TanH drawback of vanishing gradients once input data approaches minimum or maximum values.

In neural networks, the training set is used to learn patterns present in the data through the training process by means of a training algorithm. The neural network, however, can be easily overfitted, causing the loss on new unseen data to be much larger than the loss on the training data. It is therefore important not to overfit the network. A good method is to adopt dropout regularization to regularize a deep neural network. Dropout works by probabilistically removing, or "dropping out," neurons to a hidden layer (Srivastava, 2014). It has the effect of simulating many networks with very different networks.

In addition, the performance of a neural network model depends on the dataset used for its training and validation. Generally, Holdback is commonly used for ANN validation. The Holdback approach randomly divides the original data into the training and validation sets by specifying the proportion of the original data to use as the validation set. The random selection is based on stratified sampling across the model's factors in an attempt to create training and validation sets that are more balanced than ones based on simple random sampling. In the present work, an artificial neural network model was developed to model the daily average solar panel energy values in the southern California area using various meteorological, climatic and radiometric conditions data for a period of 1 year.

2.2 Data collection

Daily data for meteorological, climatic, and radiometric conditions such as ambient air temperature, air pressure, mean wind speed, humidity, and solar radiation energy data were collected through Visual Crossing (Weather and Solar information). The chosen location in the southern California area was the city of Irvine, California. Solar panels with model REC 400AA were chosen for this evaluation. The values of the solar panel parameters like angels and range of daily solar panel energy output values are shown (Table 1). More than 35 input variables were identified as potential variables that could affect solar panel energy output. After data connection, a correlation analysis was conducted using the Pearson's correlation coefficient. Data evaluated using Pearson's correlation coefficient during correlation analysis is shown in Eq. (4).

$$r = \frac{\sum_{j=1}^{N}(X_j - \widehat{X}\,)\,(Y_j - \widehat{Y})}{\sqrt{\sum_{j=1}^{N}(X_j - \hat{X})^2}\sqrt{\sum_{j=1}^{N}(Y_j - \hat{Y})^2}} \tag{4}$$

An r>0 is indicated when two parameters have a correlation and are directly related to each other, and an r<0 means two parameters are inversely related. Where r is close to 1, both have a very close relationship and when r =0, no correlation is found. The correlation analysis for the input variables in order to predict the daily solar panel energy output was reported since input variable selection constituted a key factor in the model implementation using JMP version 17.

Table 1
Solar photovoltaic panels used in current evaluation.

Panel Number	Azimuth angle (°)	Tilt angle (°)	Latitude (N, deg， min)	Longitude (E, deg， min)	Range of daily energy outputs (Wh)
1	280	22	33.67	-117.83	135 - 2514
2	190	22	33.67	-117.83	128 - 2476
3	10	22	33.67	-117.83	120 - 2448

2.3 Artificial Neural Network architecture

The self-developed ANN was developed using the Python programming language, the Python TensorFlow library, and the Python NumPy library. This ANN which was developed incorporated a standard feedforward procedure with multiple layers of fully connected dense layers. Prior to the dense layers, however, a normalization layer was incorporated which shifted the input data to be centered around 0 by using Z-score normalization. Each input would be subtracted by the mean of the entire data set and then dividing it by the standard deviation of the data set. The new normalized data was also further scaled down to have a standard deviation of 1 around its new center to improve the model's efficiency when dealing with input data of different scales. After the normalization layer, the ANN consisted of 4 dense layers. The first three utilized the ReLu activation function. Multiple different activation functions were tested such as Tanh and linear, however, the ReLu activation function yielded the most favorable results. Each layer applied the data to the activation function and fed its output to the next layer in a process known as forward propagation. The final layer consisted of a single node with a linear activation function which allowed the model to output the predicted values. To minimize the loss and optimize the model's parameters, the Adam optimizer, a form of gradient descent, was used to improve the neural network's parameters due to its efficiency and its lower memory requirements. By taking the exponentially weighted average of the model's gradients, the Adam optimizer is able to adopt dynamic learning rates for different parameters which allow it to converge to a minimum loss very quickly. Furthermore, to combat overfitting, each of the first four layers was accompanied by dropout regularization. A trial-and-error method was adopted and the final rate of dropout was 0.2 because that corresponded with the best accuracy. This had effectively eliminated 20% of the nodes within each of the first 4 layers and ridded the model of many codependences built between various nodes working together to minimize loss that may lead to overfitting.

In this evaluation, an appropriate number of neurons in the 4 hidden layers were selected based on the results obtained to maximize the R^2. The finalization of the number of neurons in each hidden layer was done when the linear correlation coefficient (R^2) was at its maximum for both training and validation sets. The holdback validation method was chosen with 70% for training and remaining 30% for validation. Overall, the model was trained throughout 120 epochs. The value of the R^2 of the ANN model for both training and validation were calculated.

3. Results and discussion

3.1 Selection of data for ANN modeling

The main objective of the present work is to develop the most suitable ANN model to predict the daily solar energy output by using commonly available meteorological parameters. After eliminating inputs with high cross correlation, only the highly correlated data inputs to solar panel energy output are selected for the ANN model as input parameters (Fig. 3). Through correlation analysis of the input variables, a set of nine heterogeneous parameters are considered: solar direct normal irradiance, temperature, wind direction, sunshine duration, visibility, diffuse normal Irradiance, azimuth angle, wind speed, and humidity.

As expected, the most effective input parameter is solar direct normal irradiance, which is a sun radiometric parameter. Diffuse irradiance refers to all the solar radiation coming from the sky excluding solar normal radiation coming directly from the sun and the circumsolar irradiance within approximately three degrees of the sun. The azimuth angle defines solar panel orientation. Sunshine duration determines the sum of sub-period of effective solar irradiance to generate solar energy. In addition, wind speed, humidity and diffuse normal irradiance can usually characterize the meteorological situation. Then the input parameters dataset is divided into two categories with those being the training set and validation set. It is further modeled using an ANN model.

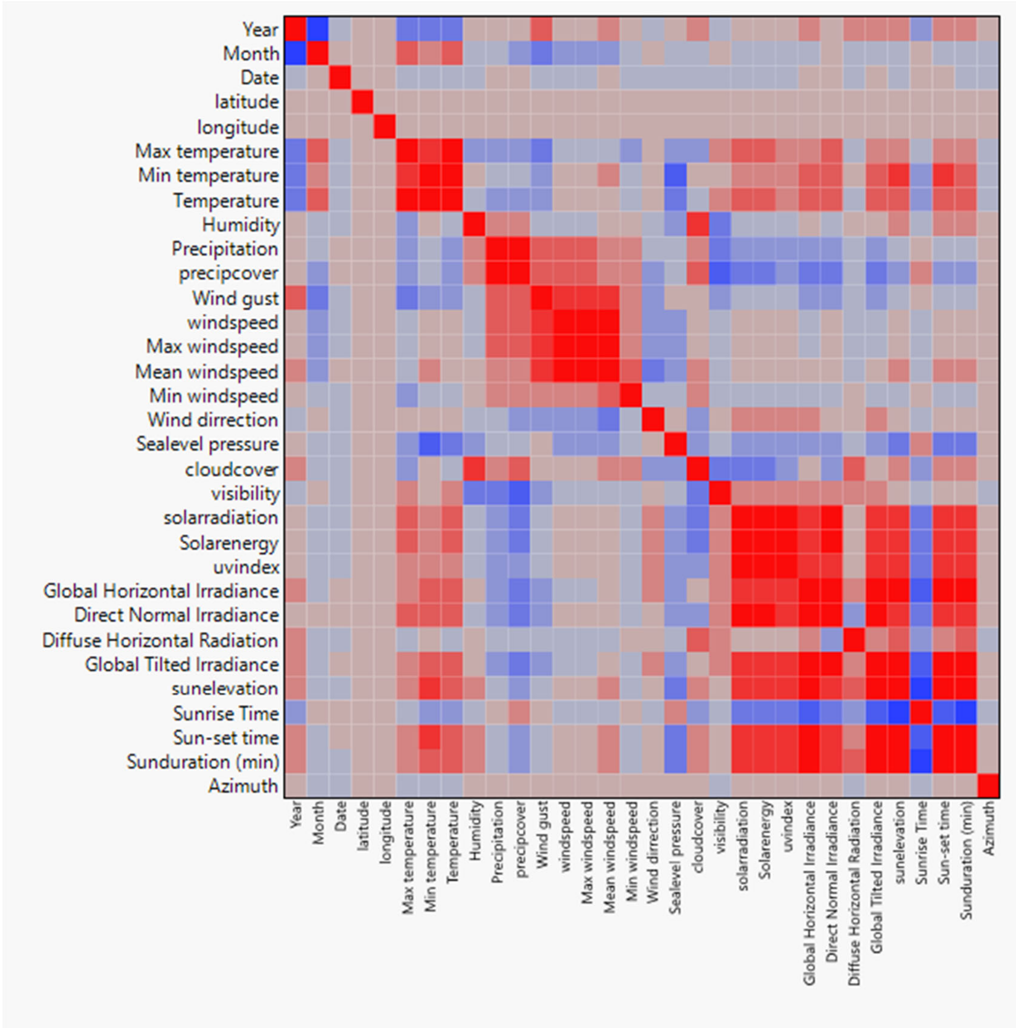


Fig. 3. Input correlational analysis for solar panel energy out. Through correlation analysis, all inputs with high cross correlation were eliminated.

3.2 Performance of ANN model

The performance of each the ANN model was evaluated by using the mean absolute error (MAE), linear correlation coefficient (R^2), and the root average square error (RMSE). The MAE, R^2 and RMSE are expressed by the following equations (5 - 7):

$$RMSE = \sqrt{\frac{\sum_{j=1}^{N}(Y_j - \widetilde{Y_j})^2}{N}} \tag{5}$$

$$MAE = \frac{\sum_{j=1}^{N}(Y_j - \widetilde{Y_j})}{N} \tag{6}$$

$$R^2 = \frac{\sum_{j=1}^{N}(\hat{Y}_j - \bar{Y})^2}{\sum_{j=1}^{N}(Y_j - \bar{Y})^2} \tag{7}$$

where

Y_j: the actually measured, daily solar energy output data.

$\widetilde{Y}_j$: the ANN predicated daily solar energy output data.

$\bar{Y}$: the average of actual measured daily solar energy output data.

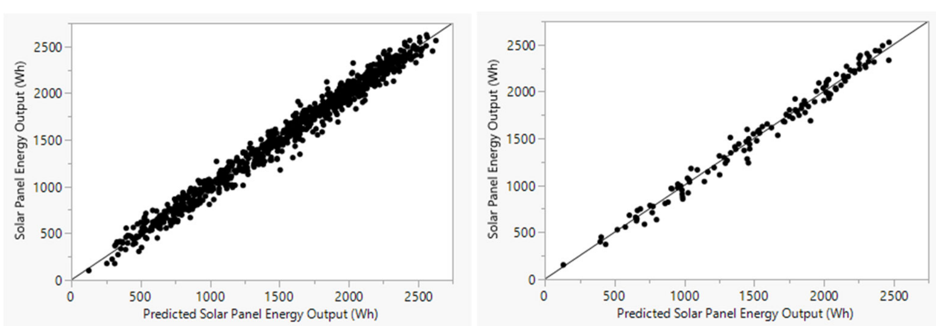
N: the total number of data points.

The RMSE is a measure of the average error between predicted and actual values relative to the standard deviation of the actual values. It indicates the level of scatter that the ANN model produces. In addition, R^2 calculates the ratio between the variation evaluated by an ANN model and the actual sample data variation. R^2 is an important parameter since it evaluates the general accuracy of a regression model. The MAE is a quantity which is used to measure how close the predicted values are with measured values. The relatively low MAE and RMSE indicated that the developed ANN model is having good prediction accuracy. The self-developed ANN model's performance in terms of MAE, RMSE and R^2 between the measured target and predicted artificial neural network output is shown (Table 2). The best results for training and validation of the self-developed model were obtained with the maximum R^2 values of more than 0.85 for both training and validation data. From the analysis of the results, it is very clear that the model is suitable for accurately predicting daily average solar panel energy output (Table 2).

Table 2
Performance of ANN model with optimal neurons for each activation function method. With a high R^2 and low MAE and RMSE, the model demonstrated high predication accuracy

Activation Function	Training			Validation		
	MAE	RMSE	R^2	MAE	RMSE	R^2
ReLu	160	280	87	184	223	86

Regression in a scatterplot for the measured and ANN predicted values of training and validation data for our self-developed ANN model is shown (Fig. 4). The minimum scatter around the predicted trend line showed important indications referring to the correlation or accuracy of the model (Fig. 4). If the linear correlation coefficient $R^2 = 1$, it means that there is an exact linear relationship between measured and predicted values. The R^2 value greater than 0.85 shows that there is a good agreement between the measured and predicted values. The actual ANN model for the present work has an R value for training and validation data as 0.87 and 0.86, respectively. In general, the R^2 values obtained clearly indicate that the proposed ANN model was best to predict the daily solar panel energy in the southern California area (Fig. 4).



(a) (b)

Fig. 4. Regression plot of the ANN model for the training (a) and validation (b) dataset s with the ReLu activation function. The scatterplots showed important indications referring to the correlation between measured and predicated data for both training and validation data sets.

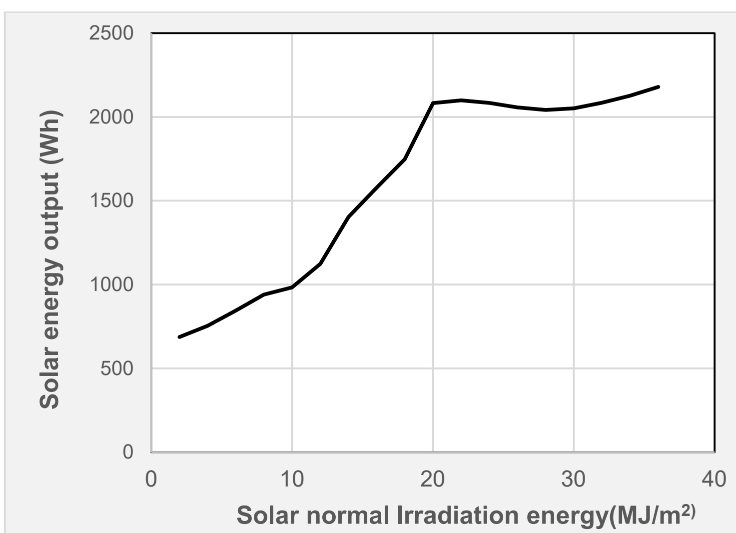
3.3 Solar output analysis

To further validate the self-developed ANN model, an analysis was conducted to evaluate the impact of various meteorological, climatic and radiometric conditions on solar energy output. In addition to the commonly expected direct solar irradiation, seven other meteorological and climatic factors affect solar panel energy outputs, such as solar diffuse irradiation, sunshine duration, visibility, azimuth angle, wind speed to humidity, etc.

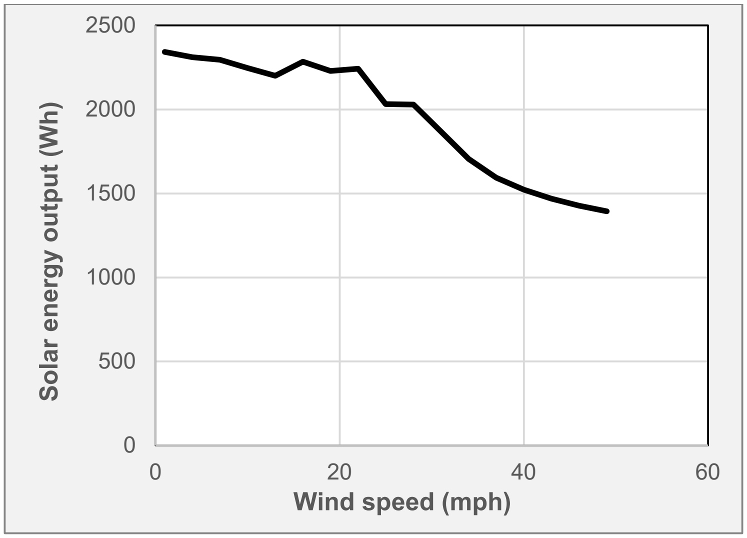
The solar panel energy output with solar direct and diffuse irradiation, azimuth angle, and wind speed data were modeled (Fig. 5). The azimuth angle determined solar panel orientation. For this study, a high azimuth angle that corresponded to facing south showed the highest energy outputs (Fig.e 5 (a)). As expected, the self-developed ANN model prediction results showed an interesting correlation for solar panel energy power with solar direct normal irradiance which indicates that high solar panel energy power and solar flux positively enhanced the performance of the energy panel output. However, the results also revealed that once the solar irradiance power or solar flux exceeded 20 MJ/m^2, the panel energy output from the photovoltaic approached its maximum and remained fairly stable regardless of the amount of solar irradiance flux reaching the photovoltaic (Fig. 5 (b)). This was consistent with another researcher finding (Njok, 2020). In addition, there is a clear indication of solar panel energy output degradation with high wind speed that was associated with density of dust, consistent with reference paper (Fig. 5 (c)) (Touati & Al-Hitmi, 2013).

In addition to the solar normal direct irradiance that directly reaches a surface, the solar diffuse irradiance as part of solar energy scattered by the atmosphere was evaluated by the ANN model. However, the solar diffuse normal irradiance showed almost random effects on solar energy output (Fig.5 (d)). This is also consistent with other research that diffused solar radiation on the performance of solar collectors was not significant (Chung et al., 2018). Based on all the statistical and theoretical analysis above, we successfully demonstrated that an ANN model with experimental data in good alignment with simulated data could be achieved.

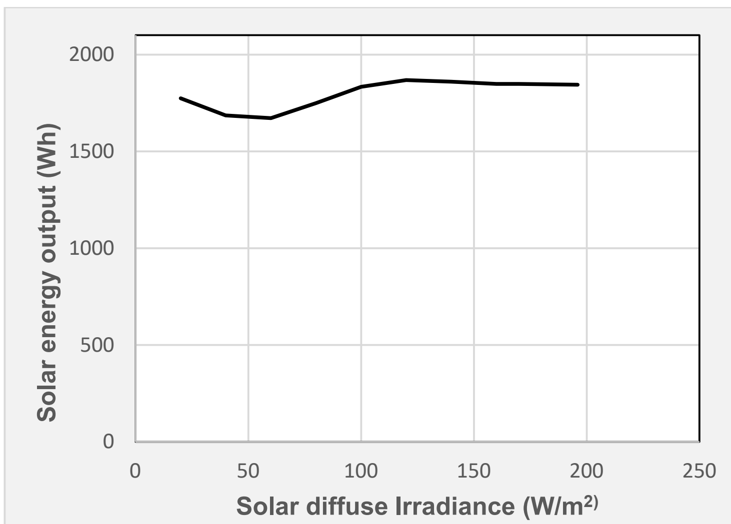
(a)



(b)



(c)



(d)

Fig. 5. The ANN model predicted solar panel energy output with solar panel orientation (a), solar direct irradiance energy (b), wind speed (c) and solar diffuse irradiance energy input (d). All ANN model predicated results are consistent with other research findings, confirming the model accuracy.

4. Final Comments

The goal of this study was to systematically evaluate the effects of various meteorological, climatic and radiometric conditions of local specific residential areas on solar photovoltaic panel energy output through ANN modeling. Consistent with expectations, an ANN was developed to model and predict the daily solar energy output in the southern California area. The ANN and its algorithms were found on the basis of achieving the minimum MAE and RMSE and the maximum R^2. From the analysis of the results, it was found that the predicted values were in agreement with the measurements. This ANN model was in full agreement with the theoretical and experimental analysis of the solar panels. The model confirmed other experimental results that solar panel energy output was highly dependent on weather and solar irradiation flux. As expected, the ANN model provided a strong foundation for the ability to predict solar energy output for a residential house in the southern California area, which suggests that it can be used to predict local area total solar energy outputs. Thus, voltage instabilities due to the fluctuations of solar renewable energy can be reduced, resulting in minimum loss of renewable energy. In addition**,** this ANN modeling approach can be extended to many other applications such as SCORE that heavily rely on solar irradiation to identify the best route to maximize solar energy utilization. Furthermore, the ANN model can be extended to optimizing the solar energy capture of residential roof design (Esfahani et al., 2021). With advancements in solar energy and accurate ANN modeling, numerous studies were concentrated on residential and commercial house design to capture incoming free solar energy.

Nevertheless, further studies are required to improve and expand on the model. Due to the complexity of solar energy output, there could be other variables that were not captured in this ANN model that still affect energy outputs such as panel tilt angle and geographical variation, etc. Another missing variable could be variation in the different types of solar panels. Different solar panels can have dramatically different efficiencies and environmental responses (Touati & Al-Hitmi, 2013). Therefore, future studies shall incorporate more variables to further improve the ANN predictability. Moving forward, this ANN model approach can be improved and extended to nearby areas with significant solar energy cost savings.

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