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Correlation analysis and MLP/CMLP for optimum variables to predict orientation and tilt angles in intelligent solar tracking systems

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Summary

Different solar tracking variables have been employed to build intelligent solar tracking systems without considering the dominant and optimum ones. Thus, several low performance intelligent solar tracking systems have been designed and implemented due to the inappropriate combination of solar tracking variables and intelligent predictors to drive the solar trackers. This research aims to investigate and evaluate the most effective and dominant variables on dual- and single-axis solar trackers and to find the appropriate combination of solar variables and intelligent predictors. The optimum variables will be found by using correlation results between different variables and both orientation and tilt angles. Then, to use the selected variables to develop different intelligent solar trackers. The results revealed that month, day, and time are the most effective variables for horizontal single-axis and dual-axis solar tracking systems. Using these variables in cascade multilayer perceptron (CMLP) and multilayer perceptron (MLP) produced high performance. These predictors could predict both orientation and tilt angles efficiently. It is found that day variable is very effective to increase the performance of solar trackers although day variable is neither correlated nor significant with both orientation and tilt angles. Linear regression predicted less than 70% of the given data in most cases, whereas nonlinear models could predict the optimum orientation and tilt angles. In single-axis tracker, month, day, and time variables achieved prediction rates of 96.85% and 96.83% for three hidden layers of MLP and CMLP, respectively, whereas the MSE are 0.0025 and 0.0008, respectively. In dual-axis solar tracker, MLP and CMLP predicted 96.68% and **97.98**% respectively, with MSE of 0.0007 for both.

KEYWORDS

linear regression, cascade multilayer perceptron, dual-axis, horizontal single-axis, intelligent solar tracking systems, multilayer perceptron neural networks, photovoltaic

1 | INTRODUCTION

Solar energy is a kind of renewable energy that obtained directly from the sun through the form of solar radiation.[1] It is a promising technology to replace the petroleum energy sources. It is the most readily available source of energy, daily renew, free, and non-polluting.[2] Solar cells and photovoltaics widely used to convert solar energy into electricity. Solar tracker is the system that used to track the position of the sun across the sky and keep the solar photovoltaics in the best position that can maximize the collected energy from the sun.[3,4] Solar tracking systems are used to increase exposure to sunlight, thereby increasing solar collectivity compared with fixed photovoltaics.[5,6] The increase can be as much as 10% to 30% depending on the geographical location and the used type of solar trackers. Several types of solar trackers exist namely, single/one-axis and dual/full-axis solar tracking systems.[7] Single/one-axis tracking system can rotate the photovoltaic system about vertical, horizontal, or polar axes,[8] whereas dual-axis solar tracking system can rotate the photovoltaic system about both vertical and horizontal axes at the same time.[9]

However, using solar tracking systems is a challenging task. These processes need several measurement results to employ and install the tracking systems such as the power radiated, tilt, and orientation angles, etc.[10]

Artificial intelligence (AI) principles have been used to drive and control solar tracking systems globally. Intelligent driver systems are the tracking systems that depend on intelligent predictors to train the system using predetermined data and use the intelligent principles to predict the next direction. Intelligent driver systems are the most promising technology to increase the advantages of solar systems due to their capability to use learning algorithms to predict the exact position of the sun.

However, choosing the suitable variables to build, install, and drive intelligent solar tracking systems is very important to find the exact position of the sun, therefore, increase the collected energy.[10] Several variables are adopted to drive and control solar tracking systems including the horizontal and vertical photovoltaic directions (orientation and tilt angles).[6] Orientation and tilt angles are used in dual-axis solar tracking system, which can move horizontally and vertically,[11] whereas single-axis tracker can move only in one direction horizontally or vertically based on the design of the solar tracking system itself.[12] It is proofed that using orientation and tilt angles is associated with the performance of photovoltaic modules in solar systems. It is found that the amount of radiated power could be significantly changed with angular difference in both azimuth and elevation. Therefore, the output of the photovoltaic modules could be changed as well.[13] In addition, obtaining the maximum power point (MPPT) is directly depend on selecting the optimum orientation and tilt angles.[14] Tilted the solar photovoltaic toward the position of the sun also could partially prevent the effect of clouds, wind, and harsh weather conditions, and help to maximize the output power.[15] However, measuring the best orientation and tilt angles is not enough to build an efficient solar tracking system. Other variables must be considered while working on such systems such as measuring the light intensity (power radiation from the sun), the photovoltaic gained power, the current and voltage flow through the photovoltaic (ie, short-circuit current [I_{sc}] and open-circuit voltage [V_{oc}]), the time to make measurements, and the weather variables.[10] Weather variables can be represented by using the month variable through the year, the changing of time through the day, and changing of days through the month.

The variation in using solar variables from a work to another has caused a variation in the generated power, performance, and the efficiency of solar tracking systems. Furthermore, many researches have been published in designing and driving solar tracking systems by using some of these variables without referring to a specific study to select the most appropriate variables to the proposed solar tracking systems. Besides, no study in the field explores the effectiveness of each solar variable on the performance of the designed intelligent solar trackers. In addition, to the best of authors' knowledge, there is lack in the published researches that observe the optimal variables to maximize the performance of solar systems.[16]

Measuring all effective variables on the solar tracking systems is very important while designing and installing solar tracking systems. However, by using all of the solar variables in building and driving solar tracking systems, it is not guaranteed that the system could produce optimal results, and it may increase processing time and consume more energy. Intelligent driver systems are proposed to reduce problems and difficulties that produced by other types of driving systems such as perturb and observation, photo sensors, and programmable controller methods.[17] These difficulties are come from the inaccurate results that obtained from these methods, depending on the weather to decide the next movement of the photovoltaic modules, the cost of maintenance compared to the performance, and there is no specific rule to follow while driving solar photovoltaics, which leads to long process and more energy consumption.[18,19] On the other hand, intelligent driving systems depend on using a training process which can faster the process to find the next trajectory of the sun across the sky, therefore, decrease the amount of consumed energy, enhance the efficiency of solar energy generation, eliminate the current limitations, minimize error rate, and increase the prediction rate.[20,21]

On the other hand, changing the parameters of the intelligent predictors that drive and control solar photovoltaics directly affect on the efficiency of solar systems.[22,23] Thus, several researches have been published in driving solar tracking systems by using several types of linear and nonlinear intelligent predictors and several solar variables. Some of these driving systems are sufficient to be used in specific regions, whereas other systems are insufficient. These inefficient systems are commonly due to the inappropriate combination of solar variables and the employed intelligent driving systems. Numerous intelligent principles such as fuzzy logic, cascade multilayer perceptron (MLP) neural network, multilayer perceptron (MLP) neural network, intelligent Adaptive neuro-fuzzy inference system (ANFIS), and combination of two or more of these techniques are utilized to control solar systems globally.[24,25] However, most of the published works are carried out using random-generated data, whereas other works used real-time data. The main difficulty in collecting real-time data is the long time to take measurements, where random-generated data can be found by using a simulation software. Therefore, an additional risk of generating a faulty data that could not cover the correct cases is very high when random-generated data are used.

Moreover, a literature review on the scope of intelligent solar tracking systems shows a lack on references that can guide researchers to select the optimum solar variables, thus, improve the performance of the proposed intelligent systems. Several researches have been published to assess different types of artificial intelligent principles in driving solar tracking systems. Different solar variables have been employed to develop these intelligent solar tracking systems. The main target of these published researches is to change the intelligent predictor architecture, improving the current techniques, and propose new intelligent predictors that can track the trajectory of the sun efficiently. Fuzzy rule models are widely utilized to characterize the fuzzy system and provide the predicted output based on the available input.[26] Fuzzy theory was used in several real-time applications including control systems.[27] Huang et al[28] designed a dual-axis solar tracking generating power system. The proposed system was controlled using fuzzy logic controller. A field-programmable gate array (FPGA) controller was connected to the proposed tracker, where light sensitive sensors, analog/digital converter, four solar panels, and two driver motors were employed for the proposed tracker. The input variables for the proposed controller were extracted from the difference in signals between east-west direction voltage and south-north direction voltage, where the output variable is the value of pulse that feeding the driver motor. The proposed model was designed as a fully automatic system in changing environment. This proposed system could reduce the number of starting motors, the cost, and results in smaller energy loss in cloudy, cloud mask, or unstable weather.

Sendoya et al[29] used fuzzy logic principle to design and implement a dual-axis solar tracking system. The aim of the proposed tracker is to predict the perpendicular position of the solar photovoltaic panels. The proposed model used two input variables including the incidence of radiation on both azimuth and elevation axis to find two output variables including the position of azimuth and elevation angles. Four light dependent resisters (LDRs) were used to measure the light intensity, voltage, current, and temperature variables that used as input to the proposed controller, where the output variable is the signal that used as input to feed, position, and drive the rotor of Yeasu G5500.

Zaher et al[30] adopted both fuzzy logic controller and image processing to design a dual-axis solar tracker. The designed controller used image processing to detect the cloud duration and the cloud coverage in the sky. Both cloud coverage and duration were used as input attributes for the proposed fuzzy logic control system, where the optimal position of the solar photovoltaic was adopted as output variable. The proposed controller was examined in cloudy, partial cloudy, and clear sky.

Al-Rousan et al[31] developed a dual-axis tracking system based on fuzzy logic principle. The aim of the proposed model is to predict both orientation and tilt angles. Day, time, and month variables were utilized as input variables, whereas orientation and tilt angles were adopted as outputs. Three different datasets were used to examine the proposed controller. The proposed model successfully increased the performance of the solar system, increased the collected energy, and decreased the error ratio.

Neural network is a non-parametric controller model that widely used in control applications as well.[32] Kayri et al[33] proposed two models of single-axis solar tracking systems by using neural network control system. The main idea of the proposed controller is to increase the accuracy rate. Wind speed, wind direction, solar elevation angle, air temperature, relative humidity, and global radiation variables were used in order to find the output power. Multilayer perceptron neural network with feed-forward backpropagation algorithm was used to implement the proposed controllers. Both Levenberg-Marquardt and Bayesian regularization error optimization methods were used with 15 neurons in each hidden layer. Testing the proposed system proved that using the error optimization method increased the performance of the proposed neural network controller.

Rabee et al[34] developed three different intelligent control systems based on multilayer feed-forward neural network architectures. The actual values of average solar radiation from five different locations were used to predict the daily average solar radiation. The first controller was implemented based on gradient descent method with one hidden layer, 10 neurons, and with hyperbolic activation function for both hidden and output layers. The second and third controllers were implemented based on Levenberg-Marquardt algorithm with Gaussian activation function in hidden layer and purelin activation function in output layer. One hidden layer with 10 neurons was used in the second controller, whereas one hidden layer with 1460 neurons was used in the third controller. The training dataset was collected practically for 3 years, whereas the testing data were collected in the fourth year. The proposed systems successfully forecasted the daily average solar radiation.

Hijawi and Arafeh[25] designed a dual-axis solar tracking system based on fuzzy logic and a proposed artificial fuzzy inference system. Luminous values that extracted from resistance of four light sensors were used as input attributes, whereas the outputs are horizontal and vertical motions of solar tracker. The data variables were collected by using actual fixed tracking system. Several intelligent principles were examined to compare with fuzzy logic controllers.

Essefi et al[35] proposed an intelligent control system based on artificial neural network principle. The idea of the proposed control system is to track the maximum power point under rapid changes of climatic conditions. The proposed control system was simulated by using a DC load. The photovoltaic array temperature and solar radiation attributes were used as inputs to predict the voltage that detect the MPPT. Linear neural network that consists of three layers, 100 nodes constitute the hidden layers, and identity activation function constructed the architecture of linear neural network. The proposed controller was tested by using MATLAB/Simulink. Sum squared error (SSE) performance function was used to evaluate the proposed controller. By simulation, the results revealed that the proposed controller has fast convergence, efficient, and robust had negligible oscillations around the MPPT. In addition, it was easily implemented. However, the proposed controller was implemented by using a linear neural network structure. In addition, 100 hidden neurons need long processing time and consume more energy. A simulation study did not cover the real-time conditions.

Armendariz et al[16] used fuzzy rule emulated networks (FREN) to control and drive a dual-axis solar tracker. A combination of neural network layers and fuzzy logic rules was used to design the tracker. Both day and time variables were adopted as input attributes, where both orientation and tilt angles were adopted as output attributes. Using FREN technique and the selected input and output variables to drive the proposed system increased the performance of solar systems compared with other mechanical controllers.

Al-Rousan et al[36] developed two tracking systems for dual- and single-axis solar photovoltaic systems. Intelligent ANFIS technique was used to design and develop the proposed trackers. Day, month, and time variables were employed as input variables to the proposed trackers, whereas the values of orientation and tilt angles were employed as output attributes for dual-axis tracker, and orientation angle was employed as output attribute for single-axis tracker. The developed drivers increased the performance of solar systems and increased the gained energy as well.

Antonio et al[37] designed an intelligent control system using fuzzy logic principle. An FPGA was used to implement the proposed fuzzy logic control system. Four brightness sensors were used to carry out the input data and convert the light intensity into four digital values. The fuzzy-based controller depends on the measurements of the brightness sensors as inputs to find the direction and the movement angle of the servomotor. The movement angle can be selected from different 1024 possible movement values. Evaluation the proposed system revealed that the proposed system allowing faster, precise, and simpler control to the solar systems.

Alata et al[38] used ANFIS principle to drive a dual-axis solar tracking model. Both hourly time and day variables were utilized as inputs to predict the isolation incident, azimuth, hour angle, altitude, declination, and hour angles output variables. The proposed tracker decreased the consumed energy compared with other methods.

El-Shenawy et al[22] proposed a dual-axis solar tracking system based on neural network principle. The proposed tracker comprises three inputs namely, longitude, day, and time variables, where the acceptance angle was employed as output variable. The proposed system controller increased the performance of the solar system.

Yang et al[39] designed a control system for MPPT and grid integration of a solar photovoltaic array by using artificial neural network. The idea of the proposed controller is to improve using neural networks in solar tracking systems. Grid AC voltage, grid AC current, output voltage of the PV array, output current of the PV array, and the maximum output power are the main variables that used to find the ratio of the invertor output voltage that generated from the DC-DC convertor. The proposed control system based on using a feed-forward back-propagation neural network with two hidden layers and six neurons in each layer. Both Marquart-Levenberg optimization algorithm and hyperbolic activation functions were adopted to implement the proposed controller. By using simulation in MATLAB Simulink and hardware in laboratory, the proposed controller was tested and evaluated. The results of evaluating the proposed artificial neural network controller revealed that it could improve the performance of the photovoltaic module systems. It was efficient to gain more output power, it was more reliable, and it was able to get stable DC voltage although it did not cover all the current transient conditions, and it tested in laboratory.

Samosir et al[40] proposed a maximum power point tracking (MPPT) based on fuzzy logic principle. A simulation study was implemented to investigate the effectiveness of fuzzy logic controller system on maximum power point tracking. The proposed fuzzy logic controller used the error that represents the slope of power-voltage characteristic curve and the change of error at instant sample as inputs to predict the change in duty ratio of the DC-DC convertor. The proposed fuzzy logic controller improved the functionality of the system.

Sene et al[41] have proposed a maximum power point tracking (MPPT) for both cloudy and sunny days based on both artificial neural network and adaptive neural fuzzy inference system principles. Two phases were adopted to find the MPPT by using neural network principles (ie, Radial Bias Function [RBF] and Levenberg-Marquardt multilayer perceptron neural network methods). Three input variables including temperature, wind speed, and solar irradiance were used to find both maximum current ($I_{\max}$) and maximum voltage ($V_{\max}$) in RBF phase, whereas both ($I_{\max}$) and ($V_{\max}$) variables were used to obtain the maximum power point in neural network phase. The same three input variables of temperature, wind speed, and solar irradiance were used to find the MPPT in ANFIS principle. The results revealed that ANFIS principle could improve the performance of sunny days, whereas MLP principle performed better for cloudy days. However, by using RBF phase to compute the variables of neural network can be considered as complex system.

Referring to the literature review, it is clear that several intelligent controllers have been proposed to drive solar tracking systems by using different solar variables. To develop the proposed intelligent solar tracking controllers, the employed solar variables vary from one published research to another. Several researches depend on light intensity sensors to build intelligent solar tracking systems, whereas others depend on power radiation and weather conditions. Most of these variables have been selected based on environmental conditions, the records from fixed panel, or records of previous works etc. In addition, many researches depend on using a random generated data or testing the proposed models in laboratory. On the other hand, time to take measurements, the load effect, and the amount of radiated power have not been considered in most of the published researches. It is found that time is the most common used variable that used in 44% of the selected researches, whereas power radiation and day are the second common variable that used in 31% of researches. Voltage and day variables are used in 31% of researches, whereas temperature and error in signals used equally in 18.8% of researches. Moreover, other variables (ie, cloud coverage, longitude, current, luminous, and temperature) are equally used to design the proposed solar tracking systems. Thus, month, day, time, voltage, and power radiation can be considered as the most common used variables. Besides, generated power cannot be measured without measuring the short-circuit current, and the open-circuit voltage, along with other effective variables. However, considering all solar variables to design and install intelligent solar tracking systems would cause a faulty learning process, it also may increase the processing time and consume more energy.

On the other hand, there is a lack of general rules to select the optimum solar variables or the optimum intelligent controller to drive the implemented solar trackers. Relatively few studies have justified their selection for the solar variables and the intelligent predictors, and few studies have compared between different intelligent controllers to improve the performance solar tracking systems. While most of the publish works are focusing on predicting the amount of solar radiation, and testing different intelligent controllers using chronological data. In addition, building and implementing intelligent solar tracker systems suffer from many problems that weaken the performance of the overall trackers. Evidently, selecting the most appropriate variables for intelligent solar tracking systems is very important topic to investigate of the relationship between dependent and independent variables in the trackers, and the most effective variables on intelligent trackers with linear and nonlinear relationships. While a such simple study would contribute to the field of renewable energy, would guide research in the field, and would improve the efficiency of the proposed solar tracking systems.

Thus, its primary goal to enhance the field of renewable energy by adding a comprehensive investigation to select of the optimum solar variables that would be efficiently combined with intelligent dual- and single-axis solar tracking systems based on real-time data to increase the capability of intelligent solar trackers.

This study aims to validate the robustness and the capability of different solar variables in predicting the optimum directions for photovoltaic modules, and to find the combination of solar variables and intelligent predictors that could produce the optimum performance in intelligent solar tracking systems. This study contributes to the field of renewable energy in three key areas: finding the most effective variables on intelligent horizontal single/dual-axis solar trackers, proposing different intelligent driving methods based on combination between the most effective variables and statistical rules, and examining linear and nonlinear intelligent predictors (ie, linear regression, MLP, and cascade-MLP) that can be employed with the most effective variables to develop high performance dual- and single-axis solar tracking systems. To the best of authors' knowledge, there are no reported studies that suggest (a) the optimum intelligent driving methods for solar tracking systems or (b) the most effective variables on intelligent solar tracking system controllers to get the maximum output of solar cells based on real experimental data.

2 | METHODOLOGY

In this paper, several dual- and single-axis solar tracking systems using various intelligent predictors with different combinations between solar variables are proposed. The proposed systems aim to find a proper study to investigate and evaluate the most effective variables for intelligent horizontal single/dual-axis solar trackers.

This section presents the methodology to propose efficient horizontal single- and dual-axis solar trackers based on selecting the most effective variables on positioning solar tracking systems. These variables will be found by using the correlation results between different input solar variables (ie, day, month, time, I_{sc}, V_{oc}, and power radiation) and the output variables (tilt or orientation angles). The proposed study is partitioned into five phases. The first phase is hardware design, which focuses on development of solar tracking system prototype. The second phase is to data collection. It involves collection of solar tracking system's variables, which will be used to identify the correct orientation and tilt angles of solar tracking systems. The third phase is correlation analysis, which is used to find the correlation between the collected variables. This phase is proposed in order to find the linear and nonlinear relationships between these variables and the optimum position of solar tracking system. The next phase is development of several solar tracking models based on the correlation results and statistical rules. The last phase is to evaluate the proposed models by using several artificial intelligence principles to drive solar tracking systems including linear regression, multilayer perceptron neural networks (MLP-NNs), and cascade multilayer perceptron neural networks (CMLP-NNs). These techniques will be used to validate the robustness and capability of the variables in predicting the photovoltaic modules motions, and also to assess the optimum combination of solar variables that could produce the optimum performance in intelligent solar tracking systems.

Six different variables will be used in this study to find the optimal orientation angles for horizontal single-axis tracking system, and the optimal orientation and tilt angles for dual-axis system. The variables that collected as inputs are month, day, time, I_{sc}, V_{oc}, and power radiation. These variables have been selected based on seasonal, weather, and environmental conditions. Besides, horizontal single-axis tracking is widely recommended by several researches and it can be considered as one of the main types of solar trackers globally,[9,42] whereas both orientation and tilt angles for dual-axis solar tracers are widely targeted to obtain the maximum power radiation and to reach the maximum power points.[43] Figure 1 shows the block diagram of the proposed methodology.

2.1 | Phase one: Hardware design

The first step in this study is to build a real mechanical solar tracker prototype. The prototype has been used to collect several measurements and variables. The designed solar tracking system has been installed at Jordan University of Science and Technology (JUST) in Jordan which is a four seasons country. The mechanical prototype can be moved horizontally and vertically. The prototype was used to attach polycrystalline KC120-1 photovoltaic module as shown in Figure 2. The electrical specifications of this module are shown in Table 1.

The prototype is connected to a voltmeter to measure the output voltage, an ammeter to measure the current, a pyranometer to measure the power radiation, and a variable load resistance (0-10KΩ). Figure 3 shows the circuit diagram of solar panel KC120-1 connected to other instruments including voltmeter, ammeter, and variable resistor to make a fully open-loop voltage and pyranometer to measure the amount of solar radiation.[6]

2.2 | Phase two: Data collection

The proposed prototype that designed in phase one was used to collect the data for both horizontal single- and dual-axis solar trackers experimentally. The flowchart of major processes that followed to collect data for horizontal single-axis tracker is presented in Figure 4. The first process shown is to fix the tilt angle of the prototype to 32°. Thirty two degree is the real longitude lines of Jordan country. The tilt angle can be fixed by moving the panel vertically to 32° from the zero-reference point of the proposed prototype. The second process is to change the orientation angle by moving the prototype horizontally to get the maximum radiated power when a shadow for the solar radiation is parallel to solar panel lines.

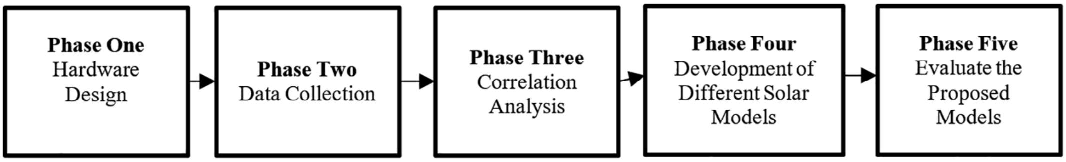

FIGURE 1 Block diagram of the proposed methodology

FIGURE 2 Manually solar tracking model with panel of model KC120-1[6] [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 Electrical Specification of Module KC120-1

Parameter	Value
Model	KC120-1
Maximum power	120 W
Maximum power voltage	16.9 Volts
Maximum power current	7.1 Amps
Open-circuit voltage	21.5 Volts
Short-circuit current	7.45 Amps
Length	1425 mm (56.1 in.)
Width	652 mm (25.7 in.)
Depth	52 mm (2 in.)
Weight	11.9 kg
Temperature coefficient of I_{sc}	6.08×10^{-3} A/°C
Temperature coefficient of V_{oc}	-8.24×10^{-2} V/°C

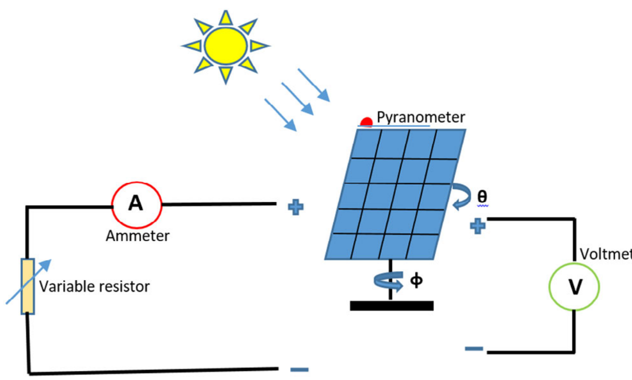

FIGURE 3 Circuit diagram of solar tracking system connected to voltmeter, ammeter, and pyranometer [Colour figure can be viewed at wileyonlinelibrary.com]

The third process is to use minimum resistance of zero and maximum resistance of 10 KΩ to make both short-circuit current and open-circuit voltage, respectively, take measurements of I_{sc}, V_{oc}, power radiation, and the value of the orientation angle. The final process is to repeat the same processes hourly from 8:00 AM to 6:00 PM for different days in a month, and for different months in a year to cover the seasonal changes for the four seasons.

The selected days are based on the recommended average days for the selected months. Average days are an astronomical concept to define the specific day for each month that can represent the whole month, and give a general idea about the measured results in that month.[44] The measurements of this research are taken for the average day or some nearby days for each month depends on the clearness of the sky.

The same processes of collecting data for horizontal single-axis solar tracking system are used to collect the data of dual-axis solar tracking systems. Figure 5 shows the flowchart of the processes of data collection for dual-axis system.

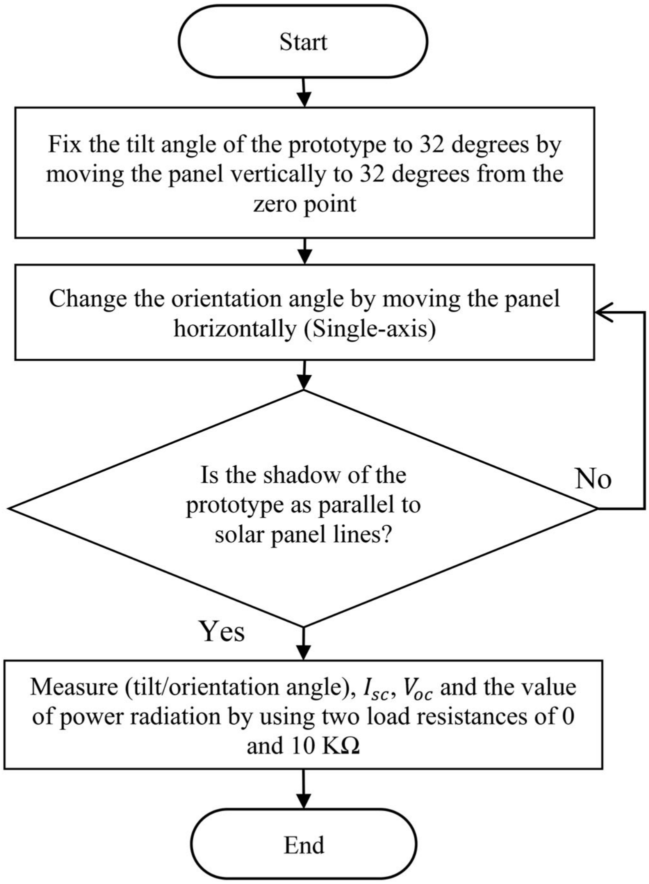

FIGURE 4 Flowchart of data collection for horizontal single-axis solar tracking

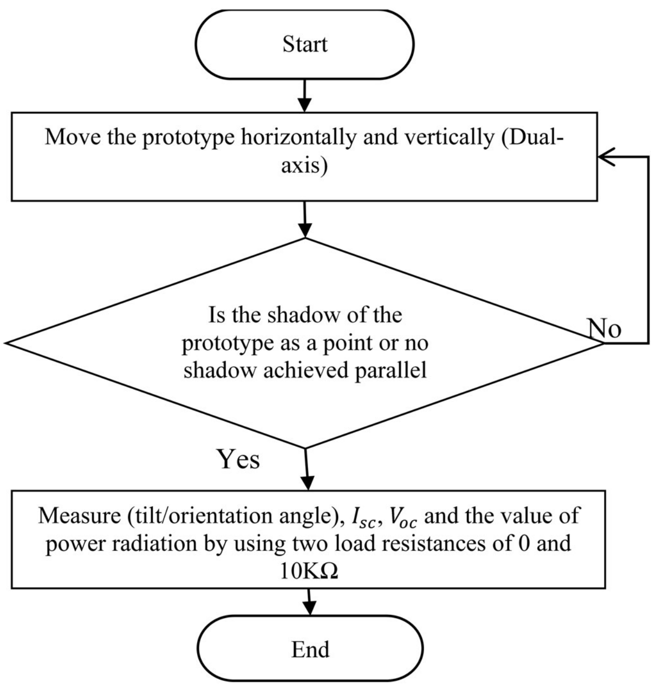

FIGURE 5 Flowchart of data collection for dual-axis solar tracking

As shown in Figure 5, the first step is to move the prototype vertically and horizontally at the same time. This step is employed to change the orientation and tilt angles until achieving no shadow for the solar radiation or a shadow as a point that represents the maximum solar radiated. The next process is to use that variable resistance, and take measurements of I_{sc}, V_{oc}, power radiation, and the value of the orientation angle as explained in horizontal single-axis solar tracker processes. The final process is also to repeat the same processes hourly from 8:00 AM to 6:00 PM for different days in a month, and for different months in a year to cover the seasonal changes for the four seasons as explained earlier.

By implementing the process of data collection for both horizontal single- and dual-axis solar trackers, data samples of month, day, time, I_{sc}, V_{oc}, and the power radiation variables are recorded. The data samples consist of different samples of real-based data for each dual- and single-axis solar tracking systems. These data samples are the dataset that are used to perform the proposed methodology of this study.[6]

2.3 | Phase three: Correlation analysis

Pearson correlation coefficient (R) is used to evaluate the correlation between two pairs of input and output variables, and it is the most widely used correlation function to find the degree of the relationship between linear variables. Pearson correlation coefficient can be calculated by using Equation (1).[45]

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{1}$$

where n is the number of samples, x_i, y_i are the single samples indexed with i, and $\bar{x}$, $\bar{y}$ are the means of samples.

The magnitude of the Pearson correlation coefficient indicates that the strength of the relationship depends on how the coefficient is close to −1 or 1; which is the range of Pearson correlation coefficient. The sign of the correlation coefficient indicates direction of the relationship between the variables. In order to find the most effective variables, three scales are used to classify the Pearson correlation namely weak, moderate, and strong relationship. Table 2 shows the accepted guidelines for interpreting the correlation coefficient.[46,47]

As shown in Table 2, the pairs of variables that got R = +1 indicate a perfect positive linear relationship between variables, whereas the pairs of variables that got R = −1 indicate a perfect negative linear relationship

TABLE 2 Accepted guidelines for interpreting the correlation coefficients

Correlation Coefficient Range	Relationship
−0.1 to 0.1	No linear relationship
+1	A perfect positive linear relationship
−1	A perfect negative linear relationship
∓0.1 to ∓(0.3 or 0.4)	Indicate a weak (negative/positive) relationship
∓(0.3 or 0.4) to ∓0.6	Indicate a moderate (negative/positive) relationship
∓0.6 to ∓1	Indicate a strong (negative/positive) relationship

between variables. Moreover, the pairs of variables $1 > |R| \geq 0.6$ indicate a strong linear relationship between variables, whereas range of $(0.3\ or\ 0.4) > |R| \geq 0.6$ and $|R| \leq (0.3\ or\ 0.4)$ indicates moderate and weak relationship, respectively. On the other hand, the correlation strength scales vary from model to another based on the input-output variables. In some cases, the values of |R| = 0.3 are adopted to denote a moderate relationship between the pairs of variables.[44,45] In other cases, the values of |R| = 0.4 are adopted to denote a moderate relationship as well.[46,48] Pearson correlation coefficient of zero value indicates no linear relationship between input and output variables. The values of R that is close to zero value are uncorrelated values but they have a strong nonlinearity dependent between input and output variables.[42,48]

In addition, a significance of the correlation coefficient is used to deciding if the linear relationship between input and output variables is strong enough to adopt a linear relationship between variables. The significance between variables denotes that the correlation between pairs of input-output variables does not occur by chance. The significant level for the pairs of variables should be less than or equal to 0.05 or 0.01 which based on predefined significant level for each pair.[49] The significant level is assumed as 0.05 or 0.01 when the probability to chance of correlation occurrence is not more than 5 out of 100 or 1 out of 100 respectively.

Moreover, correlation analysis is adopted because it can find comprehensive results in order to find linear relationship between linear-dependent variables if exist, and it can give a strong indicator to interpret a strong nonlinear relationship between nonlinear-dependent variables. On the other hand, correlation analysis is not affected by linear transformations of the data because each variable is standardized by subtracting the mean and dividing by the SD that means the same relationship can be found if a scale of measurement is changed, or a linear process is performed.

The correlation analysis and significant test are calculated for both horizontal single- and dual-axis solar trackers. The relationship between month, day, time, I_{sc}, V_{oc}, and power radiation and the orientation angle in horizontal single-axis tracker, and the relationship between month, day, time, I_{sc}, V_{oc}, and power radiation and orientation and tilt angles in dual-axis solar tracking system are measured by finding the Pearson correlation coefficients. The flowchart that represents the processes of correlation analysis is shown in Figure 6.

As shown in Figure 6, to find the correlation between input and output variables, pairs between one input variable (ie, month, day, time, I_{sc}, V_{oc}, and power radiation) and one output variable (ie, tilt or orientation angles) are created. The numbers of pairs that are created for both horizontal single/dual-axis solar trackers are 6 and 12 pairs, respectively, as shown in Table 3.

The Pearson correlation coefficients are calculated for each pair of input-output variables using Equation (1). The correlation coefficients for all pairs retrieved and sorted in descending order to determine the variables with the highest correlation coefficients and the significant test ≤0.01 or 0.05. In addition, the pairs of variables that got Pearson correlation coefficients that close to zero value will be retrieved too.

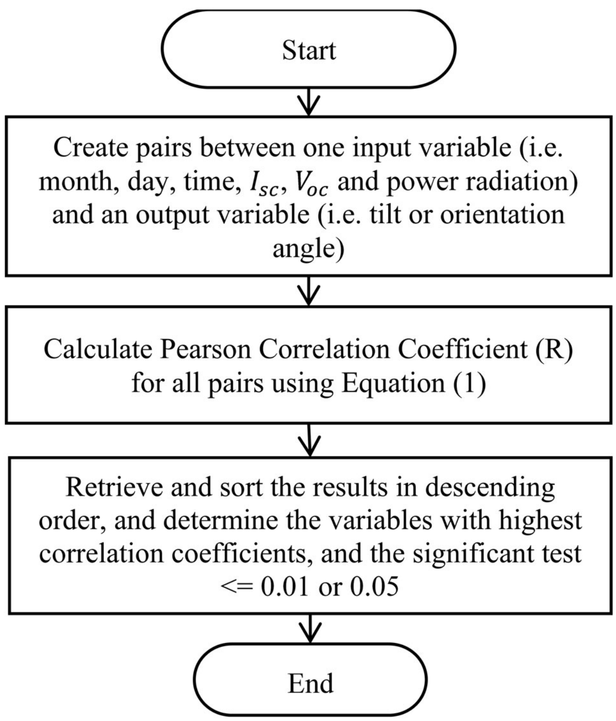

FIGURE 6 Flowchart of correlation analysis

2.4 | Phase four: Development of different solar models

The correlation analysis is performed to find the most correlated variables with both orientation and tilt angles. Based on the correlation analysis, six different solar tracking models are proposed, where the input variables of the proposed models vary from one model to another, whereas the output of single-axis solar tracking system is the orientation angle. To select the most effective variables on orientation angles and to not mislead because of relying on a specific correlation coefficient scales, input variables are selected depending on adopting the two cases of moderate correlation coefficients of 0.3, and 0.4, in addition to select the closest variables to zero with both negative and positive relationships to test any strong nonlinear relationships. The selected input variables and the scale that adopted to select input variables for single-axis solar tracking system are presented in Table 4.

As shown in Table 4, six models are proposed in order to find the most correlated variables with orientation angle for horizontal single-axis solar tracking system. The six models are selected based on the accepted guidelines for correlation strength scales of Table 2. As shown in Table 4, model 1 is the most commonly used model, which includes all input solar variables. Models 2 and 3 use 0.3 as a moderate strength scale. The second model retrieves all variables that got |R| greater than 0.3, and the third model retrieves all variables that got |R| greater than 0.3 in addition to the variables that got the closest positive correlation coefficient to zero when $0 \leq R < 0.1$ which represents a strong nonlinear relationship between input-output variables. On the other hand, models 4 to 6 use 0.4 as a moderate strength scale. Model 4 retrieves all variables that got |R| greater than 0.4. Models 5 and 6 retrieve all variables that got |R| greater than 0.4 in addition to the variables that got the closest positive and negative correlation coefficients to zero when $0 \leq R < 0.1$ and $-0.1 < R \leq 0$, respectively.

On the other hand, proposing models for dual-axis solar tracking system is more complicated than proposing models for single-axis solar tracking system due to use of both orientation and tilt angles as output variables. Different seven models are proposed to cover all possible scales and cases as shown in Table 5. The input variables that selected to propose the seven models vary from one model to another based on the scale limit that adopted each time. Model 1 is the most commonly used model, which includes all input solar variables. Models 2 to 4 use the highest correlation coefficient of tilt and the highest correlation coefficient of orientation. Model 3 employs the variables with the closest |R| to zero of orientation and tilt angles in

TABLE 3 Pairs between input and output variables

Pair	Single-axis tracking system	Dual-axis tracking system
1	Month-orientation	Month-orientation
2	Day-orientation	Day-orientation
3	Time-orientation	Time-orientation
4	I_{sc}-orientation I_{sc}	I_{sc}-orientation
5	V_{oc}-orientation	V_{oc}-orientation
6	power radiation-orientation	power radiation-orientation
7	NA	Month-tilt
8	NA	Day-tilt
9	NA	Time-tilt
10	NA	I_{sc}-tilt
11	NA	V_{oc}-tilt
12	NA	power radiation-tilt

Abbreviation: NA, not applicable.

TABLE 4 Input variables selection for single-axis tracker proposed models

Models	Input variables selection
Model 1	Use all input variables
Model 2	Retrieve all variables with $\lvert R\rvert \geq 0.3$
Model 3	Retrieve all variables with $\lvert R\rvert \geq 0.3$, and $0 \leq R < 0.1$
Model 4	Retrieve all variables with $\lvert R\rvert \geq 0.4$
Model 5	Retrieve all variables with $\lvert R\rvert \geq 0.4$, and $0 \leq R < 0.1$
Model 6	Retrieve all variables with $\lvert R\rvert \geq 0.4$, and $-0.1 < R \leq 0$

TABLE 5 Input variables selection for dual-axis tracker proposed models

Model	Input variables selection
Model 1	Use all input variables
Model 2	Retrieve the highest |R| of tilt, and the highest |R| of orientation
Model 3	Retrieve the highest |R| of tilt, the highest |R| of orientation, and the closest |R| to zero of tilt and orientation
Model 4	Retrieve the highest positive R of tilt, the highest positive R of orientation, the highest negative R of tilt, and the highest negative R of orientation
Model 5	Retrieve all variables with $\lvert R\rvert \geq 0.5$
Model 6	Retrieve all variables with $\lvert R\rvert \geq 0.4$
Model 7	Retrieve all variables with $\lvert R\rvert \geq 0.3$

addition to the highest correlation coefficient of tilt, and the highest correlation coefficient of orientation. Model 4, on the other hand, uses variables with the highest negative R of tilt, and the highest negative R of orientation in addition to the highest correlation coefficient of tilt, and the highest correlation coefficient of orientation. Models 5 to 7 adopted 0.3, 0.4, and 0.5, respectively, as a scale limit for both orientation and tilt angles. The selected input variables and the scale that adopted to select input variables for dual-axis solar tracking system are presented in Table 5.

The proposed horizontal single- and dual-axis tracking models are adopted to be used with linear and nonlinear intelligent controllers to test different intelligent solar tracking systems, and to find the tracker models that can maximize the efficiency of solar tracking.

2.5 | Phase five: Evaluate the proposed solar models based on linear and nonlinear intelligent controllers

As explained in the literature review, selecting the appropriate variables to install, design, and develop solar tracking systems not guaranteed increasing of the efficiency of the proposed solar tracking systems. However, choosing the optimum driving method to control the motions of solar tracking systems from one side to another is desired to develop high efficiency solar tracking systems as well. Therefore, solar tracking systems that based on intelligent controllers are widely used to drive the trajectory of solar tracking systems across the sky. Intelligent controllers are used to predict several criteria such as solar radiation in a specific region, the maximum power point, the trajectory of the photovoltaic modules systems, or duty cycle. The performance of solar tracking systems varies from one system to another that based on the capability of the intelligent controller to track the position of the sun. The sufficiency of intelligent controller to be used as solar tracking controller system depends on many factors (ie, the nature of the collected data, the selected input variables, the selected output variables, and the type of intelligent controller).

This section deals with the methodology to validate the robustness and the capability of the selected variables in predicting the photovoltaic modules motions and to find the combination of solar variables and intelligent classifier that could produce the optimum performance in intelligent solar tracking systems. This section is divided into two main parts based on the intelligent controller that used. One of linear intelligent predictors (ie, linear regression) is examined in the first part, whereas the second part is to test nonlinear intelligent predictors (ie, multilayer perceptron neural network (MLP), and cascade multilayer perceptron network (CMLP). Figure 7 shows the flowchart of phase five of methodology for both dual- and single-axis solar trackers.

2.5.1 | Linear regression-based solar tracking system

Linear regression prediction model has been used in solar tracking systems to find the relationship between average solar irradiance and fixed solar output.[50] The idea of using linear regression is to check the capability of linear regression systems to predict the output variables of solar tracking systems. The same procedure of driving solar tracking system by using linear regression model is used for dual- and single-axis tracking systems. The processes involved in developing the linear regression for dual- and single-axis solar tracking systems are presented in Figure 8.

Figure 8 presents the processes that conducted for linear regression predictor to develop dual- or single-axis trackers. Linear regression model is used to predict the output variable of single-axis solar tracking systems (ie, orientation angle) or the output variables of dual-axis solar tracking systems (ie, orientation and tilt angles). The first process involved is to select one of the six proposed solar tracking models of single-axis solar tracking systems or one of the seven proposed solar tracking models of dual-axis solar tracking systems. The second process is to define both independent variables (input variables based on the selected model) and dependent variable (tilt or orientation angles). The next process is to perform the linear regression method for the defined independent and dependent variables. The final process

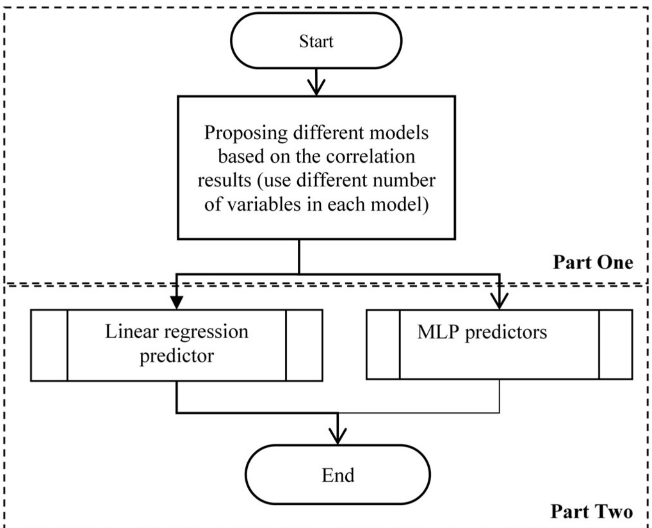

FIGURE 7 Flowchart of phase four methodology

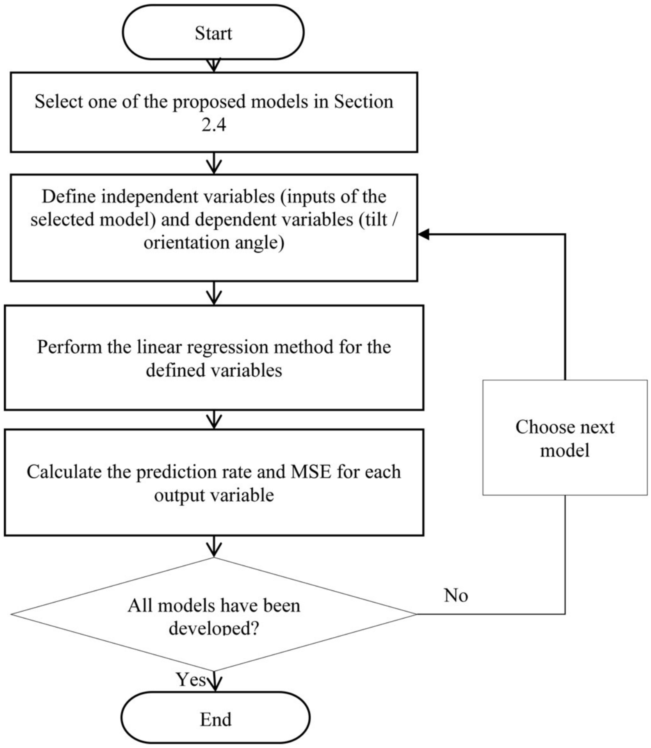

FIGURE 8 The flowchart of proposing linear regression to drive dual-axis and single-axis trackers

is to find the performance of each proposed model. Both prediction rate and mean square error (MSE) are performed criteria to evaluate linear regression, MLP, and CMLP. MSE can be calculated by using Equation (1).[51]

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

where N denotes the number of samples, $\hat{y}_i$ denotes the predicted output values, and y_i denotes the original output values.

Equation (3) presents the formula that used to calculate the prediction rate.[51]

$$\text{Prediction rate} = \left(1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}\right) \times 100\% \tag{3}$$

where $\bar{y}_i$ denotes the mean of output values.

2.5.2 | Multi-layer perceptron neural network-based solar tracking system

MLP prediction model has been used in solar tracking systems to predict orientation and tilt angles, solar irradiance, and maximum power point. The number of hidden layers that used to implement solar tracking systems varied from one research to another. Several numbers of hidden layers have been used to implement solar tracking systems including one, two, and three hidden layers. In addition, the number of hidden nodes are also varied from one to 1460 nodes. In order to perform performance comparison with linear regression systems and to cover all cases of linear and nonlinear systems, nonlinear systems are also developed in this research to perform solar tracking systems. Nonlinear-supervised multilayer perceptron neural network is selected to develop the six proposed models of single-axis solar tracking systems and the seven proposed models of dual-axis trackers. As explained in the literature review, MLP is one of the most common intelligent drivers that widely used to in solar trackers. MLP networks are used in order to improve the old driving methods of solar tracking systems due to their characteristics compared with other technologies. MLP network is sufficient to be used in driving solar tracking systems due to its characteristics in processing nonlinear and complex data even when data are imprecise and noisy,[52] and because it successfully be used as prediction model for time series data that used in solar tracking systems.[53] In addition, it is also effective in complex and nonlinear systems. However, linear neural network is only proper to those variables, which have linear relationship between them. This is due to use linear activation functions to relate both input and output variables. While using nonlinear activation function can find better nonlinear fitting for data, and can reach the local minimum faster.[54]

The same procedure of driving solar tracking systems by using MLP network is used for single-axis and dual-axis solar trackers. To obtain highly efficient dual- and single-axis solar tracking systems, the optimum architecture of MLP is performed by defining the optimum number of layers, number of hidden nodes, transfer function, and connection weights. For MLP network, three scenarios are tested with one, two, and three hidden layers, whereas the number of hidden nodes varies from 1 to 15. The hyperbolic tangent transfer function is used to find the output of the hidden layers, whereas identity transfer function is used to find the output of the output layer. The processes involved in finding the MLP controller for dual- and single-axis solar tracking systems are presented in Figure 9.

Figure 9 shows that the first process is to select one of the six proposed models for single-axis solar tracking systems or one of the seven proposed dual-axis solar tracking systems. The second process is to split the input and target data into training, validation, and testing tests. In this research, 70% of data are used for training, 15% of data are used for validation, and 15% of data are used for

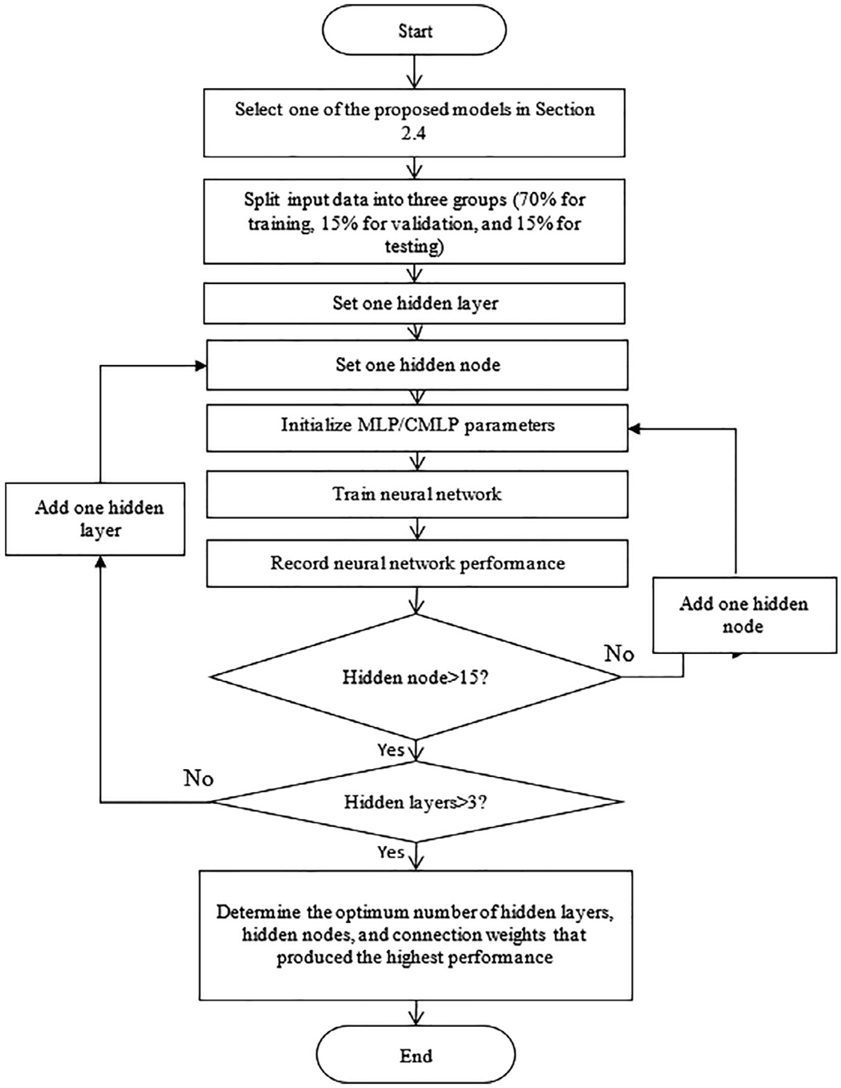

FIGURE 9 Flowchart of MLP/CMLP networks for dual-axis and single-axis solar tracking systems

testing. These three percentages are adopted in order to obtain more accurate results.[55] The third process is to determine the number of hidden layers of the MLP network. The architecture of MLP network is simplified by minimizing the number of hidden layers to decrease the processing time and the consumed energy. Thus, one hidden layer will be performed first. Then, two and three hidden layers are performed respectively.

The next process is to select the optimum number of hidden nodes. Trial and error method is performed to find the optimum number of hidden nodes.[20] Several numbers of hidden nodes are tested for each hidden layer starting from one hidden node up to 15 hidden nodes. Selecting the optimum number of hidden nodes would achieve high performance solar tracking system. The number of nodes in input layer varies from one model to another based on the selected proposed model, whereas one hidden nodes up to 15 are performed to find the optimum number of hidden nodes for hidden layers.[56,57] In addition, similar numbers of hidden nodes are adopted for the three scenarios of one, two, and three hidden layers.

The next process is to initialize the MLP parameters (ie, weights, biases, error target, and transfer functions). Weights and biases of MLP are initialized randomly, the error target for neural network is defined as 10^{-15}, the learning rate and iteration number are defined as 0.01 and 1000, which are the most commonly used in previous work. The hyperbolic tangent transfer function is used to find the output of the hidden layers, and identity transfer function is used to find the output of the output layer. Based on the literature review, these parameters are adopted as optimum parameters for MLP experimentally.

Once the network weights and biases are initialized, the network is trained in order to tune both weights and biases to be optimum. Minimization of error function is commonly used for that purpose. MSE performance function is one of the most popular performance functions in MLP neural networks.[58] Thus, MSE was selected as the error function to train the MLP neural networks.

The next process is to record the obtained performance of the developed network. Similar to linear regression model, both performance metrics of prediction rate and MSE are selected as to evaluate the MLP neural networks. At the end of the proposed methodology, the optimum MLP neural networks with optimum weight and bias values, number of hidden layers, and number of hidden nodes are obtained.

2.5.3 | Cascade multi-layer perceptron neural network-based solar tracking system

CMLP is another form of nonlinear-supervised MLP that uses the same architecture and parameters. Implementing CMLP network intelligent predictor would provide an efficient intelligent controller that can adjust the weight in the input and hidden layers to reduce the error and increase the performance of the system in a more significant and accurate process.[59] Nonlinear-supervised CMLP network is selected to develop the six proposed models of single-axis solar tracking systems and the seven proposed models of dual-axis tracking systems to evaluate whether CMLP network is capable to be used efficiently as solar tracking system controller. Moreover, CMLP networks are used in several researches instead of using MLP model.[59] The processes involved in finding the CMLP controller for dual- and single-axis solar tracking systems are similar to MLP controller as presented in Figure 9.

3 | RESULTS AND DISCUSSION

This section is to present the results of the most effective solar variables on horizontal single- and dual-axis solar trackers. Month, time, day, I_{sc}, V_{oc}, and power radiation solar variables are used to find the most effective variables on orientation angle in horizontal single-axis tracking system and in both orientation and tilt angles in dual-axis solar trackers. Then, based on the correlation analysis results, several horizontal single- and dual-axis solar trackers are proposed. These systems are validated to find the most appropriate solar variables in predicting the photovoltaic modules motions. The correlation analysis results and the proposed solar tracking systems based on the correlation analysis results are presented in the following subsections.

3.1 | Correlation analysis results

The correlation analysis results between month, day, time, I_{sc}, V_{oc}, and power radiation variables and the orientation angle of single-axis solar tracking are tabulated in Table 6.

As shown in Table 6, month is the most correlated and significant variable for the orientation angle. This result is expected due to the moving of the earth around the sun. Theoretically, as the position of the sun varies for different months, thus, month plays important role in determining the orientation angle. This relationship is clearly shown by the result of Person correlation of 0.559. The second most effective and significant variable is time. Time is correlated with orientation angle with Pearson correlation of 0.411. Time is correlated because of the strong relationship between the rotation of the earth on its axis that causes the changing of time through the day and the measured orientation angles to obtain optimal gained power.

In addition, the third most effective variable is the power radiation that measured directly in a form of solar radiation using a pyranometer measurement tool. Power radiation variable is also correlated and significant with the orientation angles with 0.337 of Pearson correlation although it is affected by the weather, temperature, and the clearness of the sky. In contrast, other parameters including the day of the month, I_{sc}, and V_{oc} have low correlation coefficients with orientation angle. The obtained results revealed that the rotation of the earth around the sun and the rotation of the earth on its orbit play an important role in determining the orientation angle in horizontal single-axis solar tracking systems. Thus, using these criteria in solar tracking system could help in developing the optimum horizontal single-axis solar tracking system.

On the other hand, the correlation analysis between month, day, time, I_{sc}, V_{oc}, and power radiation variables and both orientation and tilt angles is presented in Table 7.

From the correlation results with tilt angle in Table 7, time is the most correlated and significant variable with Pearson correlation coefficient of 0.522. V_{oc} variable is the second most correlated variable with Pearson correlation of −406, however, with inverse relationship. The third most

TABLE 6 Correlation between solar variables and orientation angle for single-axis solar tracker

Variable	Pearson correlation	Sig (2-tailed)
Month	0.559	0.000
Day	−0.042	0.606
Time	0.411	0.000
I_{sc}	0.234	0.700
V_{oc}	0.026	0.746
Power-radiation	0.337	0.000

TABLE 7 Correlation between solar variables and both orientation and tilt angles for dual-axis solar tracking system

Variable	Tilt-angle		Orientation-angle	
	Pearson correlation	Sig (2-tailed)	Pearson correlation	Sig (2-tailed)
Month	0.252	0.002	0.767	0.000
Day	−0.011	0.896	−0.112	0.167
Time	0.522	0.000	0.280	0.000
I_{sc}	−0.202	0.012	0.031	0.700
V_{oc}	−0.406	0.000	−0.313	0.700
Power-radiation	0.378	0.000	0.678	0.000

correlated variable is power radiation with Pearson correlations of 0.378, and finally the month with Pearson correlations of 0.252.

In addition, for orientation angle, the most effective variable is month, which has the highest correlation coefficient with Pearson correlation of 0.767. The second most effective variable is the power-radiation, followed by V_{oc} variable (ie, with inverse relationship) and time variable as the third and fourth most effective variables, respectively. These variables produced Pearson correlations of 0.678, −0.313, and 0.280, respectively. In contrast, I_{sc} and day variables have low correlation coefficients with Pearson correlations of −0.202 and −0.011, respectively.

Comparing the correlation analysis of both single- and dual-axis solar trackers, the results support the fact that the rotation of the earth around the sun and the rotation of the earth on its orbit have the main effects on both orientation and tilt angles. This is because the most effective variables for both orientation and tilt angles are time and month, respectively. Therefore, using these criteria will support on developing the optimum horizontal single/dual-axis solar tracking systems. On the other hand, referring to Table 7, the values of Pearson correlation coefficients that close to zero value are uncorrelated values while have a strong nonlinearity dependent between output and input variables. Therefore, both variable V_{oc} and day variables have strong nonlinear relationships with orientation angle on single-axis solar tracking system with Pearson correlation of 0.026 and −0.046, respectively, whereas day and I_{sc} variables have strong nonlinear relationships with orientation and tilt angles on dual-axis solar tracking system, respectively. Day and I_{sc} variables obtained Pearson correlation of −0.011 and 0.031, respectively.

3.2 | Proposed solar tracking systems based on correlation analysis results

To investigate of the optimum variables that can be employed to develop optimum intelligent solar tracking systems, the correlation analysis results from the previous section are used to propose six different solar tracking models for horizontal single-axis solar tracking system, whereas the most effective variables on both orientation and tilt angles are used to propose seven different models. These models are proposed to cover all possible scales and cases referring to Tables 4 and 5, respectively. This section presents the proposed horizontal single- and dual-axis solar tracking systems based on the correlation analysis results.

As shown in Table 8, six different models are proposed in order to investigate the most appropriate variables to predict the orientation angle in horizontal single-axis tracking system. Based on Table 4, model 1 includes all the six-collected input solar variables (ie, day, month, time, V_{oc}, I_{sc}, and power-radiation). Model 2 retrieves all solar variables that got Pearson correlation coefficient, R greater than or equal to 0.3. Thus, model 2 includes month, time, and power-radiation variables. The third model retrieves all variables that got |R| greater than 0.3 in addition to the variables that got the closest positive correlation coefficient to zero when $0 \le R < 0.1$. Model 3 includes month, time, and power-radiation variables in addition to V_{oc} variable that got a closest positive Pearson correlation coefficient to zero when $0 \le R < 0.1$.

Moreover, model 4 retrieves all solar variables that got Pearson correlation coefficients greater than or equal to 0.4. Therefore, model 4 includes month and time variables. Models 5 and 6 retrieve all variables while have Pearson correlation coefficient greater than or equal to 0.4, with additional criteria. In addition to month and time, V_{oc} variable which has positive Pearson correlation coefficient close to zero (ie, $0 \le R < 0.1$) is used in model 5, whereas day variable which has negative Pearson correlation coefficient close to zero (ie, $-0.1 < R \le 0$) is used in model 6.

On the other hand, seven different models are proposed in order to investigate the most appropriate variables to predict both orientation and tilt angles in dual-axis solar tracking system. The seven models are

TABLE 8 The input-output variables for single-axis solar tracking system

Model	Number of inputs	Input variables	Output variables
Model 1	6	Month, Day, Time, V_{oc}, I_{sc}, Power-Radiation	Orientation
Model 2	3	Month, Time, Power-Radiation	Orientation
Model 3	4	Month, Time, V_{oc}, Power-Radiation	Orientation
Model 4	2	Month, Time	Orientation
Model 5	3	Month, Time, V_{oc}	Orientation
Model 6	3	Month, day, Time	Orientation

TABLE 9 The input-output variables for dual-axis solar tracking system

Model	Number of inputs	Input variables	Output variables
Model 1	6	Month, day, time, V_{oc}, I_{sc}, power-radiation	Tilt, orientation
Model 2	2	Month, time	Tilt, orientation
Model 3	3	Month, day, time	Tilt, orientation
Model 4	3	Month, time, V_{oc}	Tilt, orientation
Model 5	3	Month, time, power-radiation	Tilt, orientation
Model 6	4	Month, time, V_{oc}, power-radiation	Tilt, orientation

selected based on the guidelines of correlation analysis. As shown in Table 9, model 1 includes all the six-collected input solar variables (ie, day, month, time, V_{oc}, I_{sc}, and power-radiation). Model 2 retrieves month variable as the highest Pearson correlation coefficient of tilt angle, and time variable as the highest Pearson correlation V_{oc} coefficient of orientation angle. Model 3 retrieves month and time variables in addition to the closest absolute Pearson correlation coefficient to zero of orientation and tilt angles. Therefore, model 3 includes month, time, and day variables which has a closest absolute Pearson correlation coefficient to zero (ie, $-0.1 \leq R < 0.1$).

Model 4 retrieves the highest positive and negative Pearson correlation coefficients of both orientation and tilt angles. Model 4 retrieves month and time as highest positive Pearson correlation coefficients of orientation and tilt angles, respectively. However, the highest negative Pearson correlation coefficient of orientation and tilt angles is V_{oc} variable. Thus, model 4 includes month, time, and V_{oc} variables. In contrary, models 5 to 7 retrieve all solar variables that have Pearson correlation coefficients greater than or equal to 0.5, 0.4, and 0.3, respectively. Therefore, model 5 includes month, time, and power-radiation variables, model 6 includes month, time, V_{oc}, and power radiation variables, and model 7 includes month, time, V_{oc}, and power radiation variables. As input variables of model 7 are similar to input variables of model 6, six different solar models from model 1 to model 6 are adopted in order to investigate the most appropriate variables to predict both orientation and tilt angles in dual-axis solar tracking system.

The selected input variables of horizontal single- and dual-axis tracking systems are used to investigate of the optimum variables that can be employed to develop optimum intelligent solar tracking systems by using several intelligent predictors.

3.3 | Results of the proposed solar tracking systems based on intelligent predictors

This section presents the performance of several intelligent predictors to be used in the proposed solar tracking systems. Three intelligent predictors (ie, linear regression, MLP, and CMLP) are adopted to evaluate the proposed tracking systems for each horizontal single- and dual-axis tracking systems. This idea is to investigate the optimum input variables that can be employed to develop high performance single- and dual-axis solar trackers. This section is divided into two subsections to present the results of both horizontal single-axis and dual-axis solar tracking systems. MSE and prediction rate performance criteria are used to evaluate the performance of the proposed models.

3.3.1 | Results of the proposed single-axis solar tracking systems

The results of implementing linear regression, MLP, and CMLP principles for single-axis solar tracking system are presented in this section.

Results of linear regression-based solar tracking system

The MSE and the prediction rate results of linear regression technique for single-axis solar tracking system are presented in Table 10.

As shown in Table 10, model 3 and model 1 obtained the highest and the second highest prediction rate of 66.40% and 50.60%, respectively. In addition, model 1 obtained the lower MSE then model 3 of 3.860×10^{-2} and 4.310×10^{-2}, respectively. In contrast, model 4 that used month and time variables achieved the worst results of 40.90% and 4.490×10^{-2} for both prediction rate and MSE, respectively.

However, the prediction rates of all the proposed solar tracking models are below 70%, and the difference between the prediction rates and MSE of all models is relatively small. Based on the linear regression results, finding linear formulas between the selected input variables and the orientation angle for the developed models is not applicable. This shows that the relationship between the tested values and the orientation angle could not be represented well with linear regression systems. This is because using linear regression does not achieve the main goal of finding the optimum model that produces low error rate and high prediction rate. Thus, non-linear systems could possibly improve the performance.

Results of multi-layer perceptron neural network-based solar tracking system

Selecting the optimum architecture of MLP has great influence on the MSE and the prediction rate of MLP network. The optimum architecture can be selected by finding the optimum number of layers, number of hidden nodes, transfer function, and connection weights. Trial and error method is used to train the MLP models and to find the optimum number of neurons in hidden layers.

Three scenarios are tested with one, two, and three hidden layers with number of nodes varies from 1 to 15 in order to select the optimum number of hidden nodes for each hidden layer. Referring to the proposed methodology, the MLP parameters (ie, weights and biases) are initialized randomly. The error target for neural network is defined as 10^{-15}. Hyperbolic tangent transfer function is used to find the output of the hidden layers, whereas identity transfer function is used to find the output of the output layer. In addition, the training data are divided into training, validation, and testing sets. The MSE is used as a performance criterion to assess the MLP network performance. Decision on the optimum number of neurons for each hidden layer is based on finding the minimum testing MSE. The process of finding the MSE for each case was repeated multiple times to prevent any random correlation that caused by random initialization of MLP parameters. Based on the averaging testing results, the optimum number of nodes that can be used for optimal MLP architecture is 10 for all one, two, and three hidden layers. The number of nodes in input layer varies from a model to another, whereas the same number of nodes will be used for hidden and output layers.

The overall MSE and prediction rate for the six developed models are collected for one, two, and three hidden layers with 10 hidden nodes. This will give the benefits to select the optimum solar tracking model. Tables 11 and 12 present the overall prediction rate and MSE in all the developed MLP models.

As shown in Tables 11 and 12, model 1 that used all the solar variables predicted 92.83%, 94.24%, and 94.68% when one, two, and three hidden layers are used, respectively. The MSE for one, two, and three hidden layers are 1.170×10^{-2}, 1.120×10^{-2}, and 0.880×10^{-2}, respectively. The results revealed that using three hidden layers achieved the maximum prediction rate and the lowest MSE among the three scenarios.

TABLE 10 The results of prediction rate and MSE for orientation angle of the proposed linear regression based single-axis solar tracking system

Model	Input variables	Prediction rate (100%)	MSE
Model 1	Month, day, time, V_{oc}, I_{sc}, power-radiation	50.60	3.860×10^{-2}
Model 2	Month, time, power-radiation	42.90	4.370×10^{-2}
Model 3	Month, time, V_{oc}, power-radiation	66.40	4.310×10^{-2}
Model 4	Month, time	40.90	4.490×10^{-2}
Model 5	Month, time, Voc	64.80	4.440×10^{-2}
Model 6	Month, day, time	41.90	4.450×10^{-2}

TABLE 11 Overall prediction rate (%) of the proposed MLP-based single-axis solar tracking system

	Hidden layer(s)		
Model	**1**	**2**	**3**
Model 1	92.83	94.24	94.68
Model 2	87.69	87.97	88.68
Model 3	85.27	86.85	87.69
Model 4	86.05	87.29	88.06
Model 5	84.18	86.85	87.49
Model 6	92.50	95.06	96.85

TABLE 12 Results of MSE rates for the proposed MLP-based single-axis solar tracking system

	Hidden layer(s)		
Model	**1**	**2**	**3**
Model 1	1.170×10^{-2}	1.120×10^{-2}	0.880×10^{-2}
Model 2	0.960×10^{-2}	0.930×10^{-2}	0.990×10^{-2}
Model 3	1.750×10^{-2}	1.090×10^{-2}	1.200×10^{-2}
Model 4	2.540×10^{-2}	1.900×10^{-2}	1.431×10^{-2}
Model 5	1.880×10^{-2}	1.400×10^{-2}	0.800×10^{-2}
Model 6	0.890×10^{-2}	0.370×10^{-2}	0.250×10^{-2}

In addition, using month, time, V_{oc}, and power-radiation variables in model 3 predicted less amount of data compared withs use all variables. Model 3 predicted 85.27%, 86.85%, and 87. 69% for using one, two, and three hidden layers, respectively. On the other hand, one, two, and three hidden layers achieved MSE of 1.750×10^{-2}, 1.090×10^{-2}, and 1.200×10^{-2}, respectively. The results indicate that using three hidden layers achieved better prediction rate compared with the two other scenarios. However, less prediction rate is produced as compared with model 1.

The prediction rate results of models 2, 5, and 4 using one, two, and three hidden layers are 87.69%, 87.97%, and 88.68%; 84.18%, 86.85%, and 87.49%; and 86.05%, 87.29%, and 88.06%, respectively. On the other hand, MSE by using one, two, and three hidden layers in model 2 are 0.960×10^{-2}, 0.930×10^{-2}, and 0.990×10^{-2}, respectively. The MSE for model 5 are 1.880×10^{-2}, 1.400×10^{-2}, and 0.800×10^{-2}, whereas the MSE for model 4 are 2.540×10^{-2}, 1.900×10^{-2}, and 1.431×10^{-2} using one, two, and three hidden layers, respectively. The results revealed that using two hidden layers in model 2 achieved better prediction rate and MSE compared with using one and three hidden layers. Moreover, using three hidden layers in model 5 achieved better prediction rate and MSE. For Model 4, using three hidden layers achieved better prediction rate, but using two hidden layers is better to obtain lower MSE.

In contrast, model 6 that used month, day, and time variables achieved low error rate and high prediction rate because the day variable has a strong nonlinear relationship with orientation angle. Model 6 achieved prediction rates with 92.50%, 95.06%, and 96.85%, for one, two, and three hidden layers, respectively. In addition, it obtained low MSE with 0.890×10^{-2}, 0.370×10^{-2}, and 0.250×10^{-2} for one, two, and three hidden layers, respectively. The results revealed that using three hidden layers obtained better prediction rate and MSE compare with other scenarios.

From the comparison between the results of MLP, model 6 that used month, day, and time variables, then model 1 that used month, day, time, V_{oc}, I_{sc}, and power radiation variables are the optimum models among other models with highest prediction rate and lowest MSE. In contrast, model 5 that used month, time, and V_{oc} achieved the lowest prediction rate, whereas model 4 that used month and time achieved the worst MSE.

Results of cascade multi-layer perceptron neural network-based solar tracking system

Similar to MLP network, selecting the optimum architecture of CMLP is the first process to implement CMLP network. Trial and error method is also used to train the CMLP models and to find the optimum number of neurons in hidden layers.

Similar topologies of one, two, and three hidden layers are used with number of hidden nodes vary from 1 to 15 in order to select the optimum number of hidden nodes for each hidden layer separately. The CMLP parameters (ie, weights, biases, error target, and transfer functions) are defined similar to MLP network. In addition, the decision on the optimum number of neurons for each hidden layer is based on finding the minimum MSE value.

Similar to MLP, the averaging testing results show that the optimum number of nodes that can be used for optimal CMLP architecture is 10 for all one, two, and three hidden layers. The similarity in the behavior between CMLP and MLP refers to the similarity in data samples that used to evaluate the performance of both MLP and CMLP. The number of nodes in input layer varies from one model to another, whereas the same number of nodes will be used for hidden and output layers. The overall results of the prediction rates and MSE in all the developed models based on CMLP are presented in Tables 13 and 14, respectively.

As shown in Tables 13 and 14, model 1 and model 6 successfully predicted more than 90% of the given data.

TABLE 13 Overall prediction rate (%) of the proposed CMLP-based single-axis solar tracking system

Model	Hidden layer(s) 1	2	3
Model 1	93.93	94.99	96.04
Model 2	86.85	86.40	90.11
Model 3	86.38	87.57	87.41
Model 4	87.78	89.13	89.18
Model 5	85.60	89.15	87.70
Model 6	96.35	96.52	96.83

TABLE 14 Results of MSE rates for the proposed CMLP-based single-axis solar tracking system

Model	Hidden layer(s) 1	2	3
Model 1	0.700×10^{-2}	0.540×10^{-2}	0.220×10^{-2}
Model 2	1.680×10^{-2}	2.030×10^{-2}	1.070×10^{-2}
Model 3	0.160×10^{-2}	0.100×10^{-2}	0.170×10^{-2}
Model 4	3.640×10^{-2}	$1.820 \times 10^{-2}2$	0.110×10^{-2}
Model 5	2.270×10^{-2}	1.190×10^{-2}	2.480×10^{-2}
Model 6	0.250×10^{-2}	0.250×10^{-2}	0.080×10^{-2}

Model 1 obtained 93.93%, 94.99%, and 96.04% prediction rate for one, two, and three hidden layers, respectively, whereas model 6 obtained 96.35%, 96.52%, and 96.83% for one, two, and three hidden layers, respectively. The MSE for model 1 varies from 0.700×10^{-2} for one hidden layer to 0.220×10^{-2} for three hidden layers. The MSE for model 6 varies from 0.250×10^{-2} for one hidden layer to 0.080×10^{-2} for three hidden layers. The results of models 2 to 5 predicted low prediction rates as compared to model 1 and model 6. The prediction rates for these models vary from 87.41% for model 3 to 90.11% for model 2 for three hidden layers, whereas the MSE varies from 1.070×10^{-2} for model 2 to 0.170×10^{-2} for model 3.

From the comparison between the results of CMLP, and similar to the results of MLP network, model 6 that used month, day, and time, and model 1 that used month, day, time, Voc, Isc, and power radiation perform better than other models. They achieved the highest and the second highest prediction rate and low MSE as compared with other models.

Moreover, comparing the average results of MLP and CMLP proved that CMLP network performs better than MLP model to drive single-axis solar tracking system. The overall results for both MLP and CMLP indicate that using all variables in developing solar tracking systems cannot guarantee the optimum horizontal single-axis solar tracking system, in addition, using all variables takes more processing time compared with other models.

On the other hand, the results of using month, day, and time in model 6 prove that these variables are the optimum variables to develop optimum horizontal single-axis solar tracking system although the day variable is neither correlated nor significant with the orientation angle. The strong nonlinear relationship between day and orientation variables enhanced the performance of model 6. Moreover, the experimental results prove that the day variable is the most effective solar variable in developing better solar tracking system. In addition, the combination between the statistical and experimental results in model 6 developed the optimum horizontal single-axis solar tracking system based on both MLP and CMLP networks.

3.3.2 | Results of the proposed dual-axis solar tracking systems

The results of using linear regression, MLP, and CMLP principles to implement the proposed dual-axis solar tracking models are presented in this section. The results of the proposed intelligent solar tracking controllers are presented and discussed in the following subsections.

Results of linear regression-based solar tracking system

The MSE and the prediction rate are determined for both orientation and tilt angles of the six-developed dual-axis tracking systems based on linear regression technique. The results of implementing linear regression technique to predict orientation and tilt angles are presented in Table 15.

As shown in Table 15, model 3 that used day, month, and time variables obtained the highest prediction rate for tilt angle with prediction rate of 67.20%, whereas model 1 obtained the lowest MSE among the other developed models with MSE of 0.0036. In contrast, model 1 achieved the highest prediction rate for orientation angle with prediction rate of 69.60%, whereas model 5 achieved the lowest MSE of 0.0040.

On the other hand, the prediction rates of all developed models using linear regression are below 70%. As a result, using linear formula is not sufficient to develop dual-axis tracking system. Thus, using linear regression to determine high prediction rate and the low error rate is not applicable. This finding proves that linear regression model is insufficient in developing the dual-axis solar tracking system; therefore, nonlinear models may better predict the movements of solar photovoltaics.

TABLE 15 The results of prediction rate (%) and MSE for both orientation and tilt angles of the proposed linear regression-based dual-axis tracking system

		Tilt		Orientation	
Model	**Input variables**	**Prediction rate**	**MSE**	**Prediction rate**	**MSE**
Model 1	Month, day, time, V_{oc}, I_{sc}, power-radiation	41.80	3.600×10^{-2}	69.60	1.000×10^{-2}
Model 2	Month, time	33.60	0.400×10^{-2}	40.90	4.500×10^{-2}
Model 3	Month, day, time	67.20	0.370×10^{-2}	33.80	0.400×10^{-2}
Model 4	Month, time, V_{oc}	34.70	0.400×10^{-2}	67.80	1.040×10^{-2}
Model 5	Month, time, power-radiation	39.20	0.370×10^{-2}	67.40	1.050×10^{-2}
Model 6	Month, time, V_{oc}, power-radiation	40.90	0.360×10^{-2}	68.40	1.020×10^{-2}

Results of multi-layer perceptron neural network-based solar tracking system

To evaluate the proposed dual-axis models, the overall prediction rate and MSE are adopted as performance criteria. The same procedures that mentioned for single-axis solar tracking system are followed. Based on the average testing results of the proposed MLP-based solar tracking system for dual-axis solar tracking system, the optimum number of hidden nodes is 10 for all one, two, and three hidden layers. The number of nodes in input layer varies from one model to another, whereas the same number of nodes will be used for hidden and output layers.

The overall results of MSE and the prediction rate for the six developed models are collected for one, two, and three hidden layers with 10 hidden nodes. The overall prediction rate and MSE for both orientation and tilt angles are collected. Then, the optimum solar tracking model that predicted the lowest MSE and the highest prediction rate will be determined. Tables 16 and 17 present the overall prediction rate and MSE for all the developed MLP-based dual-axis tracking systems, respectively.

As shown in Tables 16 and 17, model 3 that used month, day, and time predicted the highest amount of data for the three scenarios of one, two, and three hidden layers with prediction rate of 95.50%, 96.13%, and 96.68%, respectively. In addition, model 3 obtained low MSE of 0.280×10^{-2}, 0.160×10^{-2}, and 0.070×10^{-2} respectively. Moreover, model 1 that used all input variables also achieved high prediction rates of 95.22%, 95.80%, and 96.57% from the given data for one, two, and three hidden layers, respectively. Model 1 obtained MSE of 0.160×10^{-2}, 0.140×10^{-2}, and 0.120×10^{-2} for one, two, and three hidden layers, respectively. In contrast, model 2 that used month and time predicted the worse prediction rate of 87.78%, 89.13%, and 89.18% for one, two, and three hidden layers, respectively. In addition, model 2 obtained MSE of 0.100×10^{-2}, 0.160×10^{-2}, and 1.560×10^{-2} for one, two and three hidden layers, respectively.

TABLE 16 Overall prediction rate (%) of the proposed MLP-based dual-axis tracking systems

	Hidden layer(s)		
Model	**1**	**2**	**3**
Model 1	95.22	95.80	96.57
Model 2	87.78	89.13	89.18
Model 3	95.50	96.13	96.68
Model 4	92.84	92.72	93.10
Model 5	92.44	93.78	93.44
Model 6	91.38	93.48	94.30

TABLE 17 Results of MSE rates for the proposed MLP-based dual-axis solar tracking system

	Hidden layer(s)		
Model	**1**	**2**	**3**
Model 1	0.160×10^{-2}	0.140×10^{-2}	0.120×10^{-2}
Model 2	0.100×10^{-2}	0.160×10^{-2}	1.560×10^{-2}
Model 3	0.280×10^{-2}	0.220×10^{-2}	0.070×10^{-2}
Model 4	0.280×10^{-2}	0.15×10^{-2}	0.310×10^{-2}
Model 5	0.310×10^{-2}	0.340×10^{-2}	0.170×10^{-2}
Model 6	0.260×10^{-2}	0.370×10^{-2}	0.190×10^{-2}

On the other hand, the prediction rate results of models 4 to 6 using one, two, and three hidden layers are very close to each other with prediction rates of 92.84%, 92.72%, and 93.10%; 92.44%, 93.78%, and 93.44%; and 91.38%, 93.48%, and 94.30%, respectively. Besides that, MSE by using one, two, and three hidden layers in model 4 are 0.280×10^{-2}, 0.150×10^{-2}, and 0.310×10^{-2}, respectively. The MSE for model 5 are 0.310×10^{-2}, 0.340×10^{-2}, and 0.170×10^{-2}, whereas the MSE for model 6 are 0.260×10^{-2}, 0.370×10^{-2}, and 0.190×10^{-2} using one, two, and three hidden layers, respectively.

From the comparison between the results of MLP networks in dual-axis tracking systems, the results indicate that using three hidden layers achieved better prediction rate and lower MSE as compared with the two other scenarios in most cases. In addition, model 3 is the best developed model among other models due to achieve the lowest MSE for the scenario of three hidden layers. These results could support the results of MLP network in single-axis solar tracking models and revealed that the optimum variables to develop dual- and single-axis solar tracking systems are month, day, and time.

Results of cascade multi-layer perceptron neural network-based solar tracking system

Similar network architectures as MLP networks are adopted to develop CMLP networks. Based on the average testing results of the proposed CMLP models, the optimum number of nodes that can be used for optimal CMLP architecture is 10 for all one, two, and three hidden layers. The overall prediction rate and MSE for the six developed models are computed for one, two, and three hidden layers with 10 hidden nodes. The overall prediction rate and MSE for both orientation and tilt angles are presented in Tables 18 and 19, respectively.

As shown in Tables 18 and 19, model 1 predicted high prediction rate of 95.80%, 95.72%, and 96.20% for one, two, and three hidden layers, respectively. The MSE of model 1 varies from 0.140×10^{-2} for one hidden layers to 0.130×10^{-2} for three hidden layers. Models 4 to 6 achieved approximately close values for the prediction rate. The prediction rates of models 4 to 6 vary from 91.25% for model 4 when one hidden layer is used to 94.47% for models 5 and 6 when three hidden layers are used. The MSE for models 4 to 6 varies from 0.170×10^{-2} for model 5 when three layers are used to 0.390×10^{-2} for model 6 when one layer is used.

Compared with all other developed models, model 3 achieved high prediction rate of 93.87%, 97.37%, and 97.98% for one, two, and three hidden layers, respectively.

TABLE 18 Overall prediction rate (%) of the proposed CMLP-based dual-axis solar tracking system

	Hidden layer(s)		
Model	**1**	**2**	**3**
Model 1	95.80	95.72	96.20
Model 2	88.44	90.84	91.48
Model 3	93.87	97.37	97.98
Model 4	91.25	92.87	93.05
Model 5	93.45	93.68	94.47
Model 6	91.38	93.11	94.47

TABLE 19 Results of MSE rates for the proposed CMLP-based dual-axis solar tracking system

	Hidden layer(s)		
Model	**1**	**2**	**3**
Model 1	0.140×10^{-2}	0.120×10^{-2}	0.130×10^{-2}
Model 2	1.640×10^{-2}	0.950×10^{-2}	0.610×10^{-2}
Model 3	0.180×10^{-2}	0.160×10^{-2}	0.070×10^{-2}
Model 4	0.520×10^{-2}	0.200×10^{-2}	0.260×10^{-2}
Model 5	0.220×10^{-2}	0.190×10^{-2}	0.170×10^{-2}
Model 6	0.390×10^{-2}	0.300×10^{-2}	0.230×10^{-2}

Model 3 achieved very low MSE that varies from 0.180×10^{-2} for one hidden layer to 0.070×10^{-2} for three hidden layers. In contrast, Model 2 achieved relatively small prediction rates compared with the other developed models.

The overall results revealed that model 3 that used day, month, and time variables obtained the lowest MSE and the highest prediction rate among all the developed models when three layers are used. Thus, the best variables to develop the optimum dual-axis tracking system are month, day, and time. The comparison between the results of MLP and CMLP for dual-axis tracking systems and the results of MSE and prediction rate revealed that using CMLP obtained better results compared with MLP in most cases.

The comparison between the results of all developed models in both single-axis and dual-axis solar tracking systems revealed that using month, day, and time variables obtained the lowest MSE and the highest prediction rate among all developed models. In addition, CMLP in dual-axis solar tracking system performed better than the CMLP in single-axis tracking system. On average, CMLP achieved higher performance compared with MLP in both dual-axis and single-axis tracking systems.

3.4 | Discussion of the proposed solar tracking systems results based on intelligent predictors

Comparing all the results of the developed horizontal single-axis and dual-axis solar trackers, evaluating the three intelligent predictors revealed that using linear regression classifier is not sufficient to develop solar tracking systems. Linear regression failed to predict orientation angle and both orientation and tilt angles for dual- and single-axis solar tracking systems. This is because linear regression classifier can only perform well when all input variables have a linear relationship with output variables.

In contrast, it performs worse when nonlinear relationships are exist. However, it found from the correlation analysis, and from both MSE and prediction rate of linear regression that linear model is not applicable.

Moreover, both conventional MLP and CMLP achieved relatively close prediction rates to each other. The model that used day, month, and time variables predicted the highest amount of orientation angles in horizontal single-axis solar tracking system, and the highest amount of orientation and tilt angles in dual-axis solar tracking system. In addition, it has obtained the lowest MSE for one, two, and three hidden layers. Table 20 shows the optimum variables that can be used to obtain the highest performance using linear regression, MLP, and CMLP.

As shown in Table, linear regression obtained low performance compared with MLP and CMLP. Besides, both MLP and CMLP obtained very close prediction rate, whereas CMLP performs better with the lowest MSE for both cases of dual- and single-axis solar tracking systems. It is found that the model of month, day, time, Isc, Voc, and power radiation variables obtained very close prediction rates to the model that used month, day, and time, where MSE of this model is also relatively small.

On the other hand, the results of this research are in line with other works that suggested of using other intelligent trackers namely, ANFIS,[36,38] neural networks (NNs),[22] fuzzy logic,[31] and a fuzzy rule emulated networks (FREN).[16] Table 21 summarizes the suggested models and the main variables that used to drive the proposed models.

As shown in Table, all the presented works have used both day and time variables as input, whereas some of these works added other input variables (ie, month and longitude).[22,31,36] Output variables vary from one model to another, whereas all of the presented works aim to obtain the optimum angles to enhance the performance and maximize the output solar energy. Besides, different intelligent models were used to drive the solar photovoltaics system. Fuzzy logic, ANFIS, FREN, and NNs models were successfully examined and combined with the proposed variables

TABLE 20 Performance comparison of optimum variables for the proposed single/dual-axis tracking systems

	Single-axis tracker			Dual-axis tracker		
Intelligent driver	**Optimum variables**	**Prediction rate**	**MSE**	**Optimum variables**	**Prediction rate (%)**	**MSE**
Linear regression	Month, day, time, V_{oc}, I_{sc}, power-radiation	50.60	3.860×10^{-2}	Month, time, V_{oc}, power-radiation	Tilt: 40.90 Orientation: 68.40	Tilt: 0.360×10^{-2} Orientation: 1.020×10^{-2}
MLP	Month, day, time-3 hidden layers	96.85	0.250×10^{-2}	Month, day, time-3 hidden layers	96.68	0.070×10^{-2}
CMLP	Month, day, time-3 hidden layers	96.83	0.080×10^{-2}	Month, day, time-3 hidden layers	97.98	0.070×10^{-2}

TABLE 21 Comparison of most related research with similar findings

Reference	Intelligent models	Type of tracker	Optimum variables
Alata et al[38]	ANFIS	Dual-axis	Input: day and time Output: altitude, azimuth, declination, hour angles, and the isolation incident
El-Shenawy et al,[22]	NNS	Dual-axis	Inputs: Date, time, and longitude Output: Collector acceptance angle
Al-Rousan et al,[31]	Fuzzy	Dual-axis	Input: day, time, month Output: orientation and tilt angles
Armendariz et al,[16]	FREN	Dual-axis	Inputs: day and time Outputs: orientation and tilt angles
Al-Rousan et al[36]	ANFIS	Dual and single-axis	Inputs: month, day and time Output-single: orientation angle Output-dual: orientation and tilt angles

to achieve higher performance than conventional models combined with other variables. However, one research discussed horizontal axis solar tracking system,[36] where other works focused on studying dual-axis solar tracking systems.

4 | CONCLUSION AND FUTURE WORK

This research aims to investigate and evaluate the most effective variables on orientation angle and both orientation and tilt angles in horizontal single/dual-axis solar tracking systems, respectively. The correlation analysis results revealed that month, time, and power radiation variables have the strongest linear relationships with orientation angle. In contrast, both V_{oc} and day variables have strong nonlinear relationships with orientation angle. However, for dual-axis solar tracking system, time, V_{oc}, power radiation, then month variables have the strongest linear relationships with tilt angle. While month, power-radiation, V_{oc}, and time variables have the strongest linear relationships with orientation angle. In contrast, day and I_{sc} variables have strong nonlinear relationships with orientation and tilt angles, respectively.

In addition, it aims to select the most appropriate combination of solar variables and intelligent predictors. This would help in developing efficient intelligent solar tracker. The main target from this objective is to improve the prediction rate and MSE of conventional intelligent horizontal single- and dual-axis tracking systems. The results of intelligent predictors with the proposed models revealed that the model that used day, month, and time variables achieved the objective with MLP and CMLP predictors for both dual- and single-axis trackers. The same variables achieved high prediction rates for both MLP and CMLP predictors with three hidden layers. MLP and CMLP of horizontal single-axis solar tracking system achieved prediction rates of 96.85% and 96.83%, respectively, whereas the MSE are 0.0025 and 0.0008, respectively. However, for dual-axis solar tracker, MLP and CMLP predicted 96.68% and 97.98%, respectively, with the MSE value of 0.0007 for both.

As a future vision for the current research in the field of solar tracking systems, the focus is on improving and optimizing the current methods and principles to increase the performance and the efficiency of solar tracking systems. Several changes on the current tracking methods can be applied to maximize the solar tracker gain power. Using hybrid techniques, new optimization method for current NNs principles, and using new artificial intelligent techniques are promising methods to increase the efficiency of solar systems.

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