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Solar Tracking System by Utilized Optimized Algorithm Based Deep Learning

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***Abstract*— Solar tracking system is significant for most PV solar power systems in order to enhance the power production. In this study, a dual-axis solar tracking system-based solar tracking algorithm has been designed and implemented. However, several issues still need to be overcome for using a tracker system that includes power consumption related to the electrical part of the tracker and the estimation of the best path based on tracking technology that is utilized. The solar tracker predication algorithm can predicate the best solar path for each day in the year based on location. For this purpose, Deep Recurrent Neural Network (D-RNN) with Long-Term Short-Term units (LSTM) has been implemented to predict the path that the tracker should move with time for all the years. "Adam" optimizer has also been used in order to update network weights iteratively based on the training data. The proposed model achieved more accuracy than slandered algorithm, in which the average RMSE of proposed algorithm is 0.0512 in the training phase and 0.067 in the testing phase, while the average RMSE (Root Mean Square Error) of the traditional machine learning model is 0.0746 in training phase and 0.086 in testing phase.**

Keywords*— *Solar tracking system machine learning, deep learning, Recurrent Neural Network, long-term short-term units

I. Introduction

Renewable energy is becoming the suitable alternative method to generate power along with avoiding the issues associated with climatic change caused by the emission of greenhouse gases. Solar energy is free, practically, inexhaustible, and has no polluting deposits or greenhouse gases emissions, the solar light transformation concept to electricity, called Photo-Voltaic or PV transformation. This technique isn't relatively new, even so the enhancement of power production performance of the PV equipment is still one of major focus for many academic and/or commercial s study groups internationally[1].The PV panel power generation is dependent on the sunlight intensity. The location of the sun relating to any region of the earth variants in a cyclic track during a season. In order to make PV panels get optimum radiation, an automated solar tracking system is utilized for tracking the sun positioning at any position and any time [2]. The PV panel power generation is dependent on the sunlight intensity. The location of the sun relating to any region of the earth variants in a cyclic track during a season. In order to make PV panels get optimum radiation, an automated solar tracking system is utilized for tracking the sun positioning at any position and any time [3]. Solar trackers are the techniques which orient the PV panels continuously according to the changing of the position of the sun and to ensure that at any time the PV panel positioning should be perpendicular in the direction of the sun in order to optimize efficiency. Several tracking systems types that are available nowadays have one or two axes [4]. A single axis tracker can be classified as: horizontal, vertical, tilted and polar aligned. The horizontal can be used in tropical regions where the days are relatively shorter and sun has become high at noon time. The vertical tracer is generally used in areas in which the summer days are long and the sun does not get high. By using one axis tracker it can gain a good amount of power from the solar system. To get more power gain there needs to be using the dual-axis tacking technique [5]. The dual axis solar trackers include both horizontal and vertical axes and as a result they are capable of tracking the sun's motion suitable for placing the PV panel perpendicular in direction of the sun's ray [6]. Passive tackers operation is based on the principle of materials thermal expansion. Hence, the PV panel be perpendicular towards the sun when each side of the tracker has arrived at equilibrium. Then when the Sun's moves this led to one side becoming heated while the alternative side is less temperature this will case the solar panel to be rotated [7].

The aim of this study is to design and implement a solar tracker that utilizes a machine learning algorithm that can move the tracker in a period of time rather than using the traditional LDR that checks and moves the tracker in all time, which led to loss of more power than the proposed model. Furthermore, the proposed model predicates the path efficiently with accuracy up to 99.45%.

II. Related Works

Previous work has regularly proven that the solar panels that utilize the tracker system can raise the total energy by a significant amount. And also, they reported that the energy collection gains from dual-axis tracker systems more than fixed systems ranging from 15% to 40%, based on the time and day of year. Stamatescu et al. (2014) [8], designed and implemented a solar-tracking system for sun follower platforms. The proposed algorithm controlled the motion of a PV in order to track the sun light and to improve the gained solar energy. The algorithm is designed and programmed with LabVIEW (A systems engineering computer software for applications that can measure, test, and control along with rapid access to hardware and information insights) where the presented algorithm was developed. This implementation approach decreases the costs of tracking technique and helps it to be a cost-effective system. Huynh et al. (2016) [9], proposes an adaptable and optimum control approach for a PV system. The control method makes sure that the PV panel is continually perpendicular to sunlight and also runs at its maximum power point for continually collecting maximum power. The suggested control method is the control hybrid between the solar tracker and maximum power point tracker which can significantly enhance the produced electricity by solar PV systems. Relating to the solar tracker system, their work provides two drive methods which includes closed and open loop drives. In addition, their work is even offering an enhanced incremental conductance algorithm for the purpose of raising the maximum power point speed of the tracker during several atmospheric conditions along with ensuring that the operating point constantly moves in the direction of the maximum power point by using their proposed algorithm. The experimental and simulation results achieved validate the efficiency of the proposal placed under several atmospheric conditions. Gabe et al. (2017) [10], designed and implemented a low-cost dual-axis automated solar tracker based closed-loop controller with light-dependent resistors (LDRs) and provided solutions for some related issues that were reviewed earlier. Isaksson et al. (2018) [11], presented a comparison study for several machine learning methods and time series solutions implemented throughout five various sites in Sweden. They realize that utilizing time series solutions is a difficult procedure caused by the nonstationary energy time series. On the other hand, machine learning solutions were more straightforward to achieve. Particularly, they found that the Neural Networks and the algorithm called Gradient Boosting Regression Trees achieve best on average over all sites. Mustafa et al (2018) [12], implemented and designed a Solar tracker system of two axes) utilizing Light Dependent Resistor (LDR) of real dimensions that is simple and inexpensive. The solar panel, two-motor satellite dish, ball-joint, LDR sensor module, and electronic circuit make up the project. This project was compared to a fixed solar panel, and the results showed that the solar tracker produced more output power. Chowdhuryet al. (2019) [13], designed and implemented a standalone low cost but closed-loop dual-axis high-precision solar tracking system making use of the solar position algorithm has been implemented in an Eight-bit microcontroller system. The Almanac algorithm has been employed because of their reliability, simplicity, and fast calculation ability of the solar position. The experimental results showed that use of the solar position algorithm with the solar tracking system can help in outperforming the optical and solar tracking system by 2.1% and 13.9%, respectively. Their results proved that, even with the small-scale sun tracking system, the proposed algorithm that controls the movement of the tracking system has the ability to improve the overall system productivity. Hamad et al (2020) [14], designed and built a Low-cost solar tracking system with smart monitoring system for electrical and tracking performance data. The proposed system's main controller unit was the Arduino microcontroller. The solar panel was moved (horizontally and vertically) by two servo motors (SMs) at maximum light source location sensing by Light Dependent Resistors (LDRs). As a result, the solar panel will absorb the maximum amount of sunlight required to produce the maximum amount of electrical power, resulting in a relatively high efficiency when compared to a fixed-position solar system. Only one current sensor (ACS712 current sensor) and a voltage divider circuit were used to monitor the PV panel characteristics (voltage, current, and power consumption) in real time. The Arduino measuring data is sent to the mobile device via a Bluetooth module HC-05. The proposed system has been tested over a variety of time periods, and the results show that the dual tracking system is more efficient than a fixed system solar panel (at optimum angle that is pre-calculated). Nori et al (2020) [15], A solar tracker system is used, which includes (LDR) sensors, an Arduino UNO microcontroller for system control, and DC motors. The solar tracker's impact was measured in terms of its working time. The timer's electric circuit was used to run the system for one minute and then shut it down for 29 minutes, allowing for a comparison of the tracker's work with and without a timer. Finally, based on the amount of energy gained and lost, it was discovered that the timer system gains approximately 96.25 percent of the energy, while the solar panel loses approximately (0.238 to 0.475) percent of the energy. Alaameri et al (2022) [16], Study the weather conditions in Najaf, Iraq, including solar irradiation, temp, wind speed, and cloud density, and simulate the current proposal using MATLAB and SolidWorks software. We observe that the solar panels tracking is sufficiently stable throughout the year due to the moderate cloud density in Najaf, hence the incidence angle of the sunlight is stable, based on simulation results and field tests in 2019 and 2020. These findings suggest that the Open Loop Sun-tracking system, rather than the Closed Loop model, is more appropriate for Najaf because it is less complex and expensive.

III. Solar Tracking System

Additionally, the components R_d and R_f are known to be affected by cloud coverage. A controller for a solar panel then seeks to maximize total irradiance, Rt, hitting the panel's surface. In the case of solar trackers, a running assumption is that it is near optimal to orient the panel such that its normal vector is pointing at the sun, and thus arises the necessity for accurate solar tracking algorithms [17-18]:

$$R_t = R_d\theta_d + R_f\theta_f + R_r\theta_r \tag{1}$$

Where, R_t is the total solar irradiance hitting a panel, R_d is the direct irradiance, R_f is the diffuse irradiance (light from the sky), R_r is the reflective irradiance, and the $\theta_d, \theta_f, \theta_r$denoting the effect of the angle of incidence between oncoming solar rays and the panel's orientation, yielding the total. In case when use the algorithm to estimate the solar position, it is a difficult task over a long time period. The amount of sunlight at a given day at a given position on the earth can be estimated by finding the suns position relative to that latitude. Thus, at twelve in local solar time, the position of sun is at its highest point at that latitude. The local solar time is likewise dependent upon the angle of declination, that is a calculate of the earth tilt in accordance with its vertical axis and thus varies throughout the years. From these quantities, the sun angle in accordance with the surface at a specific position can be identified, also called the altitude angle. Fig. 1 shows the angles of the sun falling on the solar panel [19, 20].

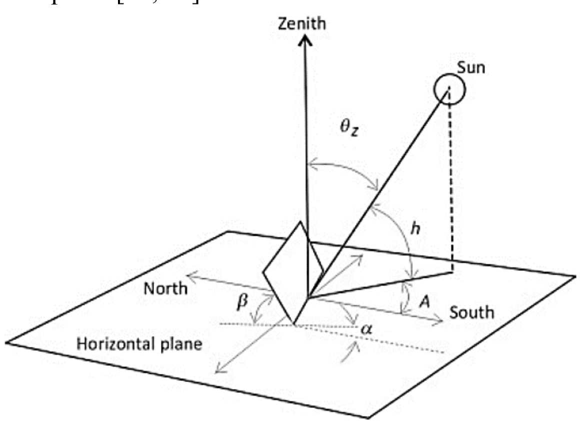

Fig. 1. Definition of angles at a specific location. L is the latitude at that site, δ is the declination angle.[20]

The sun location at any time of the day is described in terms of the azimuth and altitude angle. Hence, the azimuth angle determines the sun's position relative to the true south, or true north when calculations are conducted for the south hemisphere, of a certain location. Here, yet another important quantity must be introduced, namely the hour angle, which is defined as the number of degrees where the earth should be rotated in order to place the sun directly over the longitude [20].

IV. Methodeology

In this work, the prototype model is fabricated in moderated size for the test tracker system. The solar tracking system consists of the mechanical part, the electrical part, tracker algorithm (control the motion of solar tracker). Mechanical parts and electrical parts were integrated into the solar tracker system. Mechanical parts have been fabricated from Metal and aluminum then arranged and connected with two DC motors. Electrical part consist of microcontroller (Arduino MEGA 2560) has been used and programed to be able to save and got the position of sun angles through utilized an algorithm for calculation the solar angles in order to evaluating power generation (where current and voltage sensors was used in order to monitor voltage and current from PV panel), in a way which can allows panel to be moving in dual axis smoothly. The microcontroller controls the rotation of the PV panel via two DC motors. In order to detect x, y position, the variable resistor is used to determine position from changeable values. The other components include the GPS Module typeNEO-6MV2 is used to detect solar time and location, L298N Motor Driver to driven the two DC motors, the charging controller adjust the charging rate based on the battery's charge and protects the battery from overcharging. Fig. 2 show the block diagram of the proposed solar tracker system.

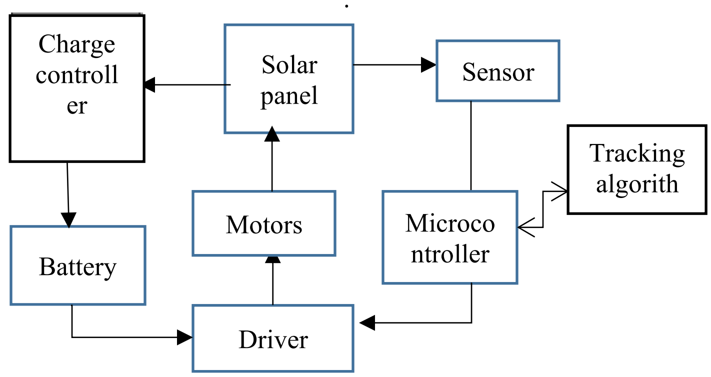

Fig. 2. Proposed solar tracker system

In this work, the Solar path predication (position in the period of time (half hour)) has been achieved by utilizing an optimized algorithm based RNN-LSTM. The Recurrent Neural Network (RNN) is a type of (ANN) which is utilized in the prediction and the modeling of sequenced data in which the result is determine by the input. However, the RNN network utilized in some applications such as speech recognition, image processing, language translation and sentiment analysis. The RNN is able to forecasting a random sequence of inputs due to the internal memory that has the ability to store information related to the previous calculation. Fig. 3 (left) illustrates the standard RNN, in which the hidden neuron is feed-back from some other neurons in a previously time step multiply by the weight (W) [21].

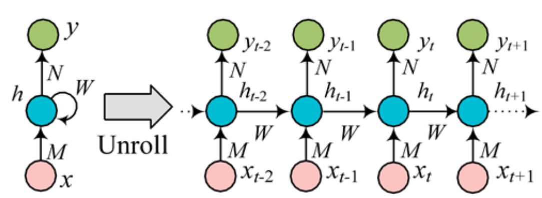

Fig. 3. Unfolded RNN (left), and Folded RNN (right) [22]

The RNN is calculated by [23]:

$$h_t = f_h\,(M \times x_t + W \times h_{t-1}) \tag{2}$$
$$y_t = f_y\,(N \times ht) \tag{3}$$

Where f represents the activation function which includes tanh, sigmoid, or ReLU. [24]. Deep Neural Networks (DNNs) involve the number of hidden layer neurons. Some studies propose that with a greater number of hidden layers, the ANN is able to represent the complicated function more effectively compared to the RNN with fewer hidden layers. The Long Short-Term Memory Unit, LSTM is a subtype of the RNN and was developed to solve the vanishing gradient problem which in some cases halted the training process of the network. This was happened due to the fact that when applying the back propagation to the RNNs network the time aspect is also considered which caused the error from the previous time steps to be reintroduced into the network which in turn caused the gradient of the weight to be vanishingly small and then preventing the weight from being updated. The LSTM solves this issue by introducing a more complex neuron than those used in regular RNNs, also known as LSTMs [25].

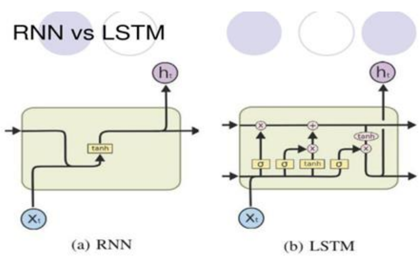

Fig. 4. Regular unit (neuron) compared to the LSTM unit [25]

The LSTM introduces several gates within the cell to manage the dataflow. These gates have weights of their own and allow the cell to learn, through the learning process, when to allow data to enter, leave or be erased. By applying this technique, the LSTM carousels vanish gradients as described above until those gradients are deleted within the cell [26].

The data have been collected and recorded from the auto scanning stage of the proposed system. In the proposed algorithm, the solar path function has been estimated in order to move the PV in the path that can get the maximum energy production. The prediction model consists of two layers: the first one is the input layer that includes long and short memory (LSTM) neurons , with the prediction nodes at the output layer has. During the testing phase, the weights of the prediction model have been obtained at the i which is used in the training phase to evaluate the prediction output in accordance to the input. Keras toolkit has been used to develop the proposed model, in which the Keras is one of the popular deep learning toolkits available. Keras toolkits, as well as other deep learning toolkits such as tensorflow, have big advantages because they are simple and convenient to use. An optimization algorithm, activation and loss parameters have been used in the learning process given by the Keras library..

V. V. PROPOSED SYSTEM STRUCTURE

In this study, a dual-axis solar tracking system-based solar tracking algorithm has been designed and implemented. The tracker can move 150 degrees in x axis and 60 degrees in y axis. The tracker controller is a microcontroller type "Arduino Uno " which is low cost and can achieve overall tracker processes. Multiple sensors has been used to gathering information required such as Voltage Sensor to monitor solar panel voltage generation, Current Sensor to monitoring the system current, the GPS sensor to determine the location as well as local time, in addition to some other electronic circuit required such as Motor Driver Module to control DC motors movement and The charging Module to regulate the voltage and current from the PV array in order to prevent overcharging and also over discharging of the battery. Another part includes 50 watt PV panel, two DC motors has been used to move panel in two axis direction, 12-volt battery to storge the power generated from PV panel and also supply electrical component of PV panel by DC voltage, SD ram is also used to save records such as position and power production. Fig. 5 shows the prototype of proposed solar tracking system.

Fig. 5. Proposed solar tracking system

The LSTM-RNN has been trained in such a way that for each iteration the input time step learns to forecast the value of the newest time step. The results from the sequence-to-sequence LSTM-RNN method in the training sequences having the values that are shifted by one time step. Fig. 6 shows the architecture of the proposed LSTM network with sequence-to-sequence (StS) regression. The first layer is to input the data sequence with the size and the range of features for the LSTM layer.

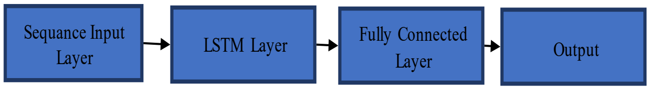

Fig. 6. The Proposed sequence-to-sequence LSTM-RNN architecture

The LSTM-RNN has been trained with the input data sequence to predict the values of the next sequence, the function should be trained to predict for one time step each time and after that updating the state of the network following every prediction. The full dataset is partitioned into training, validating and the test datasets. A processing with the Graphics unit (GPU) has been used for learning and testing stages. 70% of the dataset has been used for training, while 15% of the data has been used to evaluate the prediction performance, and the remaining 15% is used to test the model independently..

For the best fitting and to keep the training process away from the diverging, the training data sequence is standardized to get the zero mean together with unity variance. In order to have the standardized dataset the following equation has been used [27]:

$$D_{std} = \frac{D_{train} - \mu}{\sigma} \qquad (4)$$

Where . D_{std} is the standardized dataset, D_{train} is the training data, μ is the mean value of the training data, and the σ is the variance value of training data.

The predictors (X_{train}) are the training sequences with no final time step, which can be evaluated as:

$$X_{train} = D_{std}(1{:}\,end - 1) \qquad (5)$$

While the responses (Y_{train}) are the training sequences which have the value that shifted by one time step as:

$$Y_{train} = D_{std}(2{:}\,end - 1) \qquad (6)$$

To standardize the tested data (D_{std_test}), the similar parameters is used for the training data, using Equation's yield:

$$D_{std\_test} = \frac{D_{test} - \mu}{\sigma} \qquad (7)$$

$$X_{test} = D_{test-std}(1{:}\,end - 1) \qquad (8)$$

To evalute unstandardized series of the predictions (Y_{pred}), the parameters from step 2 using the standardized prediction $\overline{Y_{pred}}$

$$Y_{pred} = \sigma \times \overline{Y_{pred}} + \mu \;) \qquad (9)$$

The algorthim of LSTM-RNN can be described in follows:

Input:	Sequence Data Set
Output:	Prediction Values

Step 1:	Start.
Step 2:	Input the data sequence.
a.	Input the dataset sequence
b.	Partition the data set to 70% for the training data (Dtrain), 15% for the validating data (Dvalidate) and 15% for the testing data (Dtest).
Step 3:	Standardize the training dataset.
a.	Determine the variance (σ) and the mean (μ) for training dataset (D_{train})
b.	Compute the standardized dataset by utilizing equation 4.
c.	Specifying the predictors (X_{train}) and the responses (Y_{train}) by utilize equation5and 6.
Step 4:	Specifying the LSTM network architecture.
Step 5:	For each i_{th} iteration and n epochs, go for train the network using the desired training options.
Step 6:	Predicating the future time steps.
a.	Utilizing equations 7 and 8 to standardize the test dataset by using the same parameters that been used in the training phase.
b.	For i = 2: N predict and update state. (Where N is time steps number in test data)
Step 7:	Using Equation 9 to find the non-standardized series of the predictions (Y_{pred}) by using the parameters from step (2a) and standardized prediction $\overline{Y_{pred}}$
Step 8:	Compute the loss function and validation.
Step 9:	End.

The proposed model is predicting the values at the specific step time, The first at the time and then at the network state which is updated for every prediction. The previous predictions are used as an input to the function at every prediction step. Initially, standardized the test data in order to get 0 mean and unity variance. In order to run the network state, initially predict the training data. Then, generating the first prediction by using the last time step from the training response and then loop over with keeping the prediction and input the prior prediction to predict and update the state. After that, destandardization the prediction makes use of the variance and mean to compute priority. Finally, the RMSE are calculated and the training data together with the forecasted ones.

VI. Results and Discussion

We have tested the tracking system to compute the system accuracy to track the best angle that will produce maximum power. In the experiment we monitored the electrical power that produced by the PV panel that used the proposed tracker when run in real operation. The results have been recorded and compared with systems that have no tracker. Furthermore, we detail the cost of proposed system in order to compare with other commercial trackers that available in the markets.

A. Collecting Data

In the experiment, the auto-scanning system started scanning in horizontal direction (x-axis) and vertical direction (y-axis). The scanner started at initial point of elevation (y=30 degree), and then started scan horizontally from x=0 to x=150 in 1 degree step, where with each horizontal step it will complete full vertical scanning (from y=0 to y=60) until reaches the maximum horizontal movement (x =150 degree). The reason for using scan in x in range between 0 and 150 and y between 0 and 60 is related to the fact that the visible portion of the sun in any location at any time of day rotates 180 degrees. However, the effects of local horizon will reduce this relatively, which makes the effective motion about 150 degrees horizontal as well as the effects of local vertical is about 60 degrees [28]. The panel is placed in such a way that the center of the tracker is in the center of the sun's horizontal path (i.e., 0 degree in south) as the proposed tracker can move 150 degrees in x- direction. The scanning process can gather information that includes position (x, y), voltage and current at each position and it has been recorded (9000 records) for each period of time. In the test, the scanning process had been run 4 days (from 20 September to 23 September) at a time from 6:30am to 8:00pm. The data then utilized as input for NN to identify the ideal position that panel can produce maximum power. This data is used as a sample to predict the next days in the same month to check the accuracy and effect archive when using Adam optimizer compared with standard algorithms. The best positions with time for max power generation are shown in TABLE I and TABLE II.

TABLE I. THE GENERATED VOLTAGE BY THE PV PANEL WITH TIME FOR DAYS (20 AND 21) OF SEPTEMBER

Time HH:MM	Saturday (20 Sep.)		Sunday (21Sep.)	
	Position	*Voltage*	*Position*	*Voltage*
06:15	(4, 8)	5.8	(4, 8)	6.1
07:45	(11, 13)	17.3	(11, 13)	16.8
08:15	(14, 18)	18.6	(14, 19)	18.6
08:45	(18, 22f)	19.3	(18, 22)	19.2
09:15	(22, 24)	19.5	(22, 24)	19.5
09:45	(27, 27)	19.7	(27, 27)	19.7
10:15	(32, 31)	19.8	(32, 31)	19.8
10:45	(37, 33)	20.1	(37, 33)	20.2
11:15	(42, 38)	20.2	(42, 38)	20.5
11:45	(49, 43)	20.3	(49, 43)	20.6
12:15	(60, 12)	20.9	(60, 12)	20.7
12:45	(71, 34)	21.5	(71, 34)	21.3
13:15	(77, 38)	21.9	(77, 38)	21.8
13:45	(85, 38)	22.1	(85, 38)	22.3
14:15	(91, 45)	21.3	(91, 45)	21.4
14:45	(97, 56)	21.3	(97, 56)	21.4
15:15	(100, 53)	20.8	(100, 53)	20.8
15:45	(103, 44)	20.7	(103, 44)	20.8
16:15	(111, 38)	20.1	(111, 38)	20.2
16:45	(129, 33)	19.9	(129, 33)	20.3
17:15	(136, 29)	19.1	(136, 29)	19.2
17:45	(143, 21)	18.8	(143, 21)	18.5
18:15	(150, 12)	7.3	(150, 12)	6.3

TABLE II. THE GENERATED VOLTAGE BY THE PV PANEL WITH TIME FOR DAYS (22 AND 23) OF SEPTEMBER

Time HH:MM	Monday (22 Sep.)		Tuesday (23 Sep.)	
	Position	*Voltage*	*Position*	*Voltage*
06:15	(4, 8)	5.9	(4, 8)	5.9
07:45	(11, 14)	17.1	(12, 14)	16.9
08:15	(14, 18)	18.8	(15, 19)	18.5
08:45	(18, 22)	19.4	(18, 22)	19
09:15	(22, 24)	19.6	(22, 24)	19.3
09:45	(27, 27)	19.9	(27, 27)	19.6
10:15	(32, 31)	19.9	(32, 31)	19.6
10:45	(37, 33)	20.1	(37, 33)	20.8
11:15	(42, 38)	20.6	(42, 38)	20.3
11:45	(49, 43)	20.1	(49, 43)	20.3
12:15	(60, 12)	20.8	(60, 12)	20.8
12:45	(71, 34)	21.5	(71, 34)	21.4
13:15	(77, 38)	21.7	(77, 38)	21.7
13:45	(85, 38)	21.95	(85, 38)	22.21
14:15	(91, 45)	21.4	(91, 45)	21.1
14:45	(97, 56)	21.4	(97, 56)	21.5
15:15	(100, 53)	20.6	(100, 53)	20.5
15:45	(103, 44)	20.6	(103, 44)	20.6
16:15	(111, 38)	20.6	(111, 38)	20.7
16:45	(129, 33)	20.6	(129, 33)	20.5
17:15	(136, 29)	20.2	(136, 29)	20.1
17:45	(143, 21)	18.4	(143, 21)	18.3
18:15	(150, 12)	7.5	(150, 12)	6.2

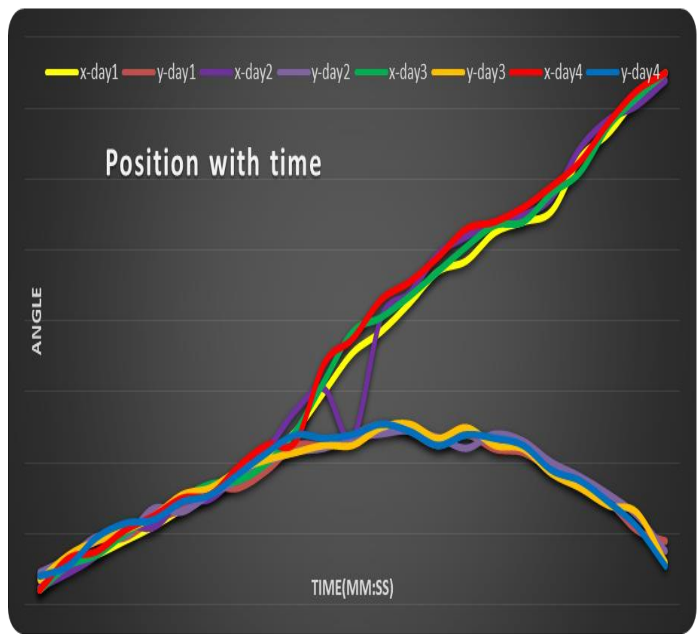

Fig. 7. Panel position changed with time for 4 days.

From TABLE I,II and Fig. 7, it can see that the tracker moves to the best location that can achieve the max power depending on data input. Hence, it can be noticed the x movement increased from 0 to 150 from sunrise to sun sunset, while y movement raised till mid-day then it will be decreased. The results show that the model successfully determines the best path. The output is then trained by the used proposed model. The results show that the average RMSE of the proposed D-RNN is 0.0512 in training and 0.067 in testing.

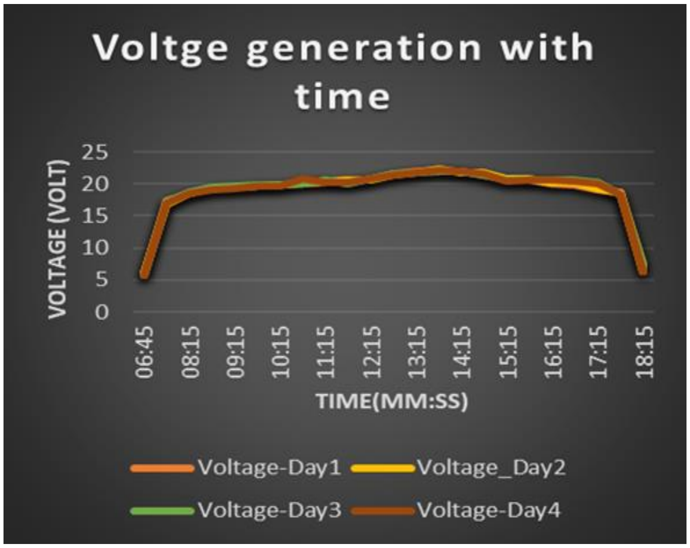

Fig. 8. Voltage generation with time for 4 days

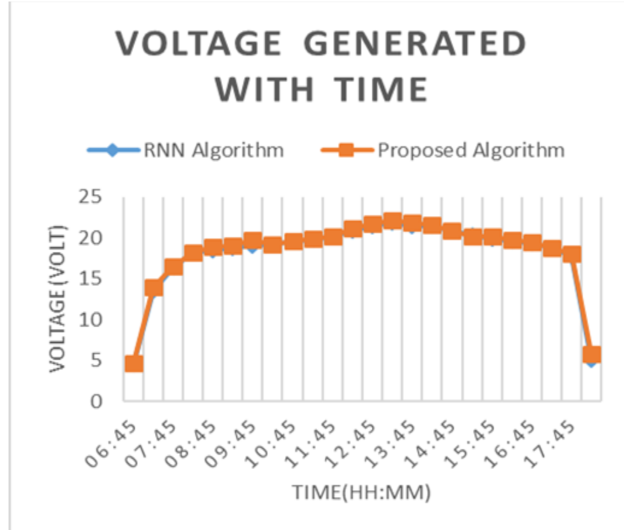

Fig. 9. Power generation results from standard RNN algorithm and enhanced RNN algorithm

The comparison results between the proposed method and the standard RNN method showed the outperform in the RMSE that the average RMSE the average RMSE of the RNN is 0.0743 in the training phase and 0.085 in the testing phase, which shows an improvement in accuracy. The proposed model is then tested for next days where we test the model to predicate the 29 November. TABLE III shows the prediction results and real records.

TABLE III. POWER GENERATION RESULTS FROM STANDARD RNN ALGORITHM AND ENHANCED RNN ALGORITHM

Time HH:MM	29 Nov predicted by RNN		29 Nov (predicated by Proposed Algorithm)	
	Position	*Voltage*	*Position*	*Voltage*
06:45	(5, 8)	4.5	(4,3)	4.7
07:15	(13, 15)	13.6	(10, 9)	13.9
07:45	(15, 17)	16.3	(10, 13)	16.5
08:15	(14, 22)	18.2	(11, 22)	18.2
08:45	(19, 24)	18.5	(14, 24)	18.9
09:15	(22, 27)	18.7	(19, 27)	19
09:45	(32, 31)	19.1	(32, 31)	19.7
10:15	(37, 33)	19.2	(37, 33)	19.2
10:45	(42, 38)	19.6	(42, 38)	19.6
11:15	(49, 43)	19.8	(49, 43)	19.9
11:45	(60, 12)	20.2	(60, 12)	20.2
12:15	(71, 34)	20.8	(71, 34)	21.2
12:45	(77, 38)	21.4	(77, 38)	21.7
13:15	(81, 37)	21.9	(85, 47)	22.2
13:45	(90, 45)	21.5	(91, 48)	21.8
14:15	(93, 49)	21.4	(98, 44)	21.6
14:45	(107, 47)	20.8	(101, 43)	20.9
15:15	(115, 44)	20.3	(112, 41)	20.2
15:45	(118, 40)	19.9	(122, 37)	20.1
16:15	(129, 37)	19.6	(128, 34)	19.7
16:45	(138, 26)	19.3	(133, 25)	19.5
17:15	(141, 19)	18.7	(139, 14)	18.7
17:45	(148, 11)	17.8	(145, 8)	18
18:15	(4, 8)	5.1	(4, 8)	5.8

From TABLE III and Fig. 8 it can observe that the tracker using algorithm with Adam optimizer gain more power than the algorithm without using optimizer, this due to the fact that the optimizer effect on system prediction that give more accurate result to predicate the x, y position that can align panel perpendicularly with sun to produce more power.

VII. CONCLUSIONS

This study aims at designing a dual-axis automated solar tracking system based on machine learning method. The tracker was designed efficiently and low-cost. he solar tracker was designed based on machine learning to calculate the best location that gives the maximum power. The model is based on recurrent neural network (RNN) with (LSTM) in order to raise the total energy collected by solar panels. The results shown and based on geographical information and solar time, the tracking algorithm can predict the best solar path for each day of the year and rearrange the path of the solar panel to the optimal path that (PV) panels generate the maximum power generation in each period of time.

REFERENCES

[1] H. H. Al-Kayiem and S. T. Mohammad, "Potential of renewable energy resources with an emphasis on solar power in Iraq: An outlook," *Resources,* vol. 8, p. 42, 2019.

[2] I. I. R. E. Agency, "Future of Solar Photovoltaic: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects," ed: IRENA–International Renewable Energy Agency Abu Dhabi, United Arab Emirates, 2019.

[3] F. S. Tahir and J. K. Mohammed, "Sun Tracking System Based On Neural Network," *Journal of Engineering and Sustainable Development (JEASD),* vol. 17, 2013.

[4] M. Panait and T. Tudorache, "A simple neural network solar tracker for optimizing conversion efficiency in off-grid solar generators," in *International Conference on Renewable Energies and Power Quality*, 2008, pp. 256-260.

[5] I. Stamatescu, I. Făgărăşan, G. Stamatescu, N. Arghira, and S. S. Iliescu, "Design and implementation of a solar-tracking algorithm," *Procedia Engineering,* vol. 69, pp. 500-507, 2014.

[6] D. C. Huynh and M. W. Dunnigan, "Development and comparison of an improved incremental conductance algorithm for tracking the MPP of a solar PV panel," *IEEE transactions on sustainable energy,* vol. 7, pp. 1421-1429, 2016.

[7] I. J. Gabe, A. Bühler, D. Chesini, and F. Frosi, "Design and implementation of a low-cost dual-axes autonomous solar tracker," in *2017 IEEE 8th International Symposium on Power Electronics for Distributed Generation Systems (PEDG)*, 2017, pp. 1-6.

[8] I. Stamatescu, I. Făgărăşan, G. Stamatescu, N. Arghira, and S. S. Iliescu, "Design and implementation of a solar-tracking algorithm," Procedia Eng., vol. 69, pp. 500–507, 2014.

[9] D. C. Huynh and M. W. Dunnigan, "Development and comparison of an improved incremental conductance algorithm for tracking the MPP of a solar PV panel," IEEE Trans. Sustain. energy, vol. 7, no. 4, pp. 1421–1429, 2016.

[10] I. J. Gabe, A. Bühler, D. Chesini, and F. Frosi, "Design and implementation of a low-cost dual-axes autonomous solar tracker," in 2017 IEEE 8th International Symposium on Power Electronics for Distributed Generation Systems (PEDG), 2017, pp. 1–6.

[11] E. Isaksson and M. Karpe Conde, "Solar power forecasting with machine learning techniques," ed, 2018.

[12] F. I. Mustafa, , S. Shakir, F. F. Mustafa, and A. T. Naiyf. "Simple design and implementation of solar tracking system two axis with four sensors for Baghdad city 2018 9th International Renewable Energy Congress, IREC 2018." (2018).

[13] M. E. Chowdhury, A. Khandakar, B. Hossain, and R. Abouhasera, "A low-cost closed-loop solar tracking system based on the sun position algorithm," *Journal of Sensors,* vol. 2019, 2019.

[14] BA Hamad, AMT Ibraheem, AG Abdullah. "Design and practical implementation of dual-axis solar tracking system with smart monitoring system." Prz. Elektrotech 1, no. 10 (2020): 153-157.

[15] AF Nori, FG Mohammed. "Design and Implementation of an Efficient Solar Tracker System." In Journal of Physics: Conference Series, vol. 1530, no. 1, p. 012150. IOP Publishing, 2020.

[16] KJ Alaameri, AJ Ramadhanand and Alexander S. Maklakov. "Design of dual-axis solar tracking system with integrated cleaning system: Case study of Najaf city, Iraq." In AIP Conference Proceedings, vol. 2386, no. 1, p. 050001. AIP Publishing LLC, 2022.

[17] D. Abel, E. C. Williams, S. Brawner, E. Reif, and M. L. Littman, "Bandit-based solar panel control," in Thirty-Second AAAI Conference on Artificial Intelligence, 2018.

[18] D. Abel, E. Reif, and M. L. Littman, "Improving solar panel efficiency using reinforcement learning," *RLDM 2017,* 2017

[19] M. Benghanem, "Optimization of tilt angle for solar panel: Case study for Madinah, Saudi Arabia," Appl. Energy, vol. 88, no. 4, pp. 1427–1433, 2011.

[20] T. P. Chang, "The Sun's apparent position and the optimal tilt angle of a solar collector in the northern hemisphere," Sol. energy, vol. 83, no. 8, pp. 1274–1284, 2009.

[21] N. Mohajerin, "Identification and Predictive Control Using RecurrentNeural Networks." 2012.

[22] B. Mehlig, "Machine learning with neural networks," arXiv Prepr. arXiv1901.05639, 2019

[23] A. Alzahrani, P. Shamsi, C. Dagli, and M. Ferdowsi, "Solar irradiance forecasting using deep neural networks," Procedia Comput. Sci., vol. 114, pp. 304–313, 2017.

[24] S. Poornima and M. Pushpalatha, "Prediction of rainfall using intensified LSTM based recurrent neural network with weighted linear units," Atmosphere (Basel)., vol. 10, no. 11, p. 668, 2019..

[25] A. Sherstinsky, "Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network," Phys. D Nonlinear Phenom., vol. 404, p. 132306, 2020.

[26] K. Thapa, A. Al, Z. Md, B. Lamichhane, and S.-H. Yang, "A deep machine learning method for concurrent and interleaved human activity recognition," Sensors, vol. 20, no. 20, p. 5770, 2020.

[27] Seb, "Feature Scaling and Data Normalization for Deep Learning," Programmathically,, 2021.

[28] P. Sharma and N. Malhotra, "Optimal Localization of Solar Panel for Better Energy Utilization," SYSTEM, vol. 75, p. 75.