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Maximum Power Point Tracking Controller of PV System Based on Two Hidden Layer Recurrent Neural Network

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ABSTRACT- Solar energy is one of the most well-known and cutting-edge energy sources in the age of renewable energy. However, because of fluctuating meteorological factors like solar insolation and temperature, the output of a solar photovoltaic system varies greatly. For the effective use of solar energy harvested using solar PV units under different climate factors, the Maximum Power Point Tracking (MPPT) technique is a crucial component that needs to be present. The MPPT system regulates the PV system's output (current and voltage) to give maximal power to the load. Conventional approaches may not efficiently use available electricity and may fail in partial shade conditions. This study describes how to build MPPT for a photovoltaic system utilizing a two-hidden-layer recurrent neural network (THLRNN). The system comprises a photovoltaic module linked to a boost DC-to-DC converter, and the THLRNN algorithm is used in this work to produce the duty cycle to the boost converter that drives the PV voltage to the optimal value. Using the MATLAB/Simulink tools, the suggested algorithm's effectivity has been verified. Furthermore, the outcomes that have been obtained have been compared with other MPPT methods (like improved grey wolf optimization algorithms and artificial neural networks), and from the results that have been obtained it was shown that the proposed technique is superior to other methods and increase the efficiency of PV system by 96.6%. Also, this method has been tested under various environmental conditions (variable irradiation and variable temperature) and found that the photovoltaic system with the proposed MPPT continuously traces the highest power point of the PV module. Additionally, the implementation of this algorithm is simple and can predict the output in a highly efficient way.

Keywords: PV module, THLRNN, DC-DC converter, MPPT.

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1. INTRODUCTION

The rising load demand, along with a significant drop in non-renewable sources of energy (fossil fuels) over the previous several years, paves the adoption of replacement energy forms to fulfill the energy need. Solar photovoltaic (PV), wind energy and hydraulic sources help to provide power generation continuity, which is a critical concern for numerous nations to ensure industry growth. They support the utilization of renewable energy forms, the use of multi-source energy techniques, the production of energy that is more environmentally friendly, and/or the preservation of the integrity of the generation and distribution of power means integrity, guaranteeing the reliability of the whole system [1, 2]. Solar energy is the utmost abundant energy source among all renewable sources, is cost-free, and has no adverse effects on the climate. Photovoltaic is a promising sustainable source of energy that has been used in a variety of industries throughout the last few decades, including construction, transportation, and residential, particularly in isolated or rural locations. PV is widely available and may be maintenance-free, unlike fossil fuels [3, 4]. The integration of the grid with photovoltaic systems is expanding globally, raising PV generation's contribution to total global power generation. In that respect, increasing the efficiency of PV systems is crucial for effective operation. This benefit may be achieved by continually drawing the greatest power possible from the photovoltaic array as the outside environment changes. MPPT is critical in the PV array operation to increase the overall system efficiency. The change in environmental circumstances over a day has been represented by the cell temperature (T) and solar irradiation (I_r). The voltage and power of the PV arrays deviate from the ideal point when (I_r) and T change. As a result, the PV array voltage is changed to meet the maximal power output. The boost converter duty cycle may be changed often to change the PV voltage [5]. Researchers from all around the world have developed numerous methods to extract as much energy as is conceivable from renewable energy sources, notably from solar panels. Choosing a certain MPPT system from the different available MPPT systems is a perplexing task because each approach has distinct advantages and limitations. Over the past three decades, several techniques for locating maximum power point (MPP) have been developed. These approaches differ in terms of the number of sensors used, the price, the effectiveness, the complexity, the ability to keep track of changes in temperature or shading, and the convergence speed [6, 7]. There has been a lot of study on MPPT for solar photovoltaic systems in recent years, and the techniques that have evolved so far may be classified into classic and soft computing methods. Traditional approaches include Global MPPT (GMPPT), incremental conductance (IC), and Hill Climbing, perturb and observe. These techniques deteriorate when there is some shade, as they can only measure maximum power under uniform illumination. These methods frequently exhibit slow tracking, weak convergence, and considerable steady-state oscillations [8]. Soft computing approaches are regarded as a top option for non-linear optimization because of their many benefits, including their capacity to deal with nonlinearity, extensive search speed exploration, and coherent capability to achieve global optimal regions. artificial neural networks (ANNs), fuzzy logic control, and heuristic and met-heuristic algorithms are examples of MPPT soft computing methodologies [8, 9].

In this work has been used a two-hidden layer recurrent neural network (THLRNN) to ensure optimal MPPT performance. An efficient PV system built on THLRNN ensures a very quick response to changes in the climate.

2. BACKGROUND

Owing to the versatility of the PV panels, researchers have made several attempts to extricate as much power as feasible from them. Numerous MPPT techniques have been developed up to this point as demonstrated in table 1. Every technique has a distinctive set of operational procedures, applications, and advantages. In [10], the perturb and observe approach was highlighted because electronic programmable circuits may easily apply it. This study used a model that integrates numerous environmental parameters to examine how PV panels behave and how MPPT trackers manage their output. In [11], to monitor the global peak under uniform irradiance conditions and partly shaded conditions, the authors offered an enhanced PSO (particle swarm optimization) algorithm. With this approach, the initial location of the particles (in this case, the converter duty cycle) may be predetermined using a strategy rather than at random. In [12], to raise the efficiency of a solar photovoltaic system, the suggested research compared two methods of control: fuzzy logic and incremental conductance (IC) algorithm. The algorithms mentioned above altered the power converter's switching frequency to track the overall maximum power point of a PV array. Reference [13] proposed a new hybrid MPPT that blends IC with a modified grasshopper optimization algorithm (GOA). The suggested modified GOA was put into practice in the first stage to identify an appropriate tracking region where the GMPP (global maximum power point) is situated. The system then advanced to the second level via utilizing incremental conductance to attain the appropriate GMPP. In [14], to get the most power out of solar systems under both constant and changing irradiance conditions, the enhanced fractional voltage-based MPPT approach was used. Reference [15] described the use of artificial neural networks (ANNs) to track maximum power points. ANNs were trained using the error-back propagation method. This technique used an NN to specify the maximum power point's reference voltage under various atmospheric circumstances. To meet the MPPT objectives without the use of inverters, [16] suggested a segmented structure of the electric thermal loads with a control algorithm. Authors of [17] proposed a GMPPT control method depends upon both the BFBIC (boost full-bridge isolated converter) topology and an IGWO (Improved gray wolf optimizer) algorithm, as well as taking into account unexpected changes in the external environment.

Table 1. Literature review of different algorithms used as an MPPT system

Ref.	Approach	Advantage	Disadvantages
[10]	P&O	Ease of realization	At stability, the point of operation oscillates about the maximum power point, resulting in a waste of the available energy output from the panel.
[11]	Improved PSO	The improved particle swam optimization technique can reach the global peak efficiently and fast under UIC and PSC	The particle swarm optimization algorithm's disadvantages involve a low rate of convergence through repetitive processes and the ease of falling into local optimal in high dimensional space.
[12]	Step IC based on fuzzy logic controller	Output power can be increased and also fluctuation can be eliminated, and react rapidly to changing weather conditions.	It is completely dependent on human knowledge and expertise
[13]	A modified grasshopper optimization algorithm with IC.	The shortest time for tracking and tracking efficiency is maximized when compared to some of the most advanced MPPT algorithms, including modified firefly and particle swarm techniques.	Complex
[14]	improved Fractional voltage based MPPT scheme	Efficient power tracking under changing illumination compared to traditional MPPT methods.	Tuned PI controller by GWO algorithm consumes more time to find the suitable PI parameters
[15]	ANN	Maximum power point tracking that is quick and precise	Less powerful than RNN
[16]	LS-MPPT	Accurate MPPT	Very complicated and the load segment number should be raised to improve accuracy.
[17]	IGWO with BFBIC	Superior results compared to several other metaheuristic algorithms	Limited solution precision, slow convergence, and vulnerability to local optimum
Proposed method	THLRNN	Efficient power tracking under various irradiance and temperature conditions and straightforward to implement	The training of the THLRNN might be difficult.

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3. PV MODELLING

The first step in analyzing a PV system's behavior is modeling. PV array modeling begins with a mathematical model of a single photovoltaic cell. Numerous models of solar cells have been recorded in the literature. The most popular model types are a two-diode and a single-diode solar cell. Compared to the 2-diode solar cell model, a single-diode type is relatively straightforward to implement [18]. Figure 1 depicts the equivalent circuit for a photovoltaic cell (single-diode type) [19].

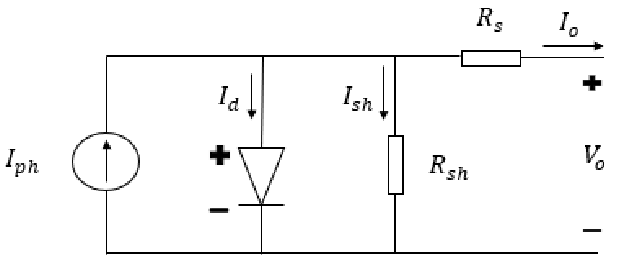

Figure 1. Circuit diagram of single diode model.

A shunt resistance (R_{sh}), a series resistance (R_s), and a photo-produced current source (I_{ph}) in parallel with a rectifying diode comprising the single-diode model. The output current I_0 of this circuit may be computed using Kirchhoff's law of current [19].

$$I_o = I_{ph} - I_{sh} - I_d \tag{1}$$

$$I_o = I_{ph} - I_{sd1}\left[\exp\left(\frac{q(V_o + I_o R_s)}{n_1 kT}\right) - 1\right] - I_{sd2}\left[\exp\left(\frac{q(V_o + I_o R_s)}{n_2 kT}\right) - 1\right] - (V_o + I_o R_{s)}/ R_{sh} \tag{2}$$

Where I_{sh} denotes the shunt current passed through (R_{sh}) and I_d denotes the current through the diode. Furthermore, I_d may be calculated using the Shockley equation, as demonstrated in *equation 3* [19].

$$I_d = I_{sd}[\exp\left(\frac{q(V_o + I_o R_s)}{nkT}\right)) - 1] \tag{3}$$

Where (*n*) is the ideal diode factor, I_{sd} is the saturation current, the charge of the electron is signified by q and is equal to 1.60217646×10^{-19}C, T is the junction temperature in Kelvin, V_0 is the output voltage, and the Boltzmann constant is denoted by k and is equal to 1.3806503×10^{-23}J/K. Furthermore, I_{sh} may be computed using Kirchhoff's law of voltage [19].

$$I_{sh} = \frac{V_O + I_O R_S}{R_{sh}} \tag{4}$$

Based on (3) and (4), the output current is [19]:

$$I_o = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V_o + I_o R_s)}{nkT}\right) - 1\right] - \frac{V_o + I_o R_s}{R_{sh}} \tag{5}$$

4. DC-DC CONVERTER

The quantity of PV array output voltage is determined by the PV module configuration. Because of the spasmodic nature of PV sources, load specifications, and the necessity to produce a continual DC voltage with maximum efficiency, most PV applications require a regulator or a DC-DC (DC chopper) converter to control or manage the output DC voltage that photovoltaic arrays provide. As the PV system installation trend shifts toward grid-connected schemes and large-scale plants, it is critical to improve the abilities of the DC chopper to obtain a large rating of power and a high level of voltage at the common coupling point. A standard boost (step up) converter can theoretically produce a large voltage gain. [20, 21]. When the boost converter duty cycle is adjusted using the MPPT algorithm, maximum power is achieved.

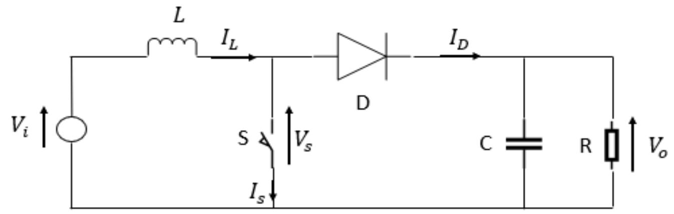

Figure 2. The boost converter schematic.

Figure 2 shows the architecture of the boost power stage, in which V_i is the input voltage, L is the input inductance, I_L is the current passing through the input inductance, V_s is the switch voltage, I_D is the diode's current, C is the capacitance, and R denotes the load [22, 23].

5. SUGGESTED MPPT SYSTEM

The MPPT is a method for obtaining the maximal power possible from a PV module. This is accomplished with the aid of a DC-DC converter, which functions in such a manner that its output continuously provides the greatest power generated by the module in a certain environment [24, 25]. This work has used an MPPT for a PV system depending on THLRNN. The THLRNN is a deep-learning prediction algorithm. It discovers the connection between the output and input datasets. THLRNNs can keep the previous data in their internal memory. The output of a THLRNN produces a predicted value for the duty cycle, and a decision is made based on these values. The duty cycle value (D) is approximated using the THLRNN. Temperature and radiation serve as the THLRNN approximator's input signals. We assume that there are optimum centers (C_1^* *and* C_2^*) optimum weight (W^*), optimum feedback weights (W_r^* *and* W_{r0}^*) and optimum base widths (b_1^* *and* b_2^*), D may be calculated as $D = W^{*T} H_2^* + \varepsilon$, where $H_2^* = H_2^*\ (x, W_r^*, W_{r0}^*, b_1^*, b_2^*, c_1^*, c_2^*)$ and ε is a small positive constant. D' is an estimation value of D utilizing a two hidden layer recurrent neural network. Then, the difference between D (unknown function) and its predicted value D' is expressed as follows: $D - D' = W^{*T} H_2^* - W^{\Lambda T} H_2^{\Lambda *} + \varepsilon$. Under different environmental circumstances, the neural networks that have been trained can produce the optimum voltage for the maximum power point. For training, a back-propagation method that depends upon a gradient descent technique has been used to update the various parameters of the THLRNN because it is simple and easy to use. Two inputs represented by temperature and irradiance and one output represented by the duty cycle are considered. A THLRNN structure with four levels, including the first layer that represents an input layer, a second layer that constitutes the first hidden layer, a third layer that depicts the second hidden layer, and the last layer that represents the output layer, is shown in *figure 3*.

In *figure 3*, the first layer sends the input signal(temperature, irradiation, and error) and gets the output signal of the feedback signals (exY) in the last layer. The feedback weight (W_{r0}), where $W_{r0} = [W_{r01}, W_{r02}, \dots, W_{r0m}]$, connects the first layer to the last layer. The input layer's output expression is [26]:

$$\theta_i = x_i \,.\, W_{roi} \,.\, exY \quad , i = 1,2, \dots \dots, m. \tag{6}$$

To complete the signal feedback, the signal is transferred from the first layer space to the second layer space, and a feedback loop is added to this layer. The Gaussian function is taken as the activation function, $H_1 = [h_1, h_2, \dots, h_n]^T$, and the *j*th node's Gaussian function is determined as [26]:

$$h_{ij} = e^{-net_{ij}} \; , net_{1j} = \sum_{i=1}^{m} \frac{\|\theta_i - c_{1j}\|^2}{b_{1j}^2} \quad , j = 1,2, \dots, n \tag{7}$$

Where the center is $c_1 = [c_{11}\; c_{12} \;\cdots\; c_{1n}]^T$, and the base width is $b_1 = [b_{11}\; b_{12} \;\cdots\; b_{1n}]^T$. Then, the signal is mapped from the second layer space to the third layer space in the third layer, as an activation function is used the Gaussian function, $H_2 = [h_{21}, h_{22}, \dots, h_{2l}]^T$, and the *k*th node's Gaussian function is computed as [26]:

$$h_{2k} = e^{-net_{2k}} \; , net_{2k} = \sum_{j=1}^{n} \frac{\|h_{1j} - c_{2k}\|^2}{b_{2k}^2} \quad , k = 1,2, \dots, l \tag{8}$$

Where the center is $c_2 = [c_{21}\; c_{22} \;\cdots\; c_{2l}]^T$, and the base width is $b_2 = [b_{21}\; b_{22} \;\cdots\; b_{2l}]^T$. As an output (*Y*), the neurons of the last layer add the Gaussian vector product computed by the third layer neurons with the weight (W). The THLRNN's output is [26]:

$$Y = W \,.\, H_2 = W_1 h_{21} + W_2 h_{22} + \dots + W_l h_{2l} \tag{9}$$

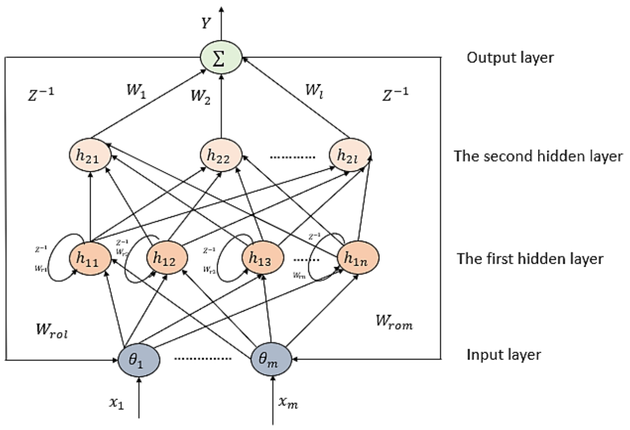

Figure 3. Structure of the THLRNN

6. TRAINING THE THLRNN

As mentioned earlier, *figure 3* depicts the neural network construction employed in this work, which has a four-layer. The input layer contains three neurons that correspond to the three-dimensional input vector $(T, I_r, e(n))$, the two hidden layers have twenty neurons (Sensitivity analysis is used to determine the number of neurons in this layer.), and the output layer contains one neuron that corresponds to the single output. Full synapses connect the levels, i.e. neurons in the first layer are completely linked to neurons in the second layer, likewise, neurons in the second layer are fully linked to neurons in the third layer, which is fully linked to the last layer. The THLRNN is trained in this study offline. To update the parameters, the network employs the error back-propagation learning technique. This algorithm can be summed up as follows:

a. Initially set the synaptic weights, centers, and bases to a tiny random integer and these weights will change during training.

b. Provide an epoch of training exemplars to the network (800 epoch is used in this work).

c. To the input layer, apply the input vector $(T, I_r, e(n))$, and the required output (the D value) to the neurons of the last layer, then compute the error signal for the output layer as follows:

$$e(n) = D - D^{\wedge} \tag{10}$$

The network's operation consists of two passes: forward and reverse. Outputs from the forward pass are computed and compared to the desired outputs. Error between the desired and actual output is computed. This error is used to adjust the network's weights, centers, and bases during the backward pass to minimize the error's size. Repeated forward and backward passes are made until the error is sufficiently small.

d. Repeat the calculation by providing new training epochs until the mean square error (MSE) calculated for the whole epoch reaches a low value. MSE is provided by:

$$MSE = \frac{1}{2N} \sum_{i=1}^{N} e_i(n)^2$$

Where *N* is the training set number in one epoch. *Figure 4* displays network performance throughout training.

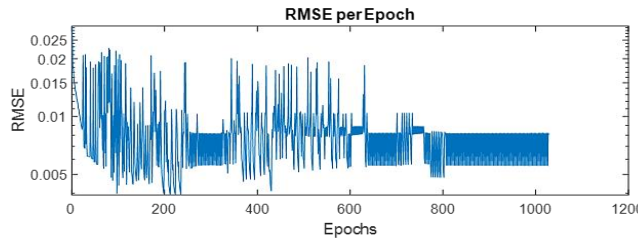

Figure 4. THLRNN MSE (training).

The performance of the training is summarized in *table 2*.

Table 2. Performance of THLRNN during training

Epoch	800
MSE	0.003

Time complexity, or the rate at which the amount of time needed to discover a solution increase with the number of

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parameters (weights), is a crucial factor to take into account when training a THLRNN. There is no set formula that specifies how many epochs you need.

7. COMPLETE SYSTEM

Figure 5 displays the full diagram of the system. The photovoltaic cell is essentially a PN semiconductor junction diode that uses solar radiation to produce electricity. Following that, the energy will be given to the load via the boost converter, which will be regulated by a maximum power point tracking controller.

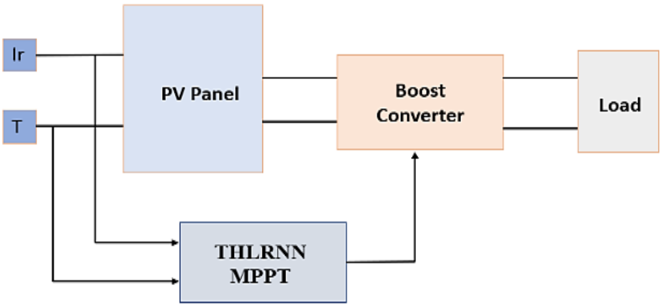

Figure 5. Schematic representation of the entire system.

The MSX-60 panel that was utilized for this work is demonstrated in *table 3*.

Table 3. Features of the STC MSX-60 PV panel

Parameters of the PV panel	Magnitude
Max. power (P_{max})	60 W
The voltage at maximum power (V_{mp})	17.1 V
Current at maximum power (I_{mp})	3.5 A
Short circuit current (I_{sh})	3.8 A
Open circuit voltage, (V_{oc})	21.1 V
Voltage/temperature coefficient (K_v)	−0.38%/° C
Current/temperature coefficient, K_I0.065%/° C	0.065%/° C
The cell number (N_s)	36

8. SIMULATION RESULTS

The results have been achieved using the MATLAB Simulink software package. The suggested PV module was linked to a boost DC-DC converter to build a PV system unit. For assessment and comparison analysis, simulation work was done utilizing a THLRNN MPPT control method, an ANN method, and an IGWO technique, respectively. Oscillation, time response, stability, and overshoot are the most crucial variables to take into account while evaluating the efficiency of each MPPT technique. *Figure 6* shows a comparison between the output power of a PV system using THLRNN, ANN, and IGWO maximum power point tracking algorithm. *Figure 6* demonstrates that the ANN method and IGWO algorithm performed poorly, contributing to high overshoot, high oscillation, and being less stable than the THLRNN.

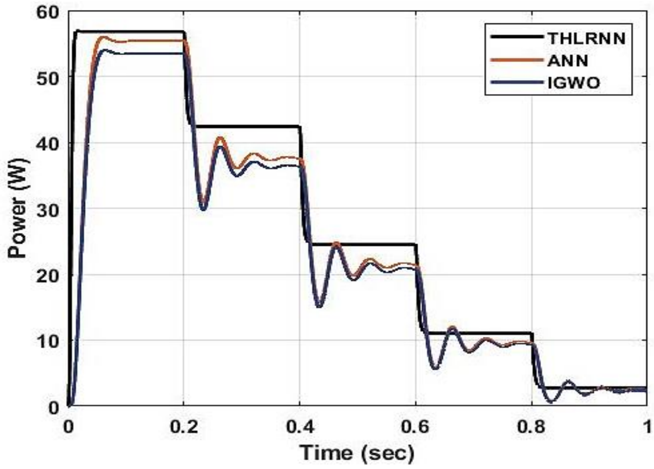

Figure 6. Comparison between the power output of PV system using THLRNN, ANN, and IGWO MPPT under a change in irradiation.

Figure 7 shows how the output voltage curve produced using the suggested technique has better output characteristics and less oscillation than the curve produced using the ANN and IGWO methods. *Figure 8* depicts the range of irradiations used in all simulations.

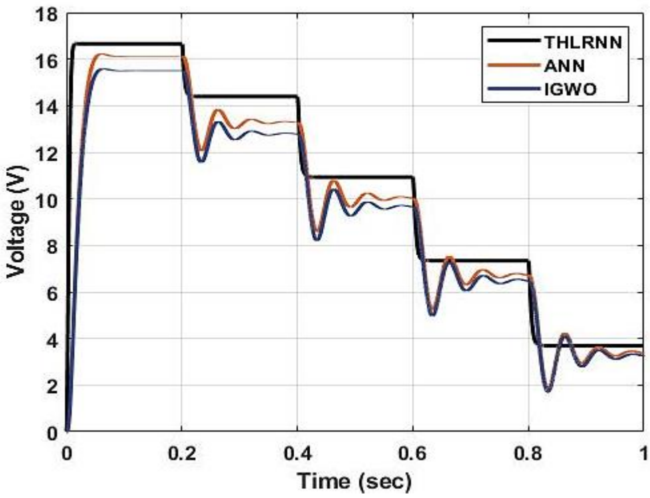

Figure 7. Output voltage with various algorithms MPPT

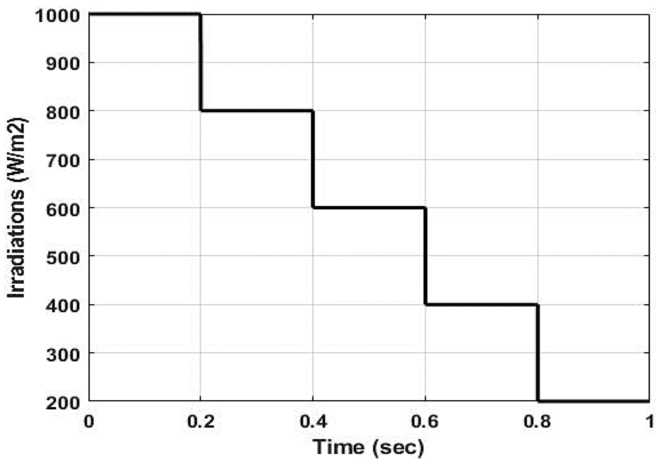

Figure 8. Variations in the irradiations with time

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The proposed technique was also tested when the radiation and temperature were changed with each other. The output power of the suggested technique has been compared with the ANN technique and the IGWO method when the irradiation and temperature change together. *Figure 9* demonstrates the output power of the system with a variation of radiation and T=50°C, while *figure 10* shows the PV output power with a variation of radiation and T=75°C. From the results obtained, we see the efficiency of the proposed system when changing the external conditions when compared with the other systems.

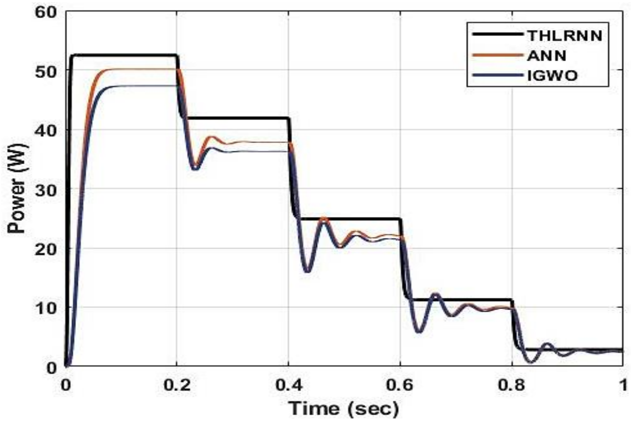

Figure 9. Comparison of the PV output power using various algorithms at various irradiations and T=50°C.

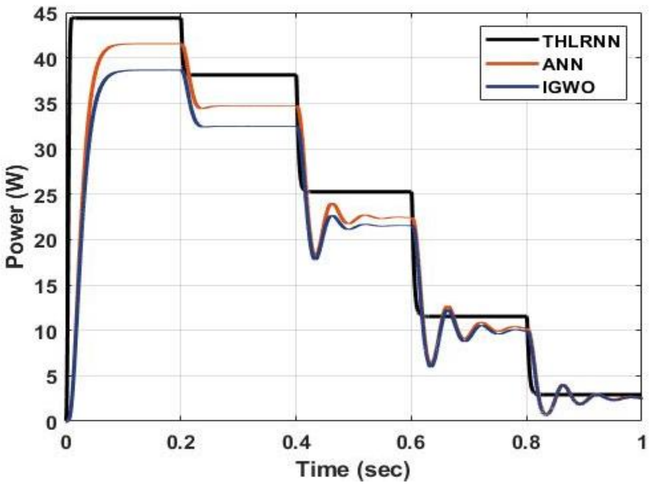

Figure 10. Comparison of the PV output power using various algorithms at various irradiations and T= 75°C.

Table 4 shows the efficiency and tracking time of the three algorithms. The data in *table 4* shows that the suggested MPPT has the highest efficiency and shortest tracking time.

Table 4. Comparison between the efficiency and tracking time of the three different algorithms

Scenario	Tracking time (s)			Efficiency		
	THLRNN	ANN	IGWO	THLRNN	ANN	IGWO
Irradiance variation	0.31	0.47	1	96%	89 %	82%
Irradiance and temperature variation	0.35	0.56	0.8	90%	81 %	64%

9. CONCLUSION

As a result of the P-V characteristics of the photovoltaic array that producing several peaks under various operating conditions, an effective MPPT technique that can provide the greatest power to the load and exhibit minimal oscillations in steady-state situations is required. To meet these needs, numerous research has been published in the literature utilizing techniques like the enhanced grey wolf optimization algorithm and the conventional artificial neural network. Nevertheless, these efforts increased the system's performance when utilized as an MPPT, there is still need for more development to minimize the oscillations and failure rate under steady-state conditions. To bring the system closer to the peak power point, an offline trained THLRNN technique has been used. The suggested MPPT approach outperforms other MPPT algorithms by Improves efficiency and minimizes power fluctuations as seen from the results obtained. In addition to, this method can be applicable to a variety of solar PV applications. The suggested method's drawback is that THLRNNs may experience vanishing or exploding gradients when using a back-propagation technique for updates the weights, bases, and centers, which might make it challenging to train the network efficiently. Metaheuristic optimizations can be used as a future work to updates the network's parameters.

Author Contributions: The research was carried out by Fatimah F. Jaber and Abdulhasan F. Abdulhasan, who also implemented the solar tracker, analyzed the data, and verified the findings.

Conflicts of Interest: "The authors declare no conflict of interest."

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