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Salp Swarm Optimized Hybrid Elman Recurrent Neural Network (SSO-ERNN) based MPPT Controller for Solar PV

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Abstract: Renewable energy technologies provide clean and abundant energy that can be self-renewed from natural sources; more support from the public to replace fossil fuels with various renewable energy sources to protect the environment. Although solar energy has less impact on the environment than other renewable sources, the output efficiency is lower due to the different weather conditions. So to overcome that, the MPPT controller is used for tracking peak power and better efficiency. Some conventional methods in MPPT controllers provide less tracking efficiency, and steady-state oscillations occur in maximum power tracking due to the sudden variations in solar irradiance. Thus, in this work salp swarm optimized (SSO) based Elman recurrent neural network (ERNN) controller is proposed to track the maximum power form PV with high efficiency. The weight parameter of ERNN layer is optimized with the help of SSO, which solve the complex problems and give maximum efficiency. The proposed method is performed in MATLAB/Simulink environment, which differs from existing plans and gives a better output efficiency. Using this proposed controller, the system can achieve high tracking efficiency of 99.74% compared to conventional processes.

Keywords: Photovoltaic system, maximum power point tracking, salp swarm optimization, recurrent neural networks, the weight of the layers, solar irradiance, duty cycle, tracked power.

I. INTRODUCTION

In today's life, there is an enormous demand for electricity for household appliances. Electricity demands play a crucial role in home and industrial applications [1]. In a developing world, there is necessary to meet our needs with electricity in all ways. So many countries have proceeded towards the latest grade of green energy called Renewable Energy in order to meet the above-mentioned demands [1]. Non-conventional energy is nothing but the naturally gifted energy that can replenish itself, while non-renewable energy has bounded supplies. Renewable energy is acquired from many natural sources such as sun, wind, water, geothermal, etc., [2]. Among these energy sources, solar energy is more advantageous than others since it does not emit any harmful pollutants into the air and also does not release greenhouse gases to the earth [3]. The only limitations of solar energy are high upfront costs and lack of efficiency. To defeat that, the maximization of power technique is utilized to catch supreme power from the solar panel. The PV module is a significant device in a PV system that comprises 30-50 PV cells in series connection [4].

This PV array is mounted where sunlight falls on it to collect solar energy from the sun. Based on the irradiance of sun light and meteorological conditions, the output from the PV module affects the extraction of extreme power [37-38]. To achieve better electrical energy that is carried to the load as maximum, an MPPT controller is used [5]. For the MPPT technique, many algorithms are put forward by the researchers. In some research, online and offline methods are grouped in this control algorithm. In the online mode, the system is controlled by measuring parameters from the PV module to track the maximum power [39]. In the offline process, some particular formulas are used to track maximum power [6]. Online process is more realistic than offline methods, so the online method is preferable. Perturb and observe (Per&Ob) [7] techniques, incremental conductance (In Cond) [8], hill climbing (Hil Climb) and fuzzy logic controller (FLCont) [9] are part of the online methods.

These above-mentioned techniques are used only for medium power applications where power extraction is unnecessary. In the Per&Ob technique, the existing energy is compared with the previous power and gives the resultant

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power. The system will process in forwarding mode when the comparable outcome is good and else in the reverse direction [2]. Due to this, high steady-state oscillations occur under peak power which is the major disadvantage of this method. Low tracking efficiency occurs during the variation in solar irradiance at steady-state operation. Even though FLCont is simple and has minimum hardware requirements, its rules are complicated. Furthermore, FLCont should not track the real power when there are sudden changes in solar irradiance [10].

To beat this drawback and achieve high tracking efficiency, a salp swarm optimized (SSO) Hybrid Elman recurrent neural network (ERNN) based MPPT controller is used. Salp colonies inspired SSO, and it is barrel-shaped animals. These animals live in swarms arranged in long chains seeking phytoplankton [11]. The SSO technique resembles the behaviour of salps in nature and is a kind of salpidae family as well as similar to jellyfish in tissues. It faces some limitations, such as since its exploitation ability is not good, convergence speed is slow [12]. To avoid this, the article combines the SSO algorithm with ERNN.

A Neural network (NN) is a computing system that performs like a neuron in the human brain, and the interconnected neurons work together to solve daily problems. The human brain is like an information processing machine connected to send and receive signals for human action and is the basic example of NN [13]. A typical NN layout includes three layers, in which the input layers provide information from the outside world to the network and pass the information to the hidden layer [40-41]. It acts as a summation layer of the incoming signals and converts them to the next layer, which makes the calculated information available to the world [14]. A Recurrent neural network (RNN) is a machine learning algorithm for sequential data which is used in natural language processing (NLP), such as the generation of handwritten text, performing machine learning and speech recognition [15]. RNN is a three-layer structure in which the hidden layer is called context units [42]. The whole history can be compressed in low dimensional space, and short-term memory is formed by RNN [16]. The training procedure of RNNs is complex and slow. There are some instability in the output properties and the adjustment of the weighting process due to the non-linear unit activation [17]. To defeat the limitations of RNN, this paper proposed a salp swarm algorithm is a hybrid with ERNN to achieve better performance in the power tracking process. ERNN is the type of RNN that shows excellent information with time management because an additional layer can attach to the hidden layer and store the information in the training process [18].

There are two physical components in NN, processing elements and connections. Neurons are the processing elements, and the connection between neurons is called links. Each connection has a weight parameter; by controlling this weight, the output is obtained. To adjust these weight parameters, a hybrid ERNN-based SSO algorithm is applied to achieve better performance, and this is the primary motivation for proposing this algorithm in this paper.

The primary involvements of this work are mentioned below,

- To capture the solar irradiance, a PV system is used, which consists of a set of PV panels that collects the photons from the sunlight.
- An MPPT controller is used to track maximum power with the help of Elman recurrent neural network-based salp swarm algorithm, which accepts the result from the PV panel and passes the output to the converter.
- The salp swarm algorithm is used to update the layers which present in the Elman recurrent neural network.
- DC load can operate with the converter's signal without decreasing its efficiency.

This paper is organized as follows, Section 2 explains the variant algorithms-based MPPT Controller for solar PV. Section 3 discusses the proposed methods, Elman Recurrent Neural Network and salp swarm algorithm. Section 4 gives the output results and discussion. Thus the paper was concluded in section 5.

II. RELATED WORKS

The conventional methods such as P&O and IC were not succeeded in the maximum power tracking process to achieve maximum efficiency from PV panels with low yields, Ahmet Gundogdu and Resat Celikel [19] implemented an artificial NN-based MPPT algorithm (A-MPPT). Temperature and voltage were given as the input of ANN, and the output of ANN was reference voltage. The output voltage from ANN was regulated using a PI controller; maximum power was generated under variable atmospheric conditions.

Imran Haseeb et al. [20] performed A- MPPT Hybrid with Boost Converter (HBC) to balance the output power. In the neural network algorithm, there was difficulty in data processing and interpretation due to a large number of weighted links in each neuron. So for that back-propagation algorithm was performed with multilayer feed-forward NN to predict a set of weights iteratively. There were two steps, offline and online, in which the offline measures were used for training ANN in terms of training algorithm and function structure, whereas the online procedures were utilized in the online action.

Although a fuzzy logic controller could solve some engineered-based problems, it does not become possible for partially shaded conditions. Hence Shaik Rafi Kiran et al. [21]

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proposed Variable Step Size Radial Basis Functional Controller (RBFC) based on FL cont for partially shaded conditions. The network was trained by two concepts, namely supervised and unsupervised concepts. Supervised concepts were used to give initial weights to neural nodes, whereas unsupervised technique was used to perform RBFC, and the learning algorithm updated the neural node weights.

Annapoorani Subramanian and Jayaparvathy Raman [22] proposed a modified seagull optimization algorithm (SOA) based MPPT controller. In that paper, modified SOA MPPT was incorporated with the Levy Flight Mechanism (LFM) to improve the global search for SOA. Moreover, the heat transfer formula in thermal exchange optimization (TEO) was incorporated to increase the local search, which means finding the best solutions for SOA. TEO functioned under newton's law of cooling; according to that, part of the agents was assumed as cooling objects and others as an environment to improve the exploitation capability of SOA.

Hegazy Rezk and Ahmed Fathy [23] suggested a stochastic fractal search (SFS) optimization-based MPPT controller. To begin the random fractal growth, the diffusion- limited aggregation (DLA) concept was applied, and SFS was structured by two phases, the diffusion and updating. In diffusion, each particle has potential energy, spreadings over its surroundings to improve the exploitation capability. Then to increase the exploration ability, SFS was updated randomly.

Van-Quang-Binh Ngo and Mohsen Latfi [24] suggested an improved krill herd (KH) algorithm for variable step size on the Per &Ob method-based sliding mode controller (SM Cont) in solar. The algorithm depended on the imitation of the behaviour of krill animals to seek food. It could deal with the non-convex optimization problems and operate with a random krill population. The KH algorithm was not dependent on high convergence speed, parameter settings and the ability to deal with discrete and continuous optimization problems. To increase the efficiency of MPPT in an on-grid PV system, SM Cont was proposed. The ϴ-Modified KH (ϴ-Modified KH) algorithm was applied to control the SMCont parameters to work with variable step size Per & Ob and produce a duty cycle for the converter.

Peak power traction in the solar recommended more searching agents in the primary point of execution to improve explorations, while in the last stage less number of searching agents were required to enhance exploitations. Ali M. Eltamaly [25] proposed a musical chair algorithm (MCA) based MPPT controller on improving that. This algorithm was based on the principle of the musical chair game, in which the number of searching agents was higher at the initial step of the exploration progression process, and the number of agents decreased by discarding the unsuitable one on each step to improve exploitation for the accurate trapping of GMPP.

Walid S. E. Abdellatif et al. [26] implemented the fuzzy logic controller (FLC) for grid-connected PV, in which the DC to DC converter was operated using the FLC algorithm. The algorithm consists of three processes: fuzzification, knowledge base and defuzzification. Crisp value as input converted into fuzzy value in fuzzification process, and the fuzzy process is based on a set of such rules as IF and THEN. After computing by that rules, the fuzzy value was converted to a crisp value and provided as an output known as the defuzzification process. Based on that, the converter was operated and could track maximum power.

Revathy et al. [27] implemented an adaptive neuro-fuzzy inference system (ANFIS) based MPPT controller method for PV applications. The algorithm incorporated the function of FL cont and ANN. Sugeno fuzzy controller was utilized for deriving the membership functions and the rule table with the base of ANN. The algorithm-based system matched the fuzzy rules for non-linear function optimization by accepting two inputs and providing one output.

III. PROPOSED METHODOLOGY

The circuit diagram of the ERNN-based SSO with the buck-boost converter is shown in Figure 1. In this structure, the PV panel collects radiant energy and heat as intake. The PV array is made up of some semiconductor devices which change the photons of the sunlight into electric power due to the formation of the electric field. The parameters from the panel are in the form of DC, which are the inputs of ERNN. The context inputs from the hidden layer are fixed with some weights. This network proposes to update the optimum value of the weight SSO algorithm. Based on that, the duty factor is produced using a pulse width modulation (PWM) generator to switch the buck-boost converter (BBC) and track the maximum power. Then the BBC generates the DC signal for the applications of DC load.

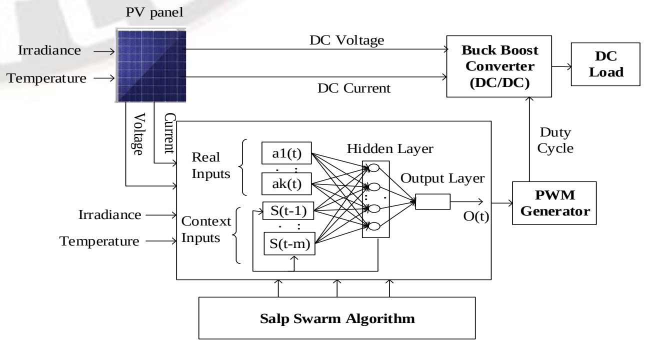

Figure 1: Circuit diagram for hybrid ERNN-based SSO with buck-boost converter

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A) Solar PV Modelling

A PV panel is nothing but a collection of PV modules, also known as a PV array. Each module consists of several PV cells. A single PV cell consists of a p-n junction semiconductor device made up of silicon. This PV cell accepts the sunlight and temperature as input signals and converts this light energy into electrical energy as output. The PV system normally shows a lack of linearity in the current-voltage and power-voltage characteristics based on the changes in temperature and solar irradiance. The diagram of the solar cell is modelled in Figure 2.

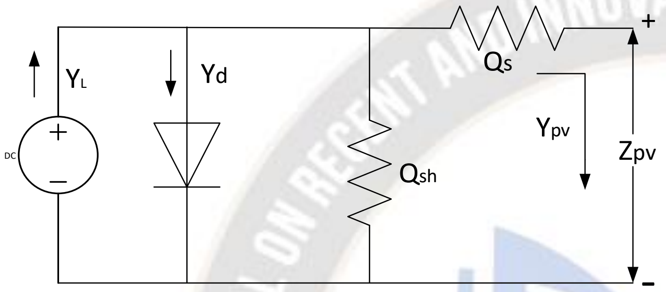

Figure 2: circuit diagram of solar cell

The electricity generated by the solar cell is,

$$Y_{pv} = Y_L - Y_0\left[\exp\left(\frac{x(Z_{pv}+Y_{pv}Q_s)}{cDEP_s}\right)-1\right]-\frac{(Z_{pv}+Y_{pv}Q_s)}{Q_p} \quad (1)$$

where, Y_{pv} is the generated current from the PV array, Y_L is the light-inducing current, Y_0 is the reverse saturation current, x is the electron charge $(1.602\times10^{-19}C)$, Z_{pv} is the output potential of the solar array, Q_s and Q_p are series and shunt resistance, respectively, C is the constant of Boltzmann $(1.38\times10^{-23}\,J/K)$.

D is the heat from sunlight, E is an ideality factor of the semiconductor [28]. The reverse saturation current Y_o is given by

$$Y_0 = Y_{0ref}\left[\frac{D}{D_r}\right]^3 \exp\left[\frac{xG_b}{cxE}\left(\frac{1}{D_r}-\frac{1}{D}\right)\right] \quad (2)$$

Where, Y_{0ref} denotes the reference reverse saturation current, D_r is the reference heat of panel, G_b is the band gap energy of semiconductor.

The power of the PV array is given by

$$S_{pv} = Y_{pv}Z_{pv} \quad (3)$$

The power from the PV array is regulated by the buck-boost converter, in which the switching devices are switched on and off due to the firing angle.

B) Converter modelling

In this paper, BBC is employed to modify the voltage production from the solar panels by either stepping down or stepping up. The representation of the BBC circuit is structured in Figure 3.

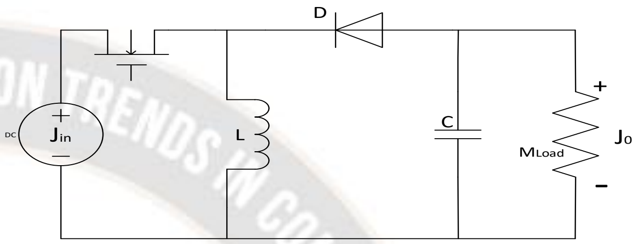

Figure 3: Circuit representation of BBC

The output voltage under steady state conditions is expressed below.

$$\frac{J_0}{J_{in}} = -\frac{R}{1-R} \quad (4)$$

Where, R is the duty factor and J_{in} is the input electric potential. The current transfer gain is mentioned in the below equation.

$$\frac{B_0}{B_{in}} = -\frac{1-R}{R} \quad (5)$$

Where, B_{in} is the input current and B_0 is the output current. From equations (4) and (5), we get

$$M_{in} = \frac{J_{in}}{B_{in}} = \frac{R^2}{(1-R)^2}\times\frac{J_0}{B_0} \quad (6)$$

$$M_{in} = \frac{J_{in}}{B_{in}} = \frac{R^2}{(1-R)^2}\times M_{Load} \quad (7)$$

Where, M_{in} is the input resistance and M_{Load} is the resistance connected on the load side [29].

The buck-boost converter works through the function of switching devices to control the output voltage.

C) Elman Recurrent Neural Network

In Recurrent NN, the network output is feedback with the network input to produce another new output and is called a feed-forward network. RNN includes context units in addition to three layers, and the typical structure of RNN with three layers is shown in Figure 4. Context units are nothing but a set

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of units given to the primary layer, which receives the data either from the hidden layer or the output layer [30, 31]. The ERNN is the type of RNN unit in which the context units receives the signal only from the hidden layer. The fixed weighting parameters are set on these feedback connections.

Figure 5 represents the architecture of ERNN, where there are two inputs to the input layer. One is actual inputs, and another one is context inputs, which are from the hidden layer. So there is a relationship between the past ones and future values.

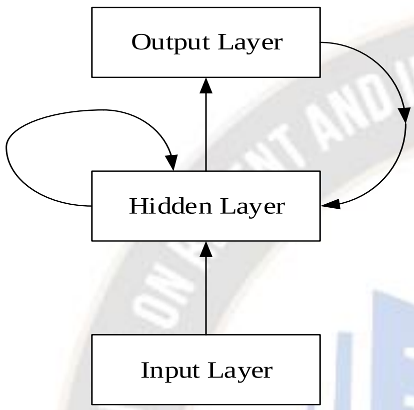

Figure 4: typical structure of RNN

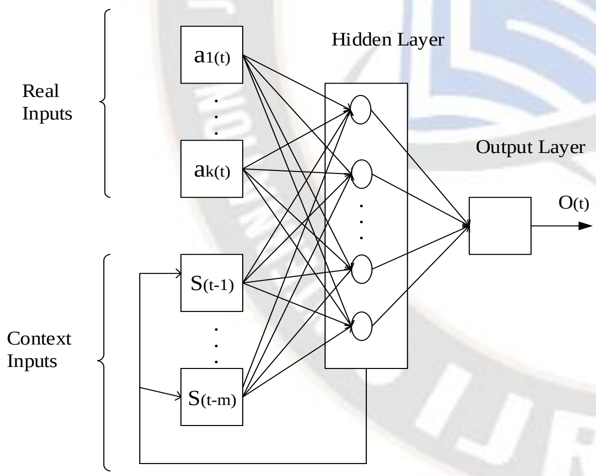

Figure 5: The architecture of ERNN

The output $O_i(t)$ can be calculated as,

$$O_i(t) = F\left(\sum_{j=1}^{i} P_{ji} S_j(t)\right) \tag{8}$$

Where, F is the function of sigmoid, S_j is j^{th} hidden unit, P_{ji} is the weight connection between S_j and i^{th} output.

The weight source S_j is expressed by

$$S_j(t) = F\left(\sum_{i=1}^{k} P_{ij} a_i(t) + \sum_{m=1}^{n} B_{mj} S_m(t-1)\right) \tag{9}$$

Where, P_{ij} is the connection's weight between S_j and i^{th} real input a_i , B_{mj} is the weight connection between S_j and m^{th} hidden past value at $t-1$ [31]. It can store the initial states and use them in upcoming states. This makes to propose ERNN based SSO MPPT controller in this paper.

1) Weight optimization by SSO

Salps are from the salpidae family, similar to jellyfish and are transparent barrel-shaped. The features of salp inspire this algorithm, and salps are based on the propulsion principle. So when the water pushes through the salp body, the salps move forward. The salps are grouped as a form of chain in the deep Ocean called the salp chain. To model the salp chain, the weight of the layers can be categorized into two groups: leaders and followers. In our proposed method, each salp is considered as a weight parameter in the layer of ERNN. The optimal weight is mentioned as a leader, and the remaining weight is followers. The follower weights are guided by the leader's weight [32]. The best value of weight is assumed as the leader and the remaining weights as followers.

In SSO, d_1 is the parameter which balances exploitation and exploration can be expressed as,

$$d_1 = 2e^{-\left(\frac{4g}{G}\right)^2} \tag{10}$$

Where, g is the real-time iteration and G is the higher number of iterations. The parameters d_2 and d_3 are randomly selected for the interval (0, 1). The setting of weight parameters in the layer is the target of the swarm in this proposed paper. The position of the weight in the n-dimensional search space is stored in the two-dimensional matrix M. The following equation is utilized to update the optimal weight position.

$$M_j^1 = \begin{cases} S_j + d_1\left(\left(vb_j - qb_j\right)d_2 + qb_j\right) & d_3 \geq 0 \\ S_j - d_1\left(\left(vb_j - qb_j\right)d_2 + qb_j\right) & d_3 < 0 \end{cases} \tag{11}$$

where, M_j^1 is the position of the optimal weight in j^{th} dimension, S_j is the weight source, and vb_j, qb_j are the upper and lower limit of the weight in j^{th} dimension, respectively. To update the following weight's position, the below equation is used.

$$M_j^i = \frac{1}{2}ct^2 + s_o t \tag{12}$$

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Where, M_j^i is the remaining weight's position in j^{th} dimension, $i \geq 2$, S_o is the starting speed, and $c = \frac{s_{end}}{s_0}$ where, $s = \frac{M - M_o}{t}$. The time in optimization indicates iteration, and the difference between the iterations is equal to 1. Assume $s_0 = 0$, now the equation is as follows.

$$M_j^i = \frac{1}{2}\left(M_j^i + M_j^{i-1}\right) \qquad (13)$$

Where, $i \geq 2$, M_j^i is the position of the remaining weight in j^{th} dimension [33].

The salp chains can be simulated using equations 11 and 13. The workflow diagram of SSO for weight optimization of ERNN is represented in Figure 6.

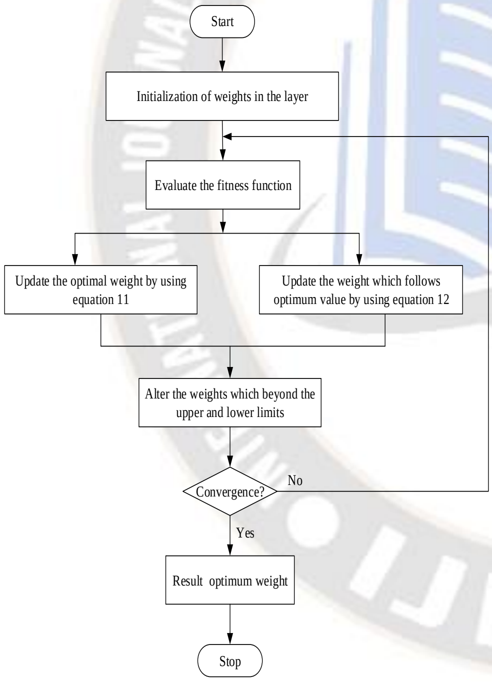

Figure 6: Flowchart of SSO for weight optimization of ERNN

IV. RESULT AND DISCUSSION

The proposed SSO-ERNN based MPPT controller and the existing techniques like RBFC controller, ANFIS controller and fuzzy controller for solar PV is implemented with the help of Matlab/Simulink, which is given in Figure 7. The results obtained from the PV panel and converter are discussed in detail. Moreover, the P-V and V-I characteristics are elaborated. The solar PV panel takes temperature and solar irradiance as input converts it to electrical energy and gives the output in the form of DC. The generated current, voltage and power from the solar cell are taken under the solar radiation range of $1000W/m^2$.

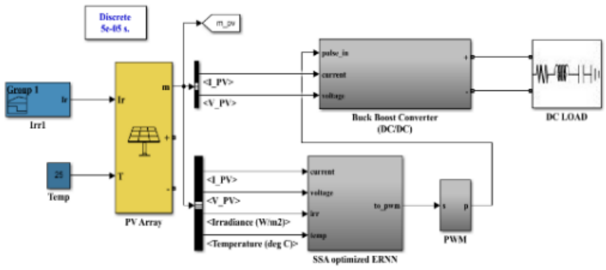

Figure 7: Simulink model (a) SSO-based peak MPPT controller, (b) RBFC, (c) ANFIS and (d) Fuzzy

From the sun, the photons of light and temperature strike on the panel and generate the DC signal, which flows to the buck-boost converter and ERNN optimized by the SSO algorithm. By utilizing the algorithm, the optimal weight of the layer is estimated, generating the duty cycle to switch on the converter. In this way, the topmost power is generated, which is connected with the load for DC applications. The representation of the solar cell modelling parameters can be seen in Table 1.

TABLE 1: Solar cell modelling parameter representation

Parameter	Values
Open circuit voltage (OCV)	115.24V
Short circuit current (SCC)	11.12A
Current at MPP	11.02A
Voltage at MPP	92.5V
Maximum power	850W

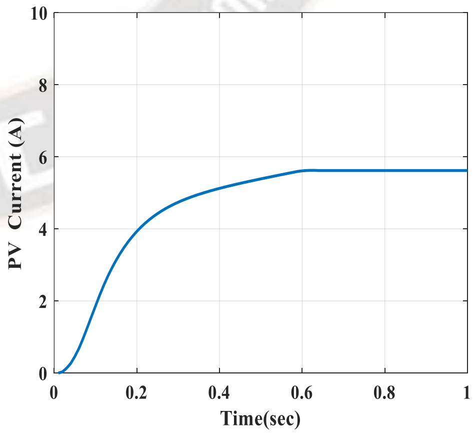

Figure 8: Output current of solar panel

Figure 8 reveals the output current from the solar panel for a variable radiation level of $1000W/m^2$. The graph shows that the current increases with time and constantly flows after reaching the maximum. The output current from the PV panel

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reaches the maximum of 5.5A in the time range of 0.2 and 0.4 seconds.

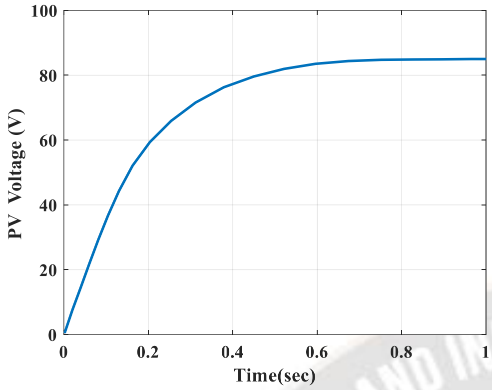

Figure 9: Produced voltage of solar panel

The generated voltage from the PV panel is plotted for the solar irradiance of $1000W/m^2$ in Figure 9. The PV voltage reaches the peak value of 85V at the time range of 0.2 and 0.4 seconds and then maintains constant.

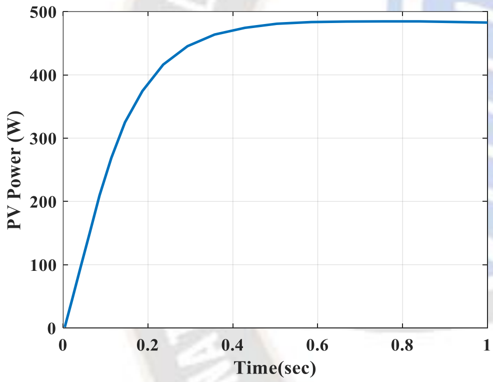

Figure 10: Generated power of PV array

When the output current and voltage rise, the output power from the PV panel increases automatically. Figure 10 shows the PV power graph in terms of time for the solar irradiance of $1000W/m^2$ in which the power increases depending on time. Power raises the maximum of 480W at a period of 0.2 and 0.4 seconds.

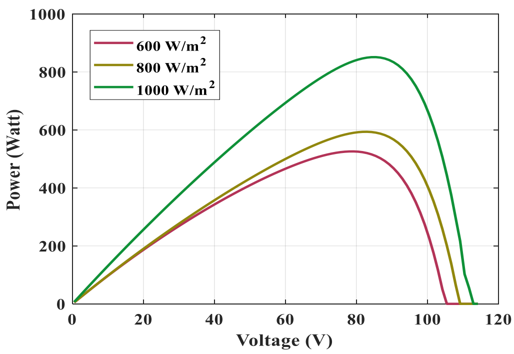

Figure 11: Watt-volt curve for different irradiance of the solar

The watt-volt curve for varying irradiance levels of $600W/m^2$,$800W/m^2$ and $1000W/m^2$ is demonstrated in Figure 11. The curve indicates that when the voltage increases, the power is also improved at each irradiance level. The power attains the maximum of 500W at $600W/m^2$ irradiance level and then reaches 600W and 850W at the illumination levels of $800W/m^2$ and $1000W/m^2$ respectively. Then the power is reduced to zero while attaining the open circuit voltage of 115V. So from that, better power is obtained for higher irradiance of $1000W/m^2$.

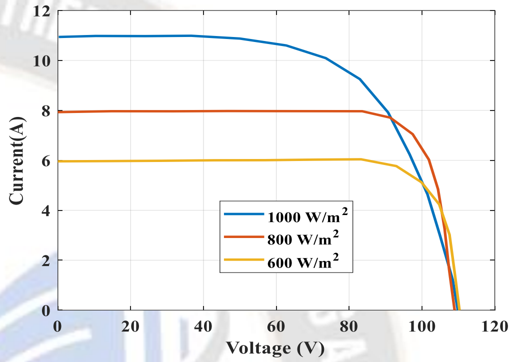

Figure12: Amps-volt graph of solar cell

Figure 12 indicates the current-voltage characteristics for various irradiance level $600W/m^2$,$800W/m^2$ and $1000W/m^2$. The current is maintained as constant for a particular voltage range and then decreases gradually. Here the current is 6A at the irradiance level of $600W/m^2$ and 8A, 11A at $800W/m^2$ and $1000W/m^2$ respectively. After that, the current reaches zero while the OCV is reached.

The signal generated from the PV panel is given to the ERNN-based MPPT controller, in which SSO is proposed to evaluate the maximum weight of the layers for tracking the maximum power. Then the duty cycle is generated to switch to the BBC. The performance results of the proposed work are compared with three conventional methods, such as radial basis functional controller (RBFC) [21], FL Cont [26] and adaptive neural-fuzzy inference system (ANFIS) [27].

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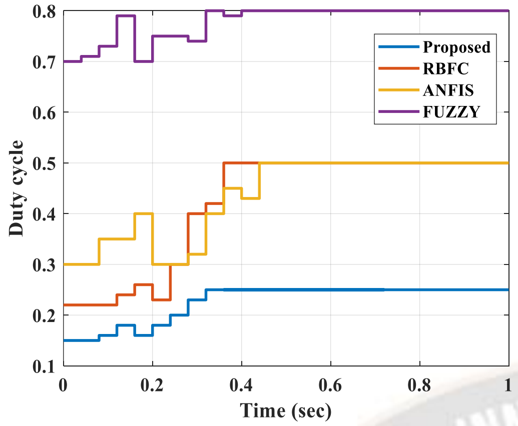

Figure 13: Duty cycle graph for proposed system

The duty cycle graph is shown in Figure 13, in which the graph is plotted in terms of time. The graph demonstrates that the duty cycle for the proposed system is lower than the three conventional methods. So the BBC is switched on at the less duty factor of 0.15 sec. The produced current, voltage and power from the converter are elaborated below.

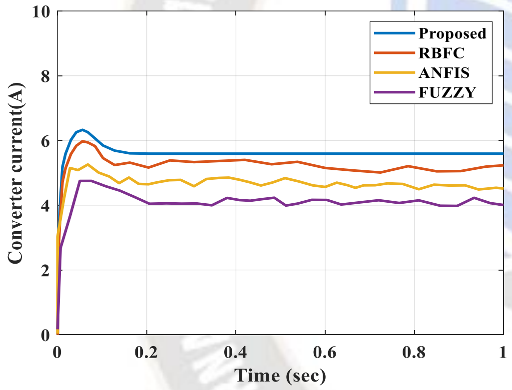

Figure 14: Output current from the converter

The comparative analysis of the output current from the converter with conventional methods is represented in Figure 14. In this graph, the output current reaches the maximum at 0.1 sec and then maintains constant. The plot reveals that the output current for the proposed system reaches the maximum value of 6.1A, which is higher and oscillation free compared to the conventional methods.

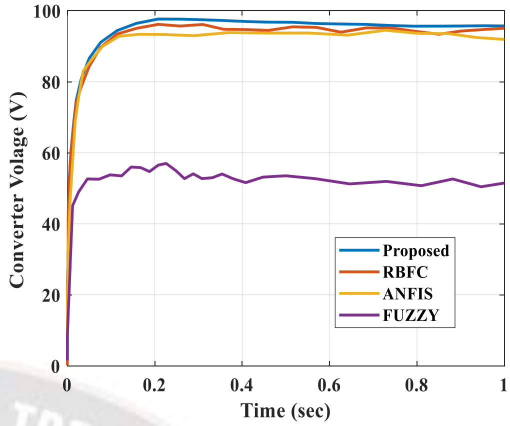

Figure 15: Output voltage of BBC

The generated potential from BBC is demonstrated in Figure 15, which reaches the peak voltage value at 0.1 sec. So from that, the produced voltage for the proposed method is greater than the conventional methods, which means the maximum voltage is 95V.

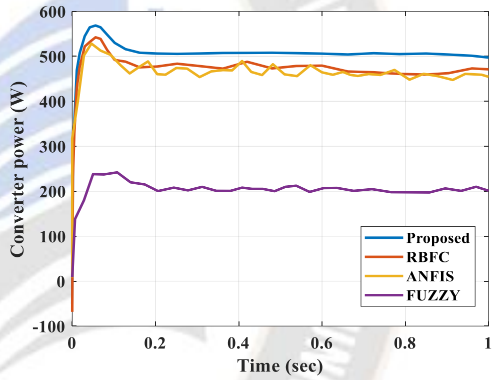

Figure 16: Output power of the converter

Figure 16 shows the output power of the converter compared with three conventional methods. If the output current and voltage are increased, the output power will rise automatically. So the output power from the buck-boost converter attains the peak power of 578W at a time of less than 0.1 sec. The graph shows that the proposed method's output power is better than conventional methods. The output from the converter is shared with the DC load for the DC source applications.

The following equations can express the efficiency of the power tracking process and the power loss.

$$\eta = \frac{Extracted\ power}{Maximum\ power} \times 100 \tag{14}$$

$$Powerloss = \frac{Maximum\ power - Tracked\ power}{trackedpower} \times 100 \tag{15}$$

Where η is the tracking efficiency?

The final analysis of the proposed technique is matched up with conventional methods, which are structured in Table 2.

Figure 17 shows the convergence graph for SSO, KHO and PSO by varying number of iterations. The proposed SSO converged at 23rd iteration, KHO converged at 49th iteration and PSO is converged at 60th iteration. When compared to existing techniques, the proposed SSO quickly converged.

TABLE 2: Comparable analysis of proposed method with conventional methods

parameters	FUZZY based MPPT	RBFC based MPPT	ANFIS based MPPT	SSO-based MPPT (proposed)
Maximum power (W)	265	558.75	510.17	580
Duty cycle (s)	0.7	0.22	0.3	0.15
State settling time (s)	0.4	0.35	0.45	0.3
Tracking efficiency (%)	94.4	98.51	98.12	99.74
Extracted power (W)	250.16	550.45	500.58	578.5
Power loss (%)	0.05	0.014	0.018	0.002

D) Discussion

Implementing MPPT in a stand-alone PV system using the neural network estimator (NNE) used in [34] determines the relationship between OCV and the voltage at maximum power. The paper suggests that the greater power obtained from a PV panel is 50W at an open circuit voltage of 20V for the solar illumination of $1000\ W/m^2$. Our proposed technique achieves the highest PV cell power of 850 W at an open circuit voltage of 115 V. The higher power extraction is based on a group teaching optimization algorithm (GTOA) [35] from sunlight under partial shading and complex partial shading conditions. The current transient for GTOA based MPPT controller is 3.5A, and the maximum power can be tracked at 0.15 sec. In our proposed method, the output current is 6A in terms of time, and also the maximum power is tracked at a time of less than 0.1 sec. The maximum power of the PV module in an artificial bee colony (ABC) algorithm [36] based MPPT controller is 65W, and the work can extract the power is 60Wwith a tracking efficiency of 99.6%. The maximum power of our paper is 580W, and the tracked power is 578W, with a tracking efficiency of 99.74%. By comparing the conventional methods' current, OCC, output power, and tracking efficiency, the proposed SSO-based ERNN for MPPT controller is the most effective technique for MPPT in solar PV. The analysis shows that the proposed method provides better maximum power tracking results but the algorithm did not work at partial shading condition when the PV array and patterns were increases. Thus in future, the proposed system will be examined in various form of complex partial shading condition with the help of novel technique.

V. CONCLUSION

In this work, the solar PV system with BBC is utilized and to optimize the leader of weight in the neural network, SSO based ERNN technique is adapted in the MATLAB/Simulink model. The result of this work is differentiated from other conventional MPPT controller techniques such as fuzzy, ANFIS and RBFC based MPPT methods in terms of MPP, settling time, power losses, tracking efficiency and duty cycle. The current-voltage curve and power-voltage curve also result in various illumination ranges. To the performance analysis, the new work supports working with solar energy compared to the existing methods. This new technique can be feasible to track the power of 578.5W out of the maximum power, which is 580W, with a minimum duty cycle of 0.15 sec. So from that, only 0.002% of power can be loosed, and the tracking efficiency of fuzzy based MPPT is 94.4%. Then the efficiency of the work of RBFC and ANFIS based MPPT is 98.51% and 98.12%, respectively. Using this proposed controller, the system can achieve high tracking efficiency of 99.74% compared to conventional methods. Future work plans to model the MPPT controller with solar PV based on a hybrid algorithm to avoid uncertainties in neural network layers.

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