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Article

Spotted Hyena-Bat Optimized Extreme Learning Machine for Solar Power Extraction

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Abstract: Artificial intelligence, machine learning and deep learning algorithms have been widely used for Maximum Power Point Tracking (MPPT) in solar systems. In the traditional MPPT strategies, following of worldwide Global Maximum Power Point (GMPP) under incomplete concealing conditions stay overwhelming assignment and tracks different nearby greatest power focuses under halfway concealing conditions. The advent of artificial intelligence in MPPT has guaranteed of accurate following of GMPP while expanding the significant performance and efficiency of MPPT under Partial Shading Conditions (PSC). Still the selection of an efficient learning based MPPT is complex because each model has its advantages and drawbacks. Recently, Meta-heuristic algorithm based Learning techniques have provided better tracking efficiency but still exhibit dull performances under PSC. This work represents an excellent optimization based on Spotted Hyena Enabled Reliable BAT (SHERB) learning models, SHERB-MPPT integrated with powerful extreme learning machines to identify the GMPP with fast convergence, low steady-state oscillations, and good tracking efficiency. Extensive testing using MATLAB-SIMULINK, with 50000 data combinations gathered under partial shade and normal settings. As a result of simulations, the proposed approach offers 99.7% tracking efficiency with a slower convergence speed. To demonstrate the predominance of the proposed system, we have compared the performance of the system with other hybrid MPPT learning models. Results proved that the proposed cross breed MPPT model had beaten different techniques in recognizing GMPP viably under fractional concealing conditions.

Keywords: Global maximum power point tracking; artificial intelligence; machine learning; deep learning; spotted hyena-BAT algorithm

1 Introduction

The utilization of energy is dramatically expanding internationally. Energy utilization is probably going to arrive at its pinnacle, driven by rising per capita power utilization on one hand and expansion in financial advancement on the other. To repay the high use of energy, sustainable power sources are the suitable answers for covering this energy interest and turned into an essential type of energy because of their adaptability and adaptability [1].

The Solar power framework is considered as one of the most encouraging sustainable energy sources because of its cost-effectiveness, high efficiency, and high abundance compared with other conventional energy source such as oil, biogases and natural gases [2]. Despite of its advantages, output active power P from solar varies according to the solar irradiance and an environmental temperature *T*, especially under dynamic Partial Shading Conditions (PSC) due to the non-linear characteristic of PV cells [3]. The unsatisfactory power extraction is yielded due to the characteristics mentioned above and remains on the darker side of the research. To alleviate this problem, Maximum Power Point Tracking (MPPT) [4] has become the shining research to track the maximum peak and ensure the system operates only in the peaks.

Several MPPT techniques such as Hill-Climbing [5], Perturb and Observe [6], and incremental conductance [7] are used nowadays, which are used to track the uniform peak power without the influence of PSC. However, the output power from the solar power system generates multiple peaks under PSC, including one Global Maximum Power Point (GMPP) and several local peaks. Many reformed meta-heuristic algorithms [8–16] have been used on the conventional MPPT techniques to track the global peak power. However, it's resulted in infrastructure complexity and also an increase in time of complexity.

Recently, the integration of Artificial Intelligence in MPPT techniques is aimed to resolve and rectify the problem mentioned above. Artificial Intelligence (AI) based MPPT techniques such as HERBS-MPPT [17], Artificial Neural Networks (ANN) Based MPPT [18], Genetic Algorithm (GA)-ANN based MPPT [19], Fuzzy ANN based MPPT [20] are extensively used for tracking the maximum peak power in which the HERBS-MPPT has proven its superiority over the other MPPT algorithms. Unfortunately, HERBS-MPPT suffers from trapping problems at local MPPT under maximum PSC or sudden irradiance change due to MPPT failure.

Motivated by this drawback in HERBS-MPPT, this paper proposes Spotted Hyena Enabled Reliable BAT (SHERB) learning models, SHERB-MPPT, the new hybrid optimization technique which works on the principle of Spotted Hyena over BAT algorithms with high-speed Extreme Learning Machine (ELM) to detect the GMPP effectively with high speed convergence, high performance, and zero trapping problems. This proposed method can be represented as reliable, which means consistently well in performances. The paper tells the following information, A novel hybrid integration of the spotted hyena with bat algorithm has been proposed with ELM has been proposed to achieve better tracking efficiency and high speed, which is designed using MATLAB based solar test beds have been designed to collect the different data based on the environmental temperature and solar irradiations. These datasets are used to train the proposed model, which is then used for better analysis.

The rest of the paper is organized as follows: Section-2 discusses the works proposed by more than one author. The working mechanism of the proposed framework is presented in Section-3. The experimental setup and findings with comparative analysis are detailed in section-4. Finally, the paper is concluded with future enhancement in Section-5.

2 Related Works

The fundamental MPPT procedures for Photo Voltaic (PV) frameworks are investigated and summed up and isolated into three gatherings as indicated by their control hypothetical and streamlining standards [21]. The principle benefit of these systems is that it covers the wise calculations on MPPT. In any case, this study needs an expansion to manage complex conditions like PSCs. It should utilize the current control techniques to give full play to their separate potential benefits, creating qualities and staying away from shortcomings.

The arrangement of the most applied MPPT calculations. It additionally has tended to a few characterizations of the MPPT strategies [22]. MPPT technique raking dependent on broad terms like following velocity, proficiency, cost, and intricacy is given. This paper is a yield of a total composing study which can be a valuable mechanical assembly and extraordinary reference for the experts working PV system region. This study needs an update to manage more MPPT examinations dependent on the constant climate.

A counterfeit neural organization-based MPPT regulator for sunlight-based PV framework [23]. As per reproduction results, the ANN-based MPPT calculation predicts the most significant force in various irradiance and temperature more precisely than that of MPPT calculation without ANN. For better execution, the versatile neuro-fluffy-based regulator can be utilized instead of the ANN-based regulator for MPPT. A quick hybrid strategy is introduced, which joins the Particle Swarm Optimization (PSO) technique with the ANN technique [24]. In this crossbreed strategy, the ANN empowers the current PSO technique to follow MPP rapidly by giving more exact starting molecule places of the PSO calculation. Notwithstanding this, the following pace and productivity of the proposed mixture technique lead to the conviction that this strategy may give a few commitments to advancing of sun-oriented energy.

The improved MPPT strategy using the state assessment by the consecutive Monte Carlo (SMC) sifting is helped by the expectation of MPP using an ANN [25]. Recreation results show that the proposed improved MPPT technique accomplishes high proficiency and is strong to quick irradiance change under various clamor levels. Notwithstanding, this technique has the deadly weakness that its continuous presentation is inferior, as it can't change the functioning mark of the PV exhibit rapidly enough as the outside climate changes. An arbitrary timberland Random Forest (RF) model to further develop MPPT execution is described in [26]. The RF model breezes through the Bland–Altman appraisal within the abundance of 95% sufficiency. The proposed procedure responds quickly to fast-changing biological conditions; subsequently, the strategy can be embraced for continuous MPPT. At any rate, the power following speed is low.

A computation for an ANN-based MPPT controller for wind energy structure and mutt PV/wind is discussed in [27]. The fundamental mark of this investigation is to show the Total Harmonic Distortion (THD) potential gains of PV, wind, and scattered lattice voltage and current profiles, all of which show redesigns in power quality when the micro grid is joined to harmless to the ecosystem power sources. The saw THD potential gains of the proposed system are under 5% as per standard (IEEE 1547). But, it is excessively costly for a little force framework. Moreover, a nitty-gritty correlation of mainstream AI-based MPPT strategies is for the sun-oriented force framework [3]. They are intended to follow GMPP rather than nearby MPP in reducing the impacts of PSC. In any case, the majority of the strategies are expensive and complex to assemble and require more datasets contrasted and ordinary MPPT methods. This survey is required to give a definite knowledge of the most recent headway of AI-based MPPT strategies for the application in the sun-oriented force framework.

A profound learning-based model DPLSTM utilizing LSTM and crossover enhancement is described in [28] to resolve such issues in the "12306 tagging framework". This structure used a mean fundamental percentage error, mean absolute error, and a root means square error to assess the proposed model's exhibition utilizing genuine information. An examination with the standard time series anticipating calculations showed the prevalence of the proposed model. Notwithstanding, mistake investigation/lingering arrangement examination showed that the proposed model could be streamlined. Then a novel GMPPT technique depends on using an AI calculation [29]. The mathematical outcomes introduced in the paper show that the time needed for distinguishing the worldwide MPP, when obscure halfway concealing examples are applied, is decreased by 80.5%–98.3% by executing the proposed Q-learning-based GMPPT calculation. However, the exchanging gadget will influence the dynamic and consistent state qualities of the framework following.

3 Proposed Framework

The proposed framework is implemented through the PV system with SHERB-MPPT algorithm.

3.1 PV Modeling

It is critical to construct a numerical model for PV cells to have high power tracking. Fig. 1 shows the typically used single diode equivalent circuit that enables the PV cells with its characteristics. It is a PN junction that works on the principle of photovoltaic effects to get electricity. The diode is parallel to the current source, which changes with temperature and irradiance. SHERB-MPPT, the new hybrid optimization technique, works on the principle of Spotted Hyena over BAT algorithms with high-speed ELM to detect the GMPP effectively with high speed convergence, high performance, and zero trapping problems.

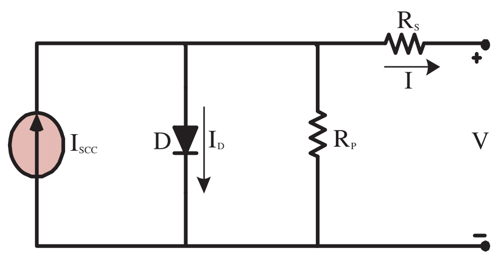


Figure 1: Single diode model

The following equation provides the current 'I' or 'I_L', neglecting shunt resistance.

$$I = I_{SCC} - I_D \tag{1}$$

As per Eq. (1), the value of current in the PV cell is denoted by excluding the shunt resistance effect.

$$I_D = I_{o,ref}\left[\exp\left(\frac{q(v + IRS)}{KAT}\right) - 1\right] \tag{2}$$

The short circuit current,

$$I_{scc} = \frac{G}{G_{ref}}\left[I_{scc,ref} + Kj(T - T_{ref})\right] \tag{3}$$

where, $T = cell$ temperature in K, $G_{ref} = 1000W/m^2$, q = electron charge is 1.6×10^{-19} C, A = ideality factor is 1.5 and K = Boltzmann constant is 1.38×10^{-23} J/K. I_{SCC} denotes the short circuit current at the reference condition, G denotes the irradiance in W/m^2, the reference temperature is denoted by T_{ref} in K, K_J denotes the temperature coefficient at $I_{SCC},_{ref}$ and R_S denotes the series resistance in Ω. Both R_S and R_P are important to identify the system losses. Based on Fig. 1, by taking the shunt resistance into account, the load current expression is defined in Eq. (5).

$$I_{SCC} - I_D - \frac{V_D}{R_P} - 1 = 0 \tag{4}$$

Thus, based on Eq. (4), the load current is modified in Eq. (5).

$$I(or)I_L = I_{SCC} - I_D - \frac{V_D}{R_P} \tag{5}$$

Tab. 1 exhibits the parameter values of the P1310X990 module on the basis of which the current paper is developed. These data values are also to be used in simulation work.

Table 1: P1310X990 module description

Maximum power rating (P_{max})	200 W
Voltage at maximum power (V_{mp})	24.5 V
Current at maximum power (I_{mp})	7.8 A
Open circuit voltage (V_{oc})	29.5 V
Short circuit current (I_{sc})	8.0 A
Temperature coefficient of maximum power	−0.45%/°C
Temperature coefficient of open circuit voltage	−0.37%/°C
Temperature coefficient of short circuit current	+0.06%/°C

Assuming N_S and N_P denote the number of cells connected in series and parallel and then the current equation of the PV cell is as follows:

$$I = N_P I_{SCC} - N_s I_{rs1}\left\{\exp\left(q\frac{(V + IR_s}{N_s AKT} - 1\right)\right\} \tag{6}$$

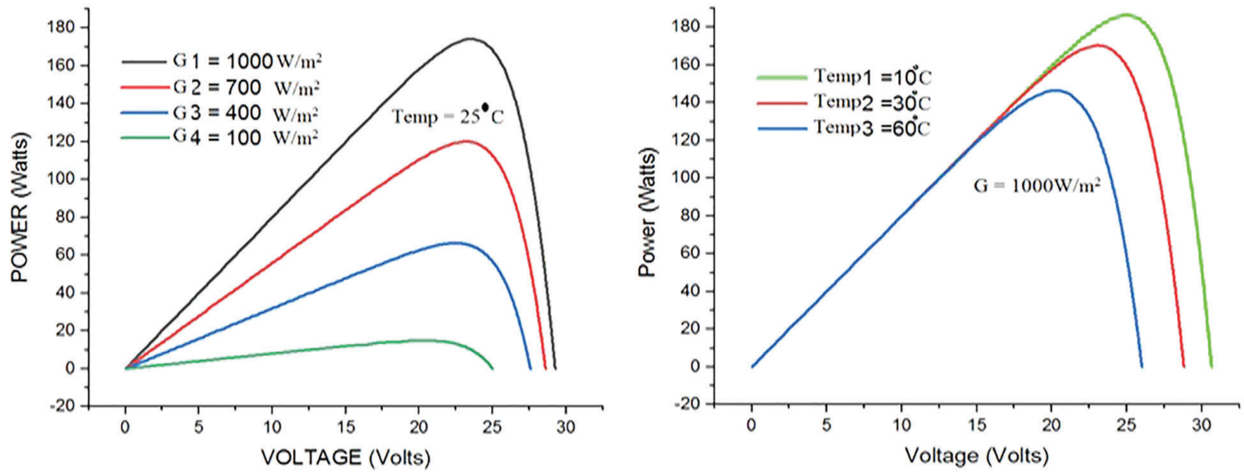
where, I_{rs1} denotes the cell reverse saturation current which is given as

$$I_{rs1} = I_{o1}\left[\left(\frac{T}{T_{ref}}\right)^3 e^{\frac{qBg}{AK\left[\frac{1}{T_{ref}} - \frac{1}{T}\right]}}\right] \tag{7}$$

where B_g is energy gap usually taken as 1.107 eV and R_P is shunt resistance in Ω. The conduct of the PV model, which changes with the sun-powered irradiance and temperature, is given in Fig. 2.

3.2 SHERB-MPPT Algorithms

Fig. 3 illustrates the functioning instrument of the proposed engineering. The proposed design comprises two significant stages, example, ELM [30–32] preparing stage and the Hybrid enhancement stages. The incremental conductance and various local peaks by the solar irradiance and temperature are used for ELM training which results in the reduced local peaks. The first phase of ELM training reduces the number of peaks from the above conditions. In the second phase, a spotted hyena [33,34] based bat algorithm is used to optimize the peaks to produce the best global power point peak. Finally, optimized maximum output power is given to the grid application using Direct Current (DC)-DC convertor.



(i) (ii)

Figure 2: Power voltage graph for solar module (i) change in solar irradiance (ii) Change in temperature

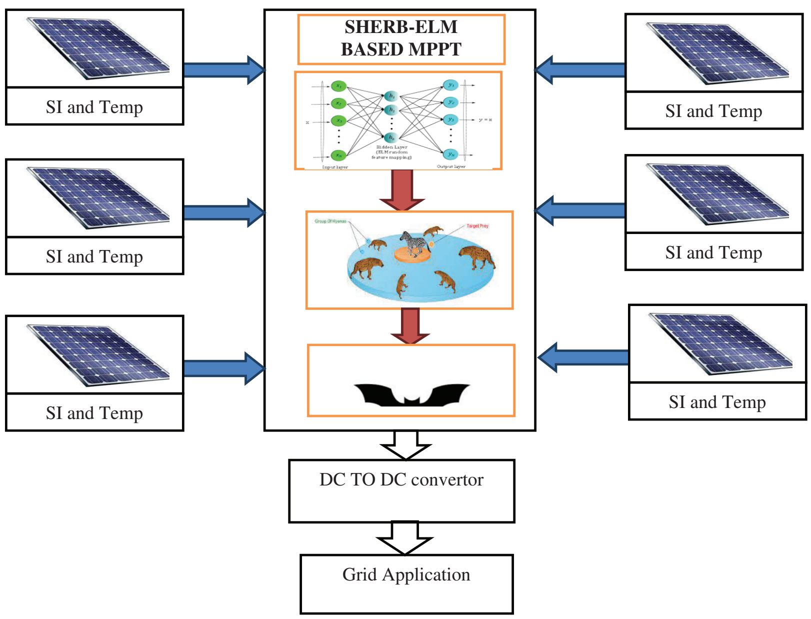


Figure 3: Proposed framework for the SHERB-ELM MPPT algorithm

As discussed in [35], though the BAT algorithm a exhibits high convergence rate at early stage, it slowly degrades in the later stage. This leads to the false detection of peaks and results in the high false alarm rates. To overcome this problem, this research proposed the hybrid combination of spotted hyena-based bat algorithm to detect optimal GMPP for any number of data. The method's dependability is evaluated under various partial shading situations [36], and the simulated results are shown to demonstrate the usefulness of the suggested Golden Section Search (GSS) based GMPPT algorithm. Further presents a new approach 12-parameter model [37] with the inherent capacity to forecast the two-diode model parameters for any meteorological data without trial runs.

The SHERB uses the hunting procedure of spotted hyena for the BAT algorithm to find the best optimal values. At the initial stage, the echolocation principle is used with the minimum loudness, frequency, and velocity.

For every iteration in the process of identifying the prey, loudness, position, frequency and velocity of bats are updated by the hyena's procedure of hunting using the following mathematical Eqs. (8)–(10).

$$\vec{F} = 2\vec{f}.\vec{rd}_2 - \vec{f} \tag{8}$$

$$\vec{f} = 5(cycle * \frac{5}{\max cycle}) \tag{9}$$

where $\vec{F}$ is vector coefficient as the population is dynamic in nature, $cycle = 1,\ 2,\ 3 \ldots \max cycle$. In the cycle of updating the best hyena, the $\vec{f}$ value linearly reduces from 5 to 0. $\vec{rd_1}$, $\vec{rd_2}$ are the random vectors residing in the limit [0, 1]. The position of the target prey is updated from the calculated values of $\vec{E}$ and $\vec{F}$ vector. The behavior of the spotted hyena is observed and located mathematically, leading to the best solution of determining the optimum solution space.

$$\vec{D}_{sh} = |\vec{E}.\vec{P}_f - \vec{P}_k| \tag{10}$$

$$\vec{P}_k = \vec{P}_j - \vec{F}..\ \vec{D}_{sh} \tag{11}$$

$$\vec{C}_f = \vec{P}_k + \vec{P}_{k+1} + \ldots + \vec{P}_{k+N} \tag{12}$$

$\vec{E}$ is vector coefficient as the population is dynamic, $\vec{P}_f$ be the position of the best spotted hyena

$\vec{P}_k$ be the position of other hyenas in search space, N is the No. of hyena in the overall population.

$$N = CountVal(\vec{P}_f,\ \vec{P}_{f+1},\ \ldots \vec{P}_{f+M}) \tag{13}$$

M is a vector with a value distributed from [0.5, 1] manually. $CountVal$ is the candidate solution count

$\vec{C}_f$ is the cluster of solutions reaching close to the optimal solution. For attacking the target, The vector $\vec{f}$ can be reduced to reach 0 until the target prey is attacked. When $|F| < 1$, the cluster of spotted hyena catches the prey. This is mathematically expressed as

$$\vec{P}(x+1) = \frac{\vec{C}_f}{N} \tag{14}$$

where the position of the vector $\vec{P}(x+1)$ updates for each search space till the best solution is attained.

The pseudo code for the proposed algorithm is given in Algorithm-1

Sl.no	Algorithm-1 Working Mechanism of Proposed SHERB algorithm
01	Initialize the BAT populations
02	Initialize the loudness, velocity, position and frequency of the Bats
03	While n = 0 :Max_iteartion
04	Update the Loundness, Velocity, Position and Frequency of Bats using mathematical Eqs. (12)–(14)
05	Calculate the fitness function to capture the (prey)
06	If (fitness function == threshold)
07	Calculate the G-best value
08	Else Go to Step 04
09	End
10	End
11	End

The significant advantage of SHERB has overcome the local convergence of the BAT algorithm, which can detect the best optimal value with a low convergence speed.

For the detection of optimal GMPP value**,** incremental conductance and various power peaks in accordance with the solar irradiance and temperature are used for ELM training which results in the local peak points. These multiple peak points, along with Short circuit current (I_{sc}), are used as the input for the proposed hybrid SHERB, which determines the global best fitness function. The fitness function of the proposed algorithm is given in Eq. (15).

$$FitnessFunction = Maximum(PeakValues) \tag{15}$$

The parameters used for the ELM training is given in Tab. 2.

The working mechanism of the proposed SHERB-MPPT is depicted in Algorithm-2

Table 2: List of ELM parameters used for the experimentation

Sl.no	ELM Training parameters	Specifications
01	No of epochs	20
02	No of inputs	02-Solar irradiance and temperature
03	No of outputs	Multi-class outputs
04	No of hidden layers	05
05	Learning rate	0.0001
06	Dropout	0.2

4 Results and Discussions

The performance of the proposed architecture has been evaluated in four different scenarios. The first scenario, three solar arrays are subjected to solar irradiance at 1000W/m^{2,} and non-uniform irradiance is applied to the other three solar cells. In the second scenario, uniform solar irradiance is exposed to two solar cells, with the remaining cells subjected to PSC. All the algorithms run on the same system. The faster the CPU works the more processes it can perform at once. A CPU with a 3 GHz clock speed, for example, may do 3 thousand million cycles per second. The cache of the CPU is the onboard memory that is used to store the information so that the processor can access it rapidly.

Sl.no	Algorithm-2 Working Mechanism of Proposed SHERB algorithm
01	Input : Incremental Conductance(I_c),I_{sc}, Voltage V_{sc} from the Solar panels
02	Output : Optimal G-best Value
03	Initialize the loudness, velocity, position and frequency of the Input parameters
04	While n = 0 :Max_iteartion
05	B_n = ELM(I_c, I_{sc}, V_{sc}) where Bn is the Multiple peaks
06	Update the Loundness, Velocity, Position and Frequency of Input parameters using mathematical Eqs. (12)–(14)
07	Calculate the fitness function using Eq. (15)
08	If (fitness function == threshold)
09	Calculate the G-best value

(Continued)

(continued)	
10	Else Go to Step 04
11	End
12	End
13	End

4.1 Experimental Datasets

To prove and validate the efficiency, the proposed algorithm's datasets which consist of different variants of temperature and irradiance, are collected using the model developed using MATLAB and Simulink. The proposed architecture uses six solar cells for 200 watts as inputs, and four varieties of partial shading trial patterns were taken into account. Fig. 4 shows the Simulink model created for one PV cell, and nearly 40,000 pattern traces were collected to evaluate the proposed architecture. Fig. 5 shows the Maximum Peak Power Detected by the Proposed Algorithm at a Solar irradiance of 300 m/W. Fig. 6 shows the simulation outputs obtained from the different scenarios of solar irradiance and temperature at 1000 m/W.

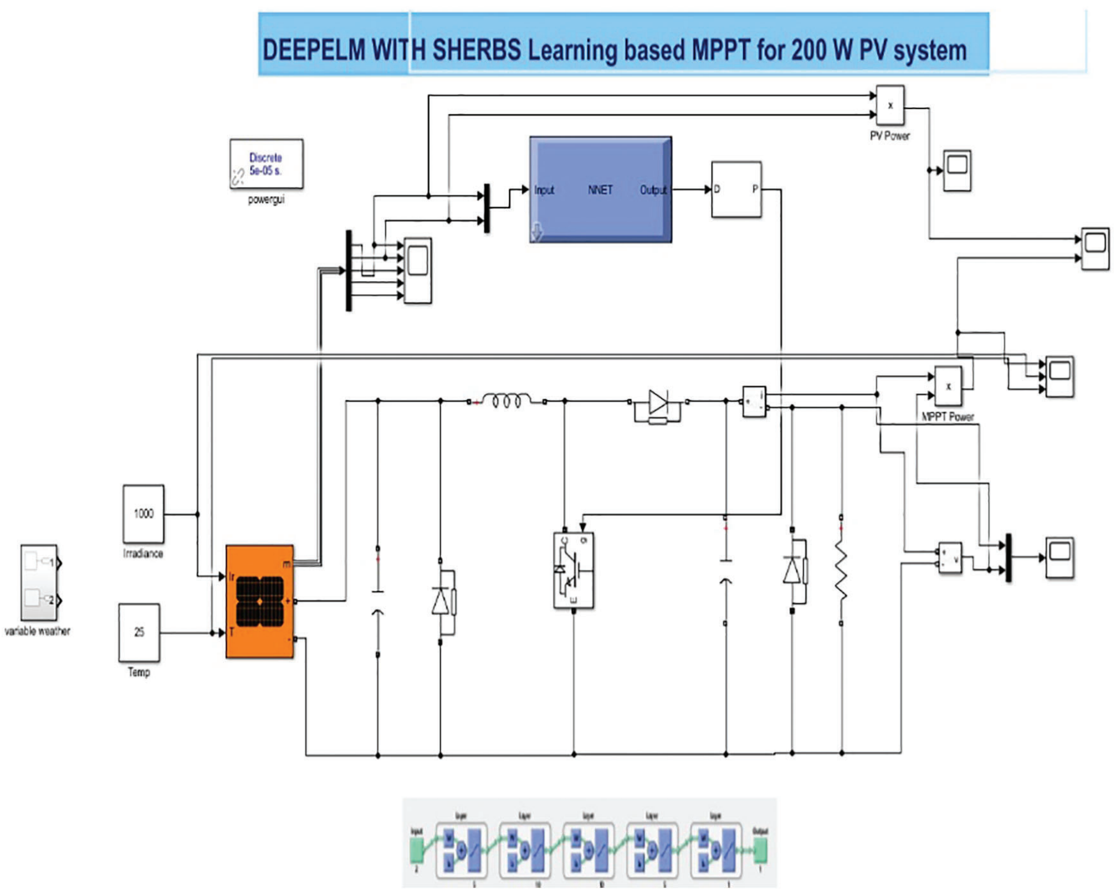


Figure 4: Proposed model developed using one PV cell for experimentation

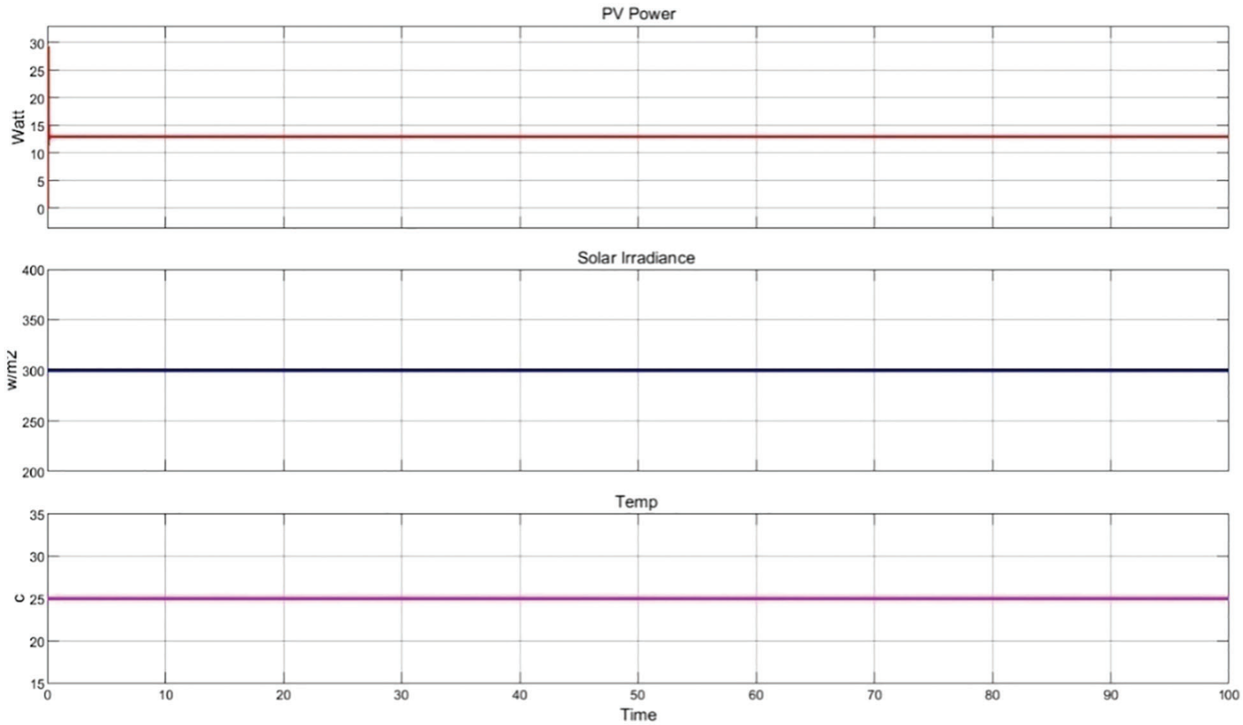


Figure 5: Maximum peak power detection at solar irradiance 300 m/W

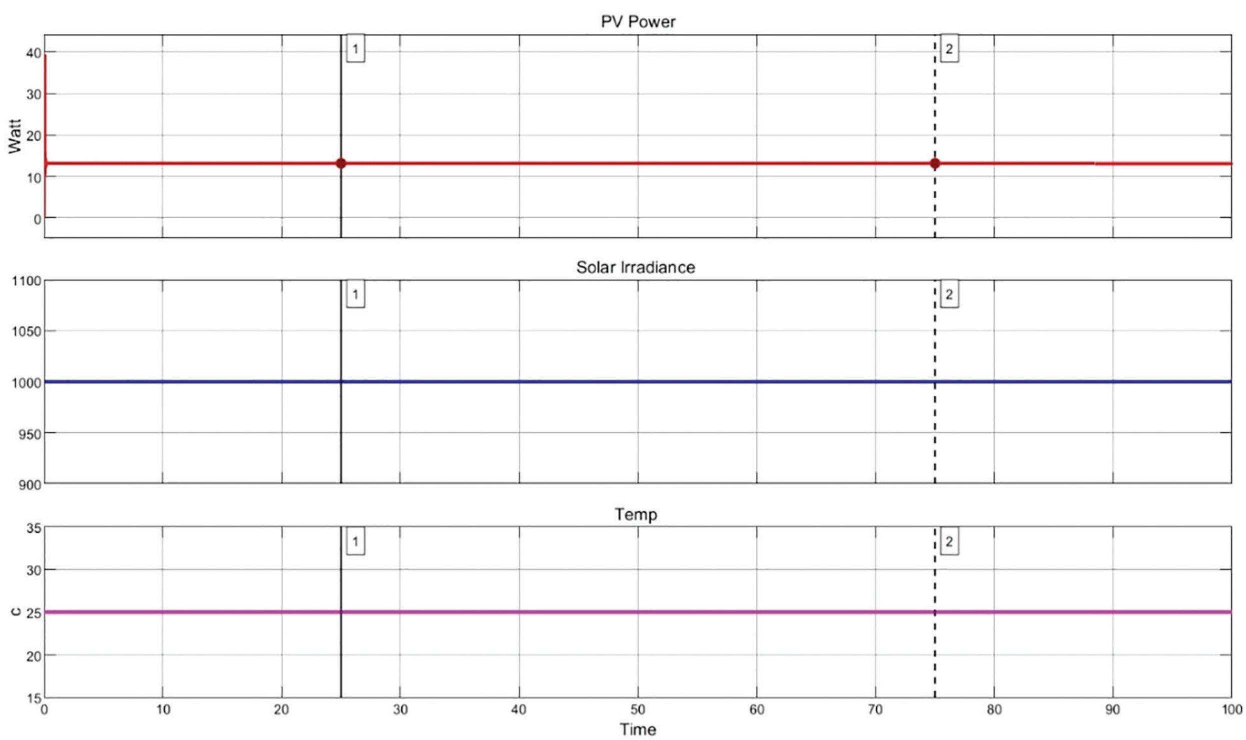


Figure 6: Simulation outputs obtained from the different scenario of solar irradiance and temperature at 1000 m/W

4.2 Tracking Efficiency

The performance of the proposed algorithm is evaluated by the metrics called tracking efficiency, which is given by the mathematical expression (16).

$$TrackingEfficiency: \frac{P_{MPPT}}{P_{MAX}} * 100\% \tag{16}$$

where P_{MPPT} is the power achieved at the time of MPPT with SHERB-MPPT algorithm, P_{MAX} is actual/maximum power obtained. In the third scenario, five cells are subjected to non-uniformity conditions, and finally, all cells were exposed to non-uniform solar irradiance. The tracking performance of the proposed architecture is depicted in Tabs. 3–6.

Table 3: Three solar cells with uniform irradiance and three with non-uniform irradiance

Trials	Irradiance (W/m^2)						Maximum power (P_{MAX}) (W)	Power at MPPT (P_{MPPT}) (W)	Tracking efficiency (η) (%)
	G_1	G_2	G_3	G_4	G_5	G_6			
1	1000	1000	1000	900	872	870	906	905.4	99.43
2	1000	1000	1000	850	862	790	857.5	856.3	99.56
3	1000	1000	1000	750	700	690	743	742.6	99.62
4	1000	1000	1000	650	540	500	649	648.2	99.56
5	1000	1000	1000	300	430	400	416.3	414.8	99.67

Table 4: Two solar cells with uniform irradiance and four cells with non-uniform irradiance

Trials	Irradiance (W/m^2)						Maximum power (P_{MAX}) (W)	Power at MPPT (P_{MPPT}) (W)	Tracking efficiency (η) (%)
	G1	G2	G3	G4	G5	G6			
1	1000	1000	890	867	823	900	859.4	859.0	99.46
2	1000	1000	800	750	689	720	745.9	743.0	99.50
3	1000	1000	750	700	656	700	684.6	684	99.60
4	1000	1000	600	634	500	420	548.5	548	99.45
5	1000	1000	300	350	300	450	293.78	293.4	99.56

Table 5: One solar cell with uniform irradiance and five with non-uniform irradiance

Trials	Irradiance (W/m^2)						Maximum power (P_{MAX}) (W)	Power at MPPT (P_{MPPT}) (W)	Tracking efficiency (η) (%)
	G1	G2	G3	G4	G5	G6			
1	1000	870	830	800	840	827	850.2	850	99.6
2	1000	819	830	750	745	698	778.45	778	99.67
3	1000	678	620	560	500	459	583.4	582.2	99.22
4	1000	430	400	420	340	320	400.3	398.4	99.4
5	1000	320	320	320	300	290	292	291.2	99.5

Table 6: All cells under partial shading conditions

Trials	Irradiance (W/m^2)						Maximum power (P_{MAX}) (W)	Power at MPPT (P_{MPPT}) (W)	Tracking efficiency (η) (%)
	G1	G2	G3	G4	G5	G6			
1	900	820	840	820	810	790	948.9	935.6	98.6
2	820	750	830	750	745	698	878.4	852.4	97.04
3	690	720	750	780	700	650	735.8	724.5	98.47
4	450	540	650	600	640	550	603.2	590.9	97.96
5	300	320	289	320	300	290	492.3	479.4	97.38

From Tabs. 3–6, it is clear that the proposed framework SHERB-MPPT has produced 99.5% for the first scenario, 99.46% for the second scenario, 99.6% for the third scenario, and 99.6% for the fourth scenario. Even though the PSC increases, SHERB-MPPT has detected a GMPP with high tracking efficiency of 99.6%. This is due to the integration of the Spotted-Hyena with the BAT algorithm and ELM training. To demonstrate the predominance of the proposed calculation, we have contrasted the proposed calculation and the current calculation, for example, PSO-ANN [18], GA-ANN [19], BAT-ANN [20, and HERBS-MPPT [17]. The techniques are compared with GA-ANN and PSO-ANN, HERBS, BAT-ANN. Also, this system is compared with proposed algorithm of HERBS. This is one of the BAT-based hybrid systems. Also, the comparative examination of MPPT techniques bio-inspired by the Bat-based optimization approach can achieve more promising results than GMPP [38]. This BAT-MPPT techniques has achieved the traction efficiency is 92.45%, which is less than our proposed algorithm is 99.6%. It shows a similar examination of the various calculations in identifying the worldwide greatest powepoint. Tab. 7 shows the maximum tracking power of second scenario.

Table 7: Maximum tracking power of second scenario

Different algorithm	(η) (%) for G1	(η) (%) for G2	(η) (%) for G3	(η) (%) for G4	(η) (%) for G5
PSO-ANN	93.6	93.6	93	92.7	93.5
GA-ANN	96	95.8	95.8	95.8	95.8
HERBS	97.8	97.8	97.8	98	97.85
BAT-ANN	97	96.3	96	96.5	97.1
Proposed algorithm	99	99	98.3	99.2	99.1

From the Tabs. 3–6, it is clear that the proposed framework SHERB-MPPT achieves better tracked power efficiency.

From Figs. 7–10, it is found that the tracking efficiency of HERBS is 98%, whereas the proposed architecture achieves 99.6%. From the figures, it is clear that the proposed architecture has outperformed the other existing algorithms when the PSC is exposed to four cells and five cells respectively, Fig. 9 shows the comparative analysis of tracking efficiency between the different algorithms for the third testing scenario. The tracking efficiency of the performance matrices of PSO-ANN, GA-ANN, HERBS, BAT-ANN and the proposed algorithm are compared as well as the proposed algorithm has high tracking efficiency, which has achieved a better tracking efficiency of 99.5%, In contrast , the other existing algorithms have seen adrop in tracking when the PSC is extended to all solar cells, as shown in Fig. It is evident that the proposed architecture has shown better and uniform tracking efficiency than the other existing algorithms under the different scenarios of partial shading conditions. Fig. 11 shows the computational time of tracking between the different hybrid learning models. From the figure, it is clear that the proposed algorithm needs less tracking time for GMPP detection.

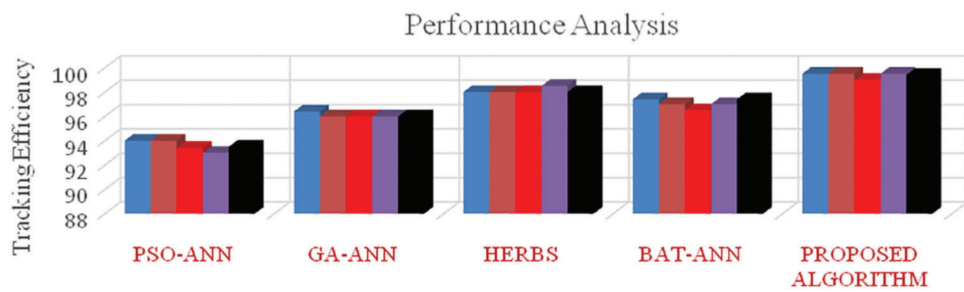


Figure 7: Comparative analysis of tracking efficiency for the 1st scenario of testing

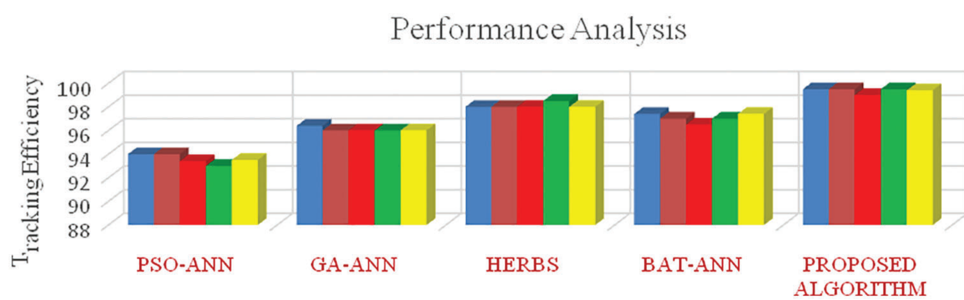


Figure 8: Comparative analysis of tracking efficiency for the 2nd scenario of testing

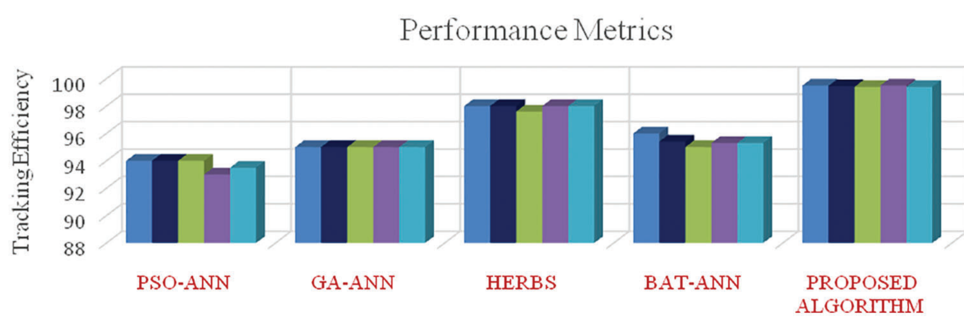


Figure 9: Comparative analysis of tracking efficiency between the different algorithms for the third scenario of testing

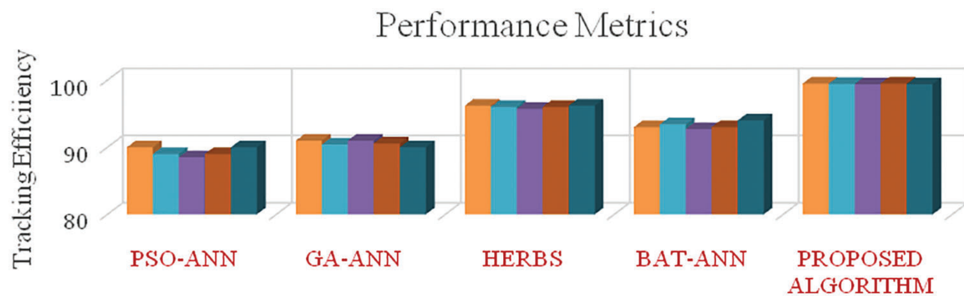


Figure 10: Comparative analysis of tracking efficiency between the different algorithms for the final scenario of testing

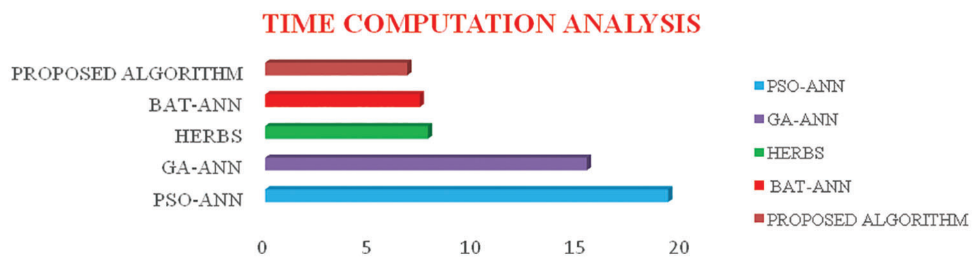


Figure 11: Time computation analysis for the different algorithm in detecting the maximum peaks

5 Conclusion

In this paper, an original crossover SHERB-MPPT approach for the most extreme power extraction in PV frameworks. The spotted hyena and BAT calculation has been utilized alongside ELMs to work on the exhibition of the PV cells during the incomplete concealing conditions. The SHERB uses the hunting procedure of spotted hyena for the BAT algorithm to find the best optimal values. At the initial stage, the echolocation principle is used with the minimum loudness, frequency, and velocity. The experimentation is carried out using six solar cells implemented using the MATLAB-SIMULINK under different operating scenarios of partial shading conditions. Simulation results show that the proposed SHERB-MPPT algorithm has outperformed other existing hybrid frameworks such as PSO-ANN, GA-ANN, HERBS-MPPT, and BAT-ANN. Extensive testing with 50000 data combinations collected in partial shade and typical circumstances. Based on simulation results, the suggested technique provides 99.7% tracking efficiency with a slower convergence speed. The tracking efficiency is as high as 99.6% in all partial shading conditions with high convergence speed. However, the proposed algorithm needs the limelight of improvisation for real-time implementation. In future, the meta-heuristic optimization algorithm should be improved to achieve a more tracking efficiency with a low speed of convergence.

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