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Original Article

Hybrid Emperor Penguin Salp Swarm Optimized Probabilistic Neural Network Controller for Maximum Power Tracking From HRES

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Abstract *- Energy harvesting using solar and wind energy is a major requirement in many applications. Also, to expand the efficacy of power generated from renewable sources, Maximum Power Point Tracking (MPPT) is crucial. Traditional MPPT controllers suffer from high error rates, slow convergence, and increased computational complexity, limiting their effectiveness. Thus, to solve these issues, an optimized Probabilistic Neural Network (PNN) controller to control the duty cycle of the boost converter has been designed. To improve performance, the proposed controller is optimized using a novel Hybrid Emperor Penguin–Salp Swarm Optimization Algorithm (HESS-SSA), which efficiently fine-tunes the neural network parameters. The proposed controller can optimize the duty cycle of the boost converter to maximize power extraction. Power extraction and duty cycle selection by HESS-SSA is compared with existing cuckoo search, Group Teaching Optimization Algorithm (GTOA), Dragonfly Optimization Algorithm (DOA), Particle Swarm Optimization (PSO) and PSO-Gravitational Search Algorithm (PSO-GSA). Proposed controller outperforms traditional optimization methods, as shown by simulation results, achieving a greater power output of 4538.89W with enhanced convergence speed and decreased error. The improved MPPT approach guarantees increased system efficiency and stability, which makes it a viable option for integrating renewable energy into independent power systems and smart grids.*

Keywords *- Hybrid renewable energy sources, Boost converter, Duty cycle, Emperor Penguin Optimization (EPO), Salp Swarm Optimization.*

1. Introduction

The search for alternative power generation techniques has been fueled by growing worldwide issues like dangerous gas emissions and skyrocketing energy prices. Clean, renewable energy sources are being actively developed by researchers to increase the production of electricity. The goal is to meet rising energy demands while lessening the impact on the environment. Wind and solar power, two forms of renewable energy, are gaining popularity. The goal of these developments is to build an energy future that is efficient and sustainable [1]. Solar and wind are generally regarded as the most reliable and prospective Renewable Energy Sources (RES) due to their non-hazardous nature [2]. Nevertheless, due to their stochastic and intermittent characteristics, solar and wind provide only a limited volume of energy [3]. Owing to the lower power production from single RES and the increasing cost of power, Hybrid RES (HRES) are used [4]. The HRES is modelled by combining two or more RES that can be worked in either stand-alone or grid-tied mode [5]. Moreover, the HRES needs effective power converters for a flexible interconnection between RES to enable the operation in grid-tied or stand-alone mode. The converter-attached HRES has been used for power quality improvement, grid-connected systems and reliability improvement [6, 7]. The basic concerns of the solar Photovoltaic (PV) scheme are solar insolation and heat. Moreover, the functioning of solar PV is explained by power-voltage and current-voltage curves [8]. A single point exists for peak power output in both solar and wind systems. The most efficient usage of HRES requires real-time tracking of the MPP [9]. As an example, engineers have used Incremental Conductance (IC), the ripple correction method, Perturb and Observe (P&O), and fractional short circuit current [10] to maximize a system's power output [11]. Among such methods, the IC method tracks MPP from the solar-wind model by examining the ratio between instantaneous and incremental conductance [12]. The major drawback of IC is the fluctuation around MPP; hence, it does not provide a satisfactory outcome. Similarly, the fuzzy logic controller can be applied in solar and wind RES but requires prior knowledge about the system [13]. However, these methods provide satisfactory outcomes in constant wind speed and solar irradiance conditions, but they are ineffective for tracing maximum power under non-uniform conditions. Partial shading happens when solar irradiance and temperature are partially obscured in photovoltaic systems. Traditional MPPT controllers fail to account for both the local and global MPP, causing them to remain stuck at the initial peak power without considering the latter. Hence, the existing MPPT controllers caused power losses under varying climatic conditions [14]. To get around these problems, a lot of meta-heuristic algorithms built on MPPT controllers have been implemented. Optimization methods are exploited to measure the supreme power output of solar PV. With greater precision, that method quickly finds the system's peak power [15]. Furthermore, soft computing approaches are adopted to extract MPP. Soft computing-based algorithms are suitable for practical application due to their improved performance and the availability of microcontrollers. Due to these benefits, soft computing methods are omnipresent in RES to extract the peak power [16].

1.1. Research Gap and Motivation

RES for MPPT with ANN-based methods has garnered a lot of attention lately. These networks are trained offline and then deployed online for real-time operation [17, 18]. Nevertheless, existing deep learning-based MPPT algorithms have poor real-time processing when operating on limited resources. Furthermore, training performance determines the accuracy of Artificial Neural Networks (ANN); as a result, the current approaches are laborious and lead to an increase in inaccuracy. Traditional algorithms' inherent faults lower overall performance, causing the model to fall into low values rather than its MPP. Therefore, the NN is utilized in conjunction with hybrid optimization to address these problems, leading to the best solution globally. Should the neural network be updated with the optimal error-reduced value, the system will achieve its maximum power output.

Numerous optimization techniques are employed in the literature to tune neural networks, but they have drawbacks such as undesired premature convergence and concerns with insufficient population diversity, which impair the neural network's overall performance. In the meantime, the salp swarm optimized probabilistic neural network [19] has a lower error and a higher rate of convergence. However, the local solution has fallen as a result of the quantity of random coefficients at the exploitation stage. The Emperor Penguin algorithm [20], which has a great exploitation technique, is therefore hybridized with that method. Therefore, this research presented a single MPPT controller for monitoring the peak power from hybrid systems. Although several ANN-based MPPT strategies have been proposed, most lack robustness and real-time adaptability due to inefficient parameter optimization. Existing deep learning-based MPPT controllers often show limited accuracy and higher computational complexity, making them less viable for embedded systems. Optimization techniques like PSO, GSA, and DOA have been used to fine-tune neural networks, but they are constrained by convergence issues and population diversity problems. Recent studies show that hybrid optimization methods can improve MPPT controller performance. However, there is a lack of research integrating hybrid algorithms with neural networks specifically for HRES. Motivated by this, the current work proposes a hybrid Emperor Penguin Optimization–Salp Swarm Algorithm (HESS-SSA) to optimize a Probabilistic Neural Network (PNN)-based MPPT controller. This approach aims to enhance convergence speed, reduce error, and ensure robust tracking of global MPP under varying environmental conditions.

1.2. Contribution

The main contribution of this work is given as follows,

- Model HRES by combining solar and wind systems to improve power generation efficiency and grid stability.
- Implement a Probabilistic Neural Network (PNN) based controller for MPPT to extract the maximum available power, and this ensures enhanced accuracy and adaptability to fluctuating renewable resources.
- A combination of two algorithms, the EPO procedure and the Salp Swarm Algorithm (SSA) procedure, is used to improve PNN performance, ensuring faster convergence and decreased computational complexity.
- Efficient duty cycle control dynamically optimizes the duty cycle of a boost converter to maximize power extraction from hybrid solar-wind sources.
- Provide a robust and adaptive MPPT solution suitable for real-time renewable energy management under varying environmental conditions.

The organization of this paper is given as follows: Section 2 discusses various methods associated with the proposed method. The workflow of the suggested method and HRES modelling, along with the MPPT controller, is illustrated in Section 3. Outcomes gained by the proposed method are elaborated in Section 4. Overall conclusion of the proposed work and its performance efficacy is given in Section 5.

2. Related Work

MPPT is a key component in improving the efficiency of solar, wind, and HRES. Different types of MPPT controllers for tracking maximum power are discussed in this section. Using a dynamic differential annealed optimization and recalling technique, Rajesh, P. et al. [21] built an upgraded Recurrent Neural Network (RNN) to track the greatest power point in a wind energy alteration scheme. The D2AORERN2 method is an acronym for "dynamic differential annealed optimization" and "recalling enhanced RNN," the two components that make up the proposed system. Performance of the suggested approach, which is implemented in

MATLAB/Simulink, is contrasted with that of other approaches, such as Hill Climb Search (HCS), PSO, and Genetic Algorithm (GA). GA, PSO, HCS, and the suggested method had respective efficiencies of 81%, 85%, 89%, and 99%. These outcomes show that the suggested strategy achieves the best efficiency and performs better than current techniques.

For photovoltaic systems that use a networked control system for observer-based control, Aslam [22] created a novel stochastic MPPT method. Networked Control Systems (NCSs) operating under an event-triggered paradigm primarily within a fuzzy system make up the suggested system. While accomplishing the targeted performance, the constructed model guarantees stochastic stability. An innovative model of the non-linear system is constructed in two stages by means of the T-P transformation: first, by assuring an acceptable controller input, and second, by assuring an appropriate vertex polytope for stability of the system.

In order to track the highest power point of a Proton Exchange Membrane Fuel Cell (PEMFC), Fan et al. [23] combined fuzzy control with a hybrid Artificial Bee Colony (ABC) algorithm. One approach to construct an MPPT control method for PEMFC was offered as an ABC-fuzzy system, which integrates fuzzy control with the ABC algorithm. In contrast to the P&O, IC, and ABC methods, the test results show that PEMFC can achieve better anti-interference capability, faster response speed, lower oscillation, lower steady-state error, and higher output power with the ABC-fuzzy examined. The ABC-fuzzy MPPT method enhances power supply efficiency and prolongs the service life of PEMFCs by increasing the device's power output.

Partially shaded solar PV systems published research by Kiran et al. [24] on reduced simulative performance analysis of variable step size ANN-based MPPT techniques. The suggested topology uses an MPPT based on a variable-step size ANN to enhance the topology. A boost converter is attached between the PV system and the load to raise the voltage of the PV supply.

In their study on an optimized neural network-based energy management system for artificial rabbits was described by Sandeep, S. D. et al. [25], and an isolated DC microgrid system that uses Photovoltaic (PV), battery, and supercapacitor technology. The proposed system employs an ARONN control system for energy management, which stands for artificial rabbits optimized neural network. By controlling the battery's low-frequency current control and the super capacitor's high-frequency current control, this technique lessens the strain on the battery. The proposed energy management and regulation solutions are shown to be effective in the simulation results.

Idrissi et al. [26] created a PI controller and an ANN to enhance MPPT for solar applications. In order to create an MPPT controller for use in PV applications, the suggested system employs the ANN method. The incorporation of a PI controller enhances its performance. Additionally, the performance of the ANN-based MPPT controller is compared to that of the traditional P&O technique. The outcomes of simulations can be examined using the MATLAB program.

Haq et al. [27] developed a concept for an adaptable global sliding mode MPPT controller specifically for standalone PV systems that are based on neural networks. The proposed method guarantees that the sliding mode continues indefinitely by eliminating the reaching phase. The system response is free of chattering and harmonic aberrations. Finally, the simulation results conducted in the MATLAB/Simulink environment validate the proposed control approach's accuracy, efficiency, and fast-tracking capabilities. To further validate the results, they are compared to the traditional non-linear backstepping controller when faced with sudden environmental changes.

An MPPT Algorithm for Stand-Alone PV Systems employing an ANN was developed by Yılmaz et al. [28] with a Boost Converter architecture. An MPPT algorithm based on ANNs is the core of the suggested system. A reference voltage is produced by training the PV panel input temperature and irradiance data using the Levenberg-Marquardt approach. By contrasting this reference voltage with the voltage produced by the PV panel, MPPT is accomplished. The suggested procedure's performance is evaluated by contrasting it with more conventional MPPT techniques like INC and P&O. According to simulation data, the ANN-based MPPT works better than traditional techniques.

Venkata Siva Krishna Rao Gadi and Mande Praveen [34] have suggested that Emperor Penguin Optimiser (EPO) and Glowworm Swarm Optimisation (GSO) are combined to create a new hybrid emperor penguin glowworm swarm optimization method. Additionally, the techno-economical approach reduces power loss, voltage fluctuations, Diesel Generator (DG) costs, and energy supply costs.

This optimization provides renewable energy sources by implementing wind turbines, DG, PV and ESS at their maximum capability. Additionally, metrics such as voltage variations, network power losses, DSM, initial and operational cost and the created model aid in the solution of the multi-objective function.

Gurumoorthi et al. [35] have presented a hybrid model that combines Quantum-inspired GA (DRL-QIGA) with Deep Reinforcement Learning (DRL). In the suggested approach, the proximal policy network is efficiently combined with the DRL to maximize power generation in real-time. DRL is appropriate for the suggested model since it can learn and adjust to changes in a real-time context. As it searches for the best solutions to the optimal power flow problem, the QIGA improves the exploitation and exploration characteristics by strengthening the global search process using the quantum computing principle.

Kuo-Hua Huang et al. [36] have developed the GA-ACO algorithm, a hybrid optimization controller that Combines Ant Colony Optimization (ACO) with GA. It is used to perform MPPT on a Photovoltaic Module Array (PVMA). In this manner, the system can continue to function at the global maximum power point even if the PVMA is partially shaded and the P-V characteristic curve has several peaks. It is demonstrated that a superior response performance of MPPT is achieved by appropriately adjusting the Gaussian standard deviation and the Pheromone evaporation rate of the suggested GA-ACO optimization.

These analyses show that many of the existing methods are MPPT controllers for single RES, and few attempts were made on HRES. Moreover, in HRES, the hybrid optimization algorithm-based MPPT controller offers better performance than a single optimization algorithm. It was found that the neural network-based approaches perform well in finding the optimum PowerPoint. Owing to these facts, the proposed work modelled the Hybrid Emperor Penguin Salp Swarm (HESS) optimized PNN controller.

3. Proposed Methodology

Combining solar PV and wind turbines in this suggested project helps create HRES. Wind and solar systems are individually connected with boost converters. A HESS optimized PNN controller is presented to track the peak power from HRES. The PNN comprises four layers for processing the data to decide the Bayesian strategy. A combination of Emperor Penguin and Salp swarm optimization techniques, the HESS algorithm optimizes the PNN layer weight; hence, it enhances the tracking ability. The proposed HESS-PNN controller provides control signals to the converters to extract peak power. The complete layout of the suggested technique is presented in Figure 1.

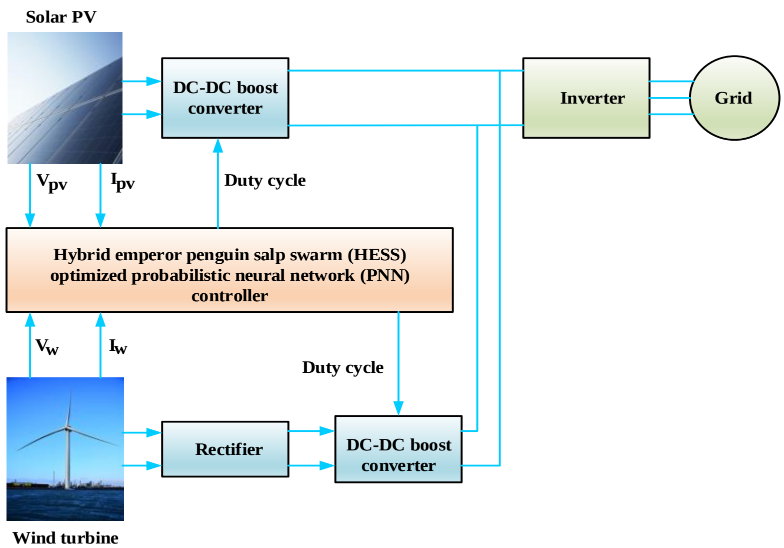


Fig. 1 Proposed methodology

3.1. Modeling of Solar PV

Solar PV works by absorbing solar energy from sunlight and converting it into electricity. PV panel obtains the irradiance from the sun, and the atom in the panel tends to move, producing charged particles. The performance of solar PV is estimated through the connection between current and voltage. The current output of solar is assumed as follows,

$$k = k_{ph} - k_0\left(exp\left(\frac{V+r_s k}{Y} - 1\right) - \frac{V+r_s k}{r_{sh}}\right) \quad (1)$$

$$Y = \frac{N_s w_n E T}{Q} \quad (2)$$

In the above equation, k_{ph} represents the photocurrent of the PV cell, the series resistance represented by r_s, k_0 represents the capacity present, V symbolize output voltage. k denotes current output, and the shunt resistance is denoted by r_{sh}. The amount of series PV cells is characterized as N_s, the Boltzmann constant is represented by E, $w_n$denotes the ideality factor, T denotes the temperature and ideality factor is denoted by Y.

3.2. Wind Energy Conversion System

Mechanical power (Pm) produced by wind can be calculated using the formula below. The following formula, which looks at the power produced by a wind turbine, can be used to express the mechanical power ($P_{turbine}$) of the wind turbine:

$$P_{turbine} = \frac{1}{2}\rho\pi r^2 d^3 U_{power} \quad (3)$$

In an ideal wind turbine, the power captured would be the one given by Equation (3). The actual power of the wind turbine here ρsignifies air density, $r$signifies turbine radius, $d$represents wind velocity, U represents power coefficients [29].

3.3. Modeling of the Boost Converter

The DC voltage is increased through a boost converter that is a part of the hybrid system. Duty cycle and switching frequency can be changed to maximize the boost converter's efficiency. An inductor, a freewheeling diode, a switching power MOSFET (S), and an output filter capacitor make up four primary parts. Figure 2 illustrates the architecture of the boost converter.

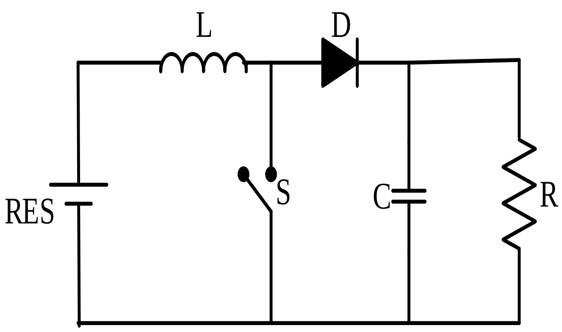


Fig. 2 Architecture of the boost converter

Output current, voltage and transfer gains are expressed as,

$$V_o = \left(\frac{1}{1-W}\right) V_{pv} \tag{4}$$

$$u_o = \left(\frac{1}{1-W}\right) u_{pv} \tag{5}$$

Here, output voltage is represented by V_o , $u_o$represents output current, V_{pv}signifies solar output voltage, u_{pv}signifies solar current, Wrepresents duty cycle [30].

3.4. Proposed HESS-PNN Controller

The MPPT controller is used to remove peak power from HRES. The existing MPPT controller had the disadvantage of a fixed step size, which led to higher power oscillations. Thus, HESS based PNN controller is suggested in this work for tracking the maximum available power from HRES. By manipulating the prices of the weights and biases connected amongst the layers of neurons, an artificial neural network can learn to perform tasks.

This network is composed of interconnected groups of simple processing elements called artificial neurons. An important aspect of a neural network is its learning process, activation role, and the way connections are organized between the layers of neurons. The PNN works based on interconnection patterns, weights and activation functions [30]. Figure 3 shows the architecture of the PNN controller.

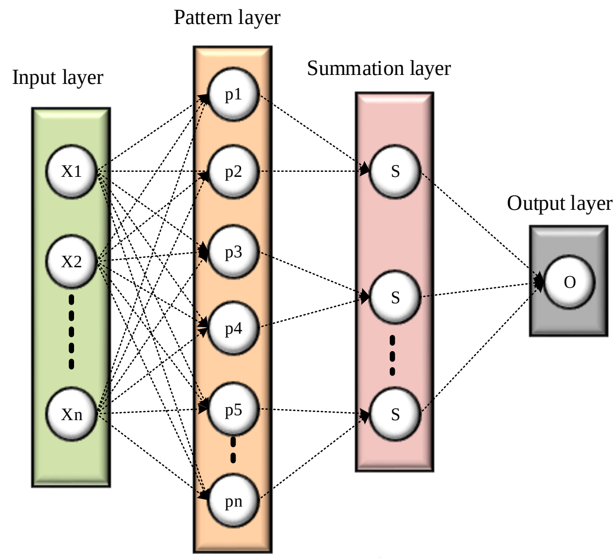


Fig. 3 Architecture of PNN

3.4.1. Probabilistic Neural Network (PNN)

PNN is a supervised learning network based on a probabilistic algorithm. The PNN will produce sufficient training data for training the Bayesian classifier. In PNN, the weights of layers are adjusted automatically, which has the advantage of a higher training speed. As an activation function, PNN processes the Gaussian function over many layers [31, 32].

Signal categorization systems and real-time fault detection are perfect applications for Probabilistic Neural Networks (PNNs) due to their quick training pace.

A radial basis layer in its architecture separates input and hidden layers, while a competitive layer connects hidden and output layers. The transformation layers of PNN are given below,

Input-Pattern Layer: This is the first stage of a PNN, and it entails feeding a sequence of shapes into the pattern layers as input. In order to multiply the input, the pattern layer receives it from the input layer.

$$\pi_{jk}(x) = \frac{1}{2\pi^{\frac{d}{2}}\sigma^d}\left(-\frac{\|x-x_{jk}\|^2}{2\sigma^2}\right) \tag{6}$$

Here, d signifies the problem dimension, σ signifies the smoothing parameter, x signifies the input, and x_{jk} signifies the pattern vector. The following equation examines the summation,

$$O_j(x) = \frac{1}{2\pi^{\frac{d}{2}}\sigma^d}\frac{1}{N_i}\sum_{k=1}^{N_i\Sigma\left(-\frac{\|x-x_{xy}\|^2}{2\sigma^2}\right)} exp \quad (7)$$

Here, N_i signifies the number of classes.

Summation to Output Layer: Finding the output helps one to ascertain the vector's last class. Changing the equation given by the hidden layer helps one to investigate its result.

$$c(x) = arg\ M\ ax\{O_i(x)\}, i = 1,2,3\ldots c \quad (8)$$

Here, Euclidean distance is estimated by $\|x - x_{jk}\|$.

3.4.2. Hybrid Emperor Penguin Salp Swarm Optimization Algorithm (HESS)

HESS is developed by combining EPO and SSA. The proposed HESS overcomes the drawbacks of lower convergence and diversity. The SSA needs higher computational efforts; thus, to overcome such issues, the EPO is added to the SSA. The information-carrying behavior of SSA is improved by adding EPO [33].

Because they are such gregarious creatures, emperor penguins hunt and forage in groups. Each penguin makes an equal contribution to the group effort as they cuddle together to survive the harsh Antarctic winters, exhibiting a strong feeling of solidarity and cooperation. The emperor penguin exhibits (1) Create and explore huddling behavior. (2) Calculate the huddle's surrounding temperature. (3) Find the distances separating every penguin. (4) Relocated effective mover.

The SSO algorithm was modeled after the flocking behavior of salps during their deep-sea foraging and navigation. A mathematical representation of this behavior is a salp chain, which is separated into two groups: followers and leaders.

The followers march sequentially after the leader, who hints at the chain from the front. The salp chain is a mathematical model for this behavior. The flow of HESS is explained below.

The position updating equation of SSA is expressed as follows,

$$S_a^1 = \begin{cases} G_i + d_1((u_a - l_a)d_2 + l_a), d_3 \geq 1 \\ G_i - d_1((u_a - l_a)d_2 + l_a), d_3 < 1 \end{cases} \quad (9)$$

Here, S_a^1 signifies the initial position in a^{th}dimension, G_i signifies the position of food basis, $u$and $l$signifies the upper and lower limits, respectively. Random numbers are represented by d_1, $d_2$and d_3.d_1 is ensures improved exploration and exploitation, which is termed as,

$$c_1 = 2e^{-\left(\frac{4c}{max}0^2\right)} \quad (10)$$

Here, c signifies the current repetition, and maxsignifies maximum iteration. The updated position of the remaining parameters is given below,

$$S_a^b = \frac{1}{2}AT^2 + V_0T, j \geq 2 \quad (11)$$

Here, S_a^b signifies the follower position, Tsignifies the time duration, and $V_o$signifies the starting speed. Moreover, Acan be calculated by,

$$A = \frac{V_{end}}{V_{initial}} \quad (12)$$

$$A = \frac{X_{current} - X_{initial}}{t} \quad (13)$$

Here V_{end} , $V_{initial}$ the final and initial speeds are signified, $X_{current}$ and $X_{initial}$ are the current and initial positions, respectively. If the initial velocity is zero, then the position updating equation is assessed by the subsequent equation,

$$S_a^b = \frac{1}{2}(s_a^b + s_a^{b-1}) \quad (14)$$

The penguin huddling behavior is used in SSA to recover the convergence speed. The following equation examines the boundary of huddling,

$$\lambda = \nabla\sigma \quad (15)$$

Here, σ and λ signifies wind velocity and gradient, respectively. Moreover, the complex potential is given as follows,

$$C = \sigma + i\alpha \quad (16)$$

Here, i signifies the constant of the imaginary C signifies the role of the polygon plane. The following equation examines the temperature of the cluster,

$$P' = \left(P - \frac{I_{max}}{W - I_{max}}\right) \quad (17)$$

$$P' = \begin{cases} 0, if r > 0.5 \\ 1, if r < 0.5 \end{cases} \quad (18)$$

Here, Wsignifies current iteration, I_{max} signifies maximum iteration, $r$signifies radius, Psignifies the duration for finding the best solution. The following equation examines the distance between two penguins,

$$\vec{D}_{EP} = Abs(S(\vec{X}).\vec{E}(a) - \vec{X}.\vec{E}_{ep}(a)) \quad (19)$$

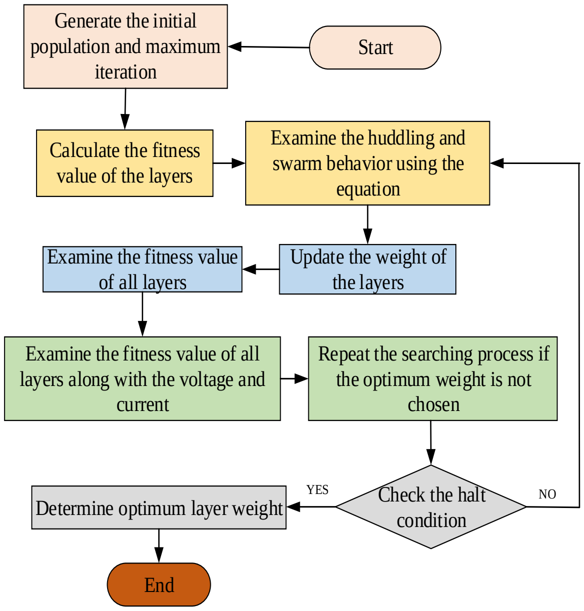


Fig. 4 Flow chart of HESS

Here, $\vec{D}_{EP}$ the gap between the search agent and the best fittest agent $a$represents the present iteration, the parameter$\vec{X}$avoids the collision, $\vec{E}$ and $\vec{E}_{ep}$represents the best optimum solution and position vector, respectively, $S(.)$signifies the social behavior.

$$\vec{r} = \left(M \times \left(P' + g_{accuracy} \times rand()\right) -\right)P' \tag{20}$$

$$g_{accuracy} = Abs(\vec{E} - \vec{E}_{ep}) \tag{21}$$

$$\vec{C} = rand() \tag{22}$$

Here, Msignifies a movement parameter that maintains the distance to avoid a collision. In most cases, the moment parameter is set as 2, P'which signifies the temperature level of the group, and the polygon grid accuracy is represented as $g_{accuracy}$ and $rand()$represents an arbitrary quantity between 0 and 1. The following equation can be used to examine social behavior,

$$S(\vec{X}) = \left(\sqrt{f.e^{-\frac{x}{c}} - e^{-x}}\right)^2 \tag{23}$$

Here e, it signifies the function of expression $f$and $c$control of the exploitation and exploration that lies in the range between [1.5, 2] and [2, 3]. The position updating equation is given by,

$$\vec{E}_{ep}(u+1) = \vec{E}_{ep}(u) - \vec{r} \times \vec{D}_{ep} \tag{24}$$

Nevertheless, the computation of SSA parameters necessitates significant processing power. The EPO procedure is used to solve this difficulty. Utilizing the EPO process's huddling habit helps SSA overcome its difficulties in managing essential information. Consequently, a new hybrid algorithm that combines the advantages of SSA and EPO is suggested. The PNN's weight is updated by the HESS to adjust the duty cycle of the boost converter.

The input layer contains four neurons, while the output layer contains two. The proposed HESS-PNN is used to tune the duty cycle of the boost converter to generate peak power. By utilizing HESS, the ideal number of layers is selected to enhance the boost converter's power tracking capability. The HESS workflow for optimizing the layer weights is depicted in Figure 4. Algorithm 1 denotes the pseudocode Emperor Penguin Salp Swarm Optimization

Algorithm 1: Pseudocode Emperor Penguin Salp Swarm Optimization

```
Start
1. Initialize the emperor penguin and salp swarm populations with a random PNN weight vector
2. Evaluate the fitness function
      Fitness=f (voltage, current)
3. While (t< MaxIter)
      For each salp
          If i==leader
               Update position using Equations (9)-(10)
          Else
               Update follower position using Equations (11)-(14)
      For each emperor penguin
           Evaluate temperature and huddling behavior using Equations (15)-(18)
            Update convergence using EPO dynamics
      Combine SSA and EPO outputs into a unified HESS update
      Update PNN weights with new positions
      Evaluate updated fitness (power output) using PNN
        If new fitness > best fitness
               Store new weights as optimal
        t ← t + 1
4. End
5. Output final PNN weights and corresponding optimal duty cycle
Stop
```

4. Results Validation

To inspect the stability of the HESS-PNN based on the MPPT controller, HRES is modelled in the MATLAB/Simulink platform. The PV and wind as HRESs are considered to be the source of the Simulink.

Additionally, the model incorporates a boost converter to increase power levels. The boost converter's ideal duty cycle was adjusted using the suggested controller. Figure 5 shows the whole Simulink process for the suggested work.

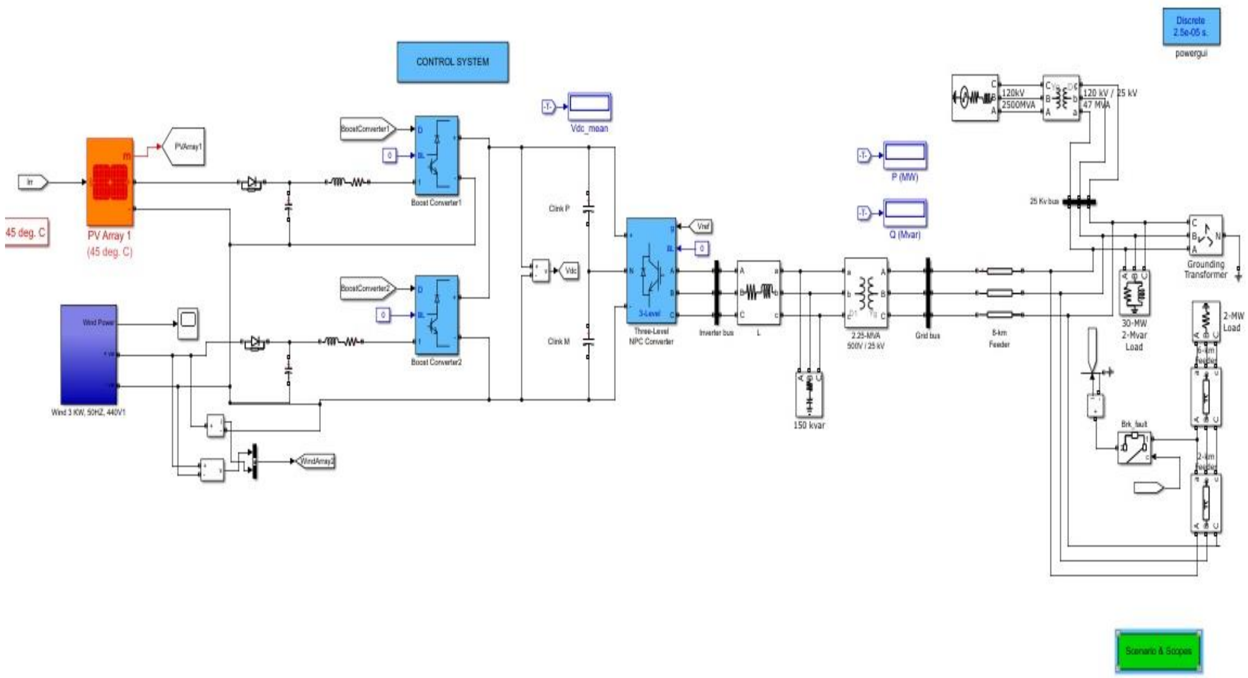


Fig. 5 Simulink model of proposed work

The HRES with the boost converter to path maximum power using the parameter values is illustrated in Table 1.

Table 1. System description

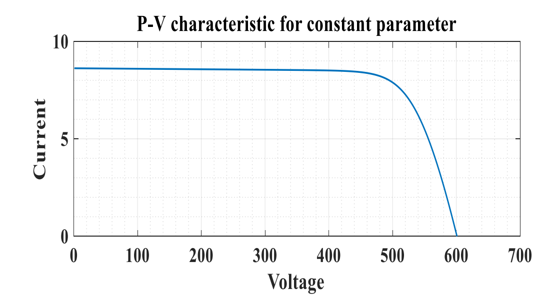
Systems	Parameter	Values
Solar PV	Cells per module	83
	Series-connected modules per string	15
	Voltage at MPP	43.4V
	Current at MPP	8.18A
	Diode ideality factor	1.0705
	Open circuit voltage	60V
	Short circuit current	8.68A
Wind	Speed	2000rpm
	Torque	10Nm
	Nominal mechanical power	5000W
	Base wind speed	12m/s
MPPT controller	Duty cycle limits	[0.8, 0.3]
	Number of initial population	10
	Number of iterations	100
Grid	Phase	3
	Frequency	60
Boost Converter	Diode on-state resistance	$1e^{-4}$ohm
	Diode snubber resistance	$1e^{6}$ohm

The proposed HESS-PNN-based MPPT controller is evaluated under two cases,

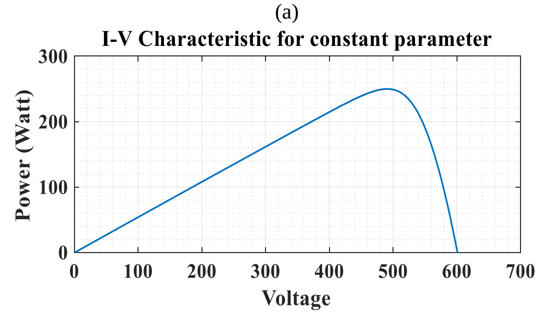
Case 1: System performance under constant sources

Case 2: System performance under varied sources

Case 1: In the first case, the system is evaluated by adding constant $1000W/m^2$solar irradiance and $12m/s^2$wind speed sources. P-V and I-V features of solar PV under constant sources are depicted in Figure 6. The results show that the curves are smooth under constant sources.



(a)



(b)

Fig. 6 Performance analysis of solar PV under constant irradiance: (a) I-V, and (b) P-V characteristics.

The control stability of the converter is examined using the modulation index, which defines the extension of the modulation to the carrier signal. The modulation index's optimum value minimizes the converter's power loss and increases the converter's stability.

The stability of the modulation index is achieved at 0.9 in 0.5 seconds. The modulation index provided by the proposed HESS-PNN is portrayed in Figure 7, as it has been seen that the suggested controller provides a constant modulation index to the converter.

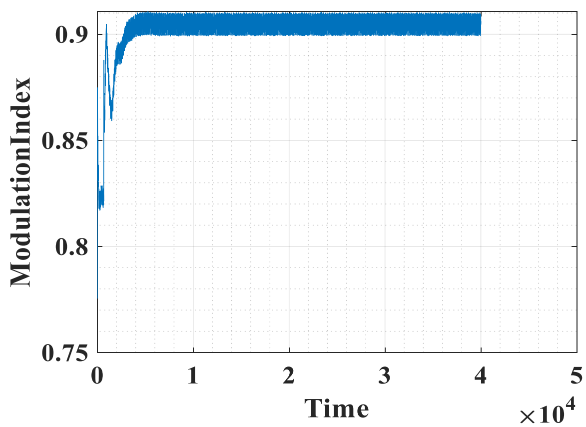


Fig. 7 Analysis of modulation index under constant source

The power extraction from HRES will be improved by choosing the optimum value for the duty cycle. The MPPT ability of the proposed controller and the existing controller is shown in Figure 8.

To measure the performance of the proposed HESS-PNN controller, the existing controllers such as GTOA [37], PSOGS [38], DFO [39], PSO [40] and cuckoo [41] optimization algorithm-based MPPT controller.

The results analysis implies that the single algorithm-based MPPT controllers provided lower power due to the lower convergence speed needed to track maximum power. In addition, the power tracking ability is poor in existing controllers due to the oscillations around peak power.

The proposed system yields 1.5×10^6 at 1 second. At the same time, the proposed method yields higher power due to the higher computational speed of the MPPT controller.

Figure 9 shows the DC link voltage of the inverter during constant source. The DC link voltage is hiked to 1028V before it settles at 1000V at 0.5 seconds. Moreover, it is verified that the DC link voltage is the same for removing maximum power from the hybrid scheme. The purpose of the DC link voltage is to supply a steady flow of voltage, which ensures the MPPT and protects the power electronic component.

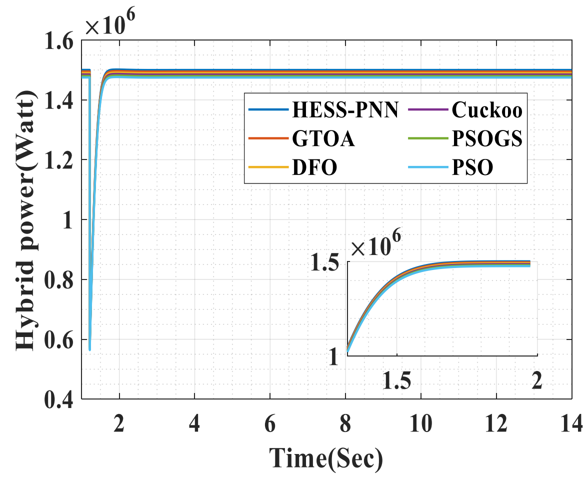


Fig. 8 Comparative analysis of MPPT controller

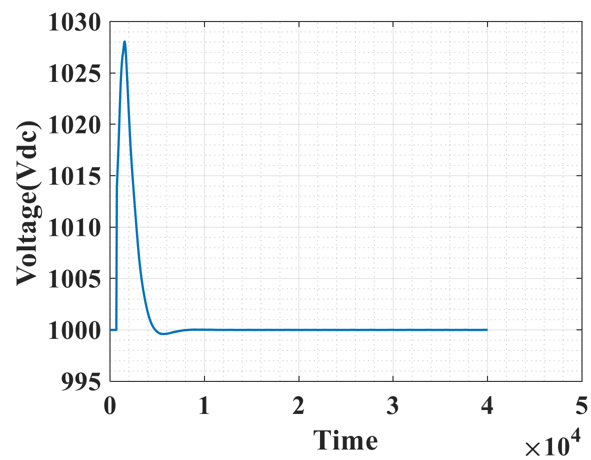
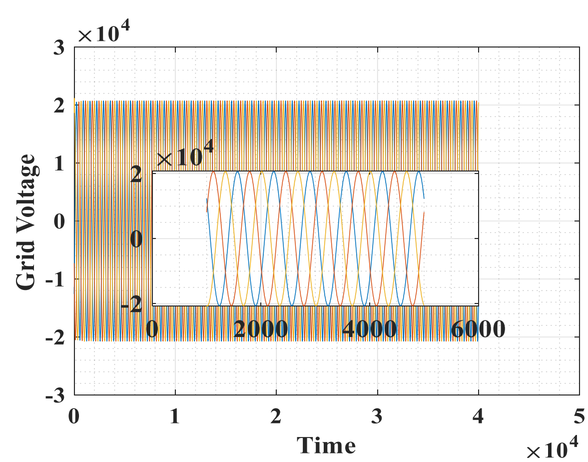
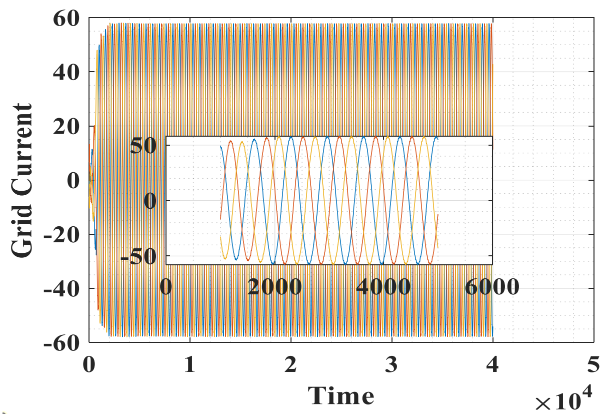


Fig. 9 Analysis of DC link voltage

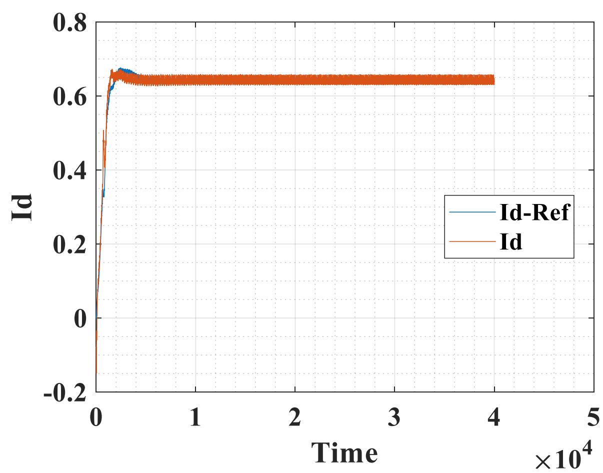
The grid's voltage and current are displayed in Figure 10. The enhanced power extraction raises the voltage and current that are fed into the grid. The grid's current in the d-q frame implies that the proposed controller model reaches the reference values.



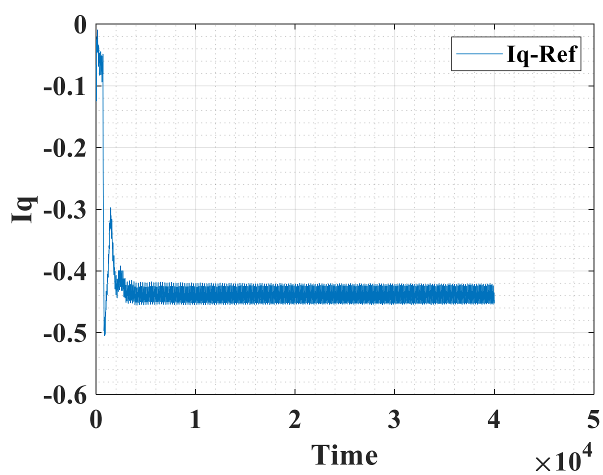
(a)



(b)



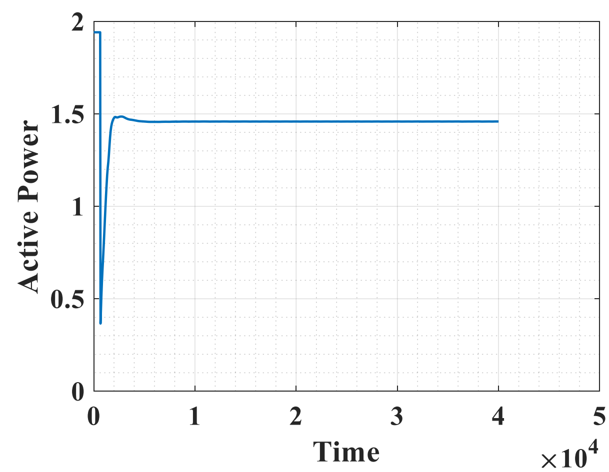
(c)



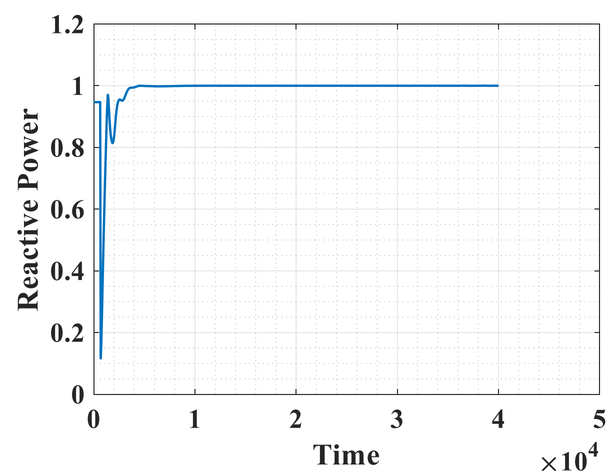
(d)

Fig. 10 Performance analysis of grid in constant sources: (a) Voltage, (b) Current, (c) Id, and (d) Iq.

Active and reactive power on the grid side during constant sources is depicted in Figure 11. It was found that reactive power compensation performed well in the system with the proposed controller. In order to guarantee dependable and effective power distribution, the electrical grid is essential. Numerous variables, including system flexibility, economic benefits, and energy stability, make it necessary.



(a)



(b)

Fig. 11 Estimation of (a) Active power, and (b) Reactive power on the grid side under constant sources.

Case 2: In the second case, system functioning is analyzed by varying the sources of irradiance from $1000W/m^2$to $200W/m^2$. The P-V and I-V curve of solar PV is depicted in Figure 12. By analyzing the waveforms, it is found that the power increases with the increasing level of irradiance.

A boost converter is added to HRES, and an MPPT controller is used to optimize power output from HRES. Selecting the appropriate duty cycle value improves the boost converter's power conversion capability.

Thus, a PNN-based MPPT controller is used, whereas a HESS-PNN optimizes the layer weights. The modulation index waveform provided to the converter by the proposed controller is depicted in Figure 13.

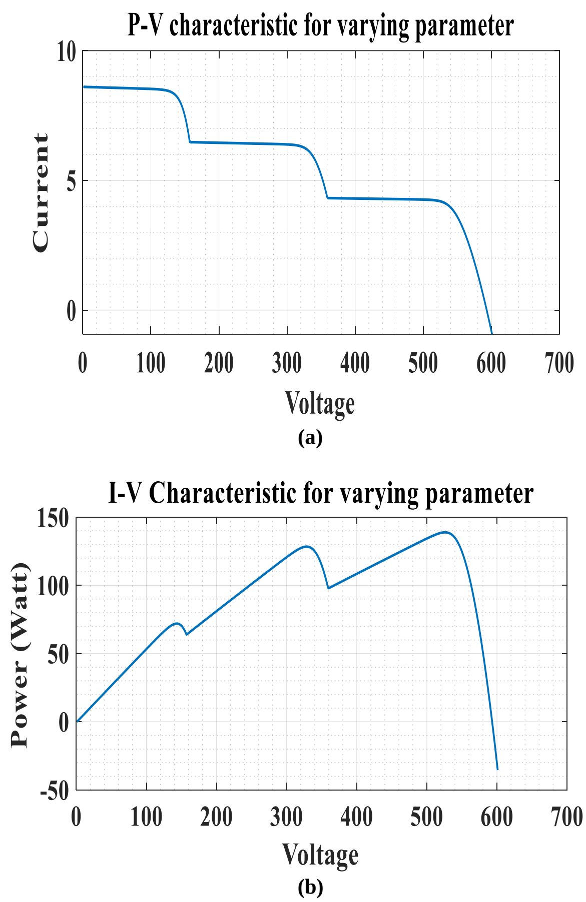


Fig. 12 Performance analysis of solar PV under varied irradiance: (a) I-V, and (b) P-V.

Power obtained from the hybrid solar PV-wind structure is depicted in Figure 14. The power removed from the hybrid system indicates that the power production from both sources varies due to the varying irradiance levels. Power tracking varies due to the various sources that cause oscillations around the system and lead to power loss. The comparative analysis of the MPPT controller for peak power extraction indicates that the proposed controller yields higher power under varied sources owing to the optimum tuning of the converter duty cycle.

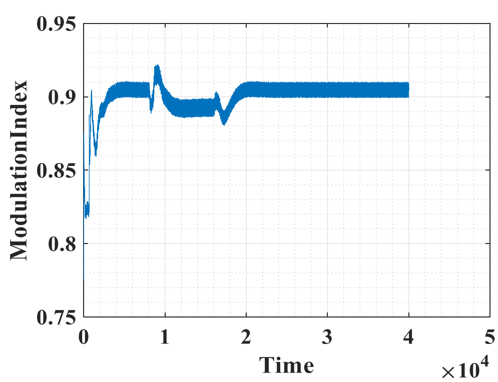


Fig. 13 Analysis of modulation index under varied sources

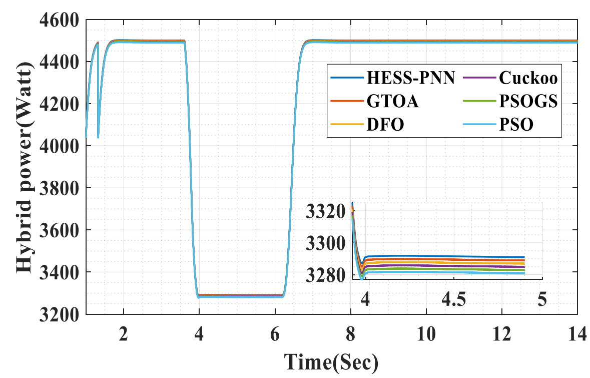
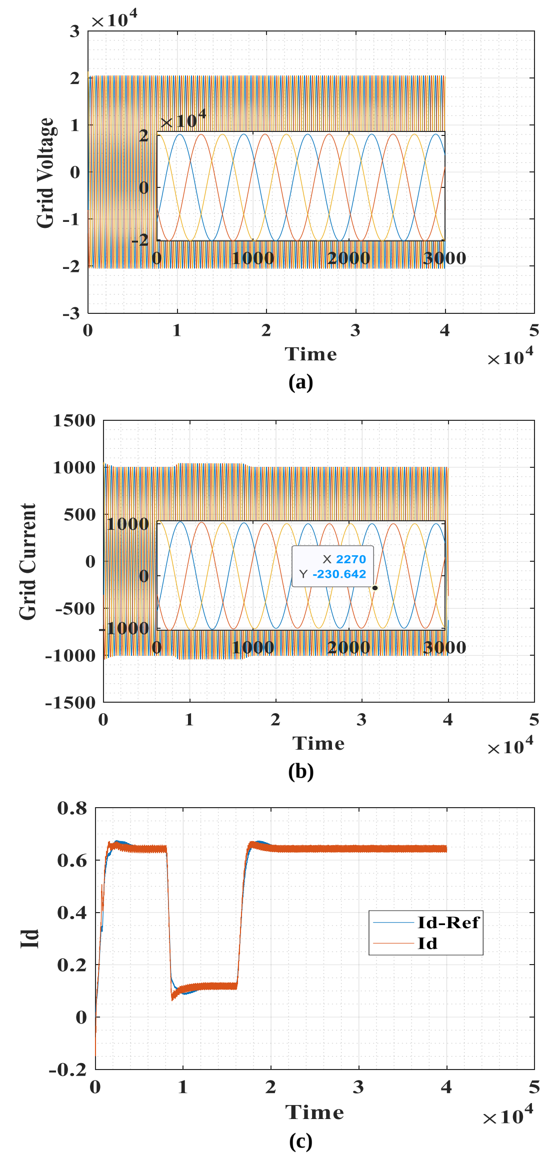
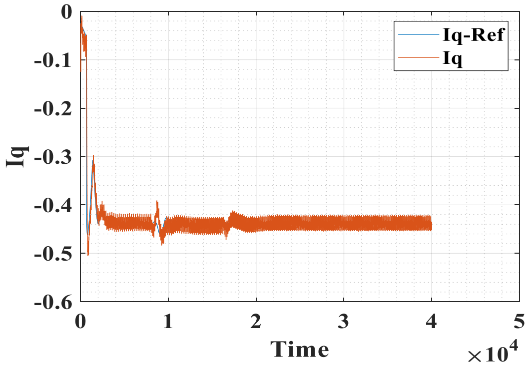


Fig. 14 Comparative analysis of the MPPT controller in varied sources

Figure 15 shows the grid voltage and current under various sources. As can be observed, the proposed MPPT controller increases the power to the grid in the given manner.

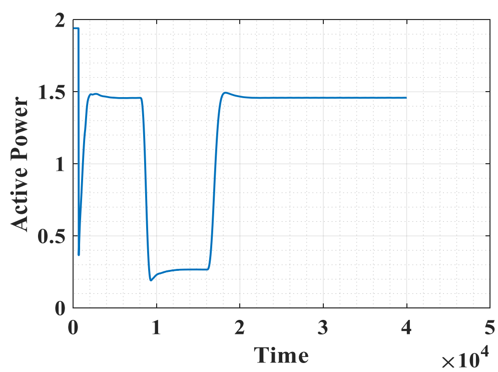




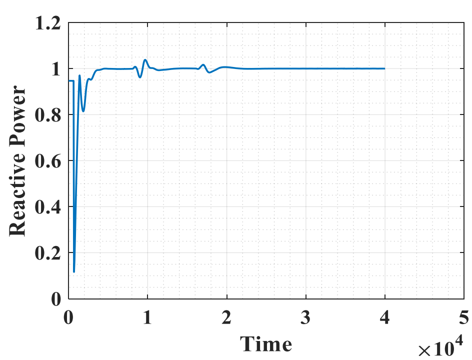
(d)

Fig. 15 Performance analysis of grid in varied sources: (a) Voltage, (b) Current, (c) Id, and (d) Iq.

Figure 16 shows the grid-side analysis of active and reactive power. By examining outcomes, the proposed method provides better reactive power compensation under varied sources. Moreover, it is found that the real power to the grid varied due to a varying range of sources. In contrast, the proposed controller minimizes the reactive power to the grid.



(a)

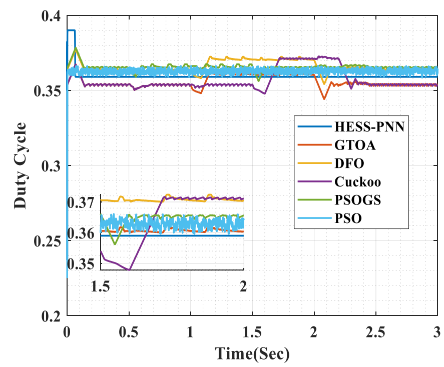


(b)

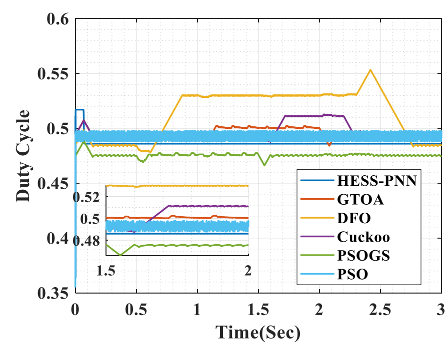
Fig. 16 Estimation of (a) Active power, and (b) Reactive power on the grid side.

4.1. Discussion

By contrasting the effectiveness of the suggested controller in duty cycle selection by using an optimization technique to compare its performance with that of the current MPPT controller. Figure 17 shows the relative analysis of the MPPT controller concerning the provision of an optimal duty cycle in constant sources. According to the findings, the optimal duty cycle cannot be achieved by the PSO-tuned MPPT controllers because of their reduced convergence rate. In addition, the PSOGS yields a better duty cycle, which also creates oscillations in the system for an increased duration. The cuckoo algorithm provides varied duty cycles. Thus, it cannot improve the converter performance. However, the proposed controller can yield an optimum duty cycle due to the better convergence speed when adopting the hybrid algorithm. The relative analysis shows that the suggested controller yields a better duty cycle on both the constant and varied sources due to its higher tracking ability.



(a)



(b)

Fig. 17 Investigation of MPPT controllers for duty cycle selection under: (a) Constant sources, and (b) Varied sources.

Table 2. Quantitative performance comparison of various MPPT

MPPT Controller	RMSE (W)	MAE (W)	Tracking Efficiency (%)	Convergence Time (s)
Proposed HESS-PNN	**12.45**	**9.87**	**99.1**	**0.38**
PSO	34.21	27.56	96.5	0.72
PSOGSA	28.63	21.44	97.2	0.65
DFO	30.05	23.87	96.8	0.61
Cuckoo Search	37.88	30.14	95.9	0.75
GTOA	25.39	18.93	97.8	0.53

Table 2 presents a quantitative performance comparison of various MPPT controllers based on four key metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), tracking efficiency, and convergence time. The proposed HESS-PNN controller demonstrates superior performance with the lowest RMSE (12.45 W) and MAE (9.87 W), indicating higher accuracy in MPPT.

It also achieves the highest tracking efficiency of 99.1% and the fastest convergence time of 0.38 seconds. In contrast, conventional methods like Cuckoo Search and PSO exhibit higher error values and slower convergence. These results confirm that the HESS-PNN controller not only enhances tracking precision but also ensures faster and more stable MPPT performance under dynamic conditions. Proposed HESS-PNN controller leverages the synergistic strengths of a novel hybrid optimization algorithm to meticulously train a probabilistic neural network. This foundational design choice enables an unparalleled balance of global exploration, precise exploitation, rapid adaptation, and accurate tracking, leading to demonstrably superior performance in terms of power extraction, convergence speed, error minimization, and overall system stability when compared to conventional and other meta-heuristic-based MPPT techniques.

4.2. Limitations and Future Work

This study is limited to simulation-based validation using idealized converter models, without considering hardware non-linearities, sensor noise, or environmental disturbances. The computational complexity of the HESS algorithm may also challenge real-time implementation. Additionally, the work focuses only on a fixed solar-wind hybrid system. Future research will involve hardware implementation and experimental testing, exploring real-time deployment on embedded platforms, and extending the controller to multi-source hybrid systems with advanced learning techniques for improved adaptability and robustness.

5. Conclusion

This study introduces a new method for improving the boost converter's duty cycle in solar-wind HRES using the HESS-PNN controller. Unlike the traditional method, which requires separate converters, the suggested topology improves power generation efficiency while reducing system costs. A hybrid HESS algorithm, which combines the EPO and SSA to provide faster convergence and better performance, is used to optimize the controller after it has been structured using a PNN. The proposed topology is validated in variable and constant energy sources to assess the system's efficiency. Modulation index and solar PV properties are examined, and a comparison with other MPPT controllers such as GTOA, DFO, PSOGA, PSO, and cuckoo-based methods is carried out. The findings show that the HESS-PNN controller improves the boost converter's ability to choose the ideal duty cycle, hence enhancing power tracking performance across various operating conditions. These results demonstrate how the suggested approach may help hybrid renewable systems achieve more reliable and effective energy collection.

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