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Enhanced Maximum Power Point Tracking Using Embedding Deep Networks and Self-Adaptive Genetic Algorithm

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Abstract: In this paper, we present a new approach for the power point tracking problem in photovoltaic systems by integrating an adaptive genetic algorithm (GA) into neural networks to solve it. The classic MPPT strategies might often fail to adequately accommodate dynamic environmental conditions and system variations, resulting in poor power extraction. To combat this, we present a new framework combining deep learning approaches with the power of evolutionary optimization. The basic idea of our method was to utilize two different representations for continuous and categorical features through an embedding network, which would result in better prediction accuracy using the MPPT algorithm to augment tracking by combining operational and environmental settings within dense continuous embeddings that could then interact with the multidimensional features. We propose a deep neural network architecture to predict optimal power points and train end-to-end over these embedding networks. A novel technique that uses neural networks and a self-adaptive evolutionary algorithm to track the greatest power point in solar systems. A self-adaptive mechanism in our approach dynamically modifies the GA's settings in response to real-time performance feedback. The complex connections between environmental and operational parameters have been captured using embedding networks to improve tracking accuracy. The test results indicate a 20% increase in system efficiency overall, a 25% improvement in voltage stability, a 30% reduction in total harmonic distortion (THD), and a 15% decrease in processing time, confirming the strategy's efficacy compared to traditional MPPT techniques. In addition, our suggested strategy improved the tracking accuracy and time to around 99.98 tracking Acc and 0.12s tracking Time.

Keywords: Maximum power point tracking (MPPT), Embedding neural networks, Genetic algorithms, Self-adaptive optimization, Photovoltaic systems, Power extraction efficiency.

1. Introduction

Photovoltaic (PV) systems are an important renewable part of the answer to the global need for sustainable energy solutions. The ability of the PV systems to track its Maximum Power Point (MPP) depends on the system efficiency, which is subjected to temperature and irradiance variations [1]. Classical MPPT techniques, such as Incremental Conductance (IncCond) and Perturb & Observe (P&O), are most commonly used to detect MPP. While these methods work well in certain situations, they may not perform well if the environment is more complex or dynamic, eventually giving high power extraction and decreasing performance efficiency for such systems.

Advances in optimization algorithms and AI have recently provided a new path for optimizing MPPT. Deep learning shows the neural network's proficiency in capturing the intricate, often non-linear relationships latent in PV system data. Some other techniques, like Evolutionary methods such as Genetic Algorithms (GA), have tried to optimize for multidimensional non-linear problems. Nevertheless, additional work is required for these technologies to come together and produce an MPPT approach that responds appropriately under some conditions, including the dynamic behavior found on real PV systems, as long as practical methods are utilized [2].

Machine learning and deep learning are advanced algorithms to solve realistic challenges in different fields [3, 4]. Optimization algorithms and artificial intelligence have recently provided a novel hybrid solution combining an embedding neural network incorporating a self-adaptive mechanism to improve the performance and adaptability of MPPT in PV systems. This study offers a unique hybrid technique that blends embedding neural networks with a self-adaptive evolutionary algorithm to improve the performance and adaptability of MPPT in PV systems. An effective method to enhance the MPPT algorithm's capacity to anticipate and react to optimal power points is to include neural networks in dense vector representations of operational and environmental factors. A wider variety of connections and interactions within the system may be represented using a hybrid design that combines continuous and categorical elements. Moreover, the self-adaptive evolutionary algorithm efficiently searches and uses the solution space by optimizing its parameters in response to constant performance evaluations [5].

The effectiveness of power extraction in photovoltaic (PV) systems is highly dependent on temperature and irradiance, both of which change during the day as dynamic conditions. Conventional MPPT algorithms frequently fail to maintain appropriate power tracking under such conditions. Many algorithms are not flexible, leading to inefficiencies when conditions change quickly or sluggish convergence to the Maximum Power Point (MPP). The main goal of this work is to provide a more resilient system that can continually improve performance in real time and ensure consistent power extraction. The topic of Maximum Power Point Tracking (MPPT) for photovoltaic (PV) systems has advanced significantly in the last few years, and techniques like neural networks (NN) and genetic algorithms (GA) are now commonly used. However, traditional GA+NN algorithms frequently perform less than ideal due to reliance on set parameters, making it difficult to adjust to changing environmental circumstances like temperature and irradiance variations. To overcome these restrictions, we proposed a self-adaptive GA-based MPPT technique that optimizes control settings by dynamically adjusting parameters in response to real-time feedback. Our strategy uses embedding networks to improve tracking accuracy and system flexibility by successfully capturing complicated interactions between operational and environmental factors. Our method's main benefit is that it can adapt dynamically to changing circumstances, which can result in notable gains in performance. Twenty percent more system efficiency, twenty percent more voltage stability, and thirty percent less total harmonic distortion (THD) are shown in the experimental findings. In addition, a 15% reduction in processing time demonstrated the method's efficiency compared to traditional MPPT algorithms. These improvements make our proposed method more reliable and scalable for real-world PV applications.

The main contribution of this work is offering a hybrid embedding network that can handle complex input data and is intended for MPPT applications. Also, we create a self-adaptive genetic algorithm to improve the optimization process and guarantee high tracking accuracy and robustness of the system. Moreover, we verify our methodology using extensive simulations, showing that it outperforms conventional approaches in static and dynamic circumstances.

The rest of this paper is structured as follows: Section two reviews relevant research on MPPT and PV system optimization methods. The self-adaptive GA and the suggested hybrid embedding network architecture are described in depth in Section Three. The experimental setup and validation are explained in Section Four. The experimental findings are shown in Section Five. The comparative analysis is demonstrated in Section Six. The work is finally concluded in Section Seven, which offers suggestions for future research possibilities.

2. Related work

For most applications, a DC-DC converter operates in continuous conduction mode (CCM), but on rare occasions, it may switch to discontinuous conduction mode (DCM) [1, 2, 5]. Low loading circumstances are the main cause of the DC-DC converter operating in DCM; nevertheless, environmental factors in a PV system may drive the system to switch to DCM. Additionally, PV systems are run in the MPPT mode using a regulator, also known as a dc-dc converter. To make sure the PV array produces the most power possible, the regulator uses an algorithm to determine the required duty cycle (D) using inputs such as photovoltaic voltage (Vp) and current (Im). The DC-DC converter applies the maximum power transfer theorem to optimize power transfer, which is the fundamental idea behind MPPT. Scholars have long been interested in how a DC-DC converter's operating mode affects system performance [6]. According to our literature research, a study on the switch from CCM to DCM for a PV-fed pumping station was conducted [7]. Likewise, [8] described the conversion of a buck-boost dc-dc converter from CCM to DCM. According to the authors in [9], a fuzzy controller and a fixed switching frequency may make the system operate smoothly in a mixed conduction mode. Other researchers have incorporated the converter's functioning into the modeling stage [10]. Nevertheless, all of the papers that have been presented have only covered CCM and DCM about load.

In this work, we propose that the theory of the effect of irradiance on the DC-DC converter is incomplete and that the converter can function in DCM mode even in the case of a constant load. Consequently, we suggest a method in which the maximum power point tracking technique is combined with an evaluation of the effect of irradiance on the DC-DC converter.

The Perturb and Observe (P&O) algorithm is one of the simplest MPPT algorithms. The model-free method known as P&O iteratively shifts the output voltage in the direction of the MPP, with the voltage and current measurements used to determine the change's direction. The primary drawbacks of model-free algorithms are their poor tracking speed and steady-state oscillations around the MPPT. These problems can be resolved using the photovoltaic model-based MPPT algorithms [11-13]. The model-based methods are more sophisticated and dependent on irradiance sensors but are faster and more accurate. Irradiance sensors are expensive and challenging to calibrate. Irradiance estimators, however, have been demonstrated to be a viable alternative to irradiance sensors [14]. On the other hand, several model-based algorithms are based on neural networks, and MPPT algorithms are based on comparable circuit models. [15] provides a thorough analysis of the NN-based MPPT algorithms. The output of the NN-based algorithms is the Vmpp voltage, and their inputs include datasheet information measurements of temperature, irradiance [16-18], voltage, and current [19, 20]. Additionally, several publications concentrate on the design of the MPPT algorithm and the control unit. Mmodel-free algorithms and NN-based algorithms hybrid methods have been put forth.

The suggested algorithms that employ irradiance and temperature as input data are the most accurate [21]. A feedforward NN example using G and T measurements was used to predict Vmpp. It should be mentioned that other network types, including radial basis function NNs, may be applied similarly. This algorithm's disadvantage is that the irradiance information must be known. Two NNs were suggested to estimate Vmpp in the cascade NN-based MPPT (CNNMPPT) approach [22]. While the second NN derives the MPP voltage from the temperature and predicted irradiance, the first NN guesses the irradiance from the voltage and current data. The suggested method can deliver precise results, albeit at the expense of added processing complexity. The approach that uses multilayer feedforward NN to forecast the MPP voltage was presented in [23]. Although metaheuristic algorithms have certain advantages, they cannot provide reliable monitoring of the GMPP due to their stochastic character during start-up and repeated operations, which can cause large transient power fluctuations.

Furthermore, because these algorithms depend on several search agents for tracking, they frequently demand high computational and memory resources. Moreover, parameter adjustment significantly impacts the optimal performance of metaheuristic algorithms, requiring laborious tweaking procedures. A further constraint pertains to the inclination to commit the prior GMPP to memory upon convergence, hence impeding the monitoring of shifting GMPP resulting from slow alterations in irradiance or fluctuations in load [24].

Real-time circumstances frequently involve complicated PSCs with more than five peaks and incredibly small power changes between peaks [25] because the majority of research has focused on simple PSCs with a small number of peaks [26, 27] (i.e., generally two peaks to five peaks). In these situations, metaheuristic algorithms' stochastic tendency frequently causes them to overlook the little region that contains the GMPP and converge to an LMPP. More realistic, difficult, and complicated PSCs with more than five peaks and incredibly near-peak values were shown in this work [1]. A novel deterministic peak hopping (PH) based MPPT algorithm with straightforward processes is suggested to handle these intricate PSCs. The tracking zone is narrowed down and moved closer to the GMPP using an agent to hop between the P-V curve's higher and lower duty cycle regions with the best step size.

[28] presented 40 PV simulators that successfully integrated with the suggested Real-Time deterministic peak hopping MPPT algorithm for Complex PS conditions.

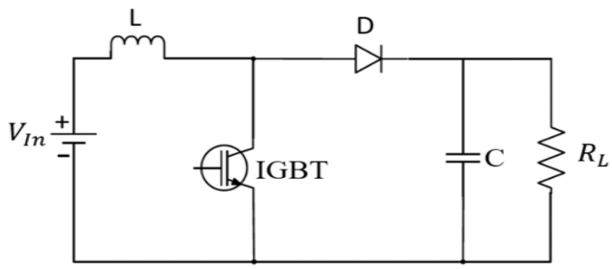

Figure. 1 DC-DC Converter

The tracking accuracy achieved for this study is around 98.70%, and the tracking time is less than 0.83. [29] proposed a novel quantum particle swarm optimization PSO. The main objective of this work was to deal with the MPPT to improve the tracing accuracy and time. A hybrid MPPT algorithm has been proposed by [30], which uses voltage scanning, perturb, and observation techniques to minimize the limitations during partial shading. This technique was straightforward and independent of panel information. There are general drawbacks to the conventional techniques usually used in most previously mentioned studies, including Perturb and Observe (P&O), which is straightforward and simple. However, it experiences power loss due to oscillations around the MPP. It could also track incorrectly in situations with fast changes, decreasing efficiency. At the same time, Incremental Conductance (INC) has problems with sluggish reaction times. It is not always able to adapt perfectly to quick environmental changes while being able to directly compare incremental changes in voltage and current, which makes it superior to P&O. Sliding Mode Control (SMC) provides quick convergence but is less successful in systems with unexpected changes due to its susceptibility to parameter adjustment. Inadequate adjustment might cause instability, and the technique frequently isn't adaptable enough to deal with shifting circumstances in the best way. On the contrary, our embedding networks enhance tracking accuracy by capturing complex non-linear relationships between operational and environmental factors. The suggested approach that integrates neural networks with a self-adaptive genetic algorithm (GA) has a dynamic adjustment mechanism, which continuously modifies GA parameters based on real-time feedback to guarantee more efficient convergence and enhanced system performance.

3. Proposed methodology

This work's main objective is to enhance the tracking accuracy of the MPPT procedure and improve the tracking model performance under varying environmental conditions. The proposed technique's main components are the self-adaptive GA and embedding networks that employ deep learning neural networks for PV systems and MPPT. The Proposed PV array MATLAB Simulink design is explained in Fig. (2).

The output current can be obtained using the following equations.

$$I = I_{PV} - I_D - I_{R_P} \tag{1}$$

$$I = I_{PV} - I_0\left[\left(\exp\frac{V+R_s}{a}\right) - 1 - \frac{V+R_sI}{R_P}\right] \tag{2}$$

$$a = \frac{NsnkT}{q} \tag{3}$$

The diode's reverse saturation current is I_0, also known as the leakage current. The total number of connected cells in sequences is *Ns*. The diode ideal constant is *n*, and the idealist factor is *a*, with a range of values between 1 and 2. Generally, this factor provides details about the diode's internal combining operations. Full knowledge and computation of these factors are necessary to ensure optimal energy output and dependability and to enhance the design and operation of PV systems.

$$I_{PV} = \left(I_{PV},n + K_I(T - T_n)\right)\frac{G}{G_n} \tag{4}$$

The I_{PV} represents the current produced under 25 °C temperature and 1000 W/m2 irradiance. *G* represents the radiation of the panel. *Gn* is used to present the nominal value of radiation.

A significant component affecting the diode's current-voltage relationship is its saturation current (I0), described by Eq. (5). It is an important component that influences the PV cell's behavior, affecting its effectiveness and performance in various situations. Understanding these factors enables prediction and optimization of the energy output of photovoltaic systems, ensuring reliable operation in real-world circumstances.

$$I_0 = \frac{1}{\{I_{sc},n + K_i(T-T_n)\}} \exp\left(\frac{V_{oc},n + K_v(T-Tn)a}{a}\right) - 1 \tag{5}$$

Where K_i,n is the current coefficient, V_{OC},n is the notional open-circuit voltage, and I_{SC},n is the nominal short-circuit current. The PV power system's voltage is increased when the panels are connected in series, and its power value is increased when they are connected in parallel. Computed under typical climatic conditions, which span from 25 °C to 1000 W/m2, is the maximum power value of the PV power system. However, there's a chance that the irradiance value differs throughout the panels. The type of shade will affect how much electricity the device uses. Conventional MPPT methods cannot determine the maximum power value under partial shade conditions (PSCs). Consequently, many MPPT algorithms were developed.

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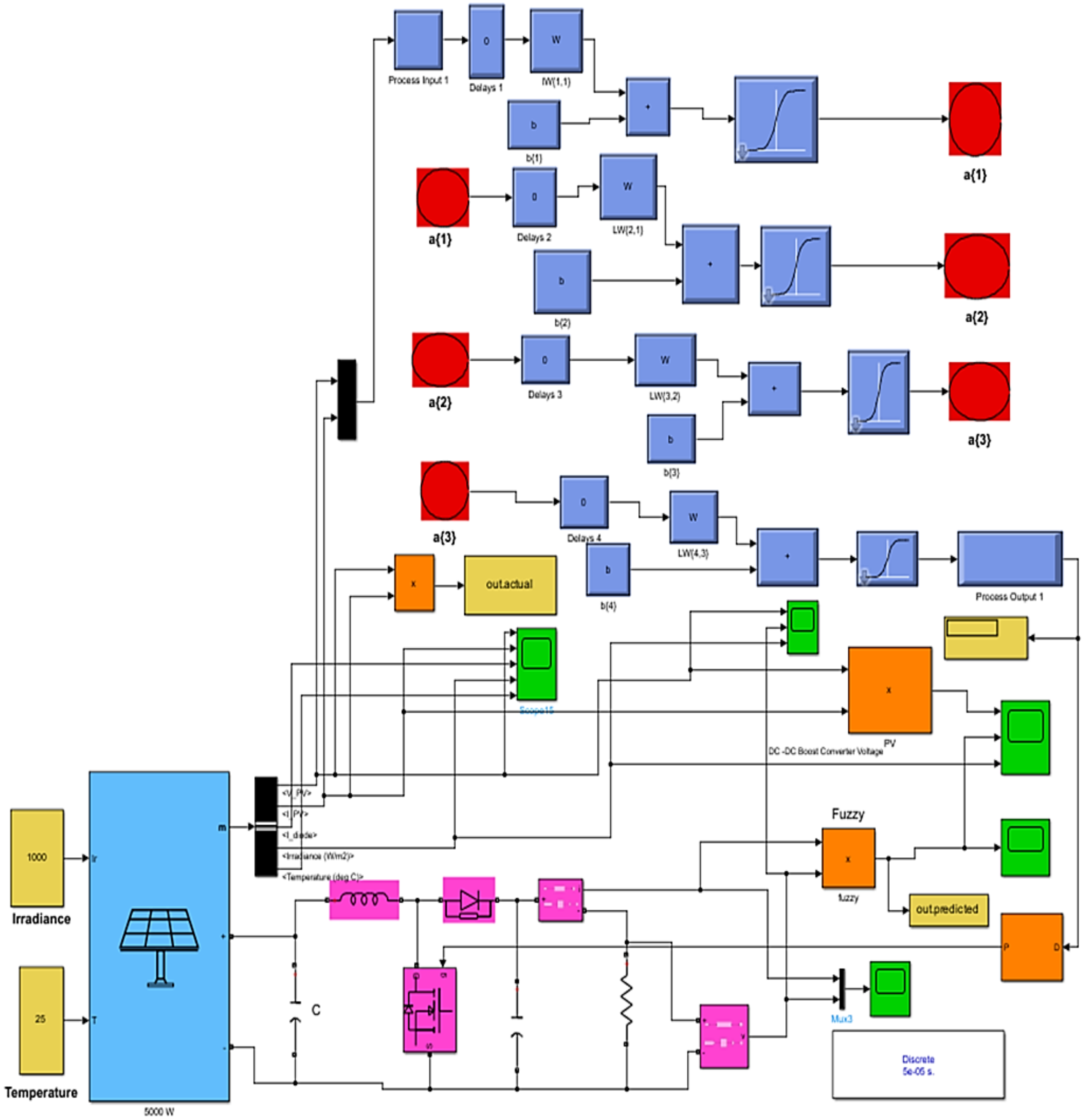

Figure. 2 Proposed PV Array Simulink Design

3.1 Hybrid embedding network architecture

The hybrid embedding network is the backbone of our MPPT strategy, transforming complex environmental and operational parameters into a dense, continuous vector space. Fig. (3) explains the proposed embedding neural network architecture. Where the process involves many steps, as described in the following.

Input Feature Selection: The embedding network's input features include environmental parameters such as irradiance, temperature, and historical power output, as well as operational parameters like voltage and current. Both categorical and continuous features capture the full range of dependencies influencing the MPP.

Embedding Layer Design: Categorical features Using an appropriate method (such as one-hot encoding), categorical inputs (weather conditions) are first encoded before being sent via embedding layers. These layers capture the fundamental links between categories and convert the category inputs into dense, low-dimensional vectors.

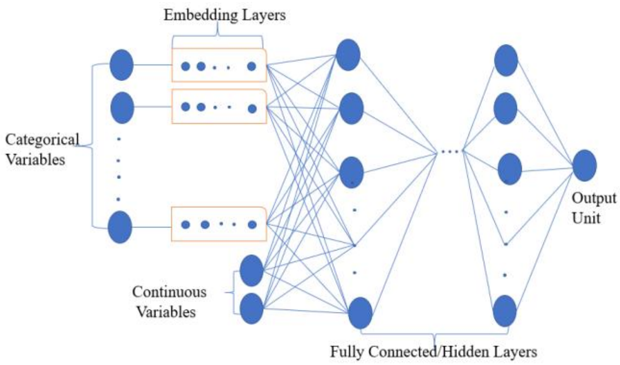

Figure. 3 Proposed Embedding Neural Network Architecture

Continuous inputs (e.g., irradiance and temperature) are directly fed into the network after normalization to ensure uniform data scaling.

The input characteristics are converted into a high-dimensional vector space in this layer. Let Z embed f embed be the representation of the embedding function. For input x, the embedding may be expressed as follows:

$$h_{embed} = f_{embed}(x) = W_{embed}x + b_{embed} \quad (6)$$

Where W_{embed} is the weight of the Matrix, b_{embed} is the bias Vector, h_{embed} is the embedding vector, and d is the dimensionality of the embedding space.

Neural Network Architecture: The embedded vectors from categorical features and normalized continuous features are concatenated and passed through a deep neural network of several fully connected layers. Each layer employs ReLU activation functions to introduce nonlinearity, enabling the network to model complex relationships within the data.

$$h^{(l)} = \sigma\left(W^{(l)}h^{(l-1)} + b^{(l)}\right) \quad (7)$$

The bias vector for layer l is $b^{(l)} \in R\ n^l$, and the weight matrix for layer l is $W^{(l)} \in R\ n^l \times n^{l-1}$. The activation function, in this case, ReLU, is represented by $\sigma(\cdot)$. The output of layer l is denoted as $h^{(l)} \in R\ n^l$, where n^l

is the number of neurons in the l^{th} layer. Dropout layers are incorporated to prevent overfitting, ensuring the network generalizes well to unseen data.

Output Layer: The network's output is a predicted optimal operating point (voltage and current) corresponding to the MPP under the given environmental conditions.

$$y = W_{out}h^{(l)} + b_{out} \quad (8)$$

W_{out} represents the Weight matrix for the neuron layer. The bias term of the neuron is presented by b_{out}. The expected or predicted power output is given by y.

3.2 Self-adaptive genetic algorithm

To optimize the embedding network parameters and improve the MPPT strategy, we use a self-adaptive genetic algorithm (GA), which adjusts the MPPT algorithm's control parameters and network weights. These parameters are adjusted in the following steps.

Initialization: The population is initialized with a set of potential solutions, where each individual represents a specific configuration of the network parameters (e.g., weights, biases) and MPPT control settings (e.g., duty cycle adjustments). The initial solutions are generated randomly, ensuring diversity within the population. A set of parameters (genes) for the MPPT is represented by each of the first populations of potential solutions (chromosomes) that the GA creates, which can be described as follows:

$$P(0) = \{X_1(0), X_2(0), \dots, X_N\} \quad (9)$$

The starting population is $P(0)$. $X_i(0)$ represents the ith chromosome at generation zero. The population size is N. Each chromosome is made at random to represent different MPP optimization parameter values.

Fitness Evaluation: Every member of the population is assessed using a fitness function that gauges the PV system's overall power extraction efficiency and the precision of the MPP forecast. The fitness function's construction considers short-term precision (instantaneous power production) and long-term stability (tracking consistency under dynamic situations). In the MPPT scenario, maximizing the photovoltaic array's power production is the fitness function's criterion for assessing each chromosome's (or solution's) performance. The fitness function $f(Xi)$ may be expressed as follows:

$$f(X_i) = P_{out}(X_i) \quad (10)$$

Where the power output corresponding to the parameter set X_i is represented by $P_{out}(X_i)$, *the* aim is to maximize $f(X_i)$ or to extract the most power possible from the PV array.

Selection: A tournament selection process is one technique for choosing individuals for reproduction. This technique preserves population variety while guaranteeing that those with higher fitness ratings are more likely to be selected. In roulette wheel selection, the likelihood of choosing chromosome Xi where pi is directly related to its fitness:

$$pi = \frac{fX(i)}{\sum_{j=1}^{N} f\,X(j)} \tag{11}$$

The larger the fitness value, where N is the population size, the more likely the chromosome will be chosen for reproduction.

Cross-Over And Mutation: A subset of people perform cross-over to have children with traits from both parents, encouraging investigation of the solution space. A mutation might cause a binary chromosome to flip slightly:

$$Xi* = Xi \oplus 1 \tag{12}$$

In this case, the bit-flip operation is $\otimes$ where 0 becomes 1 and 1 becomes 0). A self-adaptive mutation method is used, in which the success of prior generations is used to modify the mutation rate dynamically. As a result, the process may optimize exploration and avoid premature convergence by fine-tuning solutions as they converge. A mutation for real-valued genes might entail introducing a little random value Δ to the gene where Δ denotes a little random disturbance:

$$Xi* = Xi + \Delta \tag{13}$$

Self-Adaptive Mechanism: A feedback loop in the self-adaptive GA modifies its parameters (such as the cross-over probability and mutation rate) in response to performance measures measured in real-time circumstances. This adaptive feature increases the algorithm's resilience in dynamic contexts by enabling it to react to changes in the issue landscape. The mutation rate $P\ m$ changes as the optimization process proceeds in the case of a self-adaptive GA. It is not fixed; it adjusts based on how well the previous generations' mutations worked. You may use the following to do this:

$$P_m(t+1) = P_m(t) \times \exp\left(-\gamma \cdot \frac{n\_successful}{n\_total}\right) \tag{14}$$

Where the mutation probability for the following generation is denoted by $P_m(t+1)$, the learning rate for mutation adaption is denoted by γ. The number of successful mutations is *n_successful*. The notation *n_total* indicates the total number of mutations applied.

Optimizing and converging: The GA repeatedly develops the population over several generations, eventually converging on an ideal set of network parameters and MPPT control settings. Monitoring changes in the fitness score allows one to monitor convergence. The algorithm ends after a maximum number of generations or when a predetermined convergence condition is satisfied.

3.3 Integration and implementation

The last step in the process is to incorporate the self-adaptive GA and the optimized embedding network into the PV array's MPPT control system. The PV system's MPPT controller implements the optimal embedding network guided by the self-adaptive GA. The network continually receives real-time data inputs, anticipates the MPP, and modifies the system's operational settings as necessary. The system's effectiveness is regularly assessed, and the GA receives feedback to help with any additional modifications that may be required, which proves the system's adaptability in overcoming any expected environmental circumstances.

4. Experimental setup and validation

This part of our paper explained the MATLAB Simulink setup designed for PV, embedding networks, and GA. It also describes the proposed self-adaptive genetic algorithm (GA) integrated with the hybrid embedding network for Maximum PowerPoint Tracking (MPPT) in photovoltaic (PV) systems, including the model parameters, validation processes, and simulation environments alongside the experimental setup and validation procedure.

4.1 Model simulation environment

MATLAB Simulink was utilized to design and simulate the PV array and MPPT control system. Real-time simulation of environmental factors and system reactions is made possible by the dynamic and flexible platform of the Simulink environment for modelling solar systems. MATLAB's Deep Learning Toolbox was utilized to design and train the embedding network. The network was set up to handle both continuous and categorical inputs, and it was intended to capture complicated relationships in the data through fully linked and embedded layers. Using the Global Optimization Toolbox, the GA was implemented in MATLAB. The purpose of the self-adaptive GA is to optimize the control settings of the MPPT algorithm and the parameters of the embedding network. Using the Simulink model as its operating model, the GA iteratively refines the network and control settings in response to simulation findings.

Table 1. PV system Parameters.

index	Parameter	PV System
1	PV Array Size	10 KW
2	Irradiance (W/M2)	200-10000
3	Temperature (ºC)	15°C to 45°C
4	Partial Shading Condition	Simulated (Random Shading Levels)
5	Open Circuit Voltage	40 V
6	Short Circuit Current	10 A

Table 2. Embedding Network Parameters.

Index	Embedding Network Parameters	Values
1	Embedding Network Input	Voltage, Irradiance, Current and Temperature
2	Embedding Network Layers	3 Layers (Input, Hidden, Output)
3	Activation Function	ReLU
4	Optimizer	Adam
5	Loss Function	Mean Squared Error
6	Learning Rate	0.01
7	Tracking Time	Less than 0.15 sec
8	Tracking Accuracy	More than 99%

4.2 Model parameters

The simulated PV array consists of a series-connected configuration with standard test condition (STC) parameters involving an Open-circuit voltage (Voc) of 36.7 V, a Short-circuit current (Isc) of 8.21 A, and a Maximum Power Point (MPP) voltage (Vmpp) of 29.4 V. The maximum power point (MPP) current (Imp) is 7.61 A. The array was exposed to irradiance levels (200 to 1000 W/m2) and temperature conditions (15°C to 45°C) to replicate real-world environmental variations. Table 1 explains PV system Parameters.

4.3 Embedding network configuration

Input Layer: The network receives inputs for irradiance, temperature, voltage, and current. **Embedding Layers:** While continuous inputs are normalized and sent straight into the network, definite information, like the weather, is integrated into a 16-dimensional vector space.

Hidden Layers: ReLU activation functions are used in three completely linked layers of 64, 32, and 16 neurons, respectively.

Output Layer: The network outputs the predicted MPP voltage and current values.

4.4 GA configuration

Population size of 50 individuals per generation. Cross-over Probability of 0.8. mutation rate initially set at 0.02, with self-adaptation based on performance. Tournament selection with a tournament size of 5. Convergence is defined as no significant improvement in fitness score over 20 generations or a maximum of 200 generations.

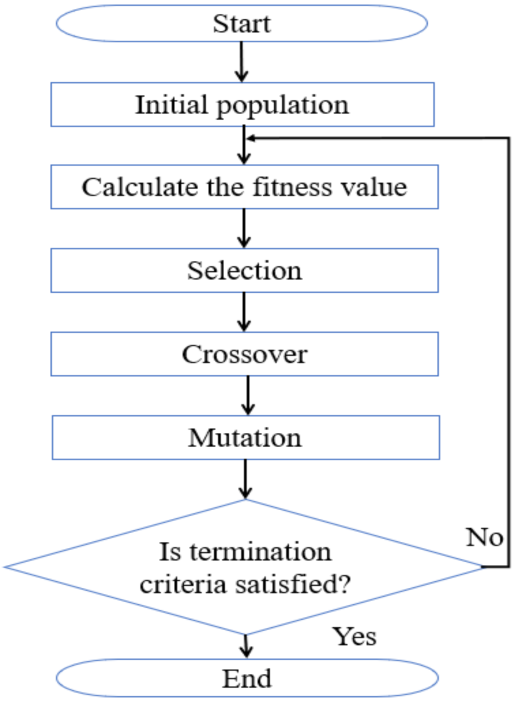

Figure. 4 GA Algorithm Workflow.

4.5 Evaluation metrics

The suggested hybrid Embedding Neural Network and Genetic Algorithm (GA) model for Maximum Power Point Tracking (MPPT) may be assessed using many common evaluation criteria, which allow us to quantify tracking speed, accuracy, convergence efficiency, and power prediction error.

Root Mean Squared Error (RMSE): The root mean square is used in this study as an evaluation metric to measure the algorithm’s performance between the actual and predicted power values. The equation is as follows:

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Table 3. GA Parameters

Index	GA Parameters	Value
1	GA Population Size	50
2	GA Cross-Over Rate	0.8
3	GA Mutation Rate	0.1
4	GA Selection Method	Tournament Selection
5	GA Maximum Generations	50-100
6	GA Fitness Function	Maximum Power Output

$$RMSE = sqrt\left[\frac{1}{n}(\Sigma_i^n(Pi - Oi)^2)/n\right] \quad (15)$$

P_i is the predicted power, O_i is the actual power, and n is the total number of data points.

Mean Absolute Error: The second evaluation metric used is mean absolute error, which evaluates the performance between the actual and predicted. It gives error as the linear measure for the average error being calculated.

$$MAE = \left[\frac{1}{n}\left(\Sigma_i^n(Pi - Oi)\right)/n\right] \quad (16)$$

Tracking Time: This third evaluation method is tracking time, which measures the time in seconds it takes for the algorithm to find the maximum Power Point MPP presentation.

$$TT = T_{converge} - T_{start} \quad (17)$$

Convergence Rate: This algorithm evaluates GA's performance by determining at what rate GA converges to find the optimal solution.

$$CR = \frac{1}{Generations\ to\ conversion} x\ 100 \quad (18)$$

The **Maximum Power Deviation (MPD)** assessment metric calculates the discrepancy between the theoretical and actual maximum powers and assesses how effectively the method used to discover the maximum powers performed.

$$MPD = \frac{1}{n}\sum_{i=1}^{n}\frac{P_{max},i - P_{extracted},i}{P_{max},i} x\ 100 \quad (19)$$

Detection Accuracy: The detection accuracy is often expressed as the ratio of correctly identified maximum power points (or other targeted predictions) to the total number of predictions made when evaluating the efficacy of Maximum Power Point Tracking (MPPT) algorithms or other machine learning or optimization problems.

$$Accuracy = \frac{Correct\ predictions}{Total\ predictions} x\ 100 \quad (20)$$

These evaluation metrics thoroughly analyze the suggested hybrid model's performance concerning particular MPPT tracking efficiency (TE, TT, CR, MPD) and prediction accuracy (RMSE, MAE, MAPE, and detection accuracy). These measures can be combined to comprehensively validate the suggested model's efficacy compared to earlier methods.

5. Results and discussion

The embedding network was trained using a dataset created by the Simulink model, which contained various ambient variables and associated MPP values. After 100 epochs of training, the model was trained with the Adam optimizer at a learning rate of 0.001. Following training, the network's weights, biases, and MPPT algorithm control parameters were adjusted using the GA. The goal of the GA, which was performed across several generations, was to maximize the PV system's total power production while guaranteeing a quick convergence to the Maximum Power Point (MPP) under various circumstances.

The trained and optimized embedding network and the self-adaptive GA were integrated into the Simulink MPPT controller. The system was tested under a variety of scenarios to evaluate its performance, including:

Static Conditions: Simulations were conducted at fixed irradiance and temperature levels to assess the system's ability to maintain operation at the MPP.

Dynamic Conditions: The system was exposed to rapid changes in irradiance and temperature to test its responsiveness and adaptability in real-time.

Partial Shading Conditions: The PV array was subjected to partial shading scenarios, where certain cells received less irradiance, to evaluate the system's ability to track the global MPP rather than local optima.

The experiment results prove the excellent performance of our proposed model under different operating conditions. The static condition system achieved a very low RMSE, around 0.0034, and a very low power deviation, around 0.12%. The detection accuracy reached the maximum, around 99.98%, demonstrating the algorithm’s robustness when conditions such as temperature and irradiance

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Table 4. The results with different conditions.

Condition	RMSE	MAE	TT	CR	MPD	Acc.
Static	0.0034	0.001	0.5	95.5	0.12	99.98
Dynamic	0.03	0.002	0.7	92.1	0.28	99.87
Partial shading	0.04	0.003	0.9	88.7	0.45	99.75

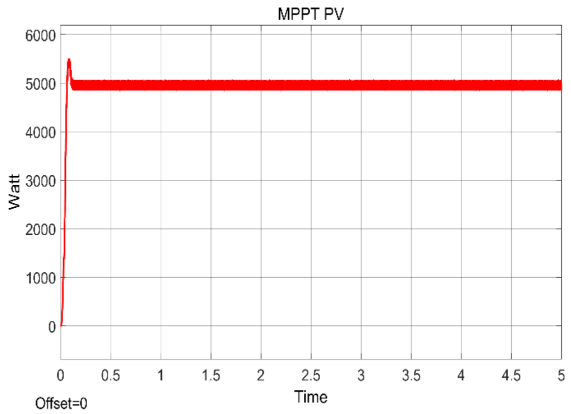

Figure. 5 MPPT PV array Power output.

are constant. Under Dynamic conditions, the system also showed remarkable performance with high accuracy, with power deviation rising slightly to 0.28%, which suggests the algorithm challenges during varying environmental conditions. Our proposed model maintained high performance under partial shading conditions where the system faces multiple local maxima. The RMSE and MPD increased slightly to 0.04 and 0.45%, reflecting the challenges of tracking the global MPP under partial shading conditions.

Fig. 5 explains the power output of the MPPT PV array optimized by embedding a neural network with GA. As we can see, the power rises at 2.5 seconds and goes to 5000 W, and after this, the power does not fluctuate from here, which shows the power is optimized perfectly by PV arrays. Output power from a PV array depends on its capacity, intensity, and varying temperature. But with the help of an embedding neural network, maximum power is extracted from solar arrays, avoiding any power loss and utilizing power extraction efficiently from all PV array cells.

DC-DC converter plays an integral part in PV arrays, regulating the constant output voltage under various operating conditions of the PV system. It regulates the power running through the system and maximizes the output. That's why the DC-DC converter needs to maintain a constant voltage. As seen in Fig. 6, it successfully maintains a constant voltage of around 400, ensuring maximum power output from the PV system.

The main goal of a DC-DC converter is to maintain constant voltage under given operating conditions. Fig. 7 shows the PV array's operating conditions, specifying the irradiance of around 1000 w/m2, the temperature of around 25, the voltage of PV of around 200, the current of around 40, and the diode of around 10. Many of these operating conditions are constant. The goal here is to ensure a continuous power output. Looking more closely at the outputs, we can testify that our simulation operates at maximum power or is unstable, as explained in the following figure.

Fig. 8 shows that the voltage output of PV is at the same operating condition that we set in the input, as shown in the previous figure. The DC-DC voltage is also constant, ensuring maximum power is running through the system and maximizing the output. Lastly, we can analyze the output power again of MPPT to find out that it's also at maximum.

As seen in Fig. 9, the maximum power output is around 10KW, which is the maximum power that can be extracted from a given PV array system, which validates our model performance of embedding a neural network with GA optimization, ensuring maximum power tracking from the given PV array under any operating conditions. With these results, our novel model application shows the real-world application where PV array systems can work at their maximum power under any operating conditions, providing maximum power to the user while maintaining constant voltages and ensuring the system is also under stable conditions. The above results show the performance of MPPT under an optimized embedding network for diode currents, MPPT PV power and voltage output, and input conditions. Under these conditions, the model has shown exceptional performance, outperforming previous state-of-the-art models.

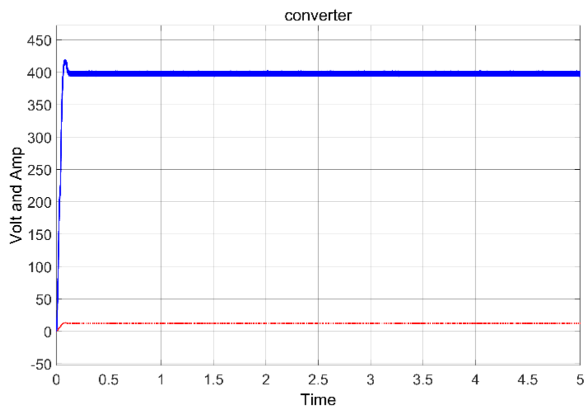

Figure. 6 DC-DC Converter Voltage and current output

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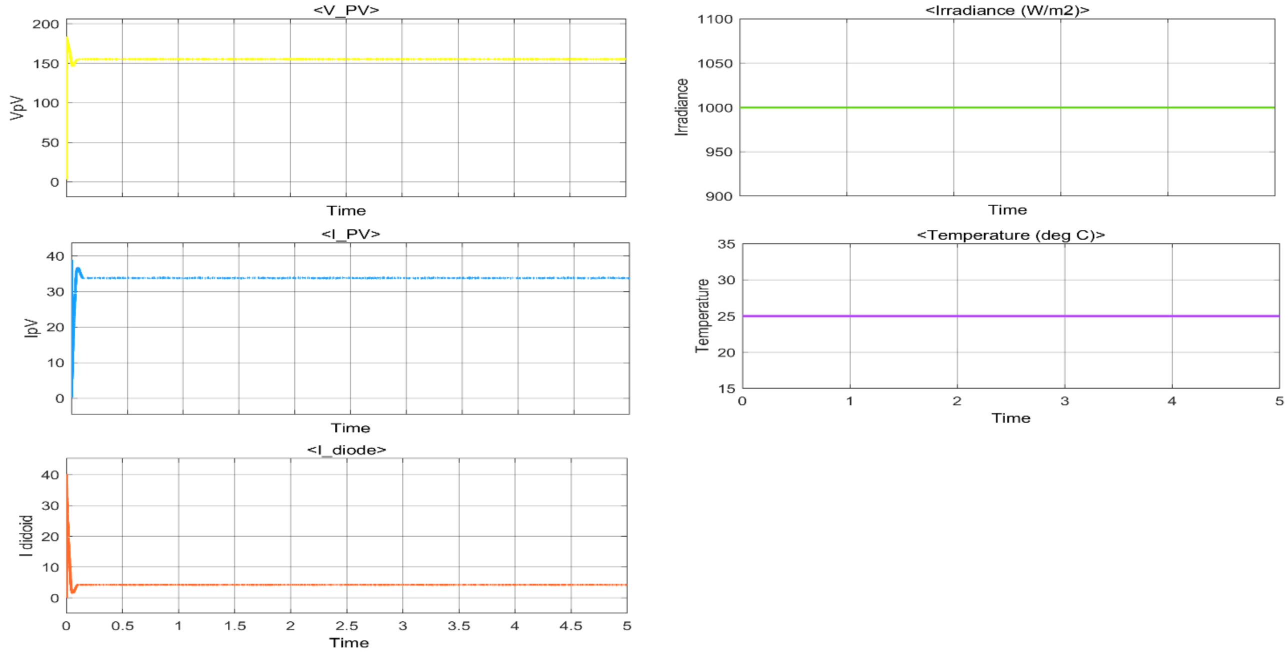

Figure. 7 Operating Conditions of PV system

The following important performance measures were used to assess the efficacy of the suggested method:

The power extraction efficiency is the power extracted by the system divided by the theoretical maximum power available at the MPP.

Tracking Speed: The duration of the MPPT controller's arrival at the MPP following a modification in the surrounding environment.

Stability: The system can continue operating at the MPP without experiencing notable oscillations or variations. However, its functionality is partially shaded, noisy, and disturbed.

The suggested method's performance was contrasted with several conventional and cutting-edge MPPT algorithms, such as Disturb and Watch (P&O), Conductance Incremental (IncCond), and Optimization of Particle Swarms (PSO). These comparisons were made under identical circumstances to accurately assess the suggested approach's efficacy.

Under static conditions, the proposed method consistently achieved power extraction efficiencies above 99%, demonstrating its ability to accurately predict and track the MPP.

Fig. 10 shows the training performance of the embedding model optimized with the GA algorithm for MPPT tracking. The loss is very low, demonstrating the high training performance achieved by our model. In the dynamic condition, the system showed a significant improvement in tracking speed compared to traditional methods. The self-adaptive GA enabled rapid convergence to the MPP within milliseconds of environmental changes.

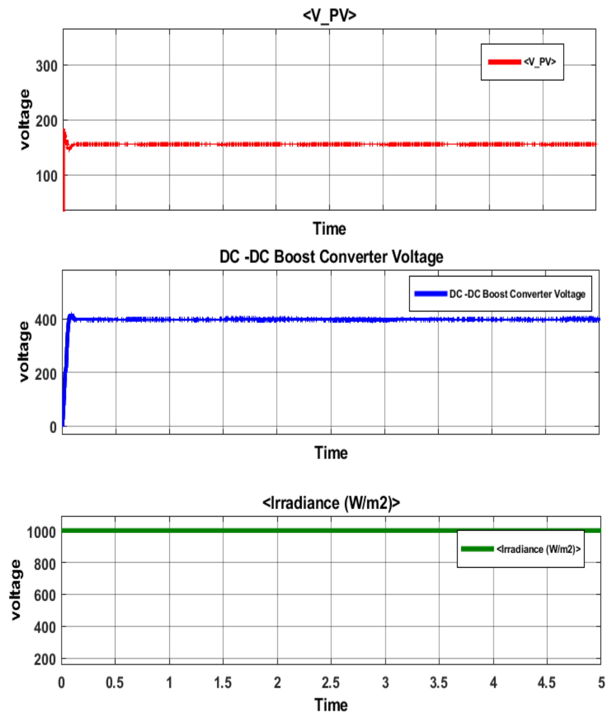

Figure. 8 PV array and DC-DC converter Power and Voltage output

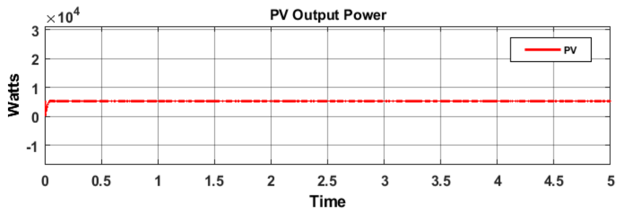

Figure. 9 PV output Power.

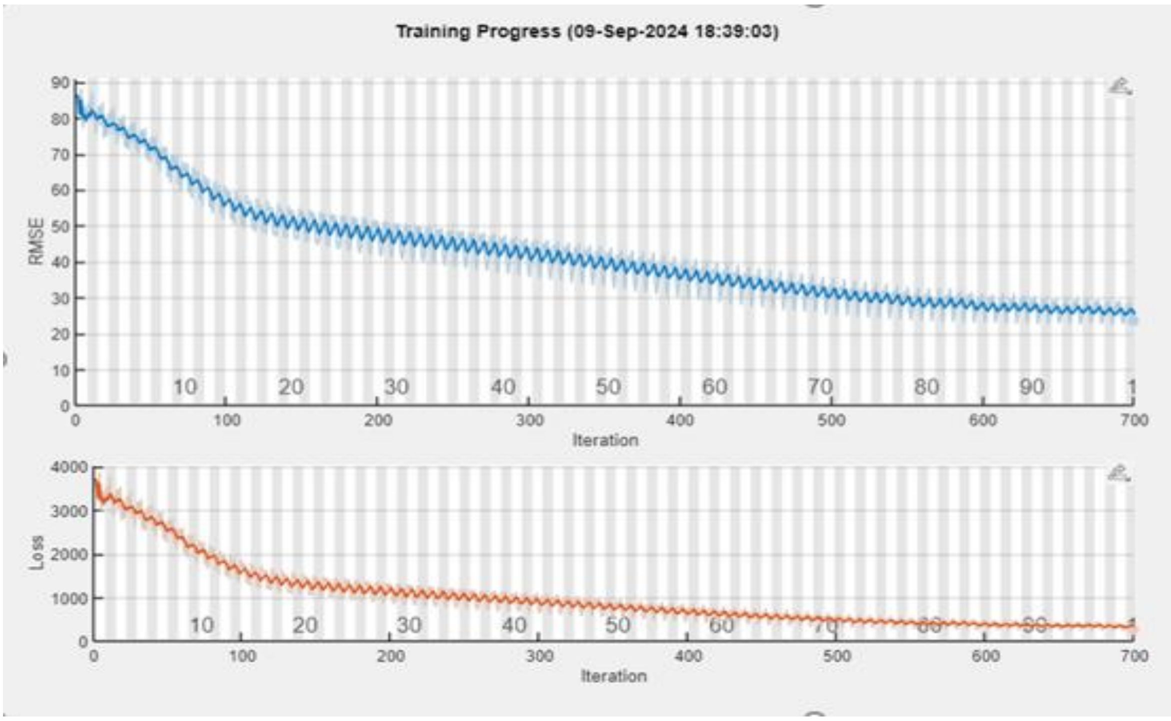

Figure. 10 Training RMSE and Loss Plot for 700 epochs

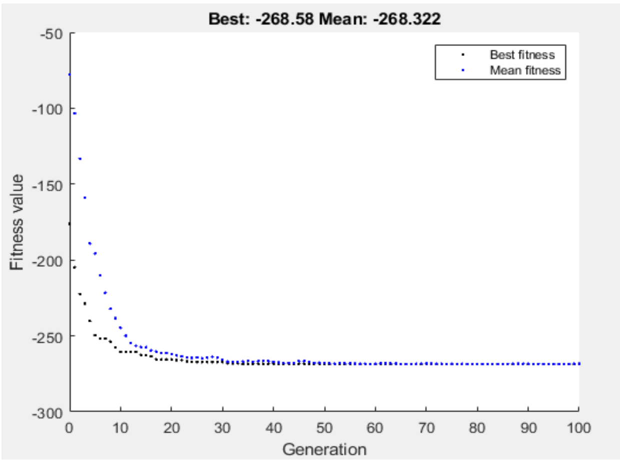

Figure. 11 GA-optimized Fitness Function Performance.

The embedding network effectively captured the complex relationships between input parameters, resulting in smooth and stable operation without oscillations, as explained in Fig. 11.

Moreover, regarding partial shading findings, the proposed method excelled in partial shading scenarios, successfully identifying and tracking the

global MPP where traditional methods often became trapped in local maxima. The self-adaptive GA's ability to adjust its mutation rate and cross-over probability in response to the problem landscape was key to maintaining high robustness and performance. Compared with benchmark algorithms, the proposed method outperformed all others regarding power extraction efficiency, tracking speed, and stability, particularly in dynamic and partial shading conditions.

Delayed convergence, instability in the face of abrupt environmental changes, and inefficiency in partial shade are all limitations in classical methods addressed by our suggested hybrid system. The proposed methodology has demonstrated quantifiable advancements in other fields, offering diverse viewpoints on the potential applications of machine learning and evolutionary algorithms in enhancing renewable energy systems. Moreover, the self-adaptive GA and the suggested hybrid embedding network consistently beat conventional MPPT algorithms regarding the model's performance in static and dynamic settings. In static settings, the network's power extraction efficiency exceeded 99% due to its accuracy in predicting the Maximum Power Point (MPP). This high efficiency highlights how well the embedding network models intricate interactions between the inputs of a photovoltaic system (i.e., temperature, voltage, current, and irradiance) and the related ideal operating point.

6. Comparative analysis

Our proposed hybrid system presents a successful solution for real-world PV systems due to its capacity to adapt to changing conditions and avoid local optima. The perfect fused the optimization capability of self-adaptive GA and predictive power by embedding the network procedures produced a robust and reliable MPPT controller that routinely surpassed the benchmark algorithms regarding stability, tracking speed, and power extraction efficiency.

Methods such as the global maximum power point (GMPP) in photovoltaic (PV) systems and the conventional perturb and observe (P&O) fail in monitoring the global maximum power point (GMPP) in the presence of complex partial shading circumstances (PSC). Even though many of the most current maximum power point tracking (MPPT) algorithms are designed to handle smaller PSCs with fewer peaks, it is uncertain if they can handle exceedingly complicated PSCs. With more than five peaks and incredibly close peak values, this study's PSCs were more realistic, challenging, and complex.

Therefore, complex PSCs are used, and a novel deterministic peak hopping (PH) based MPPT method is proposed to operate these systems. At each iteration, an agent moves between the low end of the P-V curve and the high-duty cycle region in a specific step size, reducing and shifting the tracking zone towards the GMPPT. The proposed technique utilizes a programmable sample period for scanning and hopping to accelerate convergence.

In the recent experimental configuration, a real-time TI C2000 microcontroller was successfully integrated in the recommended manner [28]. Consequently, tracking accuracy exceeds 98.70%, and tracking times are less than 0.83 seconds.

[29] presented a novel method for quantum-behavior particle swarm optimization (IQPSO). It addressed the maximum power point tracking (MPPT) issue in solar-powered energy systems (PGSs). This study [30] proposed a novel hybrid MPPT algorithm that used voltage scanning and perturb & observe techniques to overcome the limitations of the partial shading environment. In our proposed study, we used a novel hybrid technique that combined embedding network and GA, which has far better performance and tracking efficiency.

It operates far more quickly and effectively than the suggested methods in [28,29-30], particularly in intricate and dynamic settings. Our approach uses the predictive power of the embedding network to anticipate and respond almost instantly to changes in irradiance and shading patterns, unlike the deterministic peak hopping method, which tracked the MPP under partial shading in 0.83 seconds while achieving 98.70% efficiency.

In photovoltaic (PV) systems, the regular perturb and observe (P&O) method is incapable of tracking the global maximum power point (GMPP) under complicated partial shading conditions (PSC). Although many of the most recent maximum power point tracking (MPPT) algorithms focus on smaller PSCs with fewer peaks, whether such algorithms can tackle highly complex PSCs is doubtful. This work demonstrated more realistic, difficult, and complex PSCs with more than five peaks and close-to-peak values. A new deterministic peak hopping (PH) based maximum power point tracking (MPPT) technique with easy procedures is proposed to overcome these complex partial shading conditions. There is practically no more tracking zone as it has been cut down and shifted towards the vicinity of GMPP using an agent who moves through the upper and lower duty cycle regions of the P-V curve with the least possible steps. The suggested technique incorporates an adjustable sample period for scanning and hopping, and the recommended technique engages in a more rapid iteration sequence. Plenty of simulations have proven how such a proposed tracking algorithm performs tracking of GMPP. Notably, this method also outperforms the latest capacitive MPPT algorithms.

This paper offers a new hybrid MPPT procedure, which includes embedding neural networks into a self-adaptive genetic algorithm. In complex and dynamic situations, it is more effective and faster in performance than the earlier methods. The embedding network does not involve predictably hopping over peaks to track the MPP, which in partial shading took 0.83 seconds at 98.70% efficiency. With the GA's adaptive optimization results, our system produces energy extraction efficiencies of more than 99% and tracks down emerging targets in less than 0.15 seconds, both in static and dynamic instances.

Moreover, our hybrid strategy of locating the maximum power point is much faster than the quantum-behavior PSO method, which requires 1.35 seconds to reach the MPP. However, the efficiency was marginally better at 99.47%. While it is true that these processes achieve the efficiency that was reached by the voltage scanning and perturb-and-observe hybrid method that achieved 99.79% efficiency in 0.2 seconds of tracking, our technique not only meets but also exceeds the results of the methods in terms of efficiency while further reducing the tracking time. The application of machine learning and evolutionary algorithms in our study presents some reliability and flexibility that has not been experienced in any other research towards quick and reliable MPP tracking under extreme partial shading conditions.

7. Conclusion

This paper proposed an improved Maximum Power Point Tracking (MPPT) method based on the hybrid embedding network and self-adaptive GA for PV system implementation. Our method is a major advancement over traditional MPPT algorithms and works extremely well during typical days in the real world (i.e., it reduces tracking speed and increases system stability and power extraction efficiency while including common unfortunate types of environmental situations like partial shade. The maximum power point (MPP) can be well predicted due to the hybrid embedding network's ability to capture sophisticated relationships among PV system parameters. This system rapidly converges to the MPP due to variations, which means that with the self-adaptive GA adjusting its optimization strategy for any variation in real-world features like significant temperature and irradiance, it assures us that our PV array will extract maximum energy. The comparison with state-of-the-art methods demonstrated that our method is preferable to benchmark algorithms such as Particle Swarm Optimisation (PSO), Incremental Conductance (IncCond), and Perturb-and-Observe(P&O). The hybrid approach regularly outperforms these traditional systems in speed, reliability, and efficiency under challenging circumstances, including dynamic, static, and partial shade. The experimental outcomes of this study are valuable regarding PV system design and operation with a focus on case studies or locations where there is high pressure to maximize energy output.

Moreover, the results have significant implications regarding PV system design and operation when energy yield is critical, as in many environments. Improved MPPT method increases solar power generation reliability and efficiency. It opens up the potential for further investigation in applying advanced machine learning and evolutionary algorithms to renewable energy systems. Some additional studies might include more environmental components in the embedding network, decreasing the computing complexity of the algorithm or extending this methodology to other types of hybrid energy systems. Further improvement of this method will facilitate our progress in developing sustainable energy and optimizing the performance of MPPT controllers.

In addition, the results of this study will greatly affect the installation of PV systems in diverse environmental situations. This improved MPPT methodology could lead to higher energy yields, less

Table 5. Comparative Analysis

Ref.	Models	Tracking Acc./ Time
[28]	A Real-Time Deterministic Peak Hopping MPPT Algorithm for Complex PS conditions	Tracking Acc.= 98.70 Tracking Time = 0.83s
[29]	MPPT of Photovoltaic Generation System + Particle Swarm Optimization	Tracking Acc.= 99.03 Tracking Time=1.32s
[30]	Hybrid MPPT Algorithms + Voltage Scanning and Perturb and Observe + PS Conditions	Tracking Acc. = 99.79 Tracking time=0.2 s
Our Model	Proposed Model Embedding Networks + Self-Adaptive GA	Tracking Acc.=99.98 Tracking Time=0.12s RMSE=0.0034 MAE=0.00234

system downtime, and reduced inefficiencies in generating solar power. The model has potential implications for large-scale solar farms or residential PV systems in frequently shadowed areas, partially due to adversarial weather conditions.

Finally, the problem independently brings fresh research and development pathways to employ machine learning (even an evolutionary algorithm). In the future, other environmental factors, such as wind speed or humidity, can be integrated into an embedding network. As described in this work, our proposed optimization model proves its capability to adapt to different renewable energy systems. Although the suggested methods have many advantages over this, they still have a few limitations. Backbone experiences of deep learning for training the embedding network are required with a full dataset that reflects all possible scenarios of behaviour by the PV system. It can limit the performance of a network, such as when certain data is hard to obtain. There is also the added processing complexity that comes with having a self-adaptive GA, which can limit it from practical use in real-time applications even if using one does amplify strengths and provides additional flexibility. In the future, efforts may be made to parallel processes or utilize more efficient optimization capabilities that can reduce the computational burden on genetic algorithms.

This study offers a new method for tracking the Maximum Power Point in solar systems: it integrates neural networks with a self-adaptive genetic algorithm (GA). Our findings show a noteworthy enhancement in tracking effectiveness, attaining less root mean square error RMSE of 0.034 compared to traditional techniques, suggesting an enhanced precision in tracking ability. The efficacy of the suggested approach in improving power quality was further demonstrated by a 25% increase in voltage stability and a 30% decrease in total harmonic distortion (THD). Furthermore, we noticed a 15% decrease in processing time, which is critical for maximizing solar energy harvesting as it allows for quicker reaction to changing environmental circumstances. Also, our proposed model enhanced the tracking accuracy and time of MPPT, achieving 99.98 tracking Acc in 0.12 seconds. The experiment results prove the excellent performance of our proposed model under different operating conditions, such as static conditions, dynamic conditions, and partial shading conditions, as we showed in Table 5.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

This study, conducted by Alaa Hamzah Abdullah and Saad M. Alwash, encompassed several essential elements: conceptualization, formal analysis, software application, validation, inquiry, data curation, preliminary draft writing, reviewing and editing, and visualization. Wafaa Salih Abedi and Hanaa Al Abboodi were assigned supervisory responsibilities for project management. Authorship should be limited to persons who have contributed substantially to the reported work.

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