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A HYBRID ALGORITHM FOR PHOTOVOLTAIC MAXIMUM POWER POINT TRACKING USING ARTIFICIAL NEURAL NETWORK AND KINETIC GAS MOLECULAR OPTIMIZATION

D. Venkatabrahmanaidu[1], R. Thamizhselvan[2] and Ch. Chengaiah[3]
[1]Department of Electrical Engineering, Annamalai University, Annamalainagar, Tamil Nadu, India
[2]Department of Electrical Engineering, Annamalai University, Chidambaram, Tamil Nadu, India
[3]Department of Electrical Engineering, S.V.U College of Engineering, Sri Venkateswara University, Tirupati, India
E-Mail: dvb.naidupeed@gmail.com

ABSTRACT

The quest for efficient photovoltaic (PV) energy conversion systems has led to the development of Maximum Power Point Tracking (MPPT) algorithms. In this paper, we propose a novel hybrid approach that combines the power of Artificial Neural Network (ANN) with the optimization capability of Kinetic Gas Molecular Optimization (KGMO) for MPPT. We present a high-level outline of the proposed algorithm along with example MATLAB code snippets for each step, highlighting its potential for improving PV system performance. This paper proposes a metaheuristic optimized multilayer feed - forward artificial neural network (ANN) controller to extract the maximum power from available solar energy. Firstly, to improve the maximum power point (MPP) delivered by PV arrays and to overcome the drawbacks in the conventional MPPT method under irradiation variation, a hybrid MPPT controller is designed, in which the input parameters include the PV array voltage and current. The output parameter is the duty cycle of the DC/DC boost converter. The proposed approach abbreviated as ANN-KGMO MPPT controller is based on the Kinetic Gas Molecular Optimization (KGMO) Algorithm which is useful to train the developed ANN and to evolve the connection weights and biases to get the optimal values of duty cycle converter corresponding to the MPP of a PV array. Finally, the performance of the proposed control system is confirmed by simulation tests on a 2 kW PV system. In addition, the performance of an ANN-KGMO - based MPPT controller is also compared to the conventional perturb and observe (P&O) method. To analyze the results, simulations are performed by using MATLAB software.

Keywords: maximum power point tracking (MPPT), artificial neural network (ANN), kinetic gas molecule optimization (KGMO), particle swarm optimization (PSO), gravitational search algorithm (GSA) maximum power point tracking (MPPT).

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1. INTRODUCTION

The solar power system's excellent efficiency and affordability have made it widely used in modern times [1]. In comparison to conventional energy sources like oil, natural gas, and fossil fuel, it is regarded as one of the most promising renewable energy sources (RES) due to its quantity, purity, and environmental friendliness [2]. Despite its benefits, the solar power system's output active power P changes depending on the sun irradiance E_e and operation temperature T. This is particularly true when irradiations changing conditions (PSC) change quickly because of the non-linear characteristics of photovoltaic (PV) cells [3]. The intricate correlation between PV input parameters and power output leads to inadequate power extraction [4].

Maximum power point tracking (MPPT) becomes the study emphasis to increase the solar power system's efficiency η and guarantee that the operating point is always at maximum power point (MPP) to overcome the aforementioned limitation [5]. It is possible to follow peak uniform circumstances without abrupt irradiance or under PSC by employing traditional hill-climbing (HC) MPPT approaches such as incremental conductance (IC) and perturb and observe (P&O) [6].

Other methods to increase solar energy efficiency besides electronically implemented MPPTs include adjusting the tilting angle of solar panels to track the direction of the sun and integrating soft-computing weather forecasts [7]. We exclusively concentrate on AI-based MPPT methods for DC-DC converters in solar power systems. The following shortcomings of a traditional HC MPPT are intended to be addressed and corrected through the combination of many AI optimization techniques with MPPT:

a) Insufficient capacity for robustness, adaptability, and self-learning.
b) Slow transient response, high steady-state error, and power oscillation at MPP.
c) Failure to locate MPP, trapping at the local MPP, erroneous perturbation direction under PSC, or abrupt change in irradiance as a result of MPPT failure [8].

Generally speaking, the current AI-based MPPT methods anticipate and estimate the MPP along the non-linear P-V curve by using sensory data such as solar irradiance Ee, input voltage of the solar power system V_{IPV}, and input current I_{IPV} measurements. Since MPPT is a complicated, reliable, self-learning, and digitalized system, integrating AI speeds up convergence and transient reaction. Conventional HC MPPT and AI-based MPPT are the two main kinds of MPPT methodologies [9]. The terms bio-inspired MPPT, soft computing MPPT, computational intelligence (CI) based MPPT, and modern MPPT are synonyms for AI-based MPPT. Fuzzy logic control (FLC), artificial neural networks (ANN), genetic algorithms (GA), particle swarm optimization (PSO), Tabu search (TS), Cuckoo search (CS), firefly algorithms (FA), differential evolution (DE), and hybrid algorithms make up the majority of it. P&O, IC, HC, constant voltage, fractional short-circuit current, fractional open-circuit voltage, tracking of the current-voltage (I-V) curve via scanning, Fibonacci searching, MPPT segmentation searching, and extremum seeking control are the components of conventional HC MPPT approaches. For every kind of MPPT, there are multiple sources of a comparative literature evaluation. Only AI-based and hybrid MPPT approaches have been covered in the literature yet. Particularly for AI-based MPPT approaches, there are remarkably few comparative studies [9]-[11].

This paper makes the following contributions: it reviews the applicability and uses of artificial intelligence (AI) in maximum power point tracking (MPPT) for solar power systems; it overviews the research and development areas of AI in MPPT today; and it offers a comparative analysis and performance evaluation of each AI algorithm in MPPT techniques. Popular AI-based MPPT approaches are examined and assessed in this research. This paper offers a thorough understanding of the most recent developments and advancements in artificial intelligence (AI) as they relate to MPPT for solar power systems. Conventional MPPT approaches generally display the same drawbacks, such as oscillation around MPP, power fluctuation, trapping at one of the local MPPs, and inability to function normally under PSC and rapid variations in irradiance [12], [13]. AI is therefore used to get around these problems [14], [15]. Figure-1 displays a typical MPPT block diagram. Here PWM stands for pulse width modulation.

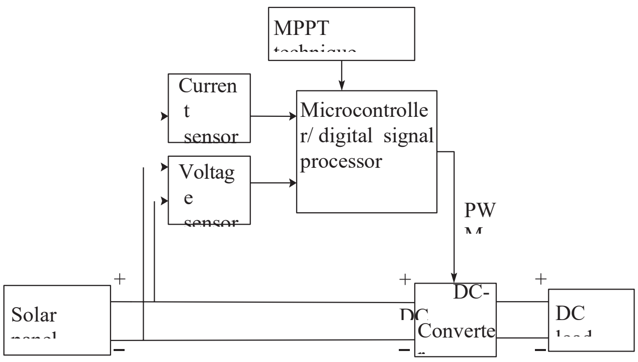

Figure-1. Block diagram of typical MPPT.

MPPT based on artificial neural networks (ANN) is frequently used as a reliable, quick, and effective method the capacity to identify nonlinear correlations between dependent and independent variables and the lack of a deep grasp of internal system features are the key benefits of using ANN approach with PV systems. The primary contribution of this work is the use of the Kinetic Gas Molecular Optimization (KGMO) controller to enhance the performance of the ANN-based MPPT. Simulating PV applications simultaneously under various weather conditions is the second focus of our effort. Under varying sun irradiation, the simulation results were compared to the traditional P&O approach. The remainder work is organized as follows: Section 2 discusses maximum power point tracking (MPPT), Section 3 details the PV module modeling, Section 3 describes the proposed system analysis, Section 4 goes into depth about the simulation findings and Comparisons, and Section 5 concludes.

2. REVIEW OF MPPT ALGORITHMS

A. Perturb and Observe (P&O)

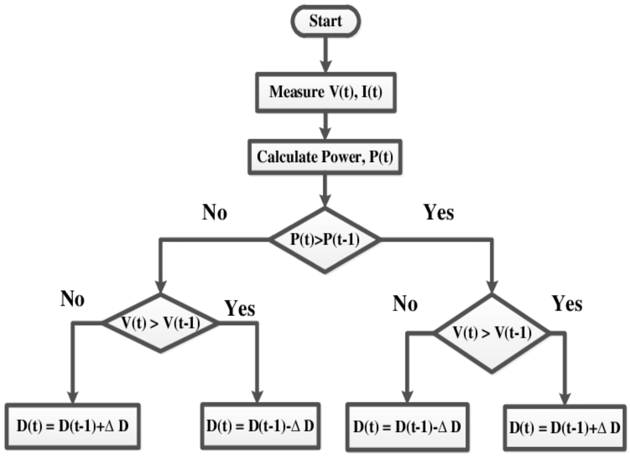

Figure-2. The P&O flowchart.

The most often used MPPT approach is perturb and observe (P&O) because of its simplicity [16], [17]. Fig 5 shows the flowchart for (P&O). The idea behind this technique is to alter the power converter control signal's duty cycle to cause a disturbance, and then monitor the PV panel's output power response. The disturbance's direction is maintained if the current power P(n) is greater than the power P(n-1) that was previously computed; if not, the direction is reversed. Its primary drawback, though, is that it continuously oscillates about the maximum power point [18]. While several adaptive P&O algorithms have been created to improve the traditional method's efficiency, these techniques are still constrained by the oscillation around the MPP.

B. ANN

Animal brain biological neural networks serve as the model for artificial neural networks, or connectionist systems. From input current, input voltage, irradiance, temperature, and metrological data, ANN collects these inputs and constantly learns to adapt the behavior of the solar power system for maximum power [19]. It is used to train and test for the non-linearity relationship between I-V and P. ANN can simulate the FLC architecture more accurately and with a simpler converter implementation [20].

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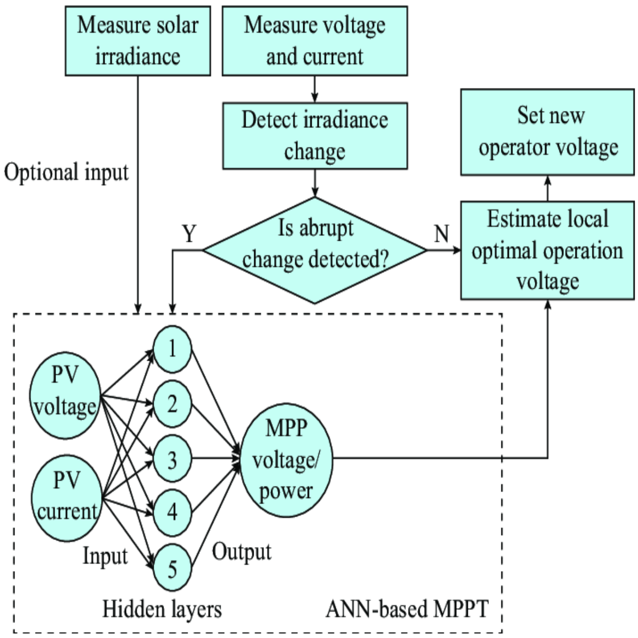

Figure-3. Structure of an ANN-based MPPT.

As illustrated in Figure-3, the dataset is obtained by feeding sun irradiances, temperature, solar power system voltage, or current to ANN to determine the relevant Pmax or Vmax output from the simulation or hardware setup collection. To teach the developed ANN how to function, these data are transformed into training data. The performance of the constructed ANN is assessed using test datasets after training, and the errors are fed back to the ANN for additional correction [21]. It can be used to provide MPP prediction in conjunction with sequential Monte Carlo (SMC) filtering state estimates. The ANN model observes the voltage and current or irradiance data in forecasting GMPP to refine the estimation by SMC, and a state space model for the sequential estimation of MPP can fit alongside the framework of the IC MPPT technique [22].

One of ANN's many benefits is its remarkable accuracy in modeling non-linearity and its ability to solve problems without the need for a model or prior information [23]. To increase tracking accuracy and speed, artificial neural networks (ANNs) can be used to model and forecast the solar power system's output power [24]. Its superior response time and reduced oscillation around MPP have been demonstrated [25]. It has been demonstrated that ANN-based MPPT can track MPP with the least amount of transient time and minimal ripple in real-world operating climate conditions [26]. The square error approach is used as the feedback correction for the error calculation [27]. The primary obstacle to the ANN's ability to function at its best without experiencing significant training error is a precise, consistent, and appropriate training set of data [28]. The advantages and disadvantages of ANN-based MPPT are shown in Table-2.

Table-1. Merits and demerits of Ann-based Mppt technique.

Merit	De-Merit
i. Fast response and tracking speed ii. Slight fluctuation in steady state iii. No need to be re-programmed	i. A massive dataset is required Complex and time-consuming ii. Tracking accuracy is affected by the PV panel model (system dependent) iii. Periodic tuning is required due to environmental change and aging iv. Difficult to be trained properly and get training data

C. Particle Swarm Optimization (PSO)

The PSO algorithm is the most widely used SI-based MPPT. This approach uses heuristics to solve the MPPT optimization problem. A particle's position indicates a potential solution, and the duty ratio indicates the solution space [29]. PSO, which is based on the idea of bird flocking, has been shown to produce results that are better suited to each iteration. Every particle in PSO follows the optimal particle. Particle population is shown in PSO, and the placements of the particles are compared with both the global and local optimum positions. To discover the optimal solution, these particles are then shifted inside the search space [30]. PSO can be easily combined with overall distribution (OD) to quickly identify the general area surrounding GMPP [31].

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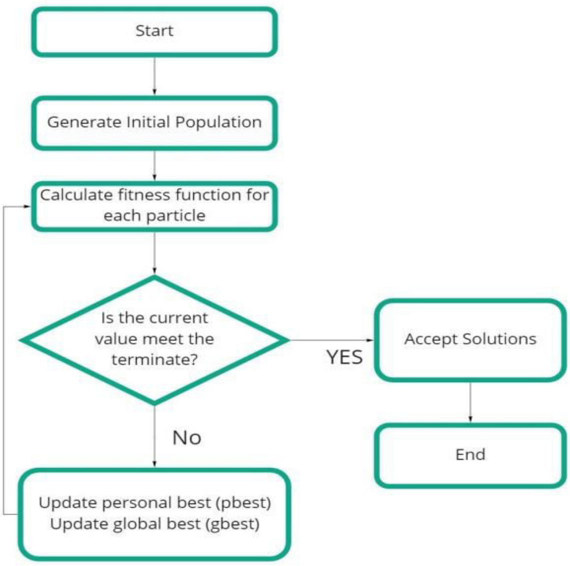

Figure-4. Flowchart of PSO.

To enhance the particle search process, a non-linear decreasing inertia weight is integrated with an enhanced PSO [32]. Every cycle for other modified PSOs results in a decrease in the learning factor and weighting value. On the other hand, an increase in the social learning element is anticipated. Additionally, the weighting factor is adjusted in response to variations in the power characteristic curve and slope. The tracking speed and stability are increased by these changes [33]. When compared to a traditional PSO, a discrete PSO (DPSO) has a simpler structure, higher performance, and a consistent solution for a lesser number of particles. For the inertia weight, just one parameter needs to be adjusted [34]. The Flowchart of PSO is shown in Figure-4.

D. Gravitational Search Algorithm (GSA)

The Gravitational Search Algorithm (GSA) is a suggested algorithm that relies on the laws of gravity and mass interactions. The pace of optimization is poor with GSA due to time-consuming computations required to calculate the total force on each mass, despite its strong performance in addressing numerous optimization issues. We present a novel method in this study that significantly increases the speed of GSA. Our method is based on multi-agent systems, in which the parallelism is expressed through the usage of several agents. Complex problems are broken down into smaller, more manageable components that are handled by various system agents in multi-agent based GSA. According to the results of our experiments, our multi-agent based GSA technique offers an efficient and effective optimization methodology that can assist scientists in a range of computational tasks related to science and engineering. The general GSA concept is displayed in Figure-5. [35]

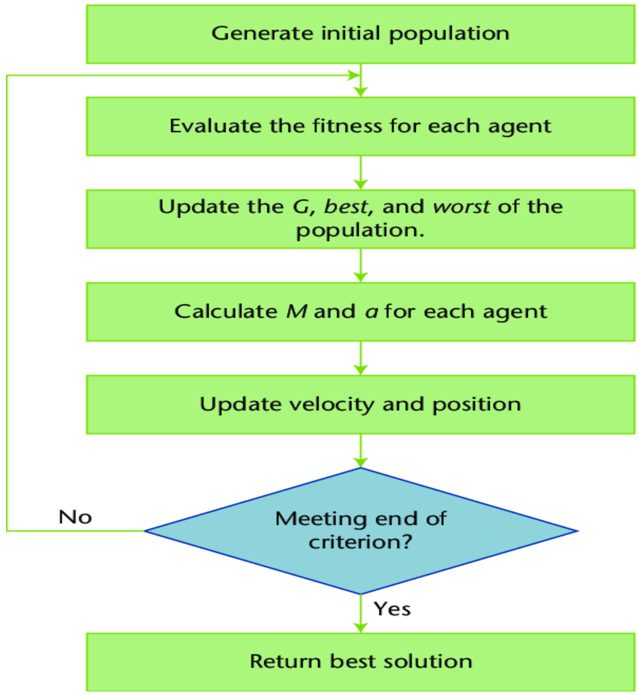

Figure-5. General principle of GSA.

The algorithm steps of GSA

a) Search space identification.

b) Randomized initialization.

c) Fitness evaluation of agents.

d) Update G(t), best(t), worst(t) and Mi for i = 1,2,. . .,s.

e) Calculation of the total force in different directions.

f) Calculation of acceleration and velocity.

g) Updating agents' position.

h) Repeat steps c to g until the stop criteria are reached.

i) End.

E. Kinetic Gas Molecule Optimization (KGMO)

Real-world optimization problems are increasingly being solved by swarm-based algorithms. The optimization algorithm Kinetic Gas Molecule Optimization (KGMO), which is based on the kinetic energy of gas molecules, is presented in this study. The kinetic theory of gases, which establishes the guidelines for gas molecule interactions in the model, applies to the agents, which are gas molecules that are moving in the search space. The suggested algorithm is tested against the corresponding outcomes of two well-known benchmark algorithms, namely Particle Swarm Optimization (PSO) and the recently created high-performance Gravitational Search Algorithm (GSA), in terms of its performance in finding the global minima of 23 nonlinear benchmark functions.

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According to the conducted simulations, KGMO performs better [44] when it comes to reducing the Mean Square Error (MSE). In 150 iterations, KGMO significantly outperformed PSO and GSA by up to 107 and 1020 times, respectively, when solving unimodal benchmark functions. Solving the multimodal benchmark functions yielded improvements of at least ten times.

The average MSE for the 3 models of benchmark functions. [36]

Table-2. Average MSE for the 3 models of benchmark functions comparison with PSO, GSA, and KGMO.

Functions	PSO	GSA	KGMO
Unimodal functions	47.22682	83.8330×10^{4}	2.40
Multimodal high-dimensional functions	66.9	59.5014×10^{1}	12.066×10^{3}
Multimodal functions with fixed dimensions	0.134	5.445	5.9168
Average MSE	21.5895×10^{1}	28.3467×10^{4}	23.1
log(Average MSE)	2.334	5.456	1.364

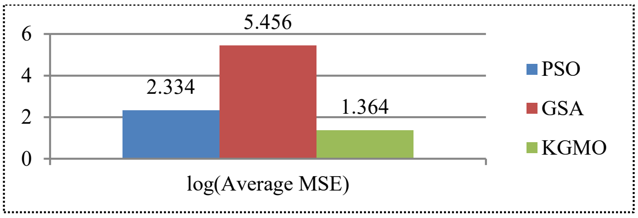

Figure-6. Chat Diagram Log (Average MSE) for the 3 models of benchmark functions compression with PSO, GSA, KGMO.

Using the 23 standard benchmark functions, a performance evaluation of the KGMO algorithm against other well-known benchmark optimization algorithms reveals that the proposed KGMO is not only more accurate and can reduce the MSE by 10^{1} and 10^{4} times compared to the PSO and GSA, respectively, but it can also converge toward the global minimum in less than 150 iterations.

3. PROPOSED SYSTEM ANALYSIS

The proposed approach abbreviated as ANN-KGMO MPPT controller is based on the Kinetic Gas Molecular Optimization (KGMO) Algorithm which is useful to train the developed ANN and to evolve the connection weights and biases to get the optimal values of the duty cycle of the converter corresponding to the MPP of a PV array. The Figure-7 is the proposed model block-diagram

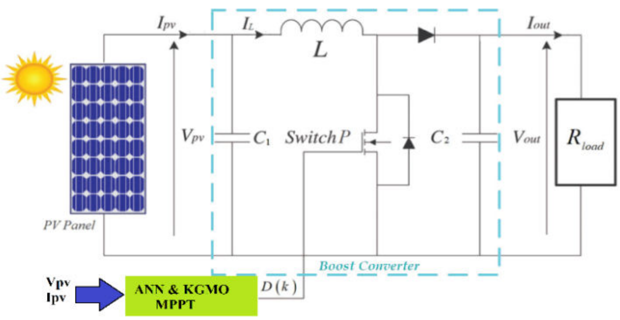

Figure-7. Block diagram of the proposed model.

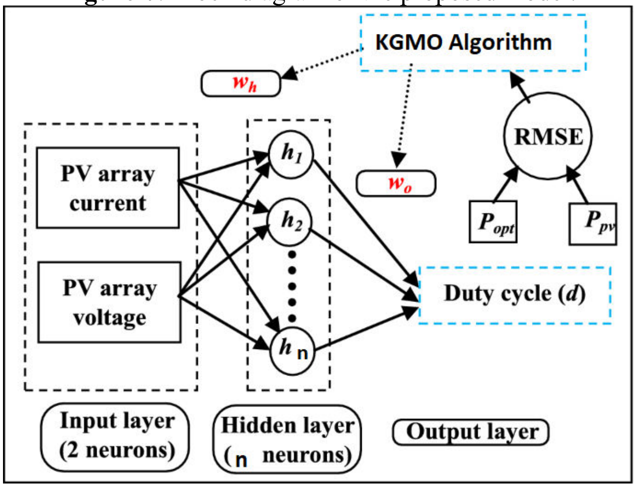

Figure-8. Proposed layout diagram.

Steps for proposed MPPT

Step 1: Data Preparation and ANN Training
Step 2: Kinetic Gas Molecular Optimization (KGMO)
Step 3: Applying KGMO-Optimized Parameters

The suggested algorithm is particularly helpful in resolving challenging optimization issues since it converges more quickly and with greater accuracy than the benchmark algorithms.

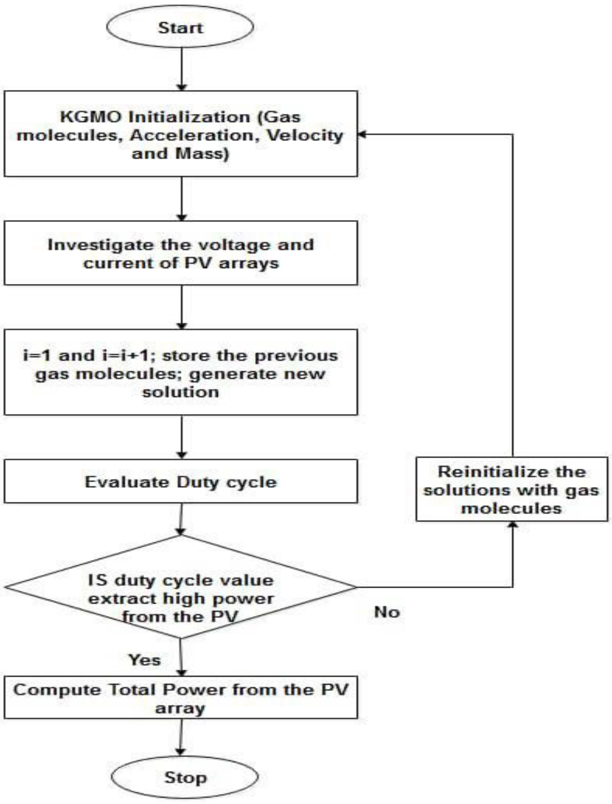

Figure-9. Flowchart of KGMO and ANN.

A. Simulation Setup and Configuration

A solar photovoltaic array converts solar energy obtained from the sun to electrical energy. Input to the PV panel is irradiance and temperature. For every temperature and irradiance maximum power point will vary. It is possible to track MPP by using different maximum power point algorithms which are developed by researchers. In this system, the specification of the (Sun Earth Solar Power TDB156-60-P 215W) PV array used is given in Table-3.

Table-3. Solar PV panel details.

Parameters	Value
Maximum output power	215.028W
No. of Parallel strings	6
No. of Series connected modules per string	6
Cells per module	60
Open circuit voltage (V_{oc})	36.8 V
Short circuit current (I_{sc})	7.92 A
Voltage at maximum power point (V_{MPP})	29.7 V
Current at maximum power point (I_{MPP}))	7.24 A

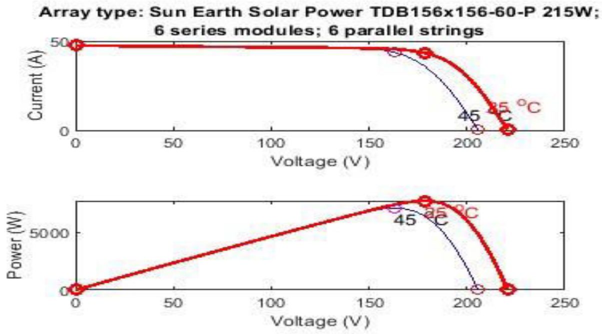

Figure-10 (a). I-V and P-V characteristics when the temperature varies and the irradiance remains constant at 1000 W/m^2.

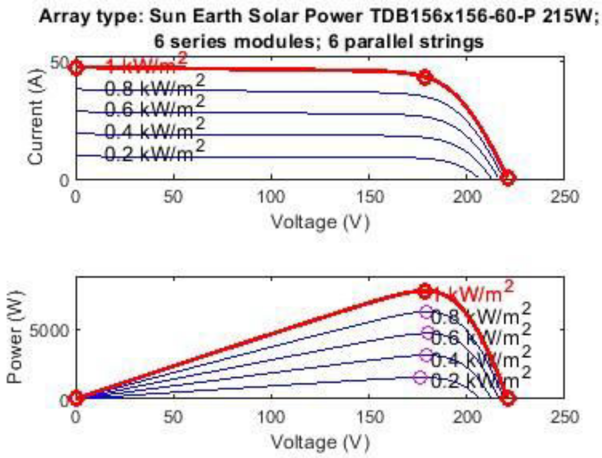

Figure-10 (b). I-V and P-V characteristics when the irradiance varies and the temperature remains constant at 25 °C.

B. Design of Boost Converter

A boost power converter is employed to transfer the power available from solar PV to load at a boosted voltage level. The peak power output is 2000W as per the data sheet. So the maximum operating power of the converter is 2000 W. The Output voltage of the panel is 200 V at its MPP.

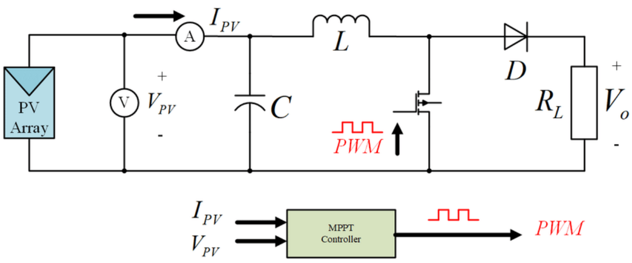

Figure-11. Boost converter.

The designed value of the boost converter is presented in Table-4.

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Table-4. Component values.

Parameters	Value
Inductance	0.15H
Capacitance(across supply)	100 e-6F
Capacitance (across the load)	470 e-6F
Resistor	80 Ohm
Output voltage	400V
Switching frequency	2.5 kHz

C. ANN based MPPT with KGMO

Steps for proposed MPPT

a) Step 1: Data Preparation and ANN Training

b) Step 2: Kinetic Gas Molecular Optimization (KGMO)

c) Step 3: Applying KGMO-Optimized Parameters

Step 1: Data Preparation and ANN Training
Historical data of solar irradiance and PV voltage/current preprocess and train an ANN to predict the optimal operating voltage for maximum power point tracking using MATLAB's Neural Network Toolbox.

```
% Load and preprocess data
load('pv_data.mat'); % Load your PV data
inputs = [solar_irradiance', pv_current']; % Input features
targets = pv_voltage; % Target output
% Create and train the ANN
net = feedforward net([5 8 12 1]); % Define ANN architecture
net = train(net, inputs, targets); % Train the ANN
```

Step 2: Kinetic Gas Molecular Optimization (KGMO)
KGMO is an optimization technique inspired by gas molecule behavior. In this step, implement the KGMO algorithm to optimize the PV operating parameters based on the ANN's predictions.

```
% Define KGMO parameters
num_molecules = 50;
num_iterations = 100;
alpha = 0.1; % Scaling factor
% Initialize molecules randomly
molecules = rand(num_molecules, 2);
for iter = 1:num_iterations
% Evaluate objective function using ANN predictions
objective_values = predict(net, [pv_voltage', molecules(:, 1)]);
% Sort molecules based on objective values
[~, idx] = sort(objective_values, 'descend');
molecules = molecules(idx, :);
% Update molecule positions
for i = 1:num_molecules
new_position = molecules(i, 1) + alpha * randn();
molecules(i, 1) = max(0, min(1, new_position)); % Ensure within bounds
new_position = molecules(i, 2) + alpha * randn();
molecules (i, 2) = max(0, min(1, new_position)); % Ensure within bounds
end
end
```

Step 3: Applying KGMO-Optimized Parameters
Finally, Using the optimized parameters obtained from KGMO to control the PV system and track the maximum power point.

```
optimized_voltage = molecules(1, 1); % Use the best molecule's voltage
% Use the optimized voltage for your MPPT control algorithm
```

The neural network structure for MPPT is given in Figure-12.

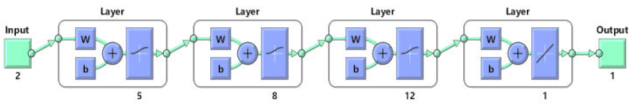

Figure-12. Neural network for MPPT.

Input to the neural network is solar PV voltage and current. Number of hidden layers is calculated by trial and error method. Output is the duty ratio to the boost converter. Training points should be obtained to start work with the ANN algorithm. It is trained by using the KGMO algorithm. The training points are obtained by varying the voltage and current inputs to the PV array and collecting values of duty ratios to boost the converter to track maximum power from solar panels for different temperature and irradiance conditions. Some training points are kept as test points to test the neural network after training. A neural network is trained by using "nntool" in MATLAB m-FILE. Figure-13 shows the neural network training with the MATLAB toolbox. The network is obtained through training by using the KGMO algorithm. The performance function of ANN is the Mean Squared Error (MSE). To train neural networks 2400 data are taken. The activation function of the input layer and the output layer is "tansig" and purelin" respectively. The training data will be obtained by conducting the solar PV system simulation.

- Input: Solar PV Voltage and Current
- Output: Duty ratio
- Number of samples: 2400
- Number of hidden layers: [5,8,12,1]
- No of epochs: 1000
- Method: Feed forward method
- Training: Kinetic Gas Molecular Optimization (KGMO)

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- Performance: Mean Squared Error

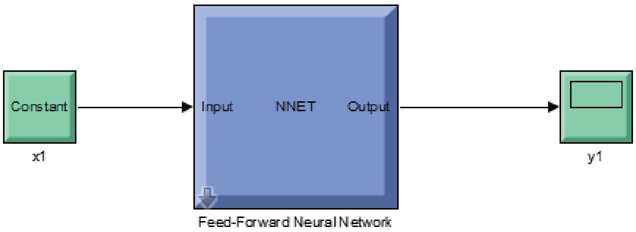
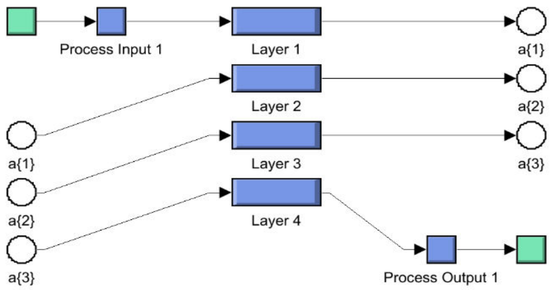
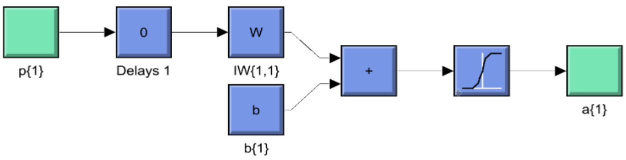


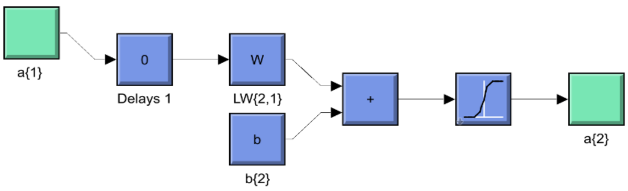
Figure-13. ANN training by MATLAB nntool.



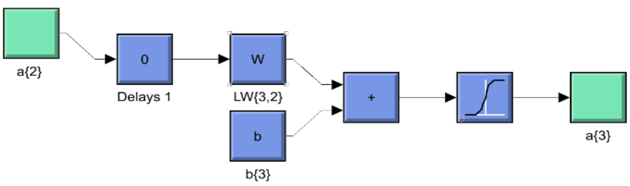
i. ANN block



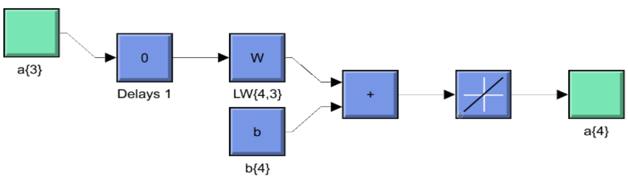
ii. Layer_1



iii. Layer_2



iv. Layer_3



v. Layer_4

Figure-14. ANN block and layers inside the block.

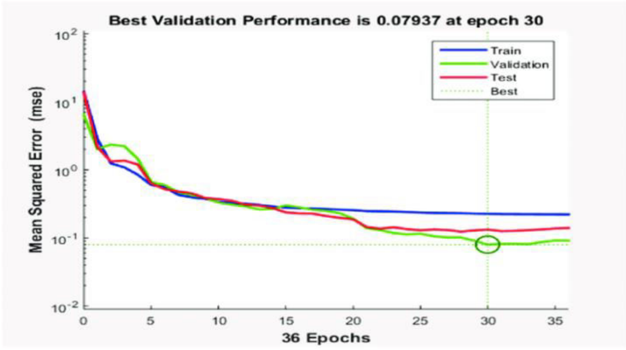


Figure-15(a). ANN performance.

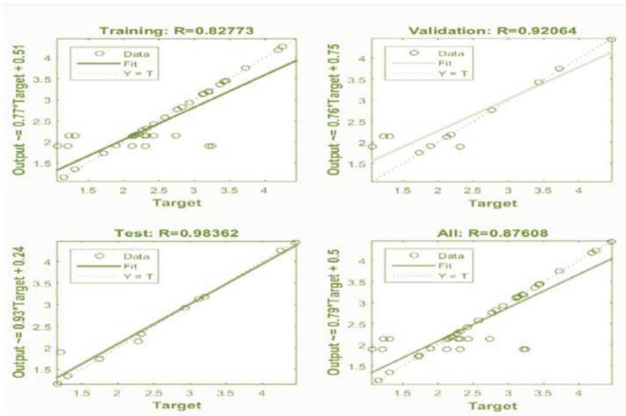


Figure-15(b). ANN performance.

In Figure-15(a), (b) ANN performance is given. From the performance of trained ANN, it is clear that Mean Squared Error (MSE) will decrease when epochs increase. A well-trained artificial neural network will have a very low mean squared error at the end of training. The low mean squared error means that the desired output and the neural network's output are close to each other.

4. SIMULATION RESULTS AND COMPARISON

Figure-16 and Figure-17 show the simulation results of P&O, and ANN-KGMO methods respectively at 25°C temperature and light intensity is varied from 1000 to 200 W/m^2 in steps at a rate of 200 W/m^2 per second. After reaching 200 W/m^2 the intensity is varied to 1000W/m^2 in a single step.

A. P&O

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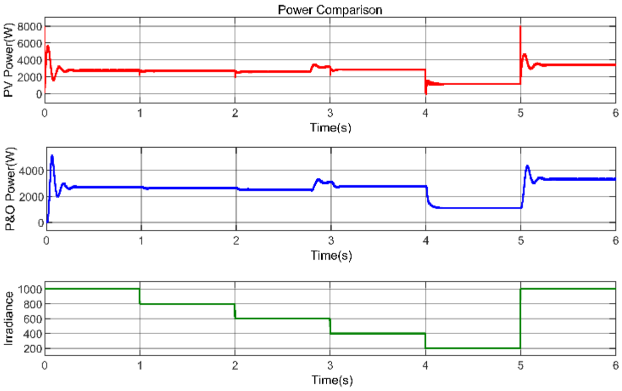

Figure-16(a). Power comparison with P&O method.

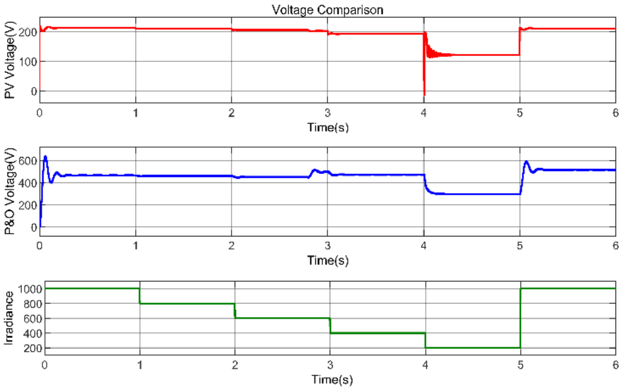

Figure-16(b). Voltage comparison with P&O method.

Figure-16 shows the simulation outcome of MPPT tracking using the hill climbing method. Boost output voltage and output power takes 0.06 sec to settle with Steady state oscillations. At low irradiance conditions, (ie; 200W/m^2) output power and converter voltage are less than the required value or base value.

B. ANN & KGMO

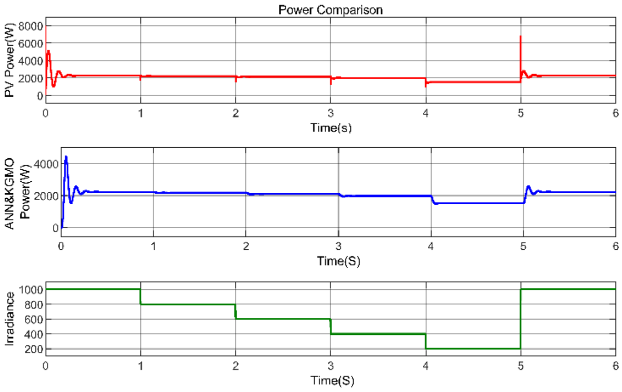

Figure-17(a). Power comparison from ANN-KGMO method.

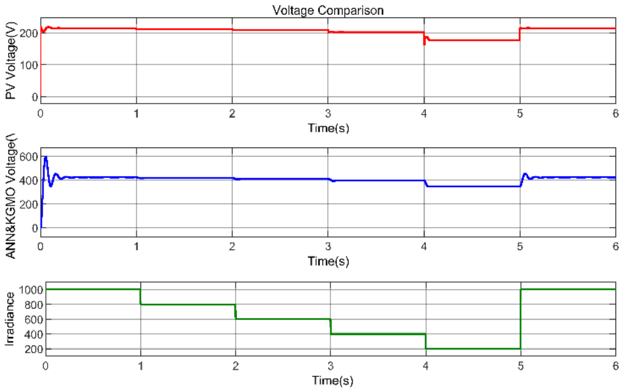

Figure-17(b). Voltage comparison from ANN-KGMO method.

Figure-17 shows the simulation outcome with ANN-KGMO based MPPT tracking algorithm is more reliable than the conventional control methods. It has less settling time with no steady state oscillations and more power output.

It is observed that ANN-KGMO based MPPT algorithm regulates the output voltage at 400V and hence the power at 2000 W with rapid step changes in the solar irradiance.

Table-5. Comparison of Mppt techniques.

Methods	Settling time (Seconds)	Inference
P&O	Almost 0.06s but with ± 5% error	More time to settle with steady-state oscillations At low irradiance gives less output
ANN	0.03s (steady) with ± 1% error	Weights are not adjusted automatically Reprogramming is not necessary as the learning mechanism is inherent. Has less steady state error
ANN-KGMO	0.02s(steady) with ± 0.1% error	Weights are adjusted automatically with KGMO Fast settling time Has least steady state error

5. CONCLUSIONS

This study has proposed and verified a hybrid algorithm to mitigate the effect of variations in solar irradiance in the process of maximum power extraction from a solar PV system. The advantage of the KGMO algorithm has been adopted with the ANN controller to adjust the Weights automatically. The simulation study has been done on a 2 kW PV system with P&O and ANN-KGMO using MATLAB/Simulink. The response of MPPT algorithms with rapid step variations in irradiance with constant temperature has been observed. The most versatile and conventional P&O method has resulted in a settling time of 0.06s with a 5% error whereas the ANN with KGMO method has settled at 0.02s with the least error of 0.1%. The maximum power extracted at a low irradiance of 200 W/m^2 with the ANN-KGMO method was 1980 W whereas the conventional P&O method could extract a maximum power of 1450 W from a 2 kW system. This concludes that the ANN-KGMO method of MPPT could harness the desired/maximum power with the least settling time and error from a PV system with rapidly changing solar irradiance conditions with the lowest solar irradiance of 200 W/m^2.

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