MPPT Algorithms for Solar Power Systems Using Artificial Intelligence: An Overview

***Mr. D Venkatabrahmanaidu[1*]**
[1*]*Research Scholar,*
Department of Electrical Engineering,
Annamalai University, Annamalainagar,
Tamil Nadu, India,
Email:dvb.naidupeed@gmail.com

Dr.R.Thamizhselvan[2]
[2]*Associate Professor,*
Department of Electrical Engineering,
Annamalai University, Chidambaram,
Tamil Nadu, India,
Email:rt10535@annamalaiuniversity.ac.in

Dr.Ch. Chengaiah[3]
[3]*Professor,*
Department of Electrical Engineering,
S.V.U College of Engineering,
Sri Venkateswara University,
Tirupati, India,
Email:chinthapudisvu@gmail.com

***Abstract*—** Artificial intelligence (AI) techniques have been widely used for maximum power point tracking (MPPT) in solar power systems over the past decade. Conventional MPPT algorithms often fail to accurately track the maximum power point (MPP) under rapidly changing environmental conditions, necessitating the integration of AI. Each AI-based MPPT technique has its own pros and cons, making the selection process challenging. Compared to conventional methods, AI-based techniques offer significant improvements in tracking accuracy, response time, and adaptability, especially under varying irradiance and temperature conditions. This paper provides a comprehensive overview of AI-based MPPT algorithms for solar power systems, exploring methodologies such as neural networks, fuzzy logic, genetic algorithms, and reinforcement learning. The principles, advantages, and implementation challenges of these techniques are highlighted. A comparative analysis with traditional MPPT techniques is presented to emphasize the enhancements brought by AI integration. While AI-based methods offer quick convergence speeds, low steady-state oscillation, and high efficiency, they also require substantial computational power and higher implementation costs. Hybrid MPPT methods, which combine the strengths of both conventional and AI-based techniques, offer a balanced approach in terms of performance and complexity. This study includes a detailed comparison and classification of six main AI-based MPPT approaches based on MATLAB/Simulink simulation results. It assesses the technological implementations and unresolved issues of AI-based MPPT techniques, providing fresh perspectives on selecting the most suitable methods. By leveraging AI, solar energy systems can achieve higher efficiency and reliability, significantly contributing to sustainable energy solutions.

Keywords— **Maximum power point tracking (MPPT), artificial intelligence (AI), fuzzy logic control (FLC), artificial neural network (ANN), genetic algorithm (GA), swarm intelligence (SI), machine learning (ML).**
DOI Number: 10.48047/nq.2021.19.11.NQ21313 **NeuroQuantology 2021;19(11):971-985**

I. 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 partial shadowing 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) in order 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 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 softcomputing 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:

1. Insufficient capacity for robustness, adaptability, and self-learning.
2. Slow transient response, high steady-state error, and power oscillation at MPP.
3. 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 I_{PV} 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 bioinspired 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 to 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]. Fig. 1 displays a typical MPPT block diagram. here PWM stands for pulse width modulation.

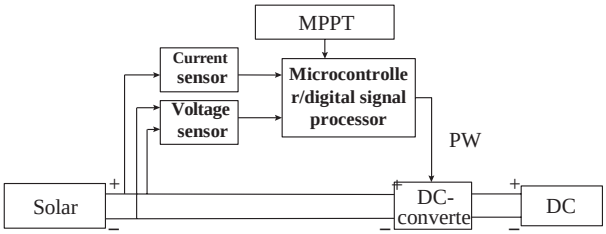

Fig. 1. Block diagram of typical MPPT

Since the designer must first mathematically model the plant before it can be managed, the process of designing a conventional control (CC) system include mathematical modeling, which includes all of the plant's dynamics and is referred to as the mathematicians' approach. On the other hand, the system behavior is required for the inputs in order to construct an IC system, and the IC system is in charge of autonomous and abstract modeling [16].

II. REVIEW OF AI-BASED MPPT TECHNIQUES

A.FLC

Fuzzy logic-based FLC control systems transform analog inputs into continuous digital values between 0 and 1 [17]. It was created to address the issues with traditional MPPT methods, such as steady-state error (SSE), excessive settling times, and oscillation around MPP. Because it does not necessitate the knowledge of an exact MPPT model, it is simple to design. FLC is hence well-liked in the past ten years [18]. P&O and IC algorithms, for example, can be integrated with FLC [19]. Fuzzy rules are created by FLC using the HC algorithm [20]. When compared to the HC algorithm, it has been demonstrated to offer greater power efficiency in the presence of load current and irradiance changes [21].

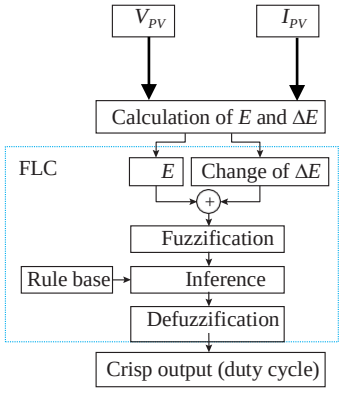

Fig. 2. Block diagram of general FLC.

TABLE I.
MERITS AND DEMERITS OF FLC-BASED MPPT TECHNIQUE

Merit	De-Merit
i. High efficiency and small fluctuation in steady state ii. Simple design and implementationOperation with inaccurate input iii. Fast tracking speed during rapid irradiance change iv. Good dynamic performance v. Combination with another algorithm	i. Difficulty in deriving fuzzy rulesand time consuming ii. Inability to automatically learnfrom the environment Complex calculation iii. Undesirable performance under PSCFuzzy rules directly affect system performance

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 the maximum power [23]. 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 [24].

As illustrated in Fig. 3, the dataset is obtained by feeding sun irradiances, temperature, solar power system voltage, or current to ANN in order to determine the relevant Pmax or Vmax output from the simulation or hardware setup collection. In order 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 [25]. It can be used to provide MPP prediction in conjunction with sequential Monte Carlo (SMC) filtering state estimate. 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 is able to fit alongside the framework of the IC MPPT technique [26].

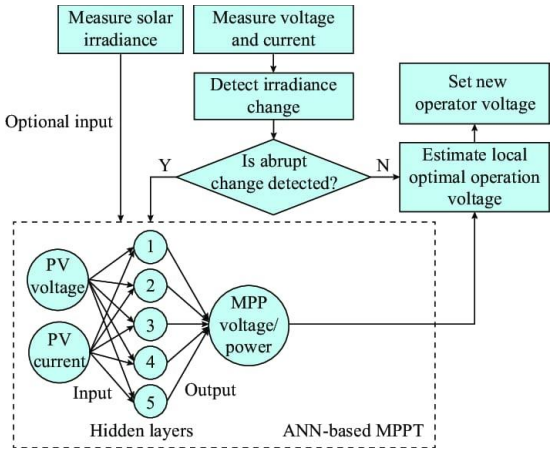

Fig. 3. Structure of an ANN-based MPPT

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 [27]. TO INCREASE TRACKING ACCURACY AND SPEED, ARTIFICIAL NEURAL NETWORKS (ANNS) CAN BE USED TO MODEL AND FORECAST THE SOLAR POWER SYSTEM'S OUTPUT POWER [28]. ITS SUPERIOR RESPONSE TIME AND REDUCED OSCILLATION AROUND MPP HAVE BEEN DEMONSTRATED [29]. 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 [30]. The square error approach is used as the feedback correction for the error calculation [31]. 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 [32]. The advantages and disadvantages of ANN-based MPPT are shown in Table.II

TABLE II.
MERITS AND DEMERITS OF ANN-BASED MPPT TECHNIQUE

Merit	De-Merit
i. Fast response and tracking speed ii. Slight fluctuation insteady 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 ageing iv. Difficult to be trained properly and get training data

C. GA

GA is a broad AI-based optimization technique that can be used to solve a variety of optimization issues. It is frequently used in MPPT to calculate the PV panel's voltage reference by altering a population of distinct solutions. By applying the voltage-step selection GA algorithm, GA generally has relatively modest oscillations, a fast convergence speed, and fast dynamics [33]. A modified GA has a smaller population, easier mutation processes, and a simpler crossover calculation [34]. In contrast to traditional MPPT, GA-based MPPT is not limited to the local MPP; rather, it can search GMPP.

Due to its streamlined approach, GA is not advised for the optimization of extremely large-scale, extremely complicated, and excessive problems, notwithstanding its efficiency. GA is initialized during the MPPT optimization process by beginning the first parent population as an array:

$$\boldsymbol{X}^{i} = [\, parent^{1} \;\; parent^{2} \;\; \ldots \; parent^{n} \,]$$

Where n is the population size; and *parenti* (i = 1, 2, ..., n) symbolizes the voltage values at which the algorithm begins the optimization process. The solar power system's generated output power is represented by the objective function f (X i). The goal function performs the assessment of fitness values for every position. They are then employed to enhance population fitness and facilitate population evolution over several generations. In contrast to traditional GA, the algorithm needs to be reinitialized especially for MPPT applications because to unforeseen variations in PSC, load, or solar irradiation. Consequently, after being met in (1) and (2), the subsequent requirements reinitialize the GA-based MPPT approach.

$$|V(k+1) - V(k)| < \Delta V \quad \text{---------->(1)}$$
$$|P(k+1) - P(k)/P(k)| > DP \quad \text{---------->(2)}$$

where k is the current measurement; and k + 1 is the next iteration of the measurement.

On the basis of chromosomal evolution, GA was created. The usual GA process is depicted in Figure 4. First, binary encoding is used for the original population. Their fitness values for every chromosome are assessed when they are translated into real numbers. Selection, crossover, and mutation are among the genetic procedures carried out in search of an ideal answer, namely the maximization of power production. The recent re-searches of GA-based MPPT are displayed together with the benefits and drawbacks in Tables V and VI.

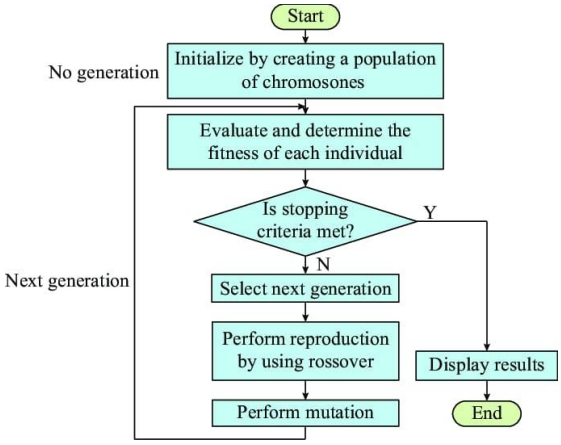

Fig. 4. Flowchart of a typical GA method in MPPT.

TABLE III.
MERITS AND DEMERITS OF GA-BASED MPPT TECHNIQUE

Merit	De-Merit
i. Low computational requirement General and uniform implementation scheme ii. MPPT is done by function valueswithout calculation iii. High stability and rapid response	i. Slow tracking speed due to series format ii. Depending on the initial condition

D. 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 [35]. PSO, which is based on the idea of bird flocking, has been shown to produce results that are better suited with 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. In order to discover the optimal solution, these particles are then shifted inside the search space [36]. PSO can be easily combined with overall distribution (OD) to quickly identify the general area surrounding GMPP [37].

To enhance the particle search process, a non-linear decreasing inertia weight is integrated with an enhanced PSO [38]. Every cycle for other modified PSO 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 [39]. 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 [40].

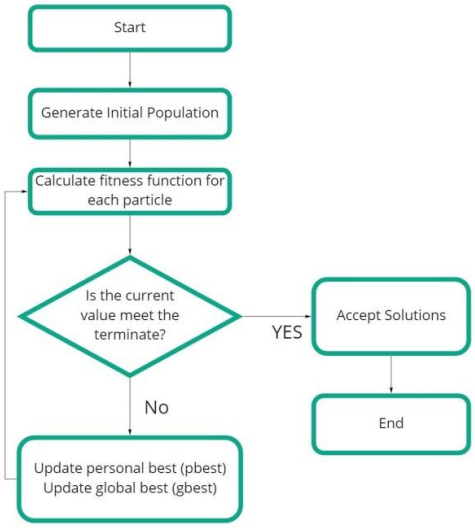

Fig. 5. Flowchart of PSO

E. Grey Wolf Optimization (GWO)

The GWO performs the desired calculations to achieve MPP. The flow chart for the GWO-based MPPT is shown in Figure 6.[42]

To improve the MPPT, the grey wolf optimization technique is being used [41]. The Grey Wolf Algorithm was first put forth by Mirjalili in 2014. This mathematical model mimics the social dynamics of a pack of grey wolves as they pursue their prey. The pack's wolves are sorted into various groups according to their strength and level of fitness. The alpha (α), beta (β), delta (δ), and omega (ω) are the distinct categories. Alpha (α) is the most fit wolf in the pack; beta (β) and delta (δ) are the next fittest wolves, and omega (ω) is the remaining group members. Next, the pack tracks, encircles, and attacks the prey using the same structure. The alpha (α), beta (β), and delta (δ) wolves are the main players in this situation. The GWO optimization model takes this similar issue into account. Similar to a wolf pack following prey, encircling the solution, and ultimately reaching the intended

solution, the model classifies the possible solutions for a given problem according to how close they are to the desired output and also advances the solutions in the direction of the desired values. The mathematical model uses the solution that falls into alpha (α) to get the best answer. The following is the equation that the GWO utilized to do this:

$$X(t+1) = Xp(t) - AxD$$

$$D = |C \times Xp(t) - Xp(t)|$$

Here, it indicates the current iteration. Xp(t) represents the position of the desired output, and X(t + 1) represents the position of the current solution. A ,C and D represent the vector coefficients, and these vectors are calculated using the below formula:

$$A = 2\,a\,r_1 - a$$
$$C = 2\,r_2$$

where the values of the vector a are linearly decreased from 2 to 0 as the iterations proceed, and r_1, r_2 are randomly chosen vectors in [0, 1].

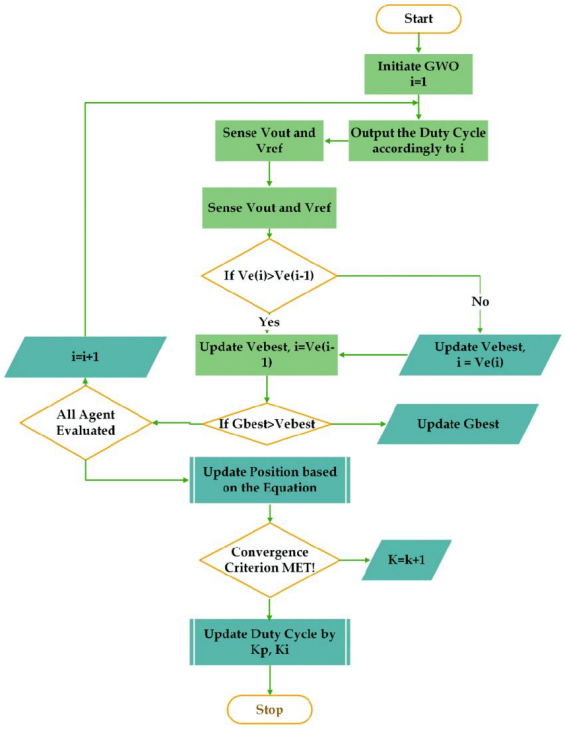

Fig. 6 Flowchart of GWO

F. 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 here.[43]

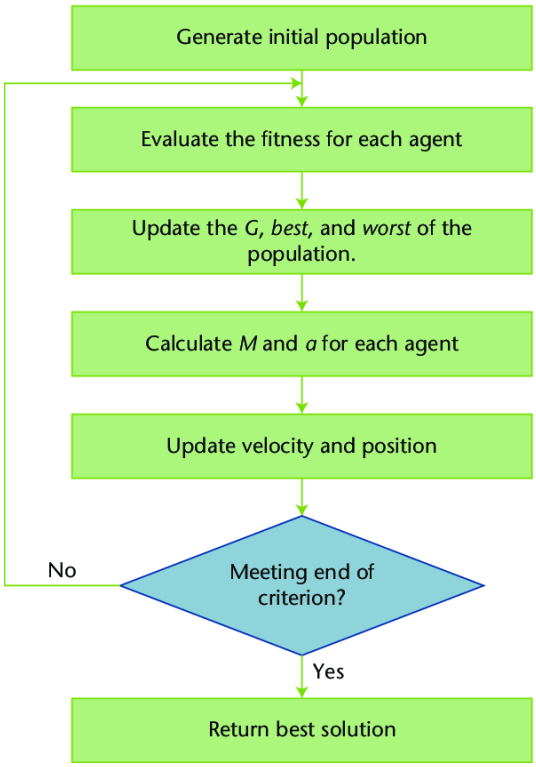

Fig. 7 General principle of GSA

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 is reached.

i) End.

G.Kinetic Gas Molecule Optimization(KGMO)

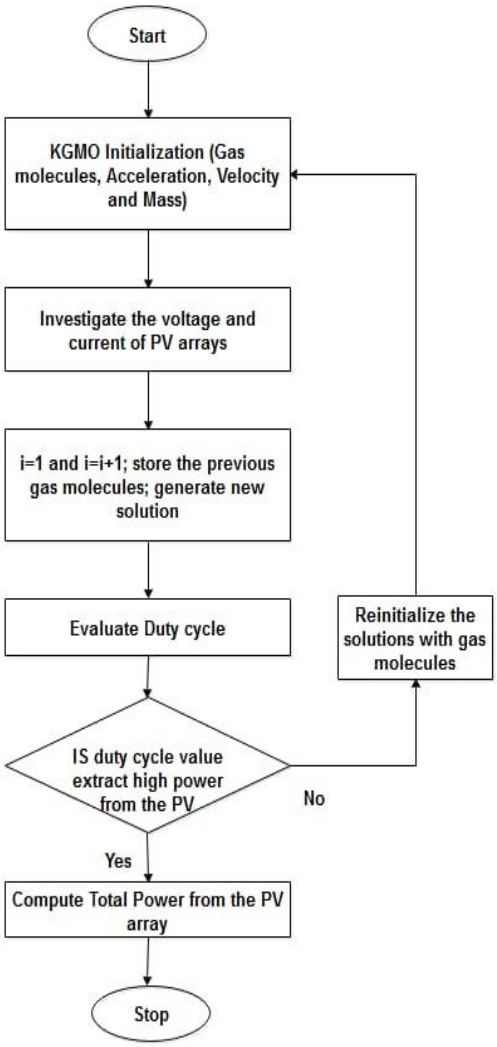

Fig. 8 Flowchart of KGMO

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

The average MSE for the 3 models of benchmark functions. [44]

TABLE IV.
AVERAGE MSE FOR THE 3 MODELS OF BENCHMARK FUNCTIONS COMPARESSION 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

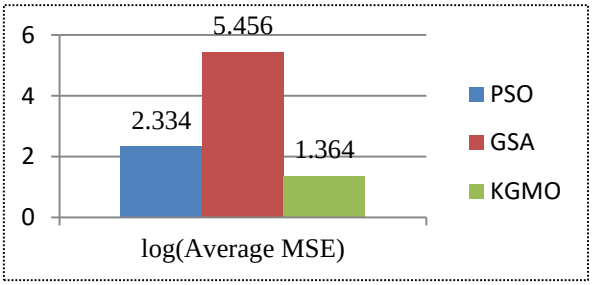

Fig. 9 Chat Diagram Log(Average MSE) for the 3 models of benchmark functions compression with PSO,GSA,KGMO

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 101 and 104 times compared to the PSO and GSA, respectively, but it can also converge toward the global minimum in less than 150 iterations.

H.Hybrid MPPT

The term "hybrid MPPT" refers to the combination of two or more MPPT that come from traditional methods or artificial intelligence. The "neural network P&O controller," which combines an ANN with a traditional P&O algorithm, is one of the most widely used hybrid MPPTs [27]. In contrast, with abrupt changes in irradiance or PSC, an improved P&O algorithm with a variable step size is intended to decrease steady-state fluctuation

or oscillation and speed up tracking. It is appropriate to merge ANN and FLC with traditional MPPT techniques like P&O and IC. The MPP is estimated by ANN in the absence of panel temperature or shading, and the outcome is further enhanced by the HC technique. Other hybrid MPPTs are PO-ANN and IC-ANN, which work in conjunction with the stacked auto-encoder (SAE) controller by transforming building blocks and deep learning (DL) training into auto-encoders. It is programmed to take the most power possible out of the solar power system using a greedy layer-by-layer strategy. Subsequently, the deep neural network is fine-tuned using standard MPPT-IC and PO using back propagation with supervised learning in order to get the maximum power [45].

An adaptive neuro-fuzzy inference system (ANFIS), which combines ANN and FLC, is another well-liked hybrid MPPT. It benefits from both FLC and ANN. An FLC-based MPPT is powered by an ANN that has been taught to estimate the ideal MPP. Fuzzy logic and ANFIS are the best, most adaptive, most versatile options for smart power management and solar power systems in any new configuration [46]. Fuzzy approach in learning complete dataset information is modeled using neuro-adaptive learning technique. The procedure involves mapping every dataset from several inputs to a single output. Input-output datasets are used by ANFIS to build a fuzzy inference system. In order to enable FIS to track the input and output data, the model calculates the membership function parameters that suit the data the best [47]. Backpropagation and least square algorithms are used in a hybrid learning technique to modify the fuzzy membership function parameters [48]. It has been demonstrated that ANFIS-based MPPT increases the solar power system's conversion efficiency [49]. In addition to its ability to anticipate and forecast meteorological data for solar power systems, the fuzzy neural network also has bit error correction capabilities [50].

ANN is deployable based on hybrid PSO and GSA, alongside with FLC. For instance, PSO-GSA generates a random initial population first and send them to ANN for data training [51]. Another hybrid MPPT technique is based on improved open-circuit voltage model-based approach and smart power scanning procedure. The smart power scanning checks the voltage values to see whether PSC is happening or not [52]. Apart from ANN, FLC is also versatile to integrate with P&O algorithm. It combines both technique advantages together [14]. Because huge step sizes guarantee fast reaction but produce excessive oscillation, and small step sizes have sluggish response and less oscillation, FLC-based P&O offers variable step sizes to ensure little oscillation and faster response [53]. The incapacity of traditional MPPT to track GMPP under PSC can also be addressed by integrating the IC approach with the PSO algorithm, which will increase tracking accuracy and convergence speed [54].

Another hybrid MPPT is the ANN-CGSVM methodology, which combines two potent machine learning (ML) methods: ANN and coarse-Gaussian support vector machine (CGSVM). One kind of non-linear SVM learning method that falls within the data mining category is CGSVM [55]. To generate big and accurate training data for MPPT, rational quadratic Gaussian process regression (RQGPR) is needed. Additionally, RQGPR and ANN must be integrated in order to use data mining and regression learner for PV MPPT [56].

The ANFIS controller and the HC method are combined in a novel ANFIS with HC (ANFIS-HC) to estimate the duty ratio offline more accurately. Since the duty ratio of MPP is computed offline by the ANFIS technique, HC's online duty cycle fine-tuning addresses the conventional MPPT's difficulty when finding GMPP under PSC [57]. Fuzzy-weighted classification labeling can be linked with traditional machine learning techniques, such as support vector machine (SVM) and extreme learning machine (ELM). This integration makes it possible to determine the ideal step size based on weather data, thanks to a supervised learning classification system [58]. Tables V present the merits and demerits of Hybrid MPPT

TABLE V.
MERITS AND DEMERITS OF HYBRID MPPT -BASED MPPT

Merit	De-Merit
i. Combination of conventional and AI-based MPPT advantages ii. Cancellation of disadvantages of conventional and AI-based MPPT iii. High accuracy and fast-tracking speed	i. Relatively complex ii. Longer computational time Costly

I. ML

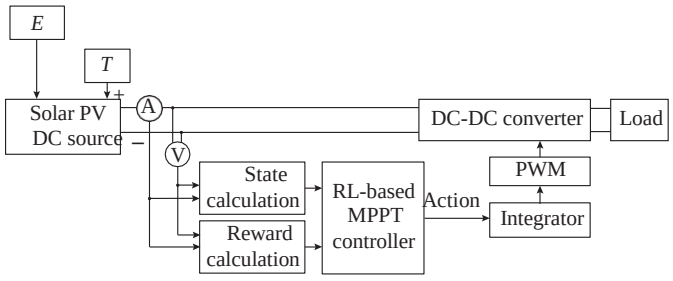

Fig. 10. General structure of RL-based MPPT.

Image segmentation, curve detection, and unsupervised classification are the areas of expertise for Bayesian machine learning. It can be used in

MPPT to attain MPP [59]. Optimized modified ELM or Bayesian machine learning (BML) can also be used for location-based weather forecasting in real time. A single layer feed forward network is trained using the ELM algorithm, which updates the weights using various PSO approaches. Their results are contrasted with those of current models, such as the forecasting model based on back-propagation [60]. The reinforcement learning (RL) approach allows for autonomous learning by monitoring the solar power system's environmental state, as shown in Fig. 10. It is employed to maximize output by training and modifying the perturbation. This table lists the advantages and disadvantages of ML-based MPPT.

TABLE VI.
MERITS AND DEMERITS OF ML MPPT -BASED MPPT

Merit	De-Merit
i. Able to take more variables into consideration ii. Weather forecast for MPPT prediction iii. High accuracy and fast racking speed	i. Highly complex and costly ii. A huge amount of data is required Longer computation time

III. Analytical Comparison of AI-based MPPT Techniques

A. Classification of AI-based MPPT Techniques

The following factors are compared amongst AI-based MPPT techniques: total cost, steady-state oscillation, tracking accuracy, tracking speed for MPP, and algorithm complexity, which impacts calculation time. Based on their decreasing popularity, the prominent AI-based MPPT techniques are broadly classified as FLC, ANN, SI, hybrid, GA, ML, and other new emerging algorithms. Owing to space constraints and other limitations, certain new algorithms might not make it into this publication. Fig. 11 displays the approximate citation popularity of AI-based MPPT versus year.

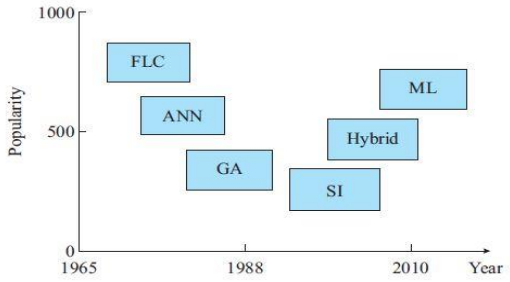

Fig. 11.The popularity of AI-based MPPT citations, broken down by year.

The year 1965 saw the invention of FLC, which gained popularity during the decade. After then, at different times, ANN, GA, SI, hybrid, and ML are developed, and over the years, AI-based MPPT has continued to benefit from their use. Three large comparative tables and one classification figure are included in the results section. The tables list each AI-based MPPT's advantages and open cases, compare all AI-based MPPT's parameters, and list the AI-based MPPT that has been made accessible recently.

The available AI-based MPPT in each category and classification is clearly depicted in the categorization graphic. The assessment of AI-based MPPT methods is typically conducted based on a number of parameters and features, such as the quantity of control variables (sensory input parameters), the platform used (software: MATLAB/Simulink; hardware: arm cortex microcontroller, Arduino, Raspberry Pi, and DSP board-dSpace), the characteristics of the solar panel, the DC-DC converter's switching frequency, the kind of DC-DC converter (buck, boost, buck-boost, Ćuk, or SEPIC), tracking/convergence speed or transient time, oscillation accuracy, and MPPT efficiency. Bio-inspired algorithms and machine learning have gained a lot of traction in recent years because of their sophisticated accuracy, speed, and performance. Input parameters are not limited to current and voltage inputs; they also include other characteristics. It contains meteorological, cloud, shading, and humidity information. All algorithms strive for great efficiency with the least amount of power loss, low steady-state oscillation, simple, cost-effective implementation, fast processing capabilities, and fast convergence or tracking speed.

B. Comparison

The more current AI-based MPPT methods are usually more sophisticated and effective, but they are also quite expensive, complex, and data-intensive. When applying MPPT in a particular setting, striking a balance between cost and complexity or performance is essential. The recently prominent AI-based MPPT techniques are categorized into seven key types in Figure 8, which include FLC, ANN, SI, hybrid, GA, ML, and developing algorithms.

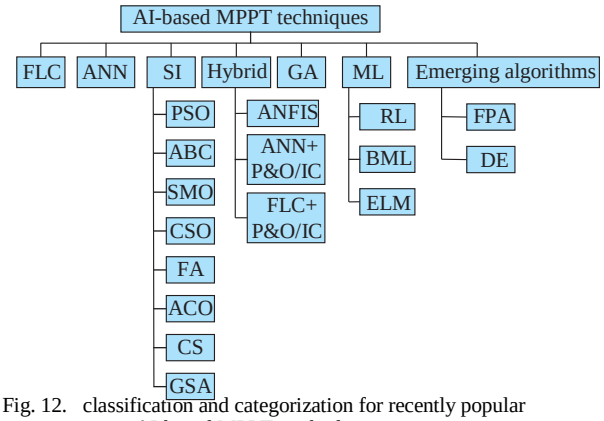

Fig. 12. classification and categorization for recently popular AI-based MPPT methods.

Because of its algorithms' quick speed and excellent accuracy, biological swarm intelligence (SI) served as the primary inspiration for the creation of the largest family of AI-based MPPT—the family of SI. There are many different subcategories within both ML and hybrid. Because the AI-based MPPT is simple to combine with one another, the hybrid MPPT is comparatively flexible. ML is yet another well-liked technique. To output the most power, it uses a variety of methods and strategies to learn from the experience or dataset. Sub-categories do not exist for FLC, ANN, or GA. The newest, most advanced MPPT

approaches, which are always expanding and getting better, are included in the developing algorithms.

Because of its algorithms' quick speed and excellent accuracy, biological swarm intelligence (SI) served as the primary inspiration for the creation of the largest family of AI-based MPPT—the family of SI. There are many different subcategories within both ML and hybrid. Because the AI-based MPPT is simple to combine with one another, the hybrid MPPT is comparatively flexible. ML is yet another well-liked method. To output the highest power, it uses a variety of strategies and methodologies to learn from the dataset or experience. Subcategories do not exist for FLC, ANN, or GA. The newest, most advanced MPPT approaches, which are always expanding and getting better, are included in the developing algorithms.

TABLE VII.
COMPARISON OF AI-BASED MPPT TECHNIQUES IN TERM OF PARAMETERS

Index	FLC	ANN	SI	Hybrid	GA	ML
Tracking accuracy	Moderate	High	High	High	Moderate	High
Tracking speed	Moderate	Fast	Fast	Fast	Moderate	Moderate
Convergence speed	Moderate	Moderate	Fast	Fast	Fast	Fast
Ability to track under PSC	Poor	Poor	High	High	High	High
Ability to track normally	High	High	High	High	High	High
Steady-state oscillation	Small	Small	Almost Zero	Small	Moderate	Small
Oscillation around MPP	No	No	No	No	No	No
Settling time	Fast	Fast	Fast	Fast	Fast	Fast
Complexity	Moderate	High	Moderate	High	High	High
Parameters required (sensor)	Voltage and current	Irradiance, temperature, voltage and current	Voltage and current (varies)	Varies	Voltage and current (varies)	Varies
Periodic tuning	Yes	Yes	No	No	No	No
Dependency of initial design	High	High	Moderate	Moderate	Moderate	Moderate
System independence	Poor	Poor	High	High	High	High
Efficiency	Poor (PSC)	Poor (PSC)	High	High	High	High
Cost	High	High	Moderate	High	Moderate	High
Computation time	Moderate	High	Moderate	High	Moderate	High
Algorithm complexity	Medium	Medium	Simple	High	High	High
Application	Grid and solar vehicles	Grid, water pump, solar vehicles and motor drives	Off-grid and on-grid	Off-grid and on-grid	Off-grid and on-grid	Off-grid and on-grid

A thorough comparison of AI-based MPPT is shown in Table VII, covering performance indices such tracking accuracy, tracking speed, convergence speed, and other metrics. It has been noted that earlier AI-based MPPT methods, including FLC and ANN, perform pretty poorly when it comes to tracking under PSC and convergence speed. The converter switch must undergo a continual periodic tuning operation in order to track MPP during PSC or abrupt changes in irradiance. To properly build an ANN-based MPPT with high accuracy, challenging training, and longer processing time, a large dataset is needed. FLC finds it challenging to precisely deduce its fuzzy rules, and it is unable to actively learn from the changing environment and behave in an undesirable manner. In contrast, because of their more recent architecture, which blends the benefits of traditional HC MPPT with the most recent developments in AI, SI, hybrid GA, and ML provide faster speed and high ability in tracking even under Different Irradiance.

IV. Simulation Results

A. Simulation Setup and Configuration

A thorough simulation based on MATLAB/Simulink R2023a is carried out to compare and validate the performance of AI-based MPPT approaches. The purpose of the simulation setup is to analyze, assess, and look at the AI-based MPPT's dynamic behavior under various lighting conditions. Every AI-based MPPT's search process is benchmarked against the ideal MPP. The block diagram displays the simulation environment in a stand-alone solar power system, as shown in Fig. 11.

The Sun Power module (SPR-305E-WHT-D) photovoltaic panel is equipped with variable solar irradiance Ee and T. To replicate the real-world setting, it is recreated under various lighting conditions. In order to produce the best possible voltage and current for MPP, a 5 kHz DC-DC boost converter is constructed, and its insulated-gate bipolar transistor (IGBT) switching devices are managed by the AI-based MPPT controller.

In order to supply AC for the three-phase balanced resistive load RL, an improved solar MPPT of DC output is converted to AC output using a DC-AC converter (inverter) based on synchronverter topology. To compare the tracking ability of FLC, ANN, SI, hybrid, GA, and ML for MPP under PSC, which is validated as indicated in Table VIII, the variable that has been altered is the MPPT controller. The simulation does not incorporate other new methods due to their dynamic development and ever-evolving algorithms. To

investigate the MPPT capacity with variable irradiance and constant temperature, two case studies have been carried out. The power output is at the DC output of the DC-DC boost converter for evaluating the optimized MPPT output. The simulation results are then compared and validated as shown in Table VIII.

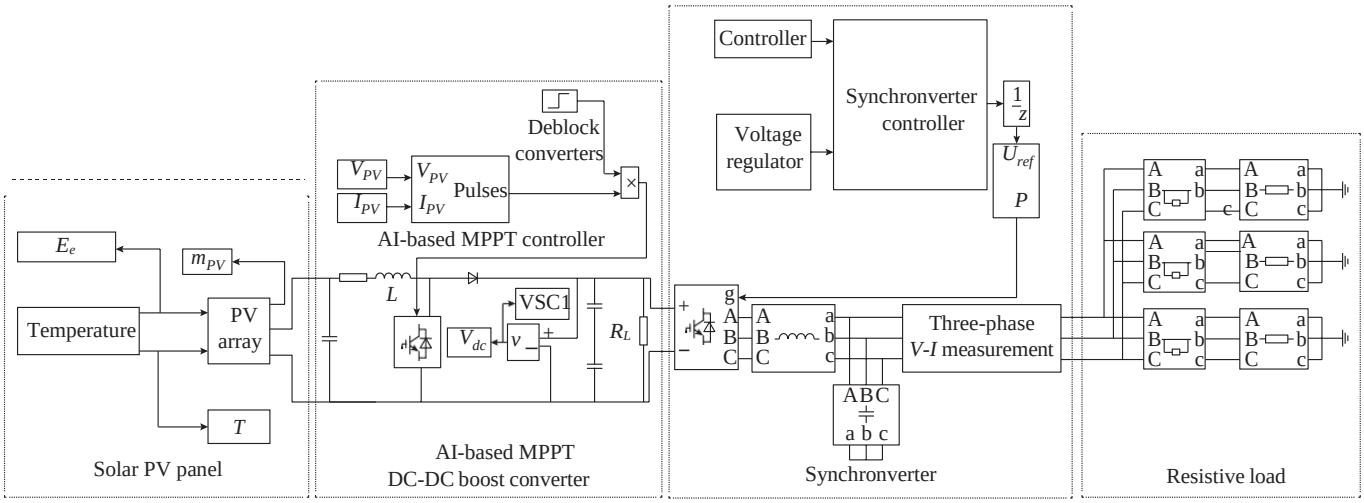

Fig. 13. MATLAB/Simulink simulation for comparison of AI-based MPPT.

(reference from Kah Yung Yap, Charles R. Sarimuthu, and Joanne Mun-Yee Lim,"Artificial Intelligence Based MPPT Techniques for Solar Power System: A review" Journal Of Modern Power Systems and Clean Energy, vol. 8, no. 6, Nov 2020)

TABLE VIII.
COMPARISON OF AI-BASED MPPT TECHNIQUES IN TERM OF PARAMETERS

AI-based MPPT	Tracking time(s)	Steady-state oscillation (%)	Affected by PSC/ varied irradiance
FLC	0.70	±3.0	Yes
ANN	0.25	<1.0	Yes
SI	0.28	±1.7	No
Hybrid	0.23	±0.1	No
GA	0.80	±10.0	No
ML	0.60	±1.5	Slightly

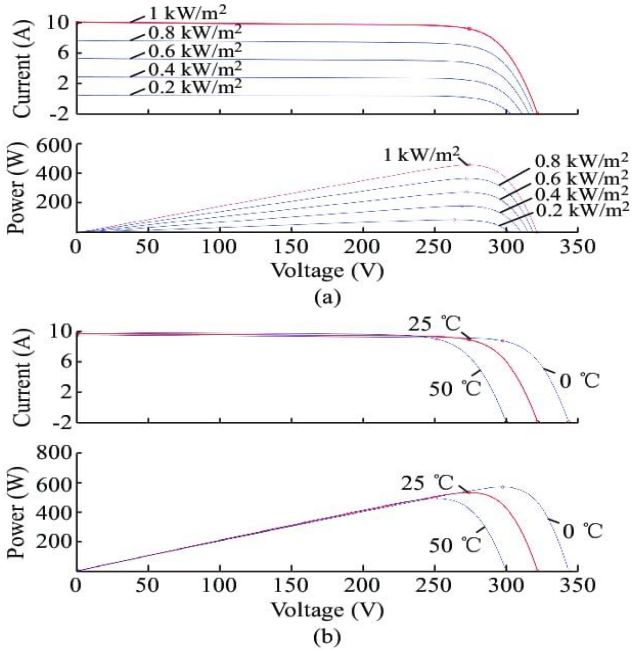

Fig. 14 (a) *I-V* and *P-V* charac- teristics when the irradiance varies while the temperature remains constant at 25 °C
14(b) presents the *I-V* and *P-V* characteristics when the temperature varies while the irradiance remains constant at 1000 W/m².

The I-V and P-V solar panel characteristic graphs are plotted under standard test conditions (STC) at 25 °C and 1000 W/m2 of solar irradiation, as seen in Fig. 14. The I-V and P-V characteristics are shown in Figure 14(a) when the temperature remains constant at 25 °C despite variations in the irradiance. In contrast, the I-V and P-V characteristics when the temperature changes but the irradiance stays constant at 1000 W/m2 are shown in Fig. 14(b). A solar power system's non-linear I-V and P-V is the primary driver behind an AI-based MPPT's search for MPP at varying temperatures and irradiances.

B.MPPT Ability

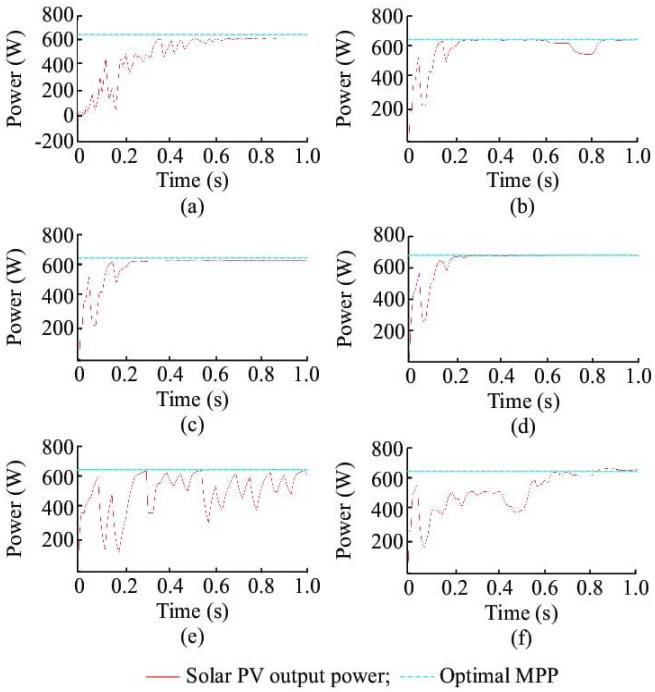

Fig. 15. MPPT ability of different algorithms. (a) FLC. (b) ANN. (c) SI.

(d) Hybrid. (e) GA. (f) ML

For MPP with constant irradiance, the tracking capability of an AI-based MPPT controller is simulated. Different algorithms' MPPT capabilities are displayed in Fig.15(a)–(f). The ideal MPP with typical temperature and irradiance at roughly 650 W is shown by the dotted blue line. As the AI-based MPPT tracks and recommends MPP to extract the maximum power from the solar power system, the red line represents the output power of the solar power system. With the exception of FLC, the performance of AI-based MPPT is found to be generally acceptable.

C.Comparative Evaluation and Verification of Findings

Table VIII summarizes and presents the comparison of AI-based MPPT techniques in terms of MPPT time, steady-state oscillation at MPP and the ability to resist the adverse effect of PSC or varying irradiance, which occurs at around t = 0.7s. It is observed that FLC is underperforming by exhibiting higher tracking time for MPP with high SSE and affected by PSC. However, SI and hybrid-based MPPT perform satisfactorily with the minimum tracking time, low SSE and the minimum disturbance under PSC. These analyses are tally with Table VII and the findings from the existing literature and researches on AI-based MPPT. Both simulation results and literature review findings are mutually verified and validated. Nevertheless, different scenarios and applications result in different choices of AI-based MPPT. Hence, it is recommended to choose the appropriate and most suitable AI- based MPPT based on the design criteria and requirements.

D. Analysis.

The voltage step can affect MPPT algorithms. It takes longer to attain MPP when the voltage step is too tiny. Even though it takes less time to reach MPP when the voltage step is too large, the severe oscillation near MPP prevents MPP from being reached [61]. A abrupt change in irradiance is needed as an input to observe the MPPT output and see whether it is responding to rapid changes in input in order to determine the convergence or tracking speed [62]. The EN 50530 [22] standard test provides triangle irradiance waveforms with varying ramp gradients to assess the effectiveness of MPPT. Rapid change or PSC situations are also employed to test the MPPT's performance and reaction. Typically, an MPPT testing environment's usual circumstances include a temperature of 25 °C, a maximum solar irradiance level of 1000 W/m2, and an angle of incidence α of 90° [14].

The ability of AI-based MPPT to find GMPP in PSC or with changing temperature and irradiance is another crucial feature. One possible reason for MPPT's failure could be the algorithm's incapacity to find GMPP. It won't be able to generate the ideal power output since it will be trapped at the local MPP. The foundation of SI techniques is typically the search for the best answer within the search space. For ACO [63], a monkey for spider monkey optimization (SMO), a cuckoo for CS, and a firefly for FA, the acting players in the optimization can be recollections of an ant. By establishing a range, the conditional algorithm determines when the maximum power has been fulfilled. The oscillations are brought on by variations in an operation point, uneven solar insulation distribution, and the algorithm's incapacity to distinguish GMPP in the presence of numerous local MPPs. When it comes to performance metrics, the oscillation time is the interval of time between modifications until the output reaches steady state, or when there is no longer any oscillation. Tracking speed, also known as convergence speed, measures how quickly MPPT follows the actual MPP. On the other hand, η is defined as the output power Pout= Vout*Iout, divided by PMPP, which equals $V_{MPP}I_{MPP}$, or the power tracked by MPPT. For the steady-state form to exist without oscillation, settling time is necessary [64].

The complexity of the implementation, the necessary sensors, the capacity to identify multiple local maxima, response time, costing and its application, transient time, settling time, steady-state error, overshoot, and ripples in the PV panel's output voltage are the selection criteria for AI-based MPPT [65]. In general, tracking GMPP under PSC is not successful with traditional or HC approaches. During the steady state, they oscillate around MPP, and tracking MPP takes longer and is less efficient. The disadvantages of traditional MPPT are not present with AI-based MPPT techniques, although they do come with a larger price tag and more complicated modeling and calculation. Since they integrate and combine two or more algorithms, hybrid approaches are generally the best among all algorithms and help to mutually cancel open issues [22]. Comparing, assessing, and analyzing the outcomes of simulation and experimentation is often how the experimental result is validated.

In addition to MPPT, an inverter acts as a middleman between the solar power system and the electrical grid. Therefore, for both DC to AC conversion and anti-islanding prevention, an efficient inverter is essential [66]. Optimized inverter increases power extraction without adversely affecting PV DC output to AC [67]. A proportional integral derivative (PID) controller is recommended for controlling D output to pulse width modulation using MPPT techniques due to its performance optimization, minimal rising time for output voltage, adaptability, stability, and minimal overshoot [59], [68]. AI-based MPPT techniques can generally be applied to standalone (off-grid), grid-connected (on-grid), and other specialized applications such as solar cars, solar lights, water heaters, DC motors, and water pumps. On-grid systems are linked to the electric utility grid, whilst off-grid systems are directly connected to loads.

V. SUGGESTIONS AND FUTURE DIRECTIONS FOR RESEARCH

The recommendation made in this section is that AI-based MPPT be used in solar power systems and related future research fields. Since the most recent AI-based MPPT algorithms offer improved performance and stability, the traditional MPPT techniques are being phased out. The most recent developments in ML and DL are necessary for the creation of the AI-based MPPT. The ability to look for MPP and the algorithm's complexity are the key obstacles.

Conventional MPPTs, such as open current, open voltage, P&O, and IC, are advised for straightforward applications that don't demand high performance but are also inexpensive. With AI-based MPPT approaches, the PV cell's

non-linearity may be resolved, optimized, and predicted without remaining at the local maximum power point under PSC or different irradiations. This allows for the best possible performance, accuracy, and convergence speed. GA is faster than classical approaches for the kind of EA, although it has a tendency to stay at local minima. More processing power is needed for the enhanced GA, and several settings need to be adjusted. By comparison, DE operates quickly and precisely without utilizing probability distribution. Its population, nevertheless, may stagnate at certain less-than-ideal values. PSO has the highest performance by considering different best positions to update the population, which is also simple to be implemented in hardware and independent from the installed system [69]. However, it tends to converge prematurely and can be trapped at local minima. The choice of AI-based MPPT method is dependent on the design choice, application and design requirement. For the maximum performance, PSO is recommended due to its maturity compared with GA. DE is better than GA in term of accuracy and computation time while GA is faster than classical methods. GA and DE techniques can track the GMPP under PSC because of their capabilities of resolving multi-objective problems.

For the applications which are sensitive to the power fluctuation such as household appliances, motor, extreme low voltage (ELV), light sources, electro-heat equipment, electrical ma- chine, uninterruptible power source (UPS), computer, and electronic devices, CS and radial movement optimization (RMO) are recommended owing to their faster convergence speed to settle at GMPP with minimal fluctuation. Due to their faster convergence speed to settle at GMPP with minimal fluctuation, CS and radial movement optimization (RMO) are recommended for applications that are sensitive to power fluctuations, such as computers, electronics, light sources, electro-heat equipment, household appliances, motors, extreme low voltage (ELV), electrical machines, and UPS. Theoretically, the occurrence of voltage fluctuation is defined as a continuous change in the voltage when devices or appliances that require a higher load are extensively used. The parameters of an AI-based MPPT controller are the design complexity, ability to track GMPP, cost effectiveness, PV panel dependency, prior training requirement, dataset requirement, convergence speed, analogue or digital architecture, required sensory information, periodic tuning, stability, SSE, efficiency, and TET. The balance between the complexity and performance of the algorithm should be considered when designing AI-based MPPT. In the general context, the higher the performance of AI-based MPPT, the more complex the designed algorithm. Therefore, TET and computation time are affected.

The capacity to track GMPP is one of the AI-based MPPT's most important features. Furthermore, there isn't much hard data from real-time solar panel experiments. There are no research that provide a general design sequence for the standardized AI-based MPPT. In a grid-tied solar power system, maximum power extraction and virtual inertia must be provided simultaneously, and MPPT is an essential component that must be combined with the synchronverter to function as a DC-DC-AC converter [70]. It is ensured and maintained that the solar power system's grid voltage and frequency output at the AC grid side will remain stable [71]. The least amount of voltage fluctuation and grid frequency guarantees high power efficiency.

V. CONCLUSION

We offer a thorough analysis of well-liked AI-based MPPT methods for solar power systems. Their purpose is to monitor MPPT. The structure, cost, complexity, and platform of each technique are compared, along with the input parameters, tracking speed, oscillation accuracy, efficiency, and applications of each. The FLC, ANN, SI, hybrid, GA, ML, and other upcoming techniques are the general categories into which the AI-based MPPT techniques fall. In general, they all show fast convergence, minimal oscillation in steady state, and precise tracking—even in the face of PSC or abrupt changes in irradiance. In contrast to traditional MPPT techniques, the majority of these methods demand more datasets and are more expensive and complex to construct. Other growing and newer algorithms, such as hybrid, SI, ML, and DL, are also suggested in comparison to FLC, ANN, and GA because of their fully digitalized systems, newer architectures with adaptive learning capabilities, and fewer outstanding issues. On the other hand, because of their aging architecture, need for frequent tuning, and incapacity to track MPPT under varying temperatures and irradiations, ANN and FLC are not very popular. It is anticipated that this review will offer a thorough understanding of the most recent developments in AI-based MPPT approaches for use in solar power systems.

REFERENCES

[1] S. Kanwal, B. Khan, and M. Q. Rauf, "Infrastructure of sustainable en- ergy development in Pakistan: a review," *Journal of Modern Power Systems and Clean Energy*, vol. 8, no. 2, pp. 206-218, Mar. 2020.

[2] X. Chen, M. B. Mcelroy, Q. Wu *et al*., "Transition towards higher pen- etration of renewables: an overview of interlinked technical, environ- mental and socioeconomic challenges," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 1, pp. 1-8, Jan. 2019.

[3] S. Bhattacharyya, D. S. K. Patnam, S. Samanta *et al*., "Steady outputand fast tracking MPPT (SOFT MPPT) for P&O and InC algorithm," *IEEE Transactions on Sustainable Energy.* doi: 10.1109/TSTE. 2020.2991768

[4] Y. Yang and H. Wen, "Adaptive perturb and observe maximum power point tracking with current predictive and decoupled power control for grid connected photovoltaic inverters," *Journal of Modern Power Sys- tems and Clean Energy*, vol. 7, no. 2, pp. 422-432, Mar. 2019.

[5] K. Y. Yap, H. Chua, M. J. K. Bashir *et al*., "Central composite design (CCD) for parameters optimization of maximum power point tracking (MPPT) by response surface methodology (RSM)," *Journal of Mecha- nis of Continua and Mathematical Sciences*, vol. 1, no. 1, pp. 259-270, Mar. 2019.

[6] A. Ibrahim, S. Obukhov, and R. Aboelsaud, "Determination of global maximum power point tracking of PV under partial shading using cuckoo search algorithm," *Applied Solar Energy*, vol. 55, pp. 367-375, Mar. 2020.

[7] D. P. Mishra and S. Chakraborty, "Application of soft computing in simulation of solar power tracking," in *Proceedings of 2018 Technolo- gies for Smart City Energy Security and Power (ICSESP)*, Bhu- baneswar, India, Jun. 2018, pp. 1-5.

[8] L. Zhang, S. Yu, T. Fernando *et al*., "An online maximum power point capturing technique for high efficiency power generation of solar pho- tovoltaic systems," *Journal of Modern Power Systems and Clean Ener- gy*, vol. 7, no. 2, pp. 357-368, Mar. 2019.

[9] L. L. Jiang, R. Srivatsan, and D. L. Maskell, "Computational intelligence techniques for maximum power point tracking in PV systems: a review," *Renewable and Sustainable Energy Reviews*, vol. 85, pp. 14- 45, Apr. 2018.

[10] M. Séne, F. Ndiaye, M. E. Faye *et al*., "A comparative study of maximum power point tracker approaches based on artificial neural network and fuzzy controllers," *International Journal of Physical Scienc- es*, vol. 13, pp. 1-7, Jan. 2018.

[11] M. G. Batarseh and M. E. Zater, "Hybrid maximum power point track- ing techniques: a comparative survey, suggested classification and un- investigated combinations," *Solar Energy*, vol. 169, pp. 535-555, Jul. 2018.

[12] O. Abdalla, H. Rezk, and E. M. Ahmed, "Wind driven optimization algorithm based global MPPT for PV system under non-uniform solar ir- radiance," *Solar Energy*, vol. 180, pp. 429-444, Mar. 2019.

[13] Á.-A. Bayod-Rújula and J.-A. Cebollero-Abián, "A novel MPPT meth- od for PV systems with irradiance measurement," *Solar Energy*, vol. 109, pp. 95-104, Nov. 2014.

[14] R. Gimazov and S. Shidlovskiy, "Simulation modeling of intelligent control algorithms for constructing autonomous power supply systems with improved energy efficiency," in *Proceedings of International Sci- entific and Practical Conference*, Tomsk, Russia, Feb. 2018, pp. 1-5.

[15] A. Kihal, F. Krim, B. Talbi *et al*., "A robust control of two-stage grid-tied PV systems employing integral sliding mode theory," *Energies*, vol. 11, pp. 2791-2811, Oct. 2018.

[16] D. I. Ighneiwa and A. A. Yousuf. (2018, Feb.). Using intelligent con- trol to improve PV systems efficiency. [Online]. Available: https://arx- iv.org/abs/1802.03463

[17] A. Abbadi, F. Hamidia, A. Morsli *et al*., "MPPT based fuzzy-logic controller for grid connected residential photovoltaic power system," in *Proceedings of International Conference in Artificial Intelligence in Renewable Energetic Systems*, Tipaza, Algeria, Dec. 2019, pp. 236-244.

[18] B. A. Naidu, S. A. Kumar, and D. M. S. S. Narayana, "Fuzzy intelli- gent controller for the MPPT of a photovoltaic module in comparison with perturb and observe algorithm," *International Journal of Applied Engineering Research*, vol. 13, pp. 10058-10062, Jan. 2018.

[19] O. Kececioglu, A. Gani, and M. Sekkeli, "Design and hardware imple- mentation based on hybrid structure for MPPT of PV system using an interval type-2 TSK fuzzy logic controller," *Energies*, vol. 13, no. 7,pp. 1842-1859, Apr. 2020.

[20] B. Benlahbib, N. Bouarroudj, S. Mekhilef *et al*., "A fuzzy logic controller based on maximum power point tracking algorithm for partially shaded PV array-experimental validation," *Elektronika Ir Elektrotechni- ka*, vol. 24, pp. 38-44, Aug. 2018.

[21] H. Suryoatmojo, R. Mardiyanto, D. C. Riawan *et al*., "Design of MPPT based fuzzy logic for solar-powered unmanned aerial vehicle application," in *Proceedings of International Conference on Engineer- ing, Applied Sciences, and Technology (ICEAST)*, Phuket, Thailand, Aug. 2018, pp. 1-4.

[22] S. D. Al-Majidi, M. F. Abbod, and H. S. Al-Raweshidy, "A novel max- imum power point tracking technique based on fuzzy logic for photo- voltaic systems," *International Journal of Hydrogen Energy*, vol. 43,pp. 14158-14171, Aug. 2018.

[23] C. H. Basha and C. Rani, "Different conventional and soft computing MPPT techniques for solar PV systems with high step-up boost converters: a comprehensive analysis," *Energies*, vol. 13, pp. 371-397, Jan. 2020.

[24] J. M. Lopez-Guede, J. Ramos-Hernanz, N. Altin *et al*., "Neural model- ing of fuzzy controllers for maximum power point tracking in photo- voltaic energy systems," *Journal of Electronic Materials*, vol. 47, pp. 4519-4532, Jun. 2018.

[25] J. J. Khanam and S. Y. Foo, "Modeling of a photovoltaic array in MATLAB Simulink and maximum power point tracking using neural network," *Electrical & Electronic Technology Open Access Journal*, vol. 2, no. 2, pp. 40-46, Jul. 2018.

[26] L. Chen and X. Wang, "An enhanced MPPT Method based on ANN-assisted sequential Monte Carlo and quickest change detection," *IET Smart Grid*, vol. 2, no. 4, pp. 635-644, Dec. 2019.

[27] Chtouki, P. Wira, and M. Zazi, "Comparison of several neural network perturb and observe MPPT methods for photovoltaic applications," in *Proceedings of IEEE International Conference on Industrial Technology (ICIT)*, Lyon, France, Feb. 2018, pp. 909-914.

[28] L. Chen and X. Wang, "An enhanced MPPT Method based on ANN-assisted sequential Monte Carlo and quickest change detection," *IET Smart Grid*, vol. 2, no. 4, pp. 635-644, Dec. 2019.

[29] C. R. Algarín, S. H. Deimer, and D. R. Leal, "A low-cost maximum power point tracking system based on neural network inverse model controller," *Electronics Journal*, vol. 7, no. 1, pp. 4-20, Jan. 2018.

[30] R. Divyasharon, R. N. Banu, and D. Devaraj, "Artificial neural net- work based MPPT with CUK converter topology for PV systems un- der varying climatic conditions," in *Proceedings of IEEE International Conference on Intelligent Techniques in Control, Optimization and Sig- nal Processing (INCOS)*, Tamilnadu, India, Apr. 2019, pp. 1-6.

[31] K. Fatima, M. A. Alam, and A. F. Minai, "Optimization of solar ener- gy using ANN techniques," in *Proceedings of 2nd International Con- ference on Power Energy, Environment and Intelligent Control (PEE- IC)*, Greater Noida, India, Oct. 2019, pp. 174-179.

[32] S. D. Al-Majidi, M. F. Abbod, and H. S. Al-Raweshidy, "Design of an intelligent MPPT based on ANN using a real photovoltaic system da- ta," in *Proceedings of 54th International Universities Power Engineer- ing Conference (UPEC)*, Bucharest, Romania, Sept. 2019, pp. 1-6.

[33] H. D. Tafti, A. Sangwongwanich, Y. Yang *et al*., "A general algorithm for flexible active power control of photovoltaic systems," in *Proceed- ings of IEEE Applied Power Electronics Conference and Exposition(APEC)*, San Antonio, USA, Mar. 2018, pp. 1115-1121.

[34] Y. Huang, X. Chen, and C. Ye, "A hybrid maximum power point tracking approach for photovoltaic systems under partial shading condi- tions using a modified genetic algorithm and the firefly algorithm," *In- ternational Journal of Photoenergy*, pp. 1-13, May 2018.

[35] K. Anoop and M. Nandakumar, "A novel maximum power point track- ing method based on particle swarm optimization combined with one cycle control," in *Proceedings of International Conference on Power, Instrumentation, Control and Computing (PICC)*, Thrissur, India, Jan. 2018, pp. 1-6.

[36] N. Kalaiarasi, S. S. Dash, S. Padmanaban *et al*., "Maximum power point tracking implementation by dspace controller integrated through z-source inverter using particle swarm optimization technique for pho- tovoltaic applications," *Applied Science*, vol. 8, no. 1, pp. 145-162, Jan. 2018.

[37] H. Li and D. Yang, "An overall distribution particle swarm optimization MPPT algorithm for photovoltaic system under partial shading," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 1, pp. 265-275, Apr. 2018.

[38] M. Merchaoui, A. Saklyl, and M. F. Mimouni, "Improved fast particle swarm optimization based PV MPPT," in *Proceedings of the 9th Inter- national Renewable Energy Congress (IREC 2018)*, Hammamet, Tuni- sia, Apr. 2018, pp. 1-6.

[39] L.-Y. Chang, Y.-N. Chung, K.-H. Chao *et al*., "Smart global maximum power point tracking controller of photovoltaic module arrays," *Ener- gies*, vol. 11, no. 3, pp. 567-582, Mar. 2018.

[40] H. M. H. Farh, M. F. Othman, A. M. Eltamaly *et al*., "Maximum pow- er extraction from a partially shaded PV system using an interleaved boost converter," *Energies*, vol. 11, no. 10, pp. 2543-2560, Sept. 2018.

[41] Mohanty, S.; Subudhi, B.; Member, S.; Ray, P.K. A New MPPT Design Using Grey Wolf Optimization Technique for Photovoltaic System Under Partial Shading Conditions. IEEE Trans. Sustain. Energy 2015, 7, 1–8.

[42] Darcy Gnana Jegha, A., Subathra, M. S. P., Manoj Kumar, N., Subramaniam, U., & Padmanaban, S. (2020). *A High Gain DC-DC Converter with Grey Wolf Optimizer Based MPPT Algorithm for PV Fed BLDC Motor Drive. Applied Sciences, 10(8), 2797.* doi:10.3390/app10082797

[43] Naji, H. R., Sohrabi, M., & Rashedi, E. (2012). A High-Speed, Performance-Optimization Algorithm Based on a Gravitational

Approach. Computing in Science & Engineering, 14(5), 56–62. doi:10.1109/mcse.2011.95

[44] S. Moein, R. Logeswaran, KGMO: *A swarm optimization algorithm based on the kinetic energy of gas molecules*, Inform. Sci. (2014), http://dx.doi.org/10.1016/j.ins.2014.02.026)

[45] C. Vimalarani, N. Kamaraj, and B. C. Babu, "Improved method of maximum power point tracking of photovoltaic (PV) array using hy- brid intelligent controller," *Optik*, vol. 168, pp. 403-415, Sept. 2018.

[46] S. Nikolovski, H. R. Baghaee, and D. Mlakić, "ANFIS-based peak power shaving/curtailment in microgrids including PV units and BESSs," *Energies*, vol. 11, no. 11, pp. 2953-2975, Oct. 2018.

[47] R. Syahputra, R. O. Wiyagi, I. Soesanti *et al*., "Design of maximum power point tracking based on adaptive neuro-fuzzy system for solar array system," *Journal of Theoretical and Applied Information Technology*, vol. 96, pp. 4481-4490, Jul. 2018.

[48] A. A. Aldair, A. A. Obed, and A. F. Halihal, "Design and implementa- tion of ANFIS-reference model controller based MPPT using FPGA for photovoltaic system," *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 2202-2217, Feb. 2018.

[49] I. Abadi, C. Imron, R. D. Noriyati *et al*., "Implementation of maximum power point tracking (MPPT) technique on solar tracking system based on adaptive neuro fuzzy inference system (ANFIS)," *E3S Webof Conferences*, vol. 43, pp. 1-8, Jun. 2018.

[50] A. Ali, A. N. Hasan, "Optimization of PV Model using fuzzy- neural network for DC-DC converter systems," in *Proceedings of 9th Interna- tional Renewable Energy Congress (IREC)*, Hammamet, Tunisia, Mar. 2018, pp. 1-6.

[51] S. Duman, N. Yorukeren, and I. H. Altas, "A novel MPPT algorithm based on optimized artificial neural network by using FPSOGSA for standalone photovoltaic energy systems," *Neural Computation & Application*, vol. 29, pp. 257-278, Jul. 2016.

[52] M. E. Başo lu and B. Çakır, "Hybrid global maximum power point tracking approach for photovoltaic power optimisers," *IET Renewable Power Generation*, vol. 12, no. 8, pp. 875-882, Jun. 2018.

[53] J. Macaulay and Z. Zhou, "A fuzzy logical-based variable step size P&O MPPT algorithm for photovoltaic system," *Energies*, vol. 11, no.6, pp. 1340-1354, May 2018.

[54] Z. Wang, X. Zhang, B. Hu *et al*., "Control strategy of grid-connected photovoltaic generation system based on GMPPT method," *IOP Conference Series: Earth and Environmental Science*, vol. 121, no. 4, pp.1-9, Feb. 2018.

[55] A. M. Farayola, A. N. Hasan, and A. Ali, "Efficient photovoltaic mppt system using coarse Gaussian support vector machine and artificial neural network techniques," *International Journal of Innovative Com- puting, Information and Control*, vol. 14, pp. 323-339, Feb. 2018.

[56] A. M. Farayola, A. N. Hasan, and A. Ali, "Optimization of PV systems using data mining and regression learner MPPT techniques," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 10, no. 3, pp. 1080-1089, Mar. 2018.

[57] M. Lasheena and M. Abdel-Salam, "Maximum power point tracking using hill climbing and ANFIS techniques for PV applications: a review and a novel hybrid approach," *Energy Conversion and Management*, vol. 171, pp. 1002-1019, Sept. 2018.

[58] Y. Du, K. Yan, Z. Ren *et al*., "Designing localized MPPT for PV systems using fuzzy-weighted extreme learning machine," *Energies*, vol.11, pp. 2615-2624, Oct. 2018.

[59] F. Keyrouz, "Enhanced Bayesian based MPPT controller for PV systems," *IEEE Power and Energy Technology Systems Journal*, vol. 5,no. 1, pp. 11-17, Mar. 2018.

[60] M. K. Behera, I. Majumder, and N. Nayak, "Solar photovoltaic power forecasting using optimized modified extreme learning machine technique," *Engineering Science and Technology*, vol. 21, pp. 428-438, Jun. 2018.

[61] A. Sfirat, A. Gontean, and S. Bularka, "A new method for MPPT algo- rithm implementation and testing, suitable for photovoltaic cells," *Ad- vances in Electrical and Computer Engineering*, vol. 18, pp. 53-60,Aug. 2018.

[62] A. Kapić, Ž. Zečević, and B. Krstajić, "An efficient MPPT algorithm for PV modules under partial shading and sudden change in irradi- ance," in *Proceedings of 23rd International Scientific-Professional Conference on Information Technology (IT)*, Zabljak, Montenegro, Feb. 2018, pp. 1-4.

[63] S. Krishnan, S. Kinattingal, S. P. Simon *et al*., "MPPT in PV systems using ant colony optimisation with dwindling population," *IET Renew- able Power Generation*, vol. 14, no. 7, pp. 1105-1112, May 2020.

[64] H. Islam, S. Mekhilef, N. B. M. Shah *et al*., "Performance evaluation of maximum power point tracking approaches and photovoltaic sys- tems," *Energies*, vol. 11, no. 2, p. 365-388, Feb. 2018.

[65] R. Iftikhar, I. Ahmad, M. Arsalan *et al*., "MPPT for photovoltaic system using nonlinear controller," *International Journal of Photoenergy*, vol. 2018, pp. 1-16, Apr. 2018.

[66] K. Y. Yap, C. R. Sarimuthu, and J. M. -Y Lim, "Virtual inertia-based inverters for mitigating frequency instability in grid-connected renewable energy system: a review," *Applied Science*, vol. 9, no. 24, pp. 5300-5328, Dec. 2019.

[67] A. P. Azad, M. Padmanaban, and V. Arya, "A data lens into MPPT ef- ficiency and PV power prediction," in *Proceedings of IEEE Power &Energy Society Innovative Smart Grid Technologies Conference (IS-GT)*, Washington DC, USA, Feb. 2018, pp. 1-5.

[68] A. M. Farayola, A. N. Hasan, and A. Ali, "Use of MPPT techniques to reduce the energy pay-back time in PV systems," in *Proceedings of the 9th International Renewable Energy Congress (IREC 2018)*, Ham- mamet, Tunisia, Mar. 2018, pp. 1-6.

[69] S. Obukhov, A. Ibrahim, A. A. Z. Diab *et al*., "Optimal performance of dynamic particle swarm optimization based maximum power track- ers for stand-alone PV system under partial shading conditions," *IEEE Access*, vol. 8, pp. 20770-20785, Jan. 2020.

[70] K. Y. Yap, C. R. Sarimuthu, and J. M.-Y. Lim, "Grid integration of so- lar photovoltaic system using machine learning-based virtual inertia synthetization in synchronverter," *IEEE Access*, vol. 8, pp. 49961- 49976, Mar. 2020.

[71] H. M. Somarin and R. Parvari, "Micro-grid stabilizer design using slid- ing mode controller," *International Journal of Electrical Power & En- ergy Systems*, vol. 116, pp. 105519-105526, Mar. 2020.

AUTHORS PROFILE

Mr.D VenkataBramhanaidu was born in Andhra-Pradesh, India. He received his B.Tech degree in Electrical and Electronics Engineering from JNTU Hyderabad, Telangana, India in 2010. He received his M.Tech degree in Power Electronics and Electrical Drives from JNTU Hyderabad, Telangana in 2014. He is currently pursuing Ph.D in Electrical-Engg, Annamalai University and working as Assistant Professor in at Narayana Engineering College, Nellore, AndhraPradesh from, India. His areas of interests are Microgrid, Renewable Energy Sources Power Electronics, Electrical drives and the application of Soft Computing techniques. He has published his works in various international and national journals. Having Life Memberships of ISCA, IE(India), ISTE,IAENG and IFERP.

Dr. R. Thamizhselvan serves as an Associate Professor of Electrical Engineering at Annamalai University, located in Tamil Nadu, India. He earned his Bachelor's degree in Electrical and Electronics Engineering from Annamalai University in 2004, followed by a Master of Engineering in Power Systems in 2008, also from Annamalai University. He furthered his academic pursuits by completing his Ph.D. in Electrical Engineering in 2017.Currently, he is on assignment at Government Technical Institutions under the Directorate of Technical Education in Chennai. His research focuses including Power System Security, Renewable Energy, Microgrid, and the application of Soft Computing techniques in Power Systems. He is a lifetime member of IOE(India), ISTE&IAENG

.

Dr. Ch. Chengaiah, Professor in Sri Venkateswara University, Tirupati, Andhra Pradesh . He received his B.Tech degree in Electrical and Electronics Engineering from S.V.U College of Engineering, Tirupati, AP in 1999. He received his M.E degree in Power Systems from National Institute of Technology formerly called as REC, Tiruchirapalli, TN in 2000 and He received his Ph.D. degree in Power Systems Operation and Control from Sri Venkateswara University in 2013. With 21 years of teaching experience under his girdle, he has successfully concluded three funded research projects.His research interests include Power System and Control Engineering, Renewable Energy Systems, Power Electronics and Drives.