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Design of MPPT Algorithms Techniques Based Artificial Intelligence for Solar Power System

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Abstract
The maximum power point tracking (MPPT) in the solar power system, artificial intelligence (AI) approaches have been widely deployed over the past ten years. This is because under partial shade conditions (PSC), conventional MPPT algorithms are unable to track the global maximum power point (GMPP). A solar panel's output power versus voltage curve has a single global maximum power point (GMPP) and numerous local maximum power points (MPPs). To ensure the tracking of GMPP while boosting MPPT's overall effectiveness and performance, AI integration into MPPT is essential. Because each AI-based MPPT technique has advantages and disadvantages of its own, choosing one is difficult. In comparison to the traditional MPPT techniques, all AI-based MPPT algorithms show quick convergence speeds, low steady-state oscillation, and great efficiency. The AI-based MPPT solutions, however, need a lot of processing and are expensive to implement. Overall, the hybrid MPPT technique combines the benefits of traditional and AI-based MPPT techniques, striking a good compromise between performance and complexity. Based on the review and the outcomes of the MATLAB/Simulink simulation, a thorough comparison of classification and performance across six key AI-based MPPT approaches have been made in this study. We assess the benefits, unresolved problems, and technological applications of AI-based MPPT approaches. We want to offer fresh perspectives on selecting the best AI-based MPPT approaches.

Index Terms—Maximum power point tracking (MPPT), artificial intelligence (AI), fuzzy logic control (FLC), artificial neural network (ANN), genetic algorithm (GA machine learning (ML).

I. INTRODUCTION

The solar power system is widely used nowadays due to its cost-effectiveness and high efficiency [1]. It is considered as one of the most promising renewable energy source (RES) because of its cleanliness, abundance and environmental friendliness, compared with conventional energy sources such as oil, natural gas and fossil fuel [2]. Despite its advantages, the output active power P from solar power system varies according to the solar irradiance E_E and opera- tion temperature T, especially under rapid changing partial shading condition (PSC) due to the non-linear characteristic of photovoltaic (PV) cell [3]. The complex relationship between power output with PV input parameters results in unsatisfactory power extraction [4]. To alleviate the aforementioned limitation, maximum power point tracking (MPPT) becomes the research focus to improve the efficiency η of the solar power system and ensure that the operation point is always at maximum power point (MPP) [5]. The peak uniform conditions without PSC can be tracked effectively by using conventional hill-climbing (HC) MPPT techniques such as perturb and observe (P&O) and incremental conductance (IC) [6]. However, the power output from solar power system generates multiple peaks under PSC, including one global MPP (GMPP) and many other local peaks as illustrated in Fig. 1, which complicates the HC MPPT technique to search for the real maximum [7]. Hence, MPPT evolves into an algorithm based on evolutionary, heuristic and meta-heuristic techniques. It is designated to track global peak instead of local peaks since conventional HC MPPT techniques fail to track global peak under PSC and rapid changing of solar irradiance [8].

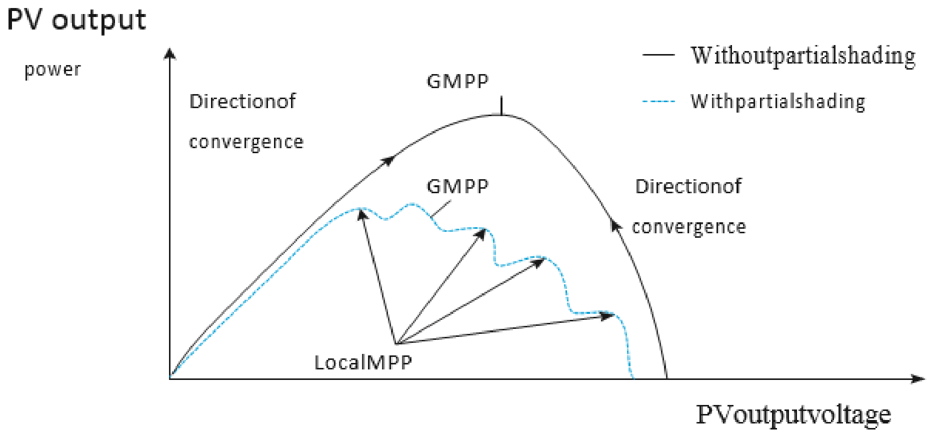

Fig. 1. Curve of power versus voltage for a solar panel under PSC.

Other strategies to increase solar energy efficiency exist besides electronically implemented MPPTs, like integrating soft computing weather forecast and adjusting the solar panel's tilt angle in relation to the direction of the sun [9]. We only pay attention to MPPT approaches for DC-DC converters in solar power systems that are AI-based. The following drawbacks of a traditional HC MPPT are intended to be addressed and corrected by the combination of various AI optimization approaches with MPPT:

1) A lack of robust, adaptive, and self-learning capacities.
2) A high steady-state inaccuracy, MPP power oscillation, and a delayed transient response.
3) Failure of MPPT, inability to locate GMPP, trapping at local MPP, and erroneous perturbation direction under PSC.

firefly algorithm (FA) and hybrid algorithms. Conventional HC MPPT techniques consist of P&O, IC, HC, constant voltage, fractional short-circuit current, fractional open-circuit voltage, scanning-tracking of current-voltage (*I-V*) curve, Fibonacci searching, global MPPT (GMPPT) segmentation searching and extremum seeking control. There are various sources of comparative literature review for all types of MPPT. Existing literature only covers AI-based and hybrid MPPT techniques. There are very limited comparative studies, specifically in AI-based MPPT techniques [11]-[13].

On the whole, the present AI-basedIn order to anticipate and estimate the GMPP along the non-linear P-V curve, the existing AI-based MPPT approaches typically use sensory data such as solar irradiance Ee, input voltage of solar power system VIPV, and input current IIPV measurements. Due to their complicated, reliable, self-learning, and digitalized systems, MPPT and AI integration speed up convergence and transient response. The two main categories of MPPT methodologies are traditional HC MPPT and AI-based MPPT [11]. Computational intelligence (CI) based MPPT, soft computing MPPT, modern MPPT, or bio-inspired MPPT are all terms used to describe AI-based MPPT. Particle swarm optimization (PSO), genetic algorithm (GA), fuzzy logic control (FLC), artificial neural network (ANN), differential evolution (DE), Tabu search (TS), and cuckoo search (CS) are the primary components.

The following are the paper's contributions: 1 The review of the applicability and uses of AI in MPPT for solar power systems; 2 current topics of AI research and development in MPPT are reviewed; There are 3 comparison analyses and performance assessments of each AI algorithm in MPPT approaches. Popular AI-based MPPT approaches are examined and assessed in this research. In-depth information about the most recent AI developments and advancements, as they are used in MPPT for solar power systems, is provided in this paper. Common drawbacks shared by all conventional MPPT methods include power fluctuation, inability to function normally under PSC, rapid irradiance fluctuations, trapping at one of the local MPPs, and oscillation around MPP [14], [15]. Therefore, AI is used to go around these

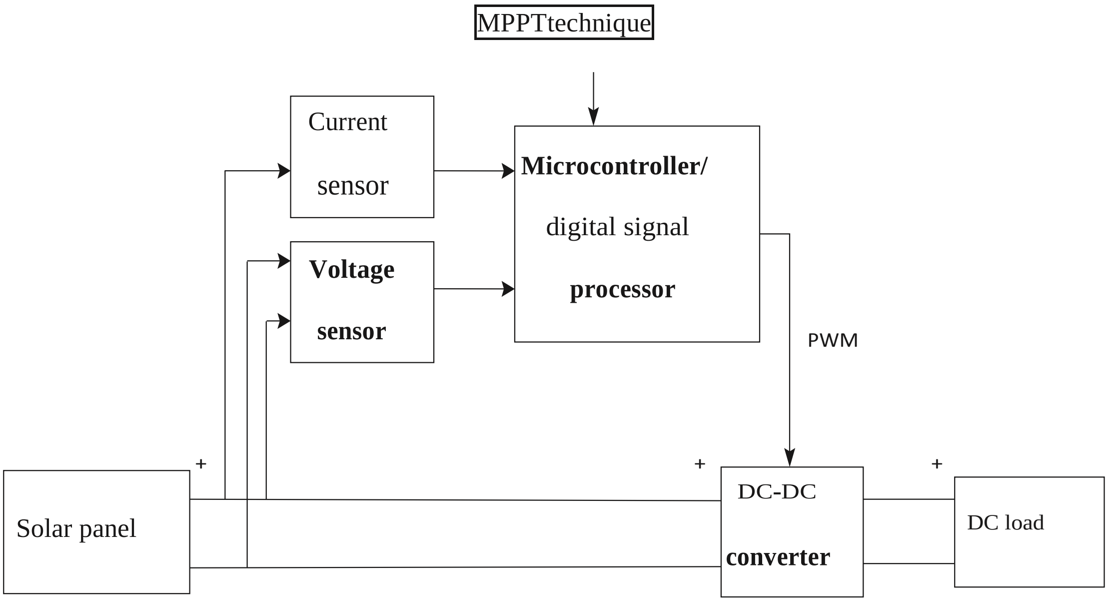

Fig. 2.Block diagram of typical MPPT.

II. REVIEW OF AI-BASED MPPT TECHNIQUES

The following are the paper's contributions: 1 The review of the applicability and uses of AI in MPPT for solar power systems; 2 current topics of AI research and development in MPPT are reviewed; There are 3 comparison analyses and performance assessments of each AI algorithm in MPPT approaches. Popular AI-based MPPT approaches are examined and assessed in this research. In-depth information about the most recent AI developments and advancements, as they are used in MPPT for solar power systems, is provided in this paper. Common drawbacks shared by all conventional MPPT methods include power fluctuation, inability to function normally under PSC, rapid irradiance fluctuations, trapping at one of the local MPPs, and oscillation around MPP , Therefore, AI is used to go around these.

A. FLC

A fuzzy logic-based control system called FLC transforms analogue inputs into continuous digital values between 0 and 1 [19]. It was created to address the shortcomings of traditional MPPT approaches, which include steady-state error (SSE), a high settling time, and oscillation around the MPP. Because it does not require knowledge of an exact MPPT model, it is simple to develop. Thus, FLC has gained popularity over the past ten years [20]. HC algorithms like P&O and IC can incorporate FLC [21]. Fuzzy rules are created by FLC using the HC algorithm [22]. When there is a change in irradiance and a load current, it has been demonstrated to offer superior power efficiency than the HC algorithm [23].

$$\frac{dP_{PV}}{dV_{PV}} = E_{rr} = \frac{P_{PV}(k)-P_{PV}(k-1)}{V_{PV}(k)-V_{PV}(k-1)} \quad (1)$$

$$D\frac{dP_{PV}}{dV_{PV}} = DE_{rr} = E_{rr}(k)-E_{rr}(k-1) \quad (2)$$

A fuzzy logic-based control system called FLC transforms analogue inputs into continuous digital values between 0 and 1 [19]. It was created to address the shortcomings of traditional MPPT approaches, which include steady-state error (SSE), a high settling time, and oscillation around the MPP. Because it does not require knowledge of an exact MPPT model, it is simple to develop. Thus, FLC has gained popularity over the past ten years [20]. HC algorithms like P&O and IC can incorporate FLC [21]. Fuzzy rules are created by FLC using the HC algorithm [22]. When there is a change in irradiance and a load current, it has been demonstrated to offer superior power efficiency than the HC algorithm [23]. and historically earlier MPPT CI implementation. The general FLC rules for MPPT are illustrated as follows, where DV stands for voltage change and DP for active power change.

1) D is decreased by -DD if DP > 0 and DV > 0, DP/DV > 0.
2) D is increased by +DD if DP > 0 and DV 0, DP/DV 0.
3) D is lowered by +DD if DP 0 and DV > 0; otherwise, DP/DV 0.

4) If DP and DV are nonzero and DP/DV is nonzero, D is increased by -DD.
5) MPP is attained if DP = 0.
The following criteria are reached for each step by applying the formula E =DP/DV and taking into account the sign of DP and DV.
1) If E <0, then D=D+ΔD. 2) If E >0, then D=D-ΔD. 3) If E =0, then D=D.
Reduced-rule FLC (RR-FLC), another variant of FLC, increases FLC's simplicity by lightening its computing burden [27]. Additionally, there are Takagi Sunken (T-S) and Mamdani design techniques for FLCs, with Mamdani-based FLCs being relatively common [28]. Fuzzification, fuzzy rules, and defuzzification are the three steps that make up FLC in most cases [29]. Using a variety of membership functions that have been established, the input variables are first transformed into linguistic variables [30]. The system's desired behavior is then applied to these variables in the following stage, which is based on the "if-then" rules. They are then transformed into numerical variables [18]. The speed and accuracy of FLC are significantly impacted by the membership functions [31]. while D of a DC-DC converter is the output variable that FLC will adjust [32], input variables. Positive large (PB), positive small (PS), zero (ZE), negative big (NB), and negative small (NS) are used to represent the linguistic variables that the input variables are allocated to [33]. To speed up processing, FLC integration with the M5P model tree (Quinlan's M5 method) is being researched [34]. The FLC-based MPPT's benefits and drawbacks, as well as current investigations, are presented in Tables I and II. I/O refers to input and output in Table II.

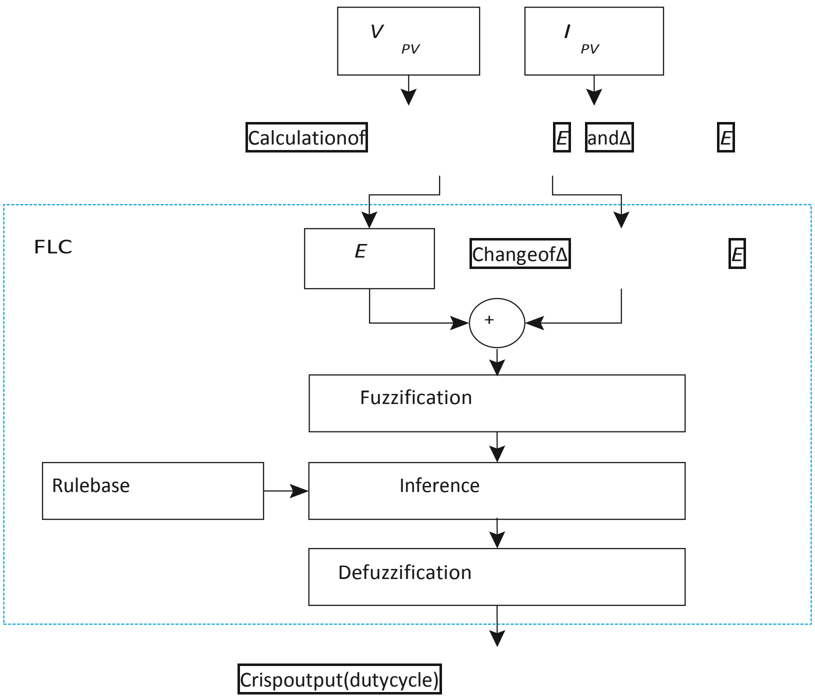

Fig. 3.Block diagram of general Err and Err as two important FLC.

TABLE I

Merit	Demerit
High efficiency and small fluctuation in steady state	Difficulty in deriving fuzzy rules and time consuming
Simple design and implementation	Inability to automatically learn from the environment
Operation with inaccurate input	Complex calculation
Fast tracking speed during rapid irradiance change	Undesirable performance under PSC
Good dynamic performance	Fuzzy rules directly affect system performance
Combination with another algorithm	

TABLE II

RECENT COMPARATIVE STUDIES OF FLC-BASED MPPT IMPLEMENTATIONS

Reference	Input parameter I/O sensor	Hardware/ software platform	Solar panel	DC-DC converter	MPPT time (s)	Steady-state oscillation (%)	MPPT efficiency (%)	Finding
[35] [22] [26] [28] [36]	Voltage and current Voltage and current Voltage and current Voltage and current Voltage and current	MATLAB/ Simulink and arduino DS1104 DSpace FPGA and MATLAB/ Simulink MATLAB/ Simulink PVPM 2540C, MATLAB/ Simulink	PV module (EP) 30W 60 W solar panel PV module (KC200GT) 230 W poly-crystalline Si	Buck Boost Boost Boost Boost	0.43 0.3 ±0.06 Less than 0.01	±4.0 ±1.7 ±1.0	98.50 98.00 99.00 99.37	FLC is used to control MPPT in a microgrid. The steadystate performance has been improved as compared with conventional P&O method Single-input T-S FLC is effective in tracking GMPP under PSC compared with conventional P&O algorithm. FLC exhibits less settling time and minimum oscillation FPGA-based FLC is flexible as the membership functions and inference rules can be reconfigured by changing very high speed integrated circuit hardware description language (VHDL) FLC is efficient in tracking GMPP value with less tracking time, compared with IC and P&O Improved M5P model (FLC-based MPPT) proves to minimise computation time and lead to energy loss.

MERITS AND DEMERITS OF FLC-BASED MPPT TECHNIQUE

B. ANN

The biological neural networks found in animal brains are the inspiration for ANNs, or connectionist systems. The relationship between I-V and PV's nonlinearity is tested and trained for using this method. The ANN retrieves these inputs from input current, input voltage, irradiance, temperature, and metrological data and constantly learns to adapt the solar power system's behavior for the maximum power [37]. With greater accuracy and easier converter implementation, ANN can be used to mimic FLC design [38].

As illustrated in Fig. 4, the dataset is acquired from the simulation or hardware setup by feeding solar irradiances, temperatures, solar power system voltage or current into ANN and obtaining the matching Pmax or Vmax output. These data are transformed into training data and sent into the created ANN to train it. After training, test datasets are used to assess how well the proposed ANN performed, and errors are fed back to the ANN for further optimization [39]. It can be used to support sequential Monte Carlo (SMC) filtering-based state estimation and MPP prediction. Alongside the IC MPPT technique's framework, a statespace model for the sequential estimation of MPP can fit, and the ANN model uses data on voltage, current, or irradiance to predict GMPP in order to improve the estimation by SMC [40].

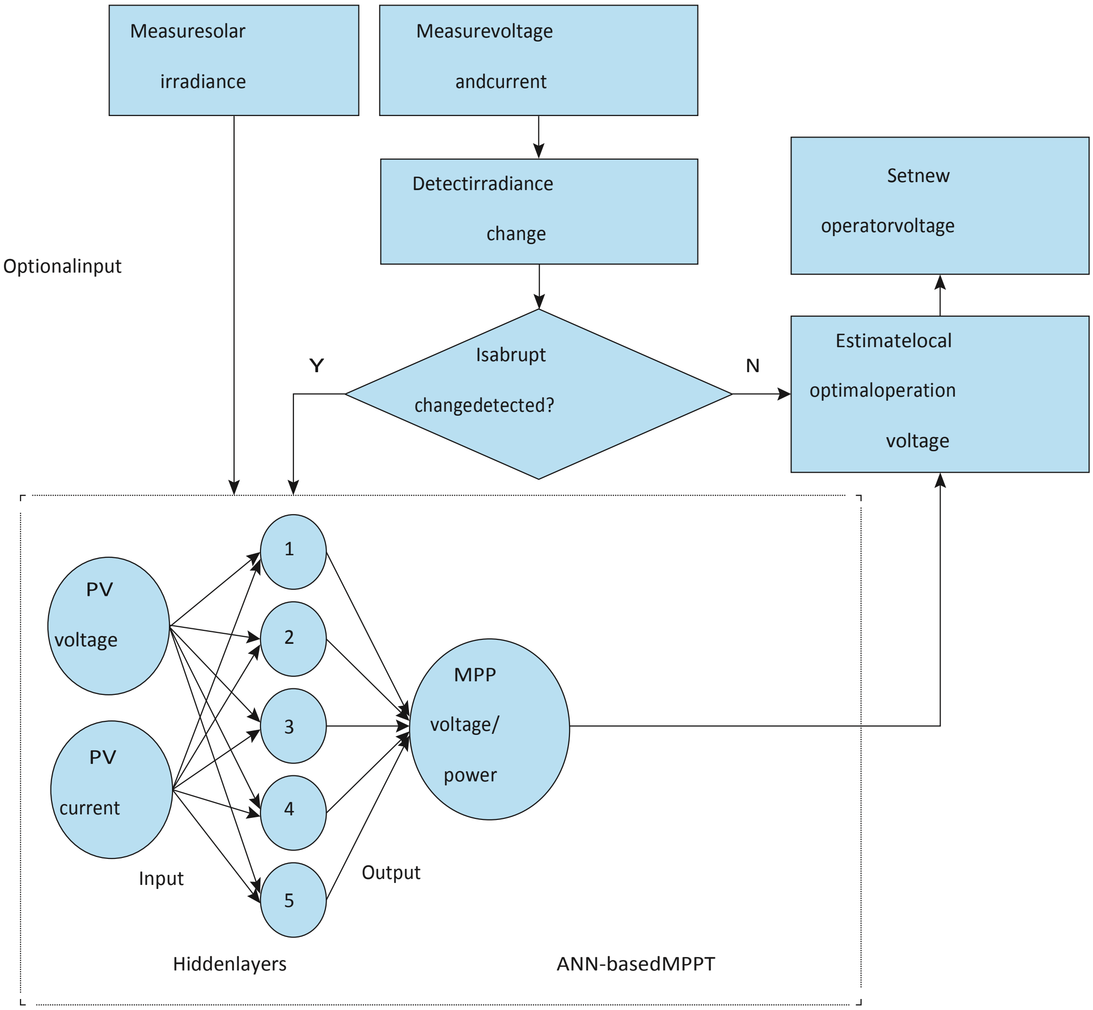

Fig. 4. Structure of an ANN-based MPPT.

These data are transformed into training data and sent into the created ANN to train it. After training, test datasets are used to assess how well the proposed ANN performed, and errors are fed back to the ANN for further optimization [39]. It can be used to support sequential Monte Carlo (SMC) filtering-based state estimation and MPP prediction. Alongside the IC MPPT technique's framework, a statespace model for the sequential estimation of MPP can fit, and the ANN model uses data on voltage, current, or irradiance to predict GMPP in order to improve the estimation by SMC [40]. without having a significant training mistake to perform at their best [46]. The advantages and disadvantages of ANN-based MPPT are listed in Table III. Table IV displays the most recent use of ANN in MPPT.

TABLE III

MERITS AND DEMERITS OF APPLICATION OF ANN IN MPPT

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

TABLE IV
RECENT COMPARATIVE STUDIES OF ANN-BASED MPPT IMPLEMENTATIONS

Reference	Specific type of MPPT controller	Input parameters I/O sensors	Hardware/ software platform	Solar panel	DC-DC converter	MPPT time (s)	Steadystate oscillation (%)	MPPT efficiency (%)	Finding
[47]	ANN	Voltage, current, atmospheric parameter	MATLAB/ Simulink and experiment	Experiment and simulated	Boost	0.06		Up to 99.68	An ANN model is deployed to learn operation variation of a solar power system. PSO is used to find optimum initial weights of ANN model
[38]	ANN modeling	Voltage and current	MATLAB/ Simulink	Simulated	Boost			Above 90	MPPT based on ANN-modelled FLC exhibits higher fault tolerance and simpler implementation
[39]	Neural network	Voltage and current	MATLAB/ Simulink	MSX 60 PV (simulated)	Buck Boost				Backpropagation trained neural network can accurately predict the MPP of a PV panel. It provides accurate and faster results than P&O based MPPT
[40]	ANN	Temperature and irradiance	MATLAB/ Simulink	Simulated		0.2-0.4	±0.1	Above 90	ANN model is based on the input voltage, input current and irradiance to predict GMPP with knowledge learned from training data
[48]	Feed forward ANN		MATLAB/ Simulink	Simulated	Boost	0.03	±0.7		ANN is trained by using "nntool" in MATLAB/Simulink model. ANN based MPPT controller has less steady-state error, fast response for sudden change in solar temperature and irradiance, compared with P&O and IC

C. GA

GA is a general AI-based optimization method applied to different optimization problems. It is widely used in MPPT by using voltage-step selection GA algorithm [49]. to compute the voltage reference of PV panel by modifying a population of individual solutions. In general, GA has relatively small oscillations, rapid convergence speed and fast dynamics A modified GA exhibits reduced population size, simplified procedures for mutation and more straightforward crossover calculations [50]. Contrary to traditional MPPT, GA-based MPPT can search GMPP rather than becoming stuck in the local MPP.

Due to its streamlined approach, GA is not advised to optimize very large-scale, extremely complicated, or excessive problems, notwithstanding its effectiveness. When doing MPPT optimization, GA is initialized by creating an array for the initial parent population: X i = [parent1 parent2 parentn] (3), where n is the population number and parenti (i=1,2,...,n) represents the initial voltage values. The output power of the solar power system is the objective function f (X i). The objective function carries out the evaluation of fitness values for each place. utilized to evolve the population and increase the fitness of the population through time. Because of abrupt changes in load, solar irradiance, or PSC, the algorithm must be reinitialized specifically for MPPT application as opposed to traditional GA. Following the fulfillment of requirements (4) and (5), the GA-based MPPT approach is reinitialized.

$$|V(k+1)-V(k)|<\Delta V \quad (4)$$

$$\frac{P(k+1)-P(k)}{P(k)} \quad (5)$$

where k is the current measurement and k+1 is the following measurement iteration.

On the basis of chromosomal evolution, GA was developed. The usual GA process is depicted in Figure 5. The initial population is first binary encoded. Their fitness values for each chromosome are assessed after they have been decoded into real numbers. For an ideal answer, specifically in the maximizing of power production, genetic operations such as selection, crossover, and mutation are carried out. The advantages and disadvantages of GA-based MPPT, as well as recent research, are displayed in Tables V and VI.

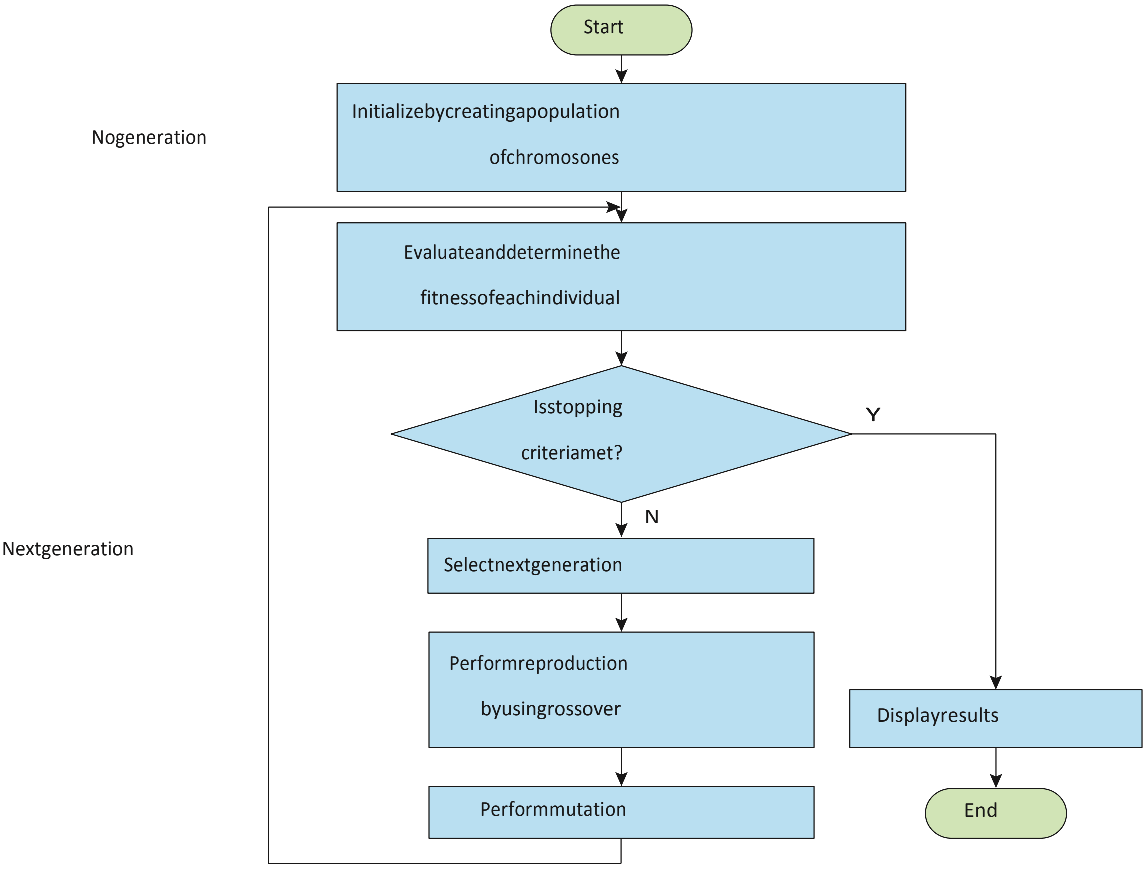

Fig. 5. Flowchart of a typical GA method in MPPT.

TABLE V MERITS AND DEMERITS OF APPLICATION OF GA IN MPPT

Merit	Demerit
Low computational requirement General and uniform implementation scheme MPPT is done by function values without calculation High stability and rapid response	Slow tracking speed due to series format Depending on the initial condition

TABLE VI

RECENT COMPARATIVE STUDIES OF GA-BASED MPPT IMPLEMENTATIONS

Reference	Input parameter I/O sensor	Hardware/software platform	Solar panel	DC-DC converter	Finding
[51]	Temperature and irradiance	MATLAB/Simulink	HT60-156265		A GA based on large variation radial basis function is used to learn data pattern of temperature and irradiance. The algorithm predicts MPP with high accuracy after dataset training
[49]	Voltage and current	dSpace and Terra-SAS control software	SHARP NU-U235F1		GA is applied to calculate voltage reference of PV panels to combine MPPT and constant power generation in solar power systems. It imitates the performance of P&O MPPT with small power oscillations and fast dynamics
[52]	Voltage and current	MATLAB/Simulink	S440M34	Boost	GA is implemented to improve the efficiency especially under PSC which results in an overall reduction of loss energy

D. PSO

The PSO algorithm is the most used SI-based MPPT. A heuristic approach is used to solve the MPPT optimization problem. A particle's position represents a potential solution, and a duty ratio represents the available space for solutions [53]. PSO, which is based on the idea of bird flocking, has been demonstrated to provide a better-fitted result with each iteration. Each particle in PSO follows the ideal candidate particle. In PSO, a population of particles is displayed, and their positions are contrasted with the regionally and globally optimal placements. The optimum answer is then found by moving these particles about in the search space [54]. PSO can be combined with overall distribution (OD), which can quickly locate the general area surrounding GMPP [55]. An enhanced PSO enhances the particle search process by integrating with a non-linear decreasing inertia weight [56]. The learning factor and weighting value are decreasing with each iteration for other modified PSO. The social learning component, however, is anticipated to rise. In addition, changes in the slope and power characteristic curves affect the weighting value. The tracking speed and stability are increased by these adjustments [57]. In comparison to a traditional PSO, a discrete PSO (DPSO) has a simpler structure, higher performance, and a consistent solution for fewer particles. For the inertia weight, just one parameter needs to be tuned [58].

E. Grey Wolf Optimization (GWO*)*

One of the contemporary heuristic optimization methods, called GWO, was influenced by the way of life of grey wolves. The terms "leader," "subleader," "lowest rank," and "lowest rank" all refer to the position of authority. A GWO-based MPPT relies on the hunting strategies of grey wolves by adhering to the priority order of,, and. The algorithm will eventually reach the prey, in this case GMPP.

F. FA

FA is a different kind of SI that is based on firefly activity and flashing. According to the philosophy, a firefly's appeal is inversely correlated with its brightness. Because of their appeal, fireflies may congregate to find the best answer in this situation. Similar to SI, FA can be used in MPPT as a form of SI to identify the best MPP [50]. The MPPT approach based on modified cat swarm optimization (MCSO) has a strong ability to detect GMPP regardless of where it is located in the search space and is system independent. It converges more quickly and accurately follows GMPP [59]. Another brand-new meta-heuristic optimization, known as MFO, is based on how moth behavior tends to converge toward the light source [60].

G. CS

A new SI algorithm called CS is based on some species of cuckoo birds that lay their eggs in the nests of other birds as a method of reproduction. This parasitic reproduction strategy is what inspired the CS optimization method. The fundamental goal of CS is to locate the proper host nest, which is analogous to looking for food. It is a random process that is model able through the use of mathematical optimization techniques. The most popular technique for simulating an animal's trajectory while seeking food is the Lévy flight model. Therefore, in CS-based MPPT, the Levy flying model is employed to describe the nest-seeking strategy of a Cuckoo bird reproduction process. The Levy flight model is a mathematical representation of a random walk where the step sizes are using the Levy distribution, defined. No matter the conditions, it boasts a quick MPPT speed and great tracking accuracy. With only three particles and one parameter to modify, it is a simpler MPPT approach [61]. Only the CS technique, meanwhile, is extremely difficult to implement and does not ensure the tracking of GMPP [62].

H. Gravitational Search Algorithm (GSA)

GSA is founded on the idea of Newtonian gravity and the laws of motion, which suggest that particles have a tendency to move faster in the direction of one another due to their attraction to one another [13]. The GSA's standard procedures are as follows:

1) The top and lower limits of the DC-DC converter's duty cycle, which typically spans from 10% to 90%, are assigned to the population size.
2) To obtain the fastest convergence, solar agents are evenly distributed amongst the search space intervals.
3) PV output power is estimated for each agent position. The mass of the agents is taken as the MPPT power.
4) The net force acting on each agent and the force G acting between the agents are calculated.
5) Each agent's acceleration an is determined.

An upgraded GSA has dynamic weight in the change factor of the gravity constant in addition to standard GSA. The modified particle velocity formula now includes the memory and population information factors [63]. Other SI algorithms that are based on biological behavior include the artificial bee colony (ABC), bird flocking, animal herding, bacterial growth, microbial intelligence, and crowd or human swarming. Table VII lists the benefits and unresolved problems with SI approaches for MPPT. The lists of recent works on SI-based MPPT are shown in Table VIII.

TABLE VII
MERITS AND DEMEEERITS OF APPLICATION OF SI INCLUDUNG PSO, GWO, FA, CS AND GSA IN MPPT

Merit	Demerit
Without requiring a massive dataset High ability in searching GMPP regardless where is GMPP Elimination of oscillation around MPP High tracking accuracy and fast convergence Simple structure, easy implementation and fast computation ability	Oscillations because of large random search Larger computational burden Requiring huge data Highly complex and time-consuming Algorithm parameters need to be carefully set

Hybrid MPPT

Hybrid MPPT is a general term to describe the integration of two or more MPPT either from AI or conventional techniques. One of the most popular hybrid MPPT is the integration of ANN with conventional P&O algorithm, which is known as “neural network P&O controller” [41]. On the contrary, an improved P&O algorithm with variable step size is to reduce the steady-state fluctuation or oscillation and accelerate the tracking speed under sudden irradiance changes or PSC. ANN and FLC are suitable to integrate with conventional MPPT methods like P&O and IC. ANN estimates the MPP without any shading conditions or panel temperature, while the HC method improves the result further. Other hybrid MPPTs include PO-ANN and IC-ANN, which integrate with the stacked autoencoder (SAE) controller by using deep learning (DL) training and building blocks to act as an autoencoder. It is trained with a greedy layer-wise pattern in extracting the maximum power from the solar power system. After that, it uses backpropagation with supervised learning to fine-tune the deep neural network with conventional MPPT-IC and PO to reach the maximum power [68]. by employing deep learning (DL) building blocks and training to function as an autoencoder. It is trained to get the most electricity possible from the solar power system using a greedy layer-wise strategy. The deep neural network is then fine-tuned using backpropagation and supervised learning to maximize power using traditional MPPT-IC and PO [68].

TABLE VIII
RECENT COMPARATIVE STUDIES OF SI-BASED MPPT IMPLEMENTATIONS

Reference	Specific type of SI	Input parameter I/O sensor	Hardware/software platform	Solar panel	DC-DC converter	MPPT time (s)	Steadystate oscillation (%)	MPPT efficiency (%)	Finding
[64] [53] [54] [55] [57] [59] [60] [61] [65] [66] [67] [63]	Pigeon PSO PSO PSO Modified PSO Modified CSO MFO CS ACO Spider monkey AFSA GSA	Voltage and current Voltage and current Voltage and current Voltage and current Voltage and current Voltage and current Voltage and current Voltage and current Voltage and current Voltage and current Voltage and current Irradiance and temperature	MATLAB/ Simulink MATLAB/ Simulink dSpace 1104 controller and MATLAB/ Simulink MC56F8245 micro-processor PIC18F8720 micro-controller & MATLAB/ Simulink DSP TMS320F2 8335 MATLAB/ Simulink Microchip DSP and MATLAB/ Simulink dSpace/ MATLAB/Simulink MATLAB/ Simulink MATLAB/ Simulink MATLAB/ Simulink	Simulated Simulated MSX-60W PV TC.P.32 PV simulator 1000 V/13 A Sanyo HIP2717 modules Chroma 62100H- 600S programable DC SunPower SPR305 WHT SAS 200W PV Simulated PV panel emulator Simulated	Boost Boost Buck Boost Boost Boost Boost Cuk Boost Boost Boost	±0.1 ±1.0 0.4 ±1.6 0.55-1.2 0.05 1.8-2.8 0.38 ±0.20 ±0.04 ±0.04	±0.050 ±0.046 ±0.050 ±1.000	±97.00 99.91 ±99.00	A pigeon-inspired optimization is used to optimize MPPT under PSC. It reduces power oscillation, improves stability and achieves desirable control results PSO combined with one cycle control is able to track GMPP under varying shading conditions PSO is applied for MPPT in obtaining the optimum duty cycle for the *Z*-source inverter to overcome the shortage of conventional MPPT technique OD PSO is implemented in MPPT to track MP. PSO has more power and lower power fluctuation compared with FA and P&O Conventional PSO has been modified to vary the weighting value, cognition learning factor, and social learning factor based on the slope and changes in power The system-independent cat swarm optimization (CSO) has high ability to find GMPP regardless of the location of GMPP in search space. It eliminates the power oscillation around MPP compared with P&O MFO is applied as a novel approach for optimal exploitation of PV sources under PSC It exhibits better performance compared with IC, FL and PSO in terms of tracking ability, efficiency and steady state Deterministic CS is deployed to remove the random number in the voltage calculation equation of the conventional CS method Ant colony optimization (ACO) based MPPT provides optimal power extraction from solar for residential applications P&O MPPT technique has been improved by

PI controller which is tuned by spider monkey algorithm to achieve good response under different atmospheric condition
Artificial fish swarm algorithm (AFSA) method can easily avoid the constraint of multiple local extreme value points and catch MPP of the current environment with high precision
Improved GSA-based MPPT achieves short tracking time and good tracking accuracy in MPPT under various of conditions compared with GSA and PSO

An adaptive neuro-fuzzy inference system (ANFIS), which combines ANN and FLC, is another well-known hybrid MPPT. It benefits from both ANN and FLC. An FLC-based MPPT is driven by an ANN that has been taught to estimate the ideal MPP. ANFIS and fuzzy logic are the best options for smart power management and solar power systems because they are adaptive, versatile, and ideal [69]. The fuzzy learning process in learning all the details about a dataset is modelled using the neuro-adaptive learning technique. The given dataset is mapped from various inputs to a single output during this process. With the aid of input-output datasets, ANFIS creates a system of fuzzy inference. In order for FIS to track input and output data, the model computes the membership function parameters, which are the best fit [70]. By combining backpropagation and least squares algorithms, a hybrid learning technique is used to modify the fuzzy membership function parameters [71]. It has been demonstrated that ANFIS-based MPPT increases the solar power system's conversion efficiency [72]. In addition to bit error correction, the fuzzy neural network can anticipate and forecast meteorological information for solar power systems [73].

Along with FLC, ANN can be deployed using hybrid PSO and GSA. As an illustration, PSO-GSA first generates a random initial population before sending it to ANN for data training [74]. Improved open-circuit voltage model-based method and smart power scanning are the foundations of another hybrid MPPT technique. The voltage levels are checked as part of the smart power scanning to determine whether PSC is occurring or not [75]. In addition to ANN, FLC is adaptable enough to be integrated with P&O algorithm. It combines the two benefits of the technique [16]. Variable step sizes are used in FLC-based P&O to provide low oscillation and quick response since large step sizes guarantee quick response but produce excessive oscillation, whereas small step sizes produce sluggish response and low oscillation [76]. The IC's integration [77].

Another hybrid MPPT is the ANN-CGSVM methodology, which combines the powerful machine learning (ML) methods coarse-Gaussian support vector machine (CGSVM) and ANN. The non-linear SVM learning method known as CGSVM is characterized as a data mining method [78]. As well as merging ANN and RQGPR to use data mining and regression learner for PV MPPT, rational quadratic Gaussian process regression (RQGPR) is needed to produce big and accurate training data for MPPT [79]. The ANFIS controller and HC approach are combined in a novel ANFIS with HC (ANFIS-HC) to more accurately estimate the duty ratio offline. The issue with traditional MPPT in seeking GMPP under PSC is solved by HC's online duty cycle fine-tuning, as the duty ratio.

TABLE X
RECENT COMPARATIVE STUDIES OF HYBRID MPPT IMPLEMENTATIONS

Reference	Specific type of MPPT controller	Input parameter I/O sensor	Hardware/ software platform	Solar panel	DC-DC converter	MPPT time (s)	Steady-state oscillation (%)	MPPT efficiency (%)	Finding
	FLC with PSO and GA		MATLAB/ Simulink						Parameters of an FLC are tuned by using hybrid PSO and GA. It exhibits 2%-8% higher output power with faster response rate and higher accuracy
[82]	ANFIS-PSO	Voltage and current	MATLAB/ Simulink linked to dSPACE DS1104 board		Boost	±0.200			ANFIS-PSO hybrid MPPT is deployed to acquire MPP with zero oscillation tracking
[83]	FLC with P&O	Voltage and current	MATLAB/ Simulink		Zeta	±0.300		98.35	The designed membership functions of FLC incorporate the advantages of the P&O-MPPT and the FL-MPPT and eliminate their drawbacks
[31]	Modified GA and FA	Voltage and current	Labview, MATLAB/ Simulink, cypress, PSoC4 ARM cortexM 0		Boost	±1.000		99.6	A fusion algorithm is deployed to integrate three nature-inspired algorithms for MPPT. It simplifies the calculation of GA with the integration of the mutation process of DE and modifies the attractive process of FA
[50]	FLC with variable step P&O	Voltage and current	dSpace	Simulated under EN 50530 standard	Buck	0.089			FLC is developed to regulate DC-link while an improved P&O with variable step size is designed to reduce PV power fluctuation
[84]	Hybrid intelligent controller (PO-ANN and IC-ANN)	Voltage and current	MATLAB/ Simulink	IV curve simulator	Boost	±0.030	±0.01		The hybrid techniques based on PO-ANN and IC-ANN are utilized in SAEs. It is trained with DL network and building blocks to enable the maximum power extraction from solar.
[68]	ANFIS	Voltage and current			Cuk	±0.400	±2/3	>91.00	
[71]		Voltage and current		SHARP 80W	Buck	0.012	0.05	91.00	ANFIS-based model on top of IC method and constant voltage method has been proposed for MPPT

MERITS AND DEMERITS OF HYBRID MPPT

Merit	Demerit
Combination of conventional and AI-based MPPT advantages Cancellation of disadvantages of conventional and AI-based MPPT High accuracy and fast-tracking speed	Relatively complex Longer computational time Costly

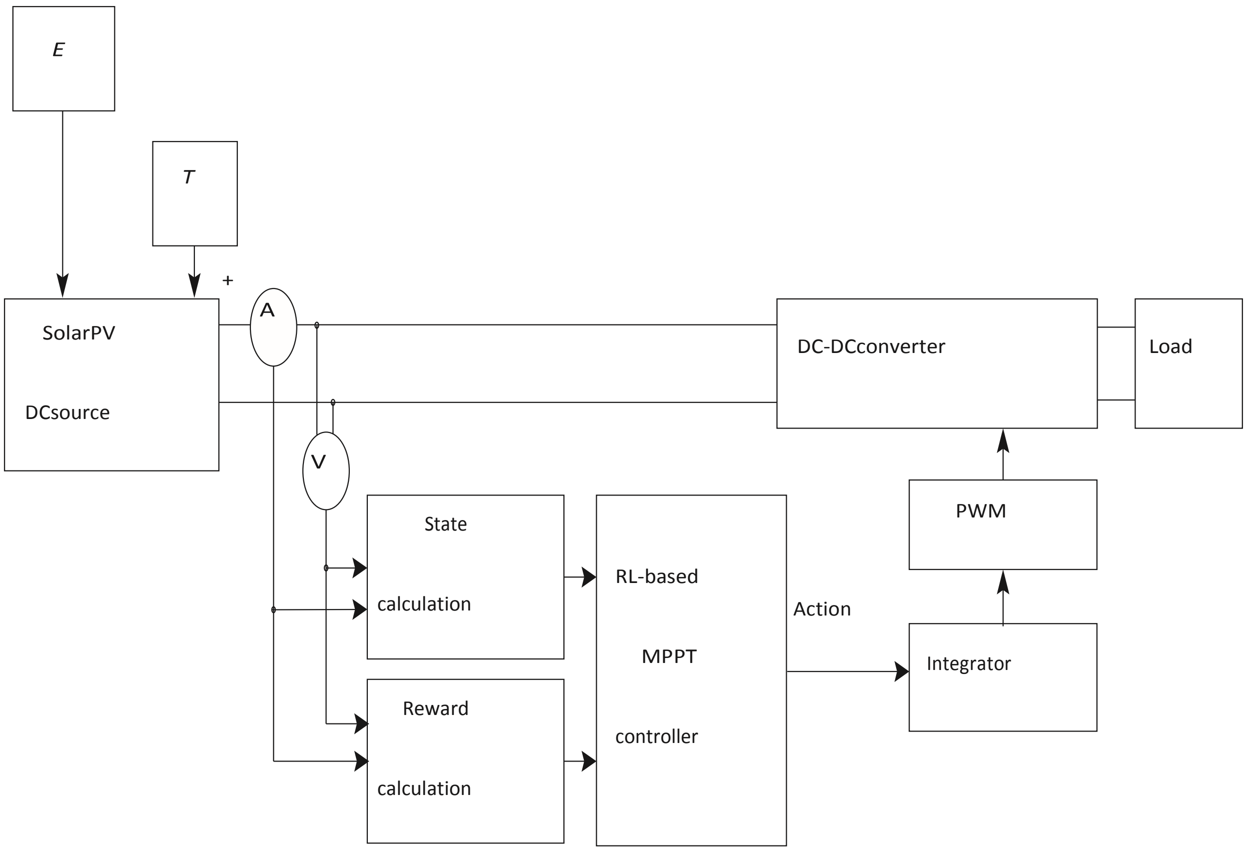

Fig. 6. General structure of RL-based MPPT.

J. ML

Bayesian ML is a method specialized in unsupervised classification, curve detection, and image segmentation. It is applicable in MPPT to achieve GMPP [85]. The real-time location-based weather forecasting is also applicable by using optimized modified ELM or Bayesian ML (BML). In order to train a single layer feed-forward network, ELM algorithm is utilized to update the weights by different PSO techniques. Their performances are compared with existing models like the back-propagation forecasting model [86]. As illustrated in Fig. 6, reinforcement learning (RL) method enables autonomous learning by observing the environment state of the solar power system. It is used to train and adjust the perturbation for the maximum output. Table XI shows the merits and demerits of ML-based MPPT, while Table XII presents the recent studies.

TABLE XII

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

TABLE XII
RECENT COMPARATIVE STUDIES OF ML-BASED AND OTHER MPPT IMPKEMENTATIONS

AI-based MPPT	Reference	Specific type of MPPT controller	Input parameter I/O sensor	Hardware/software platform	Solar panel	DC-DC converter	MPPT time (s)	Steady-state oscillation (%)	MPPT efficiency (%)
ML	[85]	BML	Voltage and current	MATLAB/Simulink and pIss controller		Boost	±1.88	Almost zero	98.9
	[86]	Modified ELM	Voltage and current	MATLAB/Simulink	Simulated			±1	
Others	[87]	DE	Voltage and current	PIC18F4520 micro-controller	Mitsubishi PV in solar array simulator	SEPIC	±2.00		99.0
	[88]	Modified FPA	Voltage and current	MATLAB/Simulink	Simulated	Boost	0.05		99.1

K. Development of New AI-based MPPT and other Emerging Metaheuristic Algorithms

Target vectors are used as the population in each iteration of the optimization approach known as DE-based MPPT. The wider the search space, the more particles are required, and the slower the convergence speed. Since DE seeks extremely huge spaces of potential solutions without ensuring an ideal one, it is a meta-heuristic [87]. A modified flower pollination algorithm (FPA), which takes its cues from the pollination of flowers, is another new algorithm. Self-pollination is the spread of ripe pollen by the wind, but cross-pollination involves communicators like birds, bees, and bats. Complete local optimization is the term used to describe this method [88]. Evolutionary algorithm (EA) and TS are two other new algorithms. EA is a general population-based met heuristic algorithm that is inspired by biological evolution, which involves recombination, mutation, and reproduction. Using local search techniques for mathematical optimization, TS is another met heuristic search strategy. The most recent research on additional new AI for MPPT control techniques is presented in Table XIII.

III. ANALYTICAL COMPARISON OF AI-BASED MPPT TECHNIQUES

A. AI-based MPPT Techniques Classification The following parameters are examined between the AI-based MPPT techniques: MPP tracking speed, tracking precision, steady-state oscillation, algorithm complexity that influences computing time, and total cost are all factors. According to decreasing popularity, the common AI-based MPPT techniques are generally divided into FLC, ANN, SI, hybrid, GA, ML, and other new emerging algorithms. Due to the space and area constraints, this document may not be able to incorporate all of the new methods. Figure 7 displays the approximate popularity of AI-based MPPT citations over time.

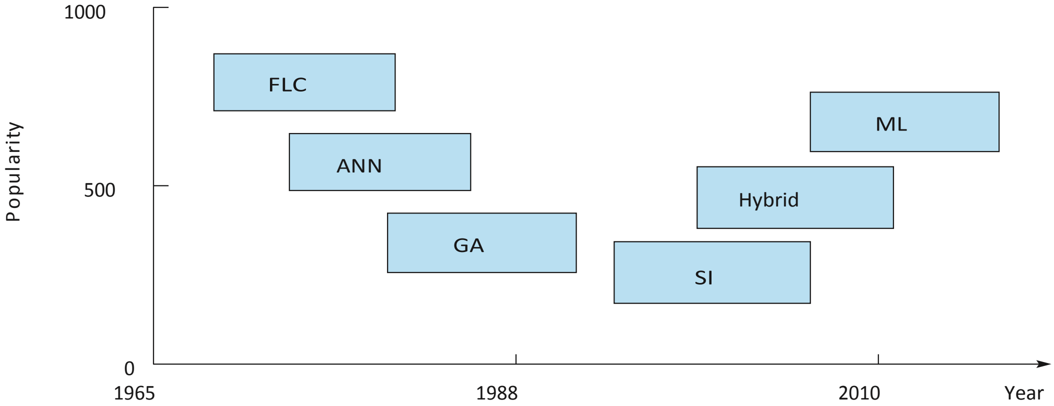

Fig. 7.Approximate citation popularity of AI-based MPPT versus year.

FLC is created in 1965 and gains popularity throughout that era. Then, in accordance with their individual timelines, ANN, GA, SI, hybrid, and ML are created; all of them continue to be useful in AI-based MPPT decades later. Three significant comparing tables and one classification graphic can be found in the results section. The tables detail the advantages and unresolved problems of each AI-based MPPT, the parameters that differ across all AI-based MPPT, and the AI-based MPPT that have been available in recent years. the utilized platform (software: MATLAB/Simulink; hardware: arm cortex microcontroller The categorization graphic effectively conveys the AI-based MPPT possibilities available for each category and classification. One of the criteria and features used to assess AI-based MPPT systems is often the number of control variables (input sensory parameters).Solar panel parameters, DC-DC converter switching frequency, type of DC-DC converter (buck, boost, buck-boost, uk, or SEPIC), tracking/convergence speed or transient time, oscillation accuracy, and MPPT efficiency. The sophistication of bio-inspired algorithms and machine learning (ML) in terms of accuracy, speed, and performance has made them highly popular in recent years. Instead of just considering inputs like current and voltage, more parameters are taken into account. It contains data on humidity, shade, clouds, and metrology. Every algorithm seeks fast tracking or convergence speed, low steady-state oscillation, easy cost-effective implementation, quick processing capability, and high efficiency with little power loss.

B. Comparison

Recent AI-based MPPT techniques are often more sophisticated and effective, but they are also more difficult, expensive, and data-intensive. For the implementation of MPPT in a particular field, a balance between performance and cost or complexity is essential. Figure 8 divides the most widely used AI-based MPPT techniques now in use into seven main categories: FLC, ANN, SI, hybrid, GA, ML, and developing algorithms.

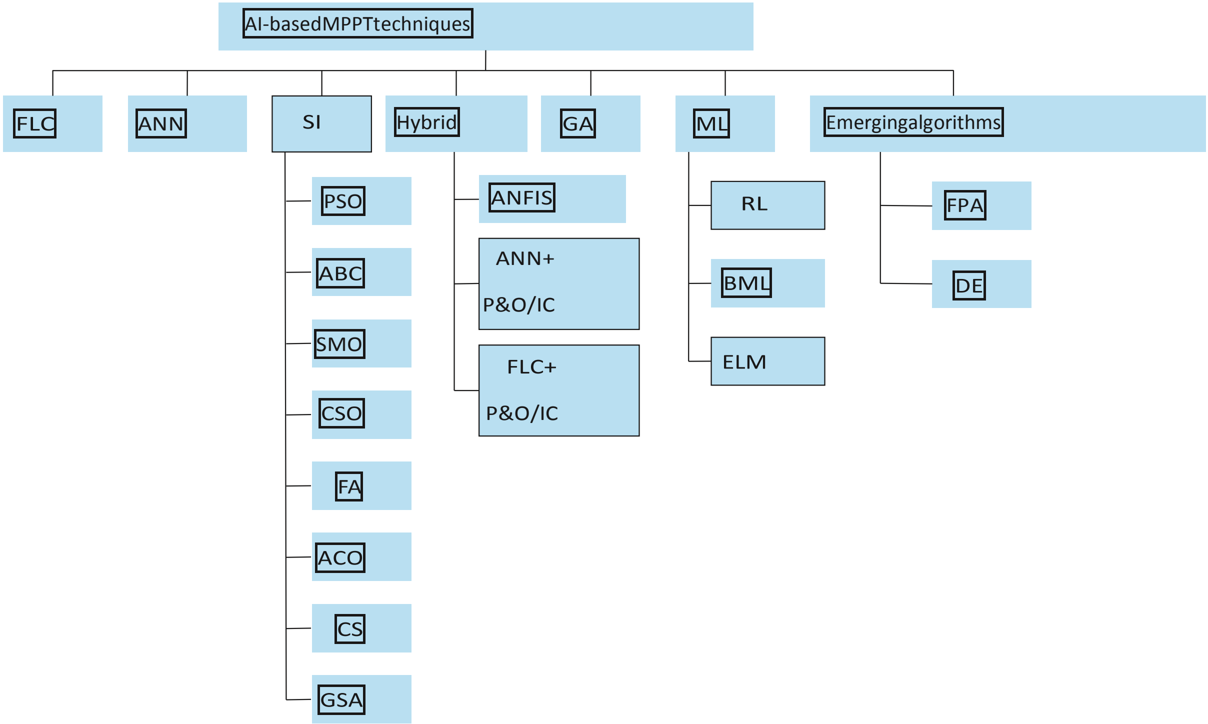

Fig. 8. Classification and categorization for popular AI-based MPPT techniques in recent years.

The family of SI is the largest in AI-based MPPT, mostly because of the algorithms' inspiration from biological swarm intelligence (SI), which has great accuracy and quick performance. There are several different subcategories within the ML and hybrid. Due to the ease of AI-based MPPT integration, the hybrid MPPT is fairly adaptable. ML is another another well-liked method. In order to output the most power, it uses a variety of methods and strategies to learn from the experience or dataset. Sub-categories are not available for FLC, ANN, or GA. The newest techniques in MPPT, which are expanding and improving, are included in the developing algorithms.

All AI-based MPPT algorithms are assessed according to their performance in each category and overall evaluation point, as shown in Figs. 9 and 10. The performance of the algorithm is implied by the numbers 0 through 10, where 0 represents poor performance and 10 indicates good performance. Table XIII provides the foundation for scoring. The conclusions are drawn from reviews of the literature on prior research aAs illustrated in Figs. 9 and 10, all AI-based MPPT techniques are evaluated in term of the performance evaluation in each category and total evaluation point, respectively. Points 0-10 imply the performance compared with other algorithms, where point 10 indicates high performance while point 0 indicates undesirable performance. The scoring is based on Table XIII. The results are established based on the literature reviews on existing studies and validated by the simulation results on MATLAB/Simulink. It is concrete that SI has scored the highest point in average, followed by hybrid, ML and GA. They are meta-heuristic methods which are able to adapt to the operation environment of the solar power system. The balance between algorithm complexity and desirable MPPT performance is achievable by using SI, hybrid MPPT, ML or GA techniques.nd are supported by simulation findings from MATLAB/Simulink. SI has clearly earned the greatest average point, followed by hybrid, ML, and GA. These meta-heuristic techniques can adjust to the operating conditions of a solar power system. Using SI, it is possible to strike a balance between algorithm complexity and desired MPPT performance.

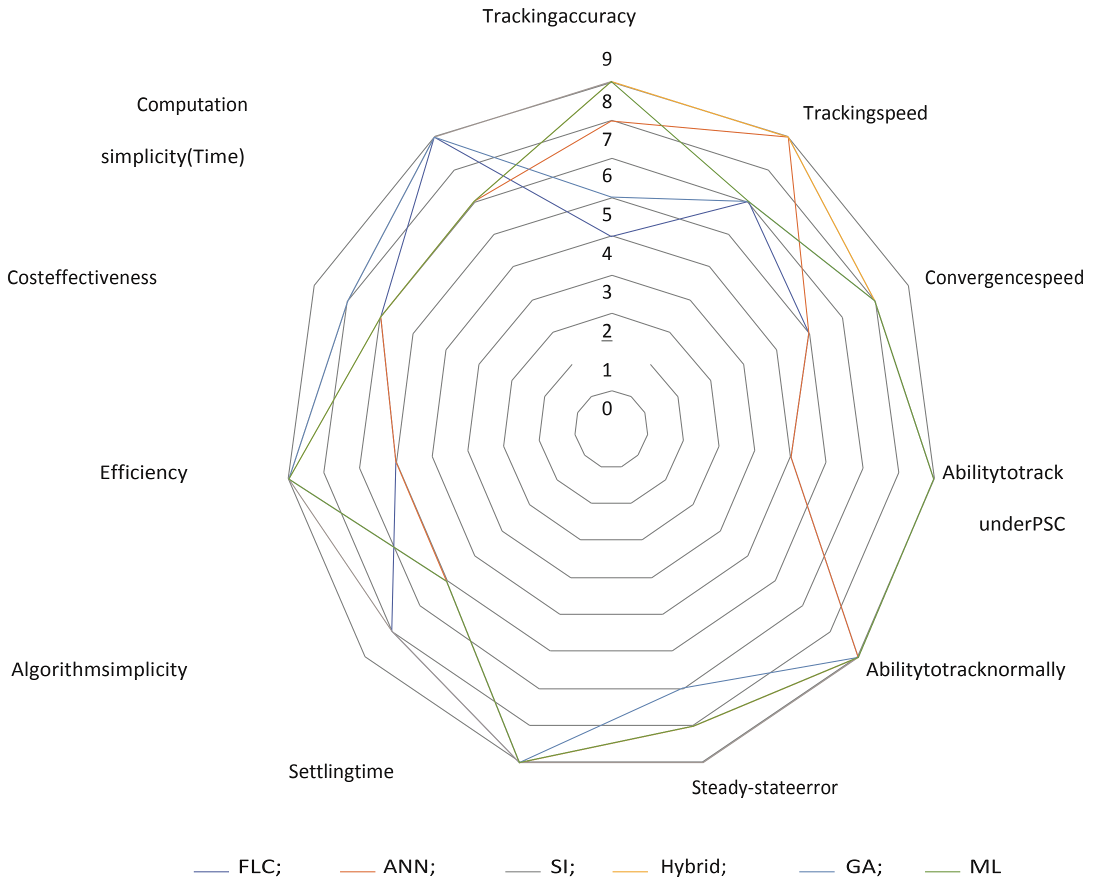

Fig. 9. Performance evaluation of each AI-based MPPT in term of each category.

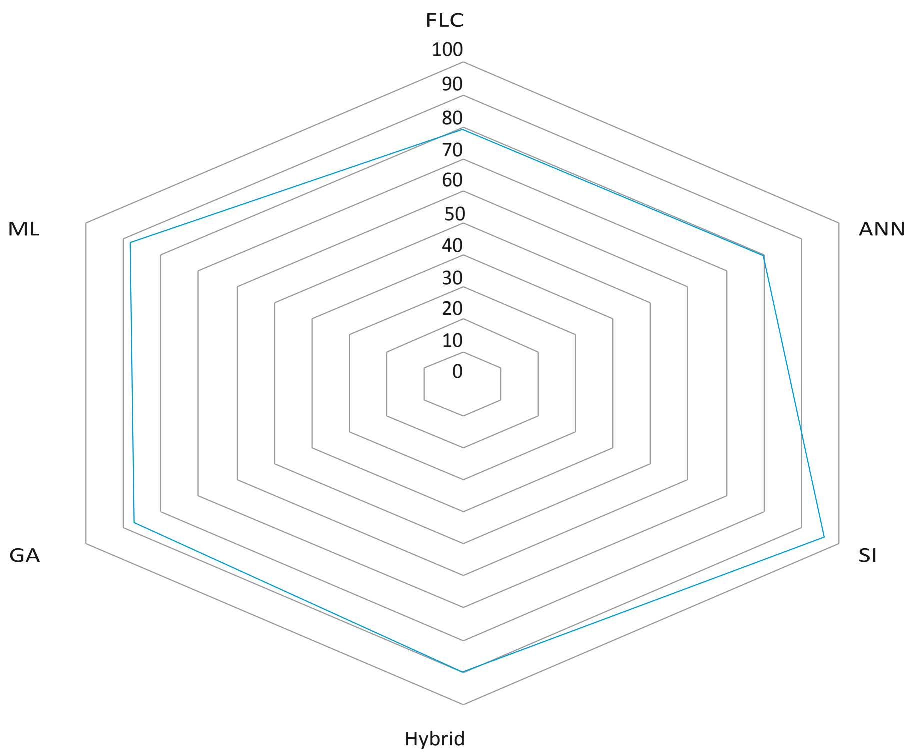

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Fig. 10. Performance of AI-MPPT techniques

TABLE XIII
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 full comparison of AI-based MPPT's performance indices, including tracking accuracy, tracking speed, convergence speed, capacity to track under PSC, and others, is provided in Table XIII. Older AI-based MPPT algorithms like FLC and ANN are shown to perform rather poorly in terms of convergence speed and their capacity to track under PSC. A continual periodic tuning operation is needed in the converter switch to track MPP under PSC or a rapid change in irradiance. To properly build an ANN-based MPPT with high accuracy, difficulty in training, and higher time consumption, a large dataset for ANN is needed. For FLC, it is challenging to precisely generate its fuzzy rules, and it is unable to actively learn from the dynamic environment, leading to undesirable performance. Due to their more recent architecture, SI, hybrid GA, and ML, in contrast, demonstrate greater speed and tracking proficiency even under PSC. which combines the advantages of conventional HC MPPT and the latest advancement of AI.

IV. SIMULATION RESULTS

A. Simulation Setup and Configuration

An thorough simulation based on MATLAB/Simulink R2020a is carried out to validate and compare the performance of AI-based MPPT approaches. The simulation setup aims to analyze, assess, and research the dynamic MPPT under PSC behavior. Each AI-based MPPT's searching procedure is compared to the ideal MPP's. The block diagram shows the simulation environment in a stand-alone solar power plant, as shown in Fig. 11. The SunPower SPR-305E-WHT-D PV module accepts inputs with different sun irradiances Ee and T. To imitate the real-world setting, it is simulated under PSC. In order to produce the best possible voltage and current for MPP, a 5 kHz DC-DC boost converter with insulated-gate bipolar transistor (IGBT) switching devices is created.

To convert optimum solar MPPT of DC output to AC output in supplying AC for the three-phase balanced resistive load RL, a DC-AC converter (inverter) based on synchronverter topology is used. To compare the tracking capabilities of FLC, ANN, SI, hybrid, GA, and ML for MPP under PSC, which is validated as indicated in Table XIV, the variable that has been altered is the MPPT controller. The simulation does not contain more new techniques due to their dynamic development and ever-evolving algorithms. To investigate the MPPT capability in PSC and typical circumstances with constant irradiance and temperature, two case studies have been conducted. To assess the optimal MPPT output, power is output at the DC output of the DC-DC boost converter. The mimicry then, as shown in Table XIV, results are validated and compared.

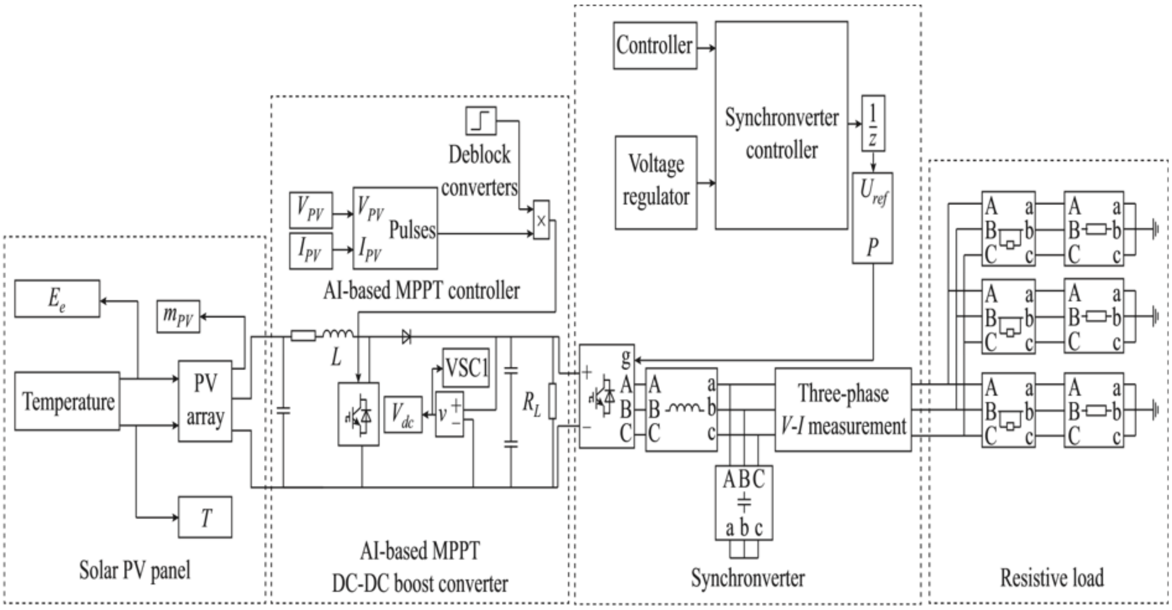


Fig. 11. MATLAB/Simulink simulation for comparison of AI-based MPPT.

TABLE XIV

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

The I-V and P-V characteristic graphs for solar panels are displayed in Fig. 12 under standard test conditions (STC) at 25 °C and 1000 W/m2 of solar radiation. The I-V and P-V characteristics are shown in Figure 12(a) when the irradiance fluctuates and the temperature stays at 25 °C. The I-V and P-V characteristics, on the other hand, are shown in Fig. 12(b) when the temperature fluctuates and the irradiance is constant at 1000 W/m2. A solar power system's non-linear I-V and P-V output is the primary driver behind an AI-based MPPT's search for MPP under various irradiance and temperature conditions.

B. PSC Analysis

By simulating PSC for the inputs of the solar panel, PSC analysis is carried out. The current is changed to allow several peaks in the P-V curves in order to replicate PSC. Additionally, it is looked into how dynamic irradiance changes can lead to MPPT failure. The look-up table is used to automatically alter the solar cells' current source. It is possible to partially shade some cells since the PSC effects on the solar module are taken into account. The occurrence of partial shadowing due to dirt, leaves, clouds, trees, and other impediments that block the sun is a typical occurrence in the real world. The performance of the AI-based MPPT under PSC for local MPP and GMPPT is shown in Figure 13.

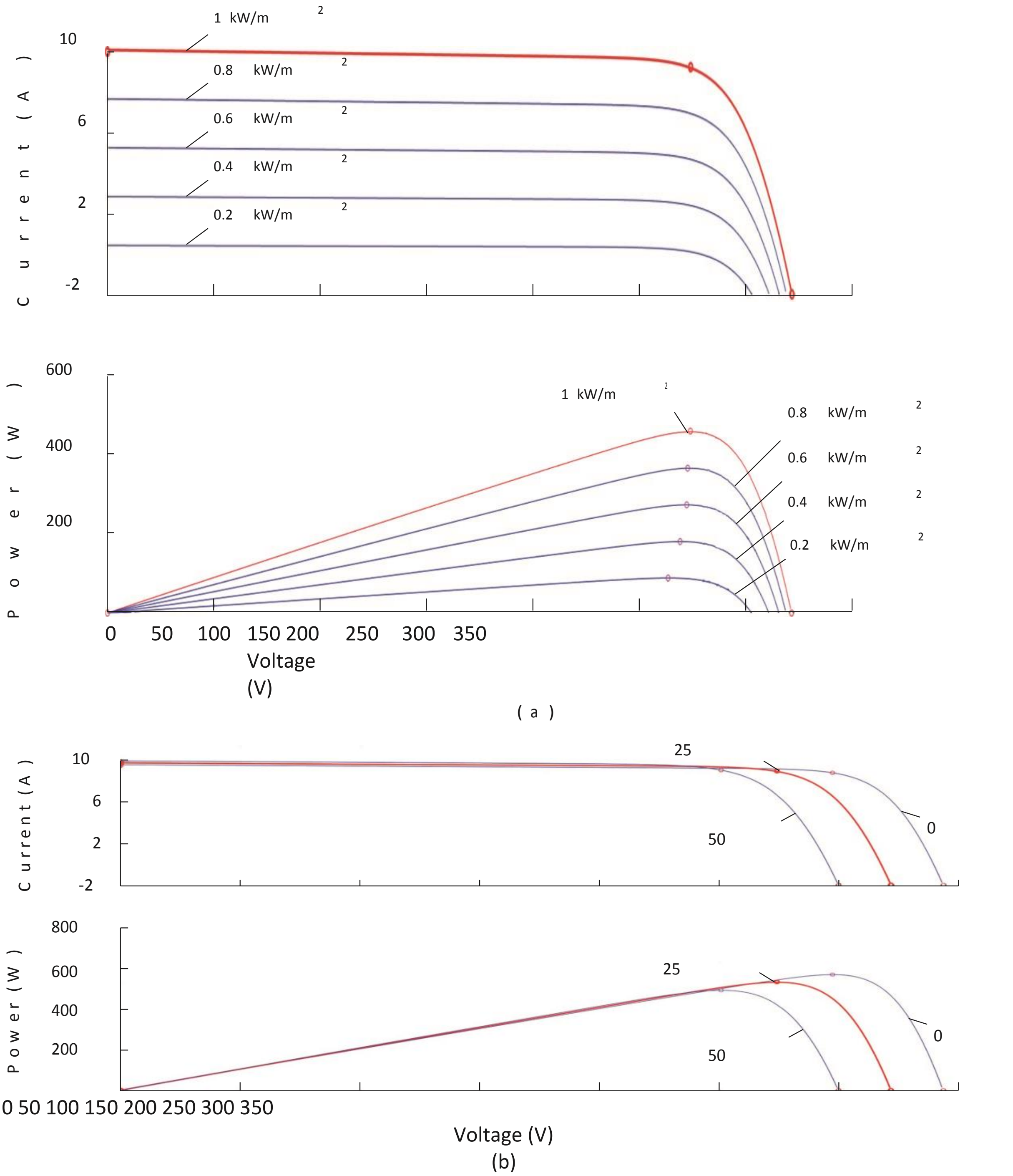


Fig. 12. *I-V* and *P-V* curves of solar panel under STC. (a) With constant temperature at 25°C and varying irradiance. (b) With constant irradiance at 1000 W/m^2 and varying temperature.

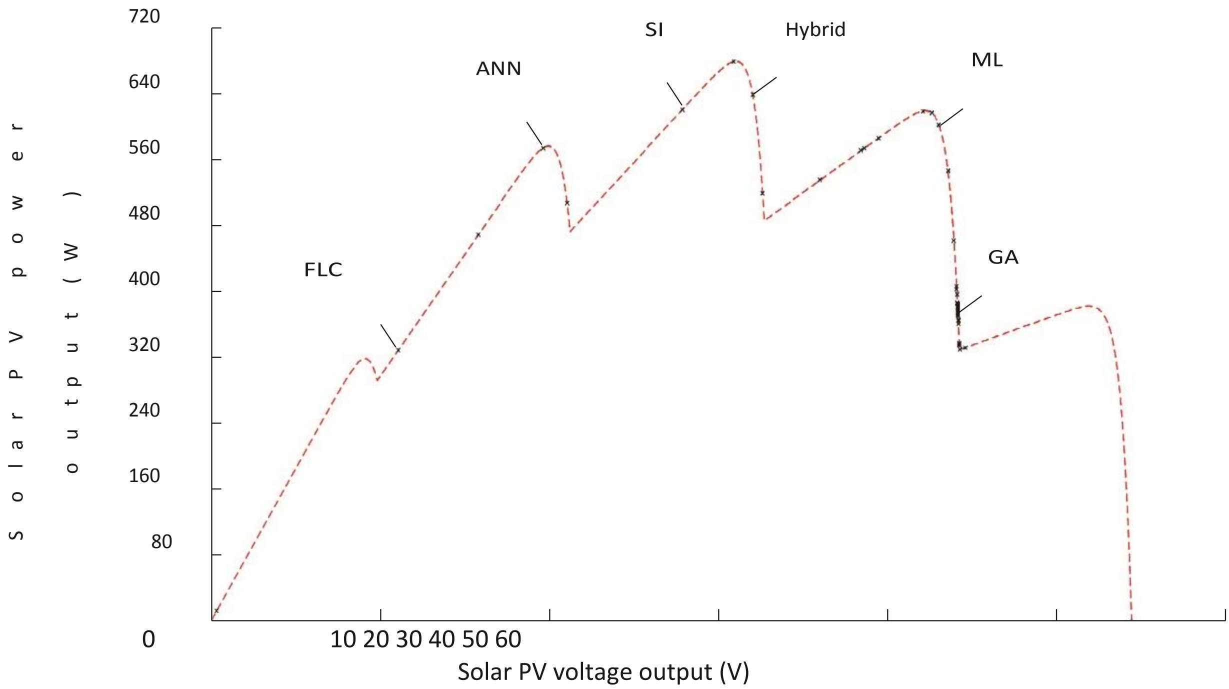
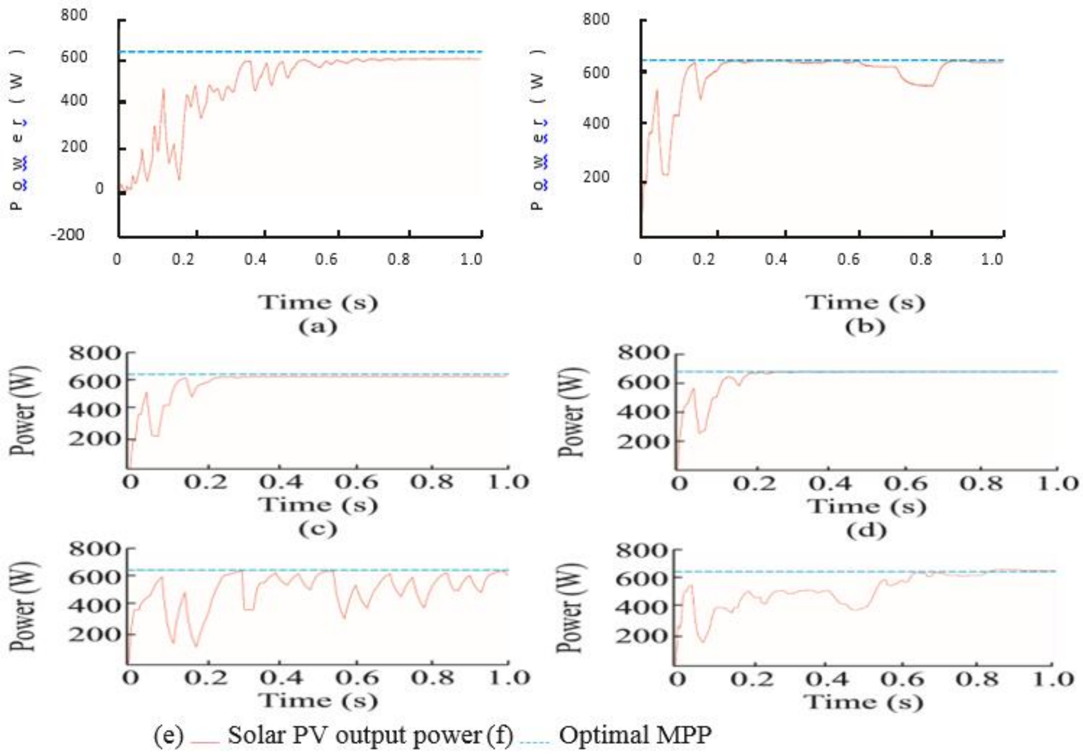


Fig. 13. Local MPP and GMPPT performance for AI-based MPPT under PSC.

It goes without saying that by following GMPP, the maximum output of a solar power system, SI and hybrid MPPT are operating at their best. This is due to algorithm optimization, population searching capability, and algorithm combination. While GA tracks the local MPP with some steady-state oscillations, ML and ANN are also functioning well. However, due to its slow transient reaction and inability to follow GMPP, FLC's performance is generally subpar. The local MPP traps it, which lowers the efficiency of power conversion.

C. MPPT Ability

Simulated tracking performance of AI-based MPPT controller for MPP under continuous illumination. Different algorithms' MPPT capabilities are shown in Figure 14(a)–(f). The blue dotted line is the ideal MPP for average temperature and irradiance, or about 650 W. As the AI-based MPPT tracks and advises MPP to extract the most power from the solar power system, the red line shows the output power of the solar power system. With the exception of FLC, it is seen that the performance of AI-based MPPT is comparatively satisfactory.



(e) ___ Solar PV output power (f) ..... Optimal MPP

Fig. 14.MPPT ability of different algorithms. (a) FLC. (b) ANN. (c) SI. (d) Hybrid. (e) GA. (f) ML.

D. Comparative Analysis and Validation of Results

In terms of MPPT time, steady-state oscillation at MPP, and the capacity to withstand the negative effects of PSC or changing irradiance, which occur at about t =0.7 s, Table XIV summarizes and compares AI-based MPPT approaches. Indicators of FLC's poor performance include increased tracking times for MPP with high SSE and PSC-affected MPP. However, SI and hybrid-based MPPT deliver satisfactory performance under PSC with the shortest tracking time, lowest SSE, and least amount of disturbance. These analyses align with Table XIII and the conclusions from previous studies and literature on AI-based MPPT. The outcomes of the simulation and the conclusions from the literature review are mutually validated. Nevertheless, different contexts and applications lead to various AI-based MPPT selections. Hence,V. Based on the design needs and criteria, it is advised to select the most appropriate AI-based MPPT.

V.DISCUSSION

Each algorithm has advantages and disadvantages that have been clearly demonstrated by the thorough comparison and analysis of several AI-based MPPT. The designer's preference exclusively determines the algorithm to be used. Vin,pv and Iin,pv are typically the input parameters of MPPT and are obtained via voltage and current sensors. Then, Pin,pv is calculated using the formula Pin,pv =Vin,pv Iin,pv. However, in order to train AI, it needs information on sun irradiance, temperature, metrological data on humidity, and shade. Some MPPT techniques use temperature and irradiance to determine MPP [91]. AI is used to forecast current and voltage while accounting for the MPPT's input variability and the nonlinear relationship between I-V and P-V. Using past data will enable the model to more accurately predict the voltage selected by MPPT.

Although it takes less time to attain MPP, too much oscillation around MPP prevents MPP from being reached [92]. An abrupt change in irradiance is required as an input to examine the output of MPPT and determine whether it is in response to the swift changes in input [93]. A standardized test called EN 50530 [31] uses triangular waveforms of irradiance with various ramp gradients to assess the effectiveness of MPPT. Rapid change or PSC situations are also utilized to assess the MPPT's performance and reaction. Typically, the highest sun irradiation level is at 1000 lux, and the temperature is 25 °C in an MPPT testing setting.

The search for GMPP under PSC or under conditions of variable irradiance and temperature is a crucial component of AI-based MPPT. The algorithm's inability to find GMPP may be the reason why MPPT failed. It won't be able to achieve the best power output because it will be trapped at the local MPP. In general, SI methods are founded on looking for the best possible answer within the search space. For ACO [94], SMO (spider monkey optimization), CS, and FA, the acting players can be compared to an ant, a monkey, a cuckoo, or a firefly. By establishing a range, the conditional algorithm determines when the maximum power has been reached. The fluctuation of an operation point is what causes the oscillations, dispersed solar insolation that is not uniform and the algorithm's failure to recognize the GMPP in the presence of numerous other local MPPs. The oscillation time, in terms of performance parameters, is the interval between changes until the output reaches steady state, or when oscillation stops. How quickly MPPT tracks the actual MPP is indicated by the tracking speed or convergence speed. On the other hand, is the output power or power tracked by MPPT.

Pout is equal to Vout Iout divided by PMPP, or VMPP IMPP. For the steady-state form without any oscillation, the settling time is necessary [95]. AI-based MPPT selection criteria are based on implementation complexity, required sensors, the capacity to detect multiple local maxima, response time, costing and its use, transient time, settling time, steady-state error, overshoot, and ripples in the PV panel output voltage [96]. The conventional or HC approaches typically fall short of tracking GMPP under PSC. During the steady state, they oscillate around MPP, and tracking MPP takes more time with less success. AI-based MPPT solutions, on the other hand, have none of the disadvantages of traditional MPPT, but they are more expensive, involve complicated calculation, and require modeling. Overall, hybrid techniques the finest of all algorithms since they mix and integrate many algorithms, helping to mutually cancel open issues [31]. The comparison, assessment, and analysis of simulation and experimental outcomes is typically used to validate experimental results.

An inverter serves as the primary media contact between a solar power system and the power grid in addition to the MPPT. In order to convert DC to AC and serve as an anti-islanding protection device, an effective inverter is crucial [97]. Without negatively impacting the PV DC output to AC, an enhanced inverter maximizes power extraction [98]. It is advised to use a proportional integral derivative (PID) controller to control D output to pulse width modulation from MPPT approaches because of its adaptability, stability, least overshoot, characteristic of fine-tuning, least output voltage rise time, and performance optimization [85], [99]. In general, grid-connected (ongrid), freestanding (off-grid), and other specialized applications, such as solar vehicles, solar lamps, water heaters, DC motors, and water pumps, can benefit from AI-based MPPT algorithms. Connected to the electric grid is on-grid. utility grid while off-grid is directly connected to loads.

VI. RECOMMENDATIONS AND FUTURE RESEARCH DIRECTION

The goal of this section is to suggest applications for AI-based MPPT in the solar power system and their potential future study topics. Since the most recent AI-based MPPT approaches have higher performance and stability, the traditional MPPT techniques are being phased out. The most recent developments in ML and DL will determine how the AI-based MPPT develops. The complexity of the algorithm and the capacity to search for GMPP are the key obstacles. It is advised to use the traditional MPPT, such as open current, open voltage, P&O, and IC, for straightforward, inexpensive applications that don't call for great performance. The AI-based MPPT algorithms are suggested for their superior performance, accuracy, and convergence speed in order to resolve, optimize, and anticipate the non-linearity of the PV cell without remaining at local MPP under PSC. GA is quicker than traditional approaches for the kind of EA, but it frequently stalls at local minima. Higher compute resources are needed for the improved GA, and several parameters need to be tuned. DE, in comparison, works quickly and accurately without using any probability distribution. They are advised for straightforward and affordable applications for the traditional MPPT, such as open current, open voltage, P&O, and IC.

This doesn't call for exceptional performance. The AI-based MPPT algorithms are suggested for their superior performance, accuracy, and convergence speed in order to resolve, optimize, and anticipate the non-linearity of the PV cell without remaining at local MPP under PSC. GA is quicker than traditional approaches for the kind of EA, but it frequently stalls at local minima. Higher compute resources are needed for the improved GA, and several parameters need to be tuned. DE, in comparison, works quickly and accurately without using any probability distribution.

However, with some suboptimal settings, its population may stagnate. PSO, which is also straightforward to implement in hardware and independent from the installed system, has the maximum performance when taking into account several optimum positions to update the population [100]. However, it often converges too soon and might become stuck at local minima. The design decision, application, and design requirement all influence the selection of an AI-based MPPT approach. PSO is advised for the best performance because to its maturity compared to GA. While GA is quicker than traditional approaches, DE is superior to them in terms of accuracy and calculation time. Because GA and DE approaches are able to solve multi-objective problems, they can track the GMPP under PSC. For the programs that are ensitive to the power fluctuation such as household appliances, motor, extreme low voltage (ELV), Due to their rapid convergence rates, CS and radial movement optimization (RMO) are advised for light sources, electro-heat equipment, electrical machines, computers, and other electronic devices in order to settle at GMPP with little variation.

Voltage fluctuation is described theoretically as a continual shift in voltage when equipment or appliances that require a higher load are frequently operated. An AI-based MPPT controller's parameters include design complexity, tracking GMPP capability, cost-effectiveness, PV panel dependency, prior training requirement, dataset requirement, convergence speed, analogue or digital architecture, required sensory data, periodic tuning, stability, SSE, efficiency, and TET. When creating AI-based MPPT, it is important to strike a compromise between algorithm complexity and performance. In general, the proposed algorithm becomes more sophisticated the higher the performance of AI-based MPPT. TET and computation time are impacted as a result. The capacity to track GMPP is one of the most important features of the AI-based MPPT. Real-world solar panel trials also lack conclusive data. Studies on a general design path for a standardized AI-based MPPT are lacking. In order to function as a DCDC-AC converter in a grid-connected solar power system and to provide the greatest power extraction and virtual inertia simultaneously, MPPT must be integrated with synchronverters [101]. The AC grid side of the solar power system is guaranteed to stabilize the grid voltage and frequency output [102]. Low grid frequency and voltage amplitudes provide high power efficiency.

VII. CONCLUSION

We offer a thorough analysis of well-liked AI-based MPPT methods for solar power systems. When reducing the effects of PSC, they are made to follow GMPP rather than local MPP. The algorithm structure, cost, platform, input parameters, tracking speed, oscillation accuracy, efficiency, and applications of each technique are compared. The FLC, ANN, SI, hybrid, GA, ML, and other upcoming techniques are generic categories for AI-based MPPT techniques. In general, even under PSC or quick changes in irradiance, they all show good convergence speed, little oscillation at steady state, and accurate tracking. However, compared to traditional MPPT techniques, the majority of these techniques are more expensive, difficult, and data-intensive to design. Comparing other emerging and newer technologies to FLC, ANN, and GA Due to their more recent architectures with adaptive learning capabilities, completely digitalized systems, and fewer unresolved concerns, algorithms like hybrid, SI, ML, and DL are also advised. As a result of their outdated architecture, need for recurring tuning, and inability to track MPP under PSC, ANN and FLC are not as desirable. This review is anticipated to give a thorough understanding of the most recent developments in AI-based MPPT approaches for use in solar power systems.

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