SVU-International Journal of Engineering Sciences and Applications (2023) 4(2): 291-302
Print ISSN 2785-9967 | Online ISSN 2735-4571
DOI 10.21608/svusrc.2023.212592.1128

Comparative Study on Conventional and Advanced Techniques MPPT Algorithms for Solar Energy Systems

Montaser Abdelsattar[1], Hamdi Ali Mohamed[2], Ahmed Fathy Abuelkhair[1,]

Abstract: The importance of an efficient maximum power point tracking (MPPT) algorithm for a photovoltaic (PV) power generation system is undebatable. It enables the system to achieve its maximum throughput in power generation and generate the best revenue under given meteorological conditions. The non-linear relationship between output power and output voltage of a solar system gives rise to the presence of maximum power point (MPP) at the power voltage curve, which needs to be tracked well through a proficient algorithm. **This paper** presents a comprehensive overview of MPPT algorithm's basic operation and the options available for its practical implementation. At first, it delineates some popular conventional MPPT algorithms including the perturbation and observation (P&O) method, incremental conductance (IC), and ripple correlation control (RCC) method. Later, the possibility of integrating state-of-the-art intelligent techniques such as fuzzy logic control (FLC), artificial neural network (ANN), particle swarm optimization (PSO), supervised, unsupervised, and reinforcement machine learning (ML) algorithms for MPPT purposes has been investigated. Operational strategies, advantages, and drawbacks of each algorithm have also been discussed. Consequently, advanced intelligence-based algorithms are found to be outperforming their conventional counterparts in terms of tracking precision, convergence speed and fluctuations at steady state. However, computational and implementational complexities associated with the most intelligence-based methods are motivating researchers to investigate hybrid solutions merging benefits of both conventional and advanced algorithms.

Keywords: Maximum power point tracking (MPPT); Perturbation and observation (P&O); Fuzzy logic control (FLC); Machine learning (ML); Artificial neural network (ANN)

Received: 29 May 2023/ Accepted: 12 July 2023

Corresponding Author: Ahmed Fathy Abuelkhair, ahmed.fathy@eng.svu.edu.eg

Montaser Abdelsattar, Montaser.A.Elsattar@eng.svu.edu.eg; Hamdi Ali Mohamed, hamdihesha@yahoo.com

1. Electrical Engineering Department, Faculty of Engineering, South Valley University, Qena 83523, Egypt

2. Department of Electrical and Computers Engineering, El-Minia High Institute of Engineering and Technology, El-Minia, Egypt

1 Introduction

Maximum power point tracking (MPPT) algorithms and their efficiencies are a significant debate in the domain of solar energy generations. All over the world, photovoltaic (PV) modules have been widely installed to convert solar power into electric power. Solar cells inside PV modules are predominantly made up of semiconductor material which inherently exhibits non-linear behavior. This non-linearity of solar cells implies the presences of a maximum power point (MPP) at power-voltage plots as depicted in Fig. 1.

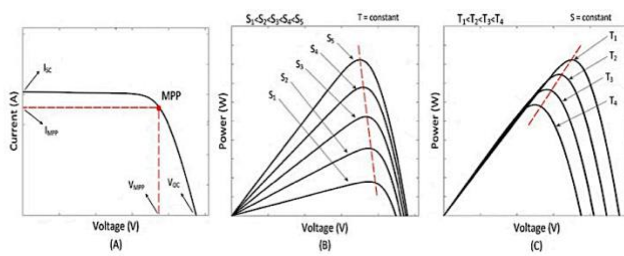

Fig. 1 (A) V-I Characteristics of a classical solar cell; (B) power–voltage plot when the temperature (T) is kept constant; (C) power–voltage plot when solar radiation (S) is kept constant [1].

However, this MPP is susceptible to various external factors including the PV module's temperature, area of a solar cell, solar irradiance and loading conditions. In varying circumstances, PV modules would generate maximum power only if they have been made adaptive to this MPP. To serve this purpose, a myriad of maximum power point tracking (MPPT) methodologies for both isolated and grid-connected solar systems had been suggested in the past [1].

MPPT is usually performed through an algorithm that continuously regulates the impedance observed by the array of solar cells. By adjusting this impedance, MPPT algorithms ensure that the solar system is performing at or in proximity to MPP under all possible scenarios and varying circumstances. Consequently, the solar system would generate maximum electrical power [2]. MPPT algorithms are typically executed by MPPT controllers which provide control signals to the system inverters specifically DC-DC converters. In isolated solar systems, such DC-DC converters are also responsible for storing output surplus energy onto battery banks. While in grid-connected solar systems, DC-DC converters are required to transfer PV generated output power to the main grid. Further, a specifically designed DC-AC inverter would also be required to transform bus DC power to grid AC power [3].

Block diagram of a typical PV solar system containing an array of solar panels, MPPT controllers, power electronic DC-DC converters, and output load is represented by Fig. 2. MPPT algorithm must be executed in real-time to account for the varying nature of relevant parameters namely temperature (T) and solar radiation (S). The control signal generated by MPPT controller could be the duty cycle (D) of DC-DC converter. So, MPPT controller should precisely be able to generate optimal D for DC-DC converter depending on the recent meteorological conditions [1].

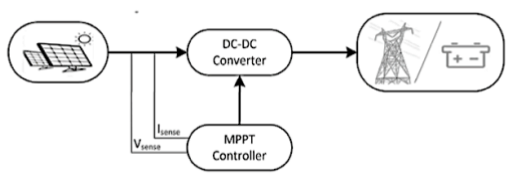

Fig. 2 Block diagram of typical PV solar system with MPPT controller [1].

Traditionally, the MPPT function had been achieved through measurement and calculation-based strategies. For instance, perturbation and observation (P&O) method, incremental conductance (IC) and ripple correlation control (RCC) were popular MPPT techniques in past. But these conventional methods were unable to achieve adequate performance especially under partial shading conditions or abrupt change in solar irradiance, where the presence of multiple local MPPs can abstain the MPPT algorithm from locking at global MPP (GMPP). Consequently, the integration of machine learning (ML) and artificial intelligence (AI) has also been welcomed here to overcome the limitations of conventional methodologies. Intelligence-based advanced algorithms are capable of self-learning, adaptable, robust, and more efficient in terms of tracking precision, transient response, convergence speed and fluctuations/error at steady-state [4]. Recently, to overcome the high computational and implementational cost of Intelligence-based advanced algorithms, researchers are suggesting hybrid solutions.

The next section of this paper attempts to categorize some of the available MPPT algorithms into four classes based on their operational principal: Measurement-based, calculation-based, intelligence-based, and hybrid algorithms. Some of the popular algorithms out of each category are being delineated in successive sections. The purpose is to highlight functional differences with advantages and disadvantages of each scheme. This paper provides its readers the complete technical understanding and guidelines to choose the best MPPT option according to one's customized specifications. Also, it encourages the researchers to experiment with hybrid solutions by merging positive aspects of different algorithmic combinations.

2 Categorization of MPPT Algorithms

An extensive amount of research and developments has been carried out and s going on in this domain of MPPT algorithms. Many researchers came up with innovative and practical approaches to perform this significant MPPT process in an effective and proficient way. The performance of a certain MPPT algorithm can be evaluated by considering parameters such as speed of convergence, precise tracking capability, cost efficiency, practical implementation, count of required sensors and design complexity [5]. This paper aims to categorize some of the available (conventional and advanced) MPPT algorithms and compare their performances based on the above-mentioned parameters. MPPT algorithms can broadly be categorized as shown in Table 1.

3 Measurement Based Algorithms

3.1 Perturbation and observation method (P&O)

This MPPT algorithm has widely been deployed in commercial and industrial PV solar systems. Also, it is quite famous in the research community and used as a foundation of many other advanced MPPT algorithms. The basic operation of a P&O method (as its name applies) is disturbing the operating point of voltage (V) after a constant period. Then, resulting variations in output power of PV array are observed. Depending on these observations, direction of further change in V is adjusted. For instance, if output power of PV array is increasing after perturbing V in a particular direction, it applies that operating point is drifting towards MPP, and this direction of change in V must further be adopted. In contrast, if the output power of PV array starts decreasing after perturbation, then the direction of change in V must be reversed [2,6]. Figure 3 represents a flowchart representation of the P&O method.

Table 1: Categories of MPPT algorithms

Categories	Description	Examples
Measurement based algorithms	These algorithms work by measuring certain parameters such as electrical properties (Voltage and current) of solar cells and characteristics of sunlight. Then, this measured the data is being processed and compared with previous measurements or predefined parameters of the MPPT algorithm.	▪ Perturbation and observation (P&O) method ▪ Perturbation and observation (P&O) method ▪ Open circuit voltage (OCV) method ▪ Short circuit current (SCC) method ▪ Pilot cell algorithm ▪ Temperature algorithm ▪ Look up table ▪ Load current or load voltage maximization ▪ The only current of PV ▪ PV output senseless control
Calculation based algorithms	These algorithms rely on specific equations and calculations to determine MPP.	▪ Incremental conductance (IC) method ▪ Ripple correlation control (RCC) ▪ State space based MPPT method ▪ Linear reoriented coordinates method (LRCM) ▪ Sliding mode control method ▪ Parasitic capacitance method
Intelligence based algorithms	They deploy state-of-the-art data science, machine learning (ML) and artificial intelligence (AI) concepts.	▪ Fuzzy logic control (FLC) ▪ Artificial Neural Network (ANN) ▪ Particle swarm optimization (PSO) ▪ Artificial bee colony optimization ▪ Supervised ML algorithms such as Decision Tree (DT) and Random Forest (RF) regressors ▪ Reinforcement ML algorithms ▪ Metaheuristic algorithms
Hybrid algorithms	In these techniques, algorithms from above three categories are being combined to enhance overall performance metrics.	▪ OCV/P&O ▪ SCC/P&O ▪ FLC/P&O ▪ PSO/P&O ▪ ANN/P&O ▪ ANN/fuzzy

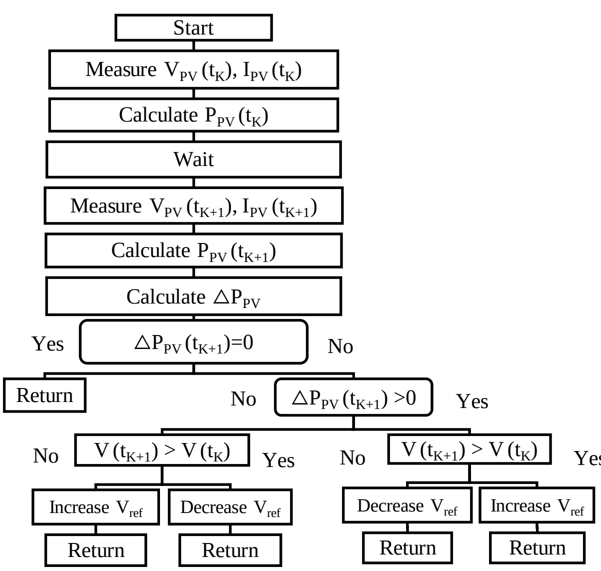

Fig. 3 Flowchart representation of P&O methodology

On the downside, its convergence time is undeterminable, and it tends to oscillate around MPP during its steady state [1]. Moreover, its accuracy suffers during rapidly altering meteorological conditions. Further, step size of perturbation is an important consideration as it impacts the overall performance of P&O algorithm [6-7]. The main advantage of this algorithm is its cost-effectiveness and straightforward implementation [6-7].

3.2 Open circuit voltage (OCV) method

Study of the physical properties of solar cells reveals that voltage at maximum power point (V_{MPP}) varies linearly with its open-circuit voltage (V_{OC}).

Mathematically, this relation can be represented as:

$$V_{MPP} = K_{OC}V_{OC}\ (K_{OC} < 1) \tag{1}$$

Where K_{OC} is called constant of proportionality, whose value is estimated by conducting experiments and continuously measuring above two voltages at different meteorological conditions [8].

Hence, V_{OC} is sampled at regular time intervals after detaching the PV system from its load. Then, V_{MPP} is calculated through the above equation by using measured V_{OC}. Also, K_{OC} needs to be evaluated time-to-time for its optimality in given circumstances and updated accordingly [1].

However, the simplicity of this MPPT algorithm comes at a price. Sampling of V_{OC} at regular time intervals causes considerable power loss as actual load is disconnected from the PV array at the time of sampling. Moreover, the sampling period (time between two neighboring sampling instances) is quite crucial parameter. If it is too short means sampling is done quite frequently, then power loss due to sampling activity would be sufficient. On the other hand, if it is too long then V_{MPP} will continue following the previous sampling value of V_{OC} until the new sampling instance arrives. Consequently, any meteorological change during this time interval wouldn't be tracked [9]

3.3 Short circuit current (SCC) method

Like OCV methodology, a linear relation can also be observed between current corresponding to maximum power point I_{MPP} and the short circuit current I_{SC} of PV system. The mathematical representation of this relation would be:

$$I_{MPP} = K_{SC} I_{SC} \; (K_{SC} < 1) \tag{2}$$

Where K_{SC} is constant of proportionality. The basic SCC operation is quite identical to the previously described OCV methodology. Therefore, they also possess similar advantages and drawbacks as mentioned above [10].

4 Calculation Based Algorithms

4.1 Incremental conductance (IC) method

By observing the power-voltage (P-V) plot of a PV system, it can easily be perceived that slope of the curve becomes zero at MPP. This methodology exploits this fact for MPPT purposes. The basic operation here is to monitor output parameters of PV array such as voltage and current. Then, the MPPT controller deploys this information and estimates instantaneous conductance and incremental conductance after performing calculations on the given information [2]. Mathematically, it can be represented as follows:

$$\frac{dP}{dV} = \frac{d(V \times I)}{dV} = 1 + V\frac{dI}{dV} \Rightarrow \frac{1}{V} \times \frac{dP}{dV} = \frac{1}{V} + \frac{dI}{dV} \tag{3}$$

Output power of PV system is differentiated over output voltage. It yields into two important terms namely instantaneous conductance 1/V as well as incremental conductance dI/dV. To perform MPPT, these two types of conductance are calculated and compared. The operating point where these two types of conductance become identical is basically our targeted MPP. Hence, slope of output power plot of PV system would be zero at MPP, incrementing while moving left to the MPP and decrementing while drifting right to the MPP [2]. Figure 4 represents a flowchart of the IC method, this methodology outperforms other MPPT techniques in terms of tracking precision and fluctuations during steady-state. Moreover, it shows improved dynamics and adaptability especially under swiftly varying meteorological conditions [1,12]. However, the practical implementation of this MPPT algorithm is quite complex and expensive as it requires sophisticated sensors and control circuitry [13].

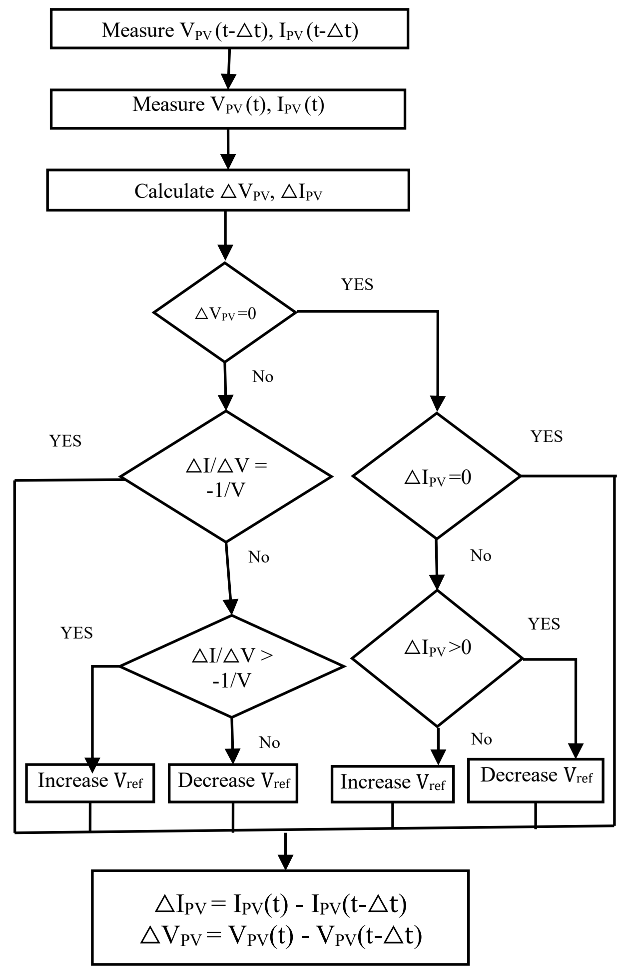

Fig. 4 Flowchart representation of IC methodology.

4.2 Ripple correlation control (RCC)

As PV system is further connected to DC/DC converter, whose switching activity causes ripples in output voltage and current signals of PV arrays.

RCC is a technique where this rippling effect is being utilized for MPPT purposes. Time derivative of PV output power is correlated with the time derivative of either PV output current or PV output power. To achieve MPP, power gradient must be forced to become zero. When operating point is located at the left side of MPP, then $V < V_{MPP}$ or $I<I_{MPP}$, implying that, operating point should be directed towards the right. On the other hand, when $V > V_{MPP}$ or $I > I_{MPP}$, an operating point needs to be directed towards left [1].

RCC algorithm can practically be implemented by simple and economical analog circuitry. It can rapidly and precisely track MPP under changing levels of solar irradiance. Also, it operates without any prior knowledge of PV system properties, which implies that this algorithm is adaptable to different types of PV systems. However, convergence speed of RCC algorithm is restricted by switching activity of DC/DC converter as well as gain of its own circuitry [13].

5 Intelligence Based Algorithms

Last decade, the application of data science, machine learning (ML) and artificial intelligence (AI) is booming at every walk of life. Many researchers came up with innovative and advanced AI algorithms for MPPT protocol of PV systems. Especially, integrating AI techniques for MPPT is inevitable during partial shading conditions (PSC), where power-voltage plot of PV panel has multiple local MPPs and only one GMPP as demonstrated by Fig. 5. Conventional MPPT algorithms would get trapped in local MPPs rather than tracking actual GMPP in such situations. On the other hand, intelligence-based algorithms would efficiently track GMPP while ameliorating overall performance of the system in terms of convergence speed and fluctuations around MPP at steady state. However, AI-based algorithms have high implementational and computational complexity. As a remedy, many hybrid algorithms have also been developed to incorporate plus points of both conventional and intelligence-based algorithms. This section presents some of the state-of-the-art AI-based algorithms [4].

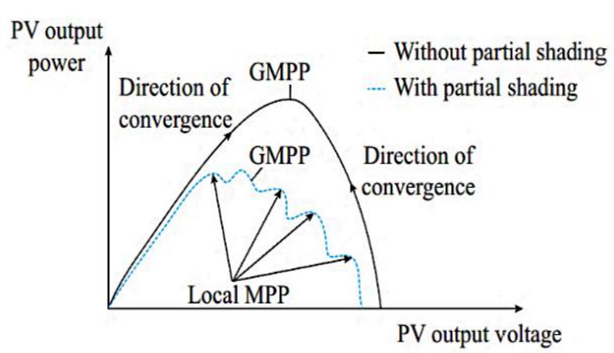

Fig. 5 GMPP, local MPPs at P-V plot of PV array with/without partial shading [4].

5.1 *Fuzzy logic control (FLC)*

The process of MPPT can also be achieved through an intelligent scheme called fuzzy logic, presented by Fig. 6. The basic operation has three levels:

➢ Fuzzification: It takes numerical variables as inputs and transform them as membership function. Here, the inputs and outputs of the system have a linguistic correlation, which is called 'Rules'. Each rule generates a fuzzy set as output. The efficiency of conversion can be increased by deploying multiple rules simultaneously [13]. In this way, fuzzy variables are obtained from real variables. The most used curves for fuzzification process are Gaussian, Triangular and trapezoidal [1].

➢ Aggregation: In this process, fuzzy sets generated by different rules are merged to achieve a single fuzzy set [13]. In case of ambiguous and inaccurate data, optimal decision can be made through single or multiple criteria methodologies [1]. Some of the methods used for aggregation process are Somme–Prod, Max– Min and Max–Prod [2].

➢ Defuzzification: This is a reverse step of the first procedure of fuzzification. As a deterministic control signal is required to operate DC-DC converter rather than fuzzy signal. The finalized fuzzy set is transformed back into numerical variables, which further produces a suitable analogue signal for converter. Mean of Maxima (MOM), Max Criterion Method (MCM) and Centre of Area (COA) are most popular defuzzification methodologies [2].

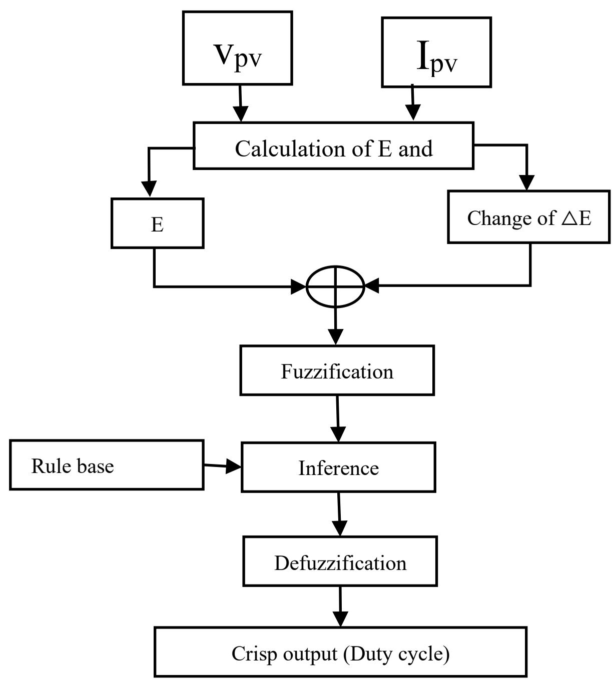

Fig. 6 Flowchart representation of FLC.

This algorithm can track MPP equally well with ambiguous and imprecise inputs. Implementation and designing is convenient as it doesn’t require a perfect mathematical model to work properly. Moreover, it has super command on tackling non-linearities [13]. Further, it shows satisfactory performance in terms of response rate and oscillation around MPP. However, varying solar irradiance can give rise to drift problems [14]. Fuzzy rules are difficult to derive as they impact system performance critically. It exhibits unsatisfactory performance under partial shading conditions [4].

5.2 Artificial neural network (ANN)

The Human brain has an intricate neural network, whose structure is mathematically modeled by ANN technique. Each cell of our nervous system comprises three components namely dendrites, the main body of cell and axon. Dendrites catch external signals from neighboring cells and transmit them to the cell body. The cell body processes these signals by performing certain operations. Finally, the axon passes the processed signals to the next cells. Hence, a neural network mainly receives, processes, and transmits signals. ANN is a similar mathematical model, which can be trained at first place, and then it processes given information with respect to its prior training. Cognitive patterns have their own importance in this process, Fig. 7 represents a flowchart of ANN-based MPPT [1].

The most widely deployed structure of ANN is multi-layered feedforward back propagation, which contains three layers: input layer, hidden layer, and output layer. The number of nodes depends on the system requirement. Nodes are linked together by edges, whose weights are adjusted during training session [1].

To track MPP, ANN is forced to learn the non-linear relationship between output power and output voltage signals of PV array. It grasps certain inputs such as temperature, input voltage signal, input current signal, solar irradiance, and other climate parameters. Then, ANN adjusts its weights during training session to imitate the behavior of a PV system. Later, the trained ANN is evaluated using test dataset and resulting errors are further used to improve the ANN performance [15, 16]. Plenty of training methods are available such as Newton method, Gradient descent, conjugate gradient, Levenberg–Marquardt algorithm, and Quasi Newton method [1].

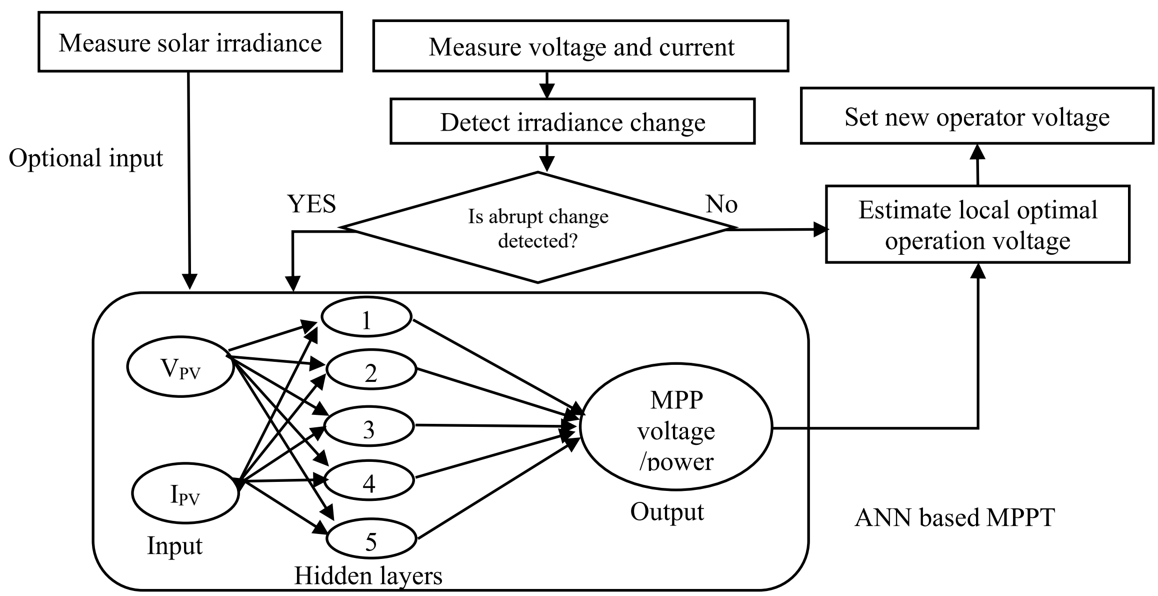

Fig. 7 Flowchart representation of ANN-based MPPT.

ANN handles non-linearities of PV system with extraordinary accuracy. It doesn’t require any preliminary knowledge of system [4]. ANN can simultaneously be used for prediction of output power generated by solar systems in near future [17]. This algorithm has found to have a minimal transient period, rippling effect, and fluctuations around MPP at steady state under real meteorological conditions [18]. However, the requirement of gigantic dataset for complicated and time-consuming training processes is a major limitation. The model of PV panel directly influences the accuracy of MPP tracking. Equipment aging and environmental variations would periodically impose the need of tuning [4].

5.3 Particle swarm optimization (PSO)

The inspiration behind this algorithm is the swarming or social conduct of bird flocks or fish schools. PSO is an evolutionary swarm-intelligence (SI) methodology that deploys population-based stochastic variables and solves multi-dimensional optimization problems [13]. Here, all potential solutions, named as particles, are considered. Then, these particles chase the best position particle and wander around the multi-dimensional search space. So, the position of each particle of the population (swarm) is compared with local best and global best particle positions. Based on these comparative results, particles are directed inside search space to find optimal solution. In this way, PSO improves the solution gradually with every passing iteration of algorithm, Fig. 8 shows flowchart of PSO algorithm [4].

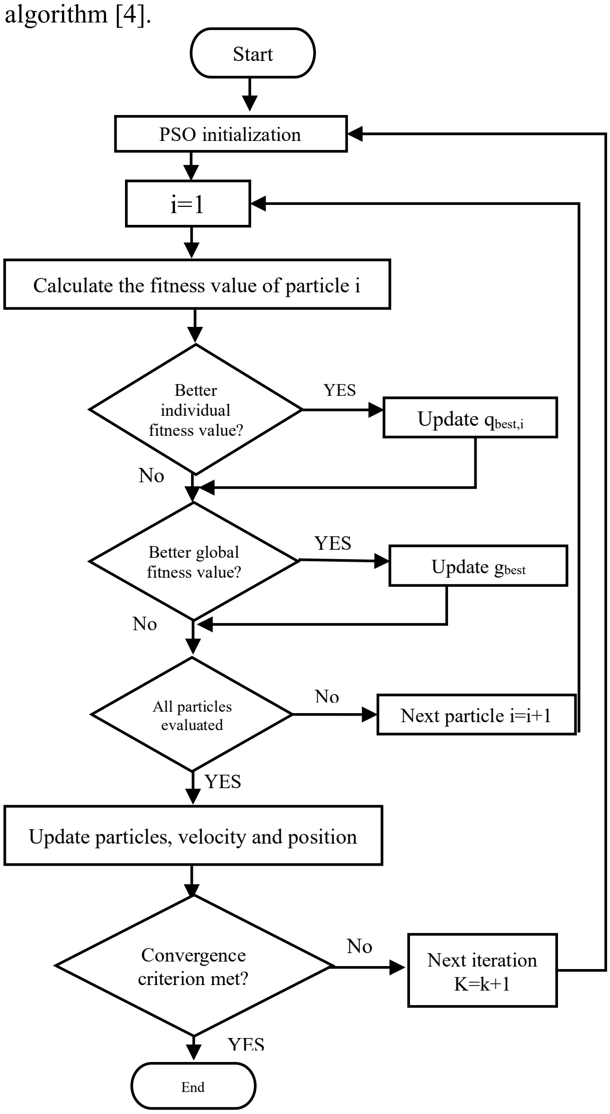

Fig. 8 Flowchart representation of PSO methodology.

PSO algorithm can further be combined with overall distribution (OD) for rapid detection of the rough GMPP area [19]. Similarly, a combination of PSO with Non-linear decreasing inertia weight technique has been suggested to ameliorate search operation of particles [20]. Another variant Discrete PSO (DPSO) has been discovered by researchers, which provides consistent outcomes as compared to original PSO, when fewer particles are involved [21].

Another famous SI-based algorithm is Firefly Algorithm (FA), which imitates the behavior of fireflies. It can also be successfully employed for MPPT purposes. Here, attractiveness is defined by the brightness of a firefly and being used as a parameter to converge into the best solution. Similarly, the well-known cuckoo search (CS) algorithm is also SI-based and inspired from reproduction approach of Cuckoo birds. They randomly search for a host nest to lay their eggs. Their search process for the best host can be modelled mathematically using optimization technique. Meanwhile, MPPT has also been achieved by other SI-based techniques such as modified cat swarm optimization (MCSO) and moth-flame optimization (MFO), reported by literature.

In general, SI-based algorithm doesn’t require a gigantic training dataset just like the case with ANN. It also provides lesser fluctuations around MPP, tracking precision and rapid convergence. Further, its implementation is also simple and uncomplicated. The main concern while using SI-based algorithms for MPPT purposes is system stability, as it involves huge random searching which also imposes the computational weight. Parameters selection is crucial to overall performance [4].

5.4 Supervised machine learning (ML) algorithm

Supervised ML model takes labelled (means input parameters and their respective output parameters) data as its input and tries to learn from it. The given labelled dataset is being divided into two portions, one is used for training of the model and the other is used for testing of the trained model. Then, this trained and tested model becomes ready to predict the unknown unlabeled data, as depicted by Fig. 9. Supervised learning basically has two types: classification where output is a discrete variable (binary or multi-class) and regression where output is a continuous variable. Examples of supervised ML algorithms include linear regression, logistic regression, nearest neighbor, gaussian naive bayes, decision trees, support vector machine, random forest and so on [22, 23].

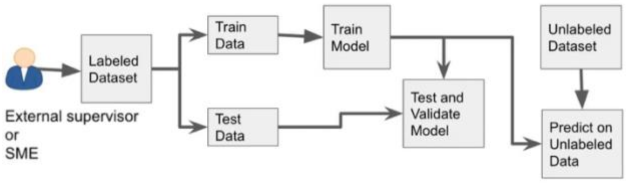

Fig. 9 Supervised ML algorithm [23].

Some cases of supervised ML being used for MPPT procedure have been included next in this section.

5.4.1 Decision tree (DT) regression ML algorithm

As its name suggests, DT model is a tree-structured system of conditional control statements, algorithm flowchart shown in Fig. 10 [25]. It basically splits the training dataset into smaller and smaller subsets, while simultaneously developing the corresponding decision tree in an incremental manner. Decision trees are a popular and practical technique of supervised learning, which can be deployed for both Regression and Classification problems (particularly decision-related problems). Some of the important terms are:

➢ Root Node: It is the top-most decision node, which represents the complete data sample and gets divided into further nodes.

➢ Decision Nodes: The interior nodes, which represent the features of training dataset and split further. Its branches demonstrate the decision rules.

➢ Leaf or Terminal Nodes: Bottom nodes which do not split any further and represent the outcome [24].

➢ Splitting: The division of a node into two or more child nodes.

➢ Pruning: This is exactly the opposite thing of splitting process. The child nodes emerging out of a decision node are being removed through Pruning [25].

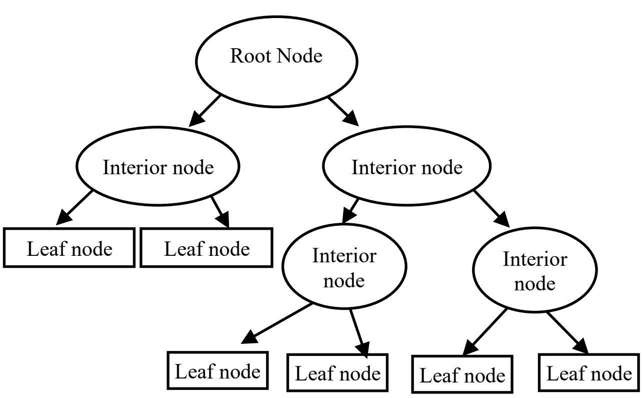

Fig. 10 DT Regression ML algorithm

To predict a particular data point, the algorithm runs through the complete decision tree by answering True/False questions at every node, until the leaf node arrives which represents the outcome. The same procedure is iterated multiple times to increase the accuracy of prediction. Decision trees are understandable and require minimal data cleaning and hyper-parameter tuning [24]. They can effectively handle complex and non-linear relationships between labels and features [25].

Recently, DT regression ML algorithm has been reported to perform MPPT efficiently in literature. As a first step, labelled data has been collected by using technical details specified in datasheets of a PV system. This data is being pre-processed for training and testing of DT regression model. Then, the trained DT model is used to predict the MPP for given situation of solar irradiance and temperature. Later, the duty cycle of boost converter is extracted accordingly from predictions. Simulation results have shown that their suggested approach is enabling PV system to be operated at MPP. They have claimed that DT based ML Algorithm is outperforming other competing methodologies including β-MPPT, Cuckoo Search (CS), and Artificial Neural Network (ANN). Moreover, predictions made by DT regressor have greater than 93.93% tracking efficiency and 0.16 s response time even during turbulent meteorological conditions. However, they didn't consider much of partial shading scenarios during their research work, which is indispensable in real world. Also, physical implementation is yet to be done as future work [26]. Furthermore, DT regressors occasionally suffer from the problem of over-fitting, which implies that a regressor fits to the training dataset too tightly that it is incapable of producing right prediction result for untrained data [24].

5.4.2 Random forest (RF) regression ML algorithm

RF regressor comes with a more efficient approach to overcome the over-fitting problem of DT regressors. It can be considered as a meta estimator, which applies different classifying decision trees on various sub-samples of the training dataset. It ameliorates predictive accuracy and controls over-fitting by taking averages of outcomes delivered by different decision trees as shown in Fig. 11 [27]. RF algorithm works as follows:

➢ It selects uncorrelated and random sub-samples from the training dataset.

➢ It builds up a separate decision tree out of each sub-sample.

➢ Every decision tree comes up with a prediction outcome.

➢ It applies a vote procedure to all available prediction results.

➢ The prediction result with the greatest number of votes would be declared as final prediction.

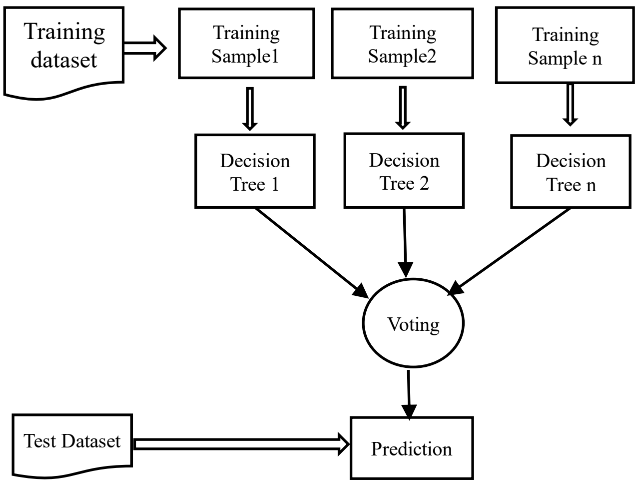

Fig. 11 RF regression ML algorithm.

RF regressor has robustness and accuracy due to cross validation by participation of multiple uncorrelated decision trees in procedure. It overcomes the problem of over-fitting by cancelling out the biases and averaging all the predictions. It can highlight the most contributing features of the big and higher dimensional training dataset [27].

RF regressor has also been deployed for MPPT purposes by researchers because of its ability to detect non-linear correlations between important meteorological parameters, namely solar irradiance and temperature. 300,000 samples of data have been deployed for modelling of a thorough solar system. They have used bootstrapping methodology for RF training purposes while paying much attention to RF parameter selection. Then, they simulated their model in MATLAB/SIMULINK and examined under real atmospheric conditions for almost 24 days as well. They have evaluated the correctness and dynamics of their model itself and compared it with other state-of-the-art methodologies such as ANN and adaptive neuro-fuzzy inference system (ANFIS). RF regressor based MPPT algorithm has performed considerably better than other two techniques and achieved greater than 95% acceptability through Bland–Altman test. However, the practical implementation of RF based MPPT algorithm in a DC-to-DC boost converter has not been done yet [28]. Similarly, another group of researchers has proposed a hybrid technique by combining RF algorithm with Quasi Oppositional Chaotic Grey Wolf Optimizer (QOCGWO) for overall performance enhancement of the system [29].

5.5 Unsupervised ML algorithms

In contrast to supervised ML algorithm, unsupervised learning takes unlabeled (only input parameters) dataset as input, then tries to discover hidden correlation and patterns between different parameters as shown in Fig. 12. It arranges given data into different groups or clusters based on their similarities and dissimilarities. Such algorithm works without any human supervision or interference. The biggest advantage of unsupervised ML is that unlabeled data can easily be gleaned as compared to labelled dataset. Moreover, unsupervised algorithms can work equally well with unstructured data having noisy, missed, or unknown values.

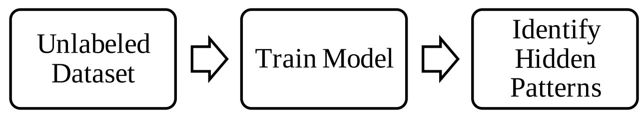

Fig. 12 Unsupervised ML algorithm.

Two major categories of unsupervised ML are Clustering and Association. In clustering, unlabeled dataset is arranged into different groups based on similarities and dissimilarities. While association works on larger datasets and discovers important correlations and associations between parameters based on certain rules. Some of the famous unsupervised ML algorithm are K-Means Clustering, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH), and Hierarchical Clustering [22, 30].

Although, clustering approaches (such as density peak-based, dilation and erosion-based clustering) have widely been recommended for diagnosis of faults and anomalies in PV arrays [31]. But unsupervised ML algorithms are not directly reported for implementation of the MPPT controller in literature.

5.6 Reinforcement ML algorithm

Reinforcement learning doesn’t requisite any training data either labelled or unlabeled. It interacts with real-time environment itself and learns by experience gradually, Fig. 13 represent reinforcement learning cycle. The goal is to improve its performance and maximize long-term rewards. It explores in an unknown environment, takes decisions, performs a series of actions, estimates reward, stores this information as ‘state-action’ pair, and then deploys it as feedback in future. Reinforcement learning is goal-oriented and problem-specific [23]. The important algorithms out of this category are: Temporal Difference (TD), Q-Learning and Deep Adversarial Networks [30].

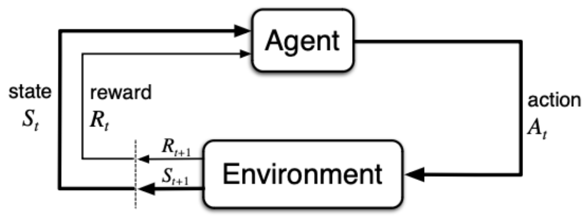

Fig. 13 Reinforcement ML algorithm [23].

A combination of deep learning and reinforcement learning, also called deep reinforcement learning (DRL) has been suggested to enhance MPPT performance. Simple reinforcement learning can handle state / action spaces which are discrete only, but this suggested approach is capable of handling continuous ones. Here, discrete action spaces are being handled by deep Q network (DQN) technique, while continuous action spaces are being controlled by deep deterministic policy gradient (DDPG) technique. The feasibility of this suggested model has been validated through MATLAB/Simulink. Comparative analysis with conventional Perturb and observe (P&O) methodology has shown a significant improvement in efficiency achieved by this DRL based MPPT controller. Also, no requirement of a preliminary model of the controller is a plus point. Controller interacts with environment itself and learns through reward feedback [31, 33].

Similarly, Q-learning based GMPPT is also being reported in literature. It eliminates the requirement of preliminary knowledge of PV module's characteristics and structure. Moreover, it shows potential to detect GMPP rapidly within a few steps of search process, which demonstrates its suitability for abruptly changing partial shading conditions. Comparative analysis with PSO based GMPPT has revealed that this suggested approach has significantly reduced (80.5%–98.3%) time to spot GMPP [34].

6 Performance Comparison of All Presented MPPT Technologies

For a quick overview, Table 2 presents a comparison of all the presented MPPT technologies. The key parameters of an algorithm's performance matrics are considered for this purpose. Such a comparison can serve as a quick guide for finding the best possible solution for customized needs.

Table 2: Comparison of presented MPPT algorithms

MPPT algorithms	Efficiency	Implementation complexity	PV array dependency	Convergence speed	Sensed parameter /input to algorithm
Perturbation and Observation (P&O) method	Low	Low	No	Varies	Voltage, Current
Open-circuit voltage (OCV) method	Low (Power loss due to sampling activity)	Low	Yes	Medium	Voltage
Short-circuit current (SCC) method	Low (Power loss due to sampling activity)	Low	Yes	Medium	Current
The Incremental Conductance (IC) method	Medium	Medium	No	Varies	Voltage, Current
Ripple Correlation Control (RCC)	Medium	Low	No	Low (limited by switching activity of DC/DC converter)	Voltage, Current
Fuzzy logic control (FLC)	Medium (Drift problem)	Medium (No perfect mathematical model required)	Yes	Medium	Numerical variables (Even ambiguous ones)
Artificial Neural Network (ANN)	Very High	High	Yes	Very Fast	
Particle swarm optimization (PSO) and other SI-based algorithms	High	Medium (No massive training dataset is required)	Yes	High	
ML algorithms	Very high	High (hectic Model training)	Yes	Very Fast	

7 Conclusion

The MPPT algorithm is a vital element of a PV solar system. It ensures that system is working at its full capacity and achieving maximum power conversions under given meteorological conditions. Many researchers have been and are still investigating novel and innovative approaches to maximize effectiveness of MPPT algorithms. **This paper** provides a quick glimpse of the progress in this field so far, by providing categorization of MPPT algorithms and delineating some popular ones out of each category. For instance, perturbation and observation (P&O) method, incremental conductance (IC) and ripple correlation control (RCC) belong to conventional methodologies, while fuzzy logic control (FLC), artificial neural network (ANN), particle swarm optimization (PSO), supervised, unsupervised, and reinforcement Machine Learning (ML) algorithms are advanced intelligent techniques. Different operational strategies, merits and demerits of each algorithm have also been discussed. Conclusively, intelligence-based algorithms are found to overcome the limitations of conventional ones, especially under partial shading and rapidly changing environmental conditions. However, high implementational and computational complexity of intelligence-based algorithm is paving a way towards hybrid techniques for MPPT purposes, which aim to maintain a balance between efficiency and complexity by incorporating plus points of the involved algorithms.

For conciseness, we have just included a few MPPT algorithms out of each category. However, this study can be expanded to accommodate more available techniques for an even more extensive outlook. Moreover, many contemporary hybrid MPPT techniques have already been developed and discussed in literature. As an extension to this study, some well-performing hybrid techniques with their operational detailing, upsides and challenges may also be included. It would be mesmerizing to know that how they are maintaining a good balance between computational complexity, cost-overhead and performance.

References

[1] M. Sarvi and A. Azadian, "A comprehensive review and classified comparison of MPPT algorithms in PV systems," *Energy Systems,* Vol. 13, pp. 281-320, May 2022.

[2] B. Bendib, H. Belmili and F. Krim, "A survey of the most used MPPT methods: Conventional and advanced algorithms applied for photovoltaic systems," *Renewable and Sustainable Energy Reviews,* Vol. 45, pp. 637-648, 2015.

[3] mathworks.com, "MPPT Algorithm: Implement maximum power point tracking algorithms for photovoltaic systems using MATLAB and Simulink," *MPPT Algorithm - MATLAB & Simulink (mathworks.com).*

[4] K. Y. Yap, C. R. Sarimuthu and J. M.-Y. Lim, "Artificial Intelligence Based MPPT Techniques for Solar Power System: A review," *Journal of Modern Power Systems and Clean Energy,* Vol. 8, pp. 1043 - 1059, October 2020.

[5] H. Jeong, H. Lee, Y.-C. Liu and K. A. Kim, "Review of Differential Power Processing Converter Techniques for Photovoltaic Applications," *IEEE Transactions on Energy Conversion,* Vol. 34, pp. 351-360, 2019.

[6] Ahmed I.M. Ali and Mahmoud A. Sayed and Essam E.M. Mohamed, "Modified efficient perturb and observe maximum power point tracking technique for grid-tied PV system" *Power Electronics, IEEE Transactions on,* Vol. 99, pp. 192-202, 2018.

[7] B. Subudhi and R. Pradhan, "A Comparative Study on Maximum Power Point Tracking Techniques for Photovoltaic Power Systems," *Sustainable Energy, IEEE Transactions on,* Vol. 4, pp. 89-98, 2013.

[8] A. Montecucco and A. R. Knox, "Maximum Power Point Tracking Converter Based on the Open-Circuit Voltage Method for Thermoelectric Generators," *IEEE Transactions on Power Electronics,* Vol. 30, pp. 828-839, 2015.

[9] A. Jawad, "A fractional open circuit voltage based maximum power point tracker for photovoltaic arrays," *ICSTE 2010 - 2010 2nd* International *Conference on Software Technology and Engineering, Proceedings,* Vol. 1, pp. 1-247, 2011.

[10] H. A. Sher, A. F. Murtaza, A. Noman, K. E. Addoweesh, K. Al-Haddad and M. Chiaberge, "A New Sensorless Hybrid MPPT Algorithm Based on Fractional Short-Circuit Current Measurement and MPPT," *IEEE Transactions on Sustainable Energy,* Vol. 6, pp. 1426-1434, October 2015.

[11] A.Abbou and A. Ziouh, "Comparative study of fuzzy logic, ripple correlation control and pilot cell methods for maximum power point tracking," *2016 International Conference on Electrical Sciences and Technologies in Maghreb (CISTEM),* Vol. 1, pp. 1-7, 2016.

[12] E. Halassa, L. Mazouz, A. Seghiour, A. Chouder, and S. Silvestre, "Revolutionizing Photovoltaic Systems: An Innovative Approach to Maximum Power Point Tracking Using Enhanced Dandelion Optimizer in Partial Shading Conditions" *2003 IEEE Power Engineering Society General Meeting (IEEE Cat. No.03CH37491),* Vol. 16, pp. 3617-3627, 2023.

[13] A. M. Eltamaly, "Chapter 4 - Performance of MPPT Techniques of Photovoltaic Systems Under Normal and Partial Shading Conditions," *Advances in renewable energies and power technologies. Elsevier,* Vol. 1, pp. 115-161, 2018.

[14] S. D. Al-Majidi, M. F. Abbod and H. S. Al-Raweshidy, "A novel maximum power point tracking technique based on fuzzy logic for photovoltaic systems," *International Journal of Hydrogen Energy,* Vol. 43, pp. 14158-14171, 2018.

[15] J. J. Khanam and S. Y. Foo, "Modeling of a Photovoltaic Array in MATLAB Simulink and Maximum Power Point

Tracking Using Neural Network," *Journal of Electrical & Electronic Systems,* Vol. 7, pp. 263-271, 2018.

[16] M. Abdelsattar, A. A. Elbaset and H. Ali, "Modeling of Photovoltaic Module Based on Two-Diode Model," *Conference: 17th International Middle-East Power Systems Conference (MEPCON 2015),* 2015.

[17] M. S. Bouakkaz, A. Boukadoum, O. Boudebbouz, A. Bouraiou, N. boutasseta and I. Attoui, "ANN based MPPT Algorithm Design using Real Operating Climatic Condition," *2020 2nd International Conference on Mathematics and Information Technology (ICMIT),* pp. 159-163, 2020.

[18] R. Divyasharon, R. N. Banu and D. Devaraj, "Artificial Neural Network based MPPT with CUK Converter Topology for PV Systems Under Varying Climatic Conditions," *2019 IEEE International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS),* pp. 1-6, 2019.

[19] Li, Hong, Duo Yang, Wenzhe Su, Jinhu Lü, and Xinghuo Yu. "An Overall Distribution Particle Swarm Optimization MPPT Algorithm for Photovoltaic System Under Partial Shading," *IEEE Transactions on Industrial Electronics,* Vol. 66, pp. 265-275, 2019.

[20] M. Merchaoui, A. Sakly and M. F. Mimouni, "Improved fast particle swarm optimization based PV MPPT," *2018 9th International Renewable Energy Congress (IREC),* pp. 1-7, 2018.

[21] H. M. H. Farh, M. F. Othman, A. M. Eltamaly and M. S. Al-Saud, "Maximum Power Extraction from a Partially Shaded PV System Using an Interleaved Boost Converter," *Energies,* Vol. 11, pp. 2543-2561, 2018.

[22] B. Rajoub, "Chapter 3 - Supervised and unsupervised learning," *Biomedical Signal Processing and Artificial Intelligence in Healthcare,* pp. 51-89, 2020.

[23] R. S. Sutton and A. G. Barto, Reinforcement Learning, second edition: An Introduction (Adaptive Computation and Machine Learning series), Bradford Books, 2022.

[24] K.Dhiraj, "Implementing Regression Using a Decision Tree and Scikit-Learn," 2020. [Online]. Available: https://heartbeat.comet.ml/implementing-regression-using-a-decision-tree-and-scikit-learn-ac98552b43d7.

[25] M.K.Gurucharan, "Machine Learning Basics: Decision Tree Regression," Medium, 2020. [Online]. Available: https://towardsdatascience.com/machine-learning-basics-decision-tree-regression-1d73ea003fda.

[26] P. V. Mahesh, S. Meyyappan and R. R. Alla, "Maximum power point tracking using decision-tree machine-learning algorithm for photovoltaic systems," *Clean Energy,* Vol. 6, pp. 762-775, 2022.

[27] A. Shafi, "Random Forest Classification with Scikit-Learn," Datacamp, Feb. 2023. [Online]. Available: https://www.datacamp.com/tutorial/random-forests-classifier-python.

[28] H. Shareef, A. H. Mutlag and A. Mohamed, "Random Forest-Based Approach for Maximum Power Point Tracking of Photovoltaic Systems Operating under Actual Environmental Conditions," *Computational Intelligence and Neuroscience,* Vol. 2017, 2017.

[29] A. A. Jain, B. J. Rabi and S. Darly, "Application of QOCGWO-RFA for maximum power point tracking (MPPT) and power flow management of solar PV generation system," *International Journal of Hydrogen Energy,* Vol. 45, pp. 4122-4136, 2020.

[30] Thanki, Rohit, and Purva Joshi. "Artificial Intelligence and Its Applications." In Advanced Technologies for Industrial Applications, pp. 49-71. Cham: Springer International Publishing, 2023.

[31] C. Kalogerakis, E. Koutroulis and M. G. Lagoudakis, " Global MPPT Based on Machine-Learning for PV Arrays Operating under Partial Shading Conditions," *Applied Sciences,* Vol. 10, pp. 700-715, 2020.

[32] B. C. Phan, Y.-C. Lai and C. E. Lin, " A Deep Reinforcement Learning-Based MPPT Control for PV Systems under Partial Shading Condition," *Sensors,* Vol. 20, pp. 3039-3056, 2020.

[33] I. Y. Fawzy, Y. Mohamad, E. Shehata and M. AbdElSattar, "A Modified Perturb and Observe Technique for Mppt of Intgrated PV System Using DC-DC Boost Converter," Journal of Advanced Engineering Trends, Vol. 40, pp. 63-77, 2021.