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Research Article

A Comprehensive Review of MPPT Techniques Based on ML Applicable for Maximum Power in Solar Power Systems

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A B S T R A C T

Solar power energy continues to be a renewable and sustainable source of energy in the coming year due to its cleaner nature and abundant availability. Maximum Power Point Tracking (MPPT) is a technique used in solar power systems to extract maximum power from photovoltaic (PV) modules by tracking the operating point of the modules. MPPT is essential for achieving optimal power output from a solar panel, particularly in variable weather conditions. Traditional MPPT techniques are subject to limitations in handling the partial shading conditions (PSC). To ensure the tracking of maximum power point while boosting the MPPT's overall efficacy and performance, Machine Learning must be integrated into MPPT. As per the reviewer work, ML techniques have the potential to play a crucial role in the development of advanced MPPT systems for solar power systems operating under partial shading conditions and to compare the performance of existing ML-MPPT in terms of accuracy, response time, and efficacy. These review papers technically analyze the result of ML-MPPT techniques and suggest the optimum ML-MPPT tactics that are Q learning, Bayesian Regularization Neural Network (BRNN), and Multivariate Linear Regression Model (MLIR) to achieve optimum outcomes in MPPT under PSC. Further, these techniques can offer efficiency greater than 95%, tracking duration less than 1sec, and error threshold of 0.05. In the future, the reviewer may propose simulation work to compare the optimal algorithms.

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1- INTRODUCTION

With the diminishing amount of non-renewable energy resources, it has become increasingly important to generate more power from renewable energy sources, one of which is solar power. Solar power is becoming more affordable and advancing in technology, making it a viable alternative. Each day, more than approximately 1366 MW of solar energy reaches the earth, providing an abundant and free source of energy. One of the primary advantages of solar power compared to traditional power sources is that photovoltaic (PV) solar cells can directly convert photon light into electrical current, even with the use of small cells. Significant research is underway to improve solar panel systems' efficiency in capturing and converting the Sun's irradiation. Recognizing the benefits of renewable energy, the Indian government committed to achieving 450*10^9 W of non-conventional energy capacity by 2022 at the Paris climate summit. As of 2020, India has an installed capacity of approximately 175 GW, according to the MNRE in India, as shown in Figure 1(Hill J. S.,2017;IEA ,2017).

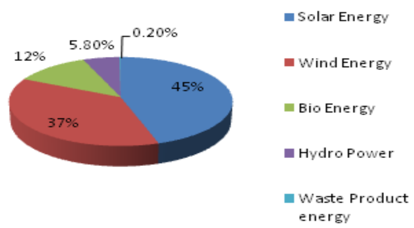

Figure 1. Percentage share of individual renewable energy in total renewable Energy production by 2022

The V-I or V-P characteristics graph in Figure 2 and 3 show the non-linear behavior of a PV cell (Rabia. et al. 2021), which varies due to the effect of solar irradiance, temperature, and dust. It is generally observed that the output current of a PV panel is affected by solar irradiance (G), while Vpv remains almost constant. The impact of high temperature on a solar

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panel decreases PV output voltage, and therefore, different approaches have been discussed in (P. Takun et al. 2011) to cool down the PV panel and increase its efficacy level. Alhuyi Nazari et al 2023; Jordehi et al. 2016) discussed the integration of a heat pump with a PV unit to cool it down and offer energy savings of more than 50%.Guedri et al.(2022)and D. Mukherjee et al. (2020) discussed how the overall efficiency of a PV cell can be increased by using thermal energy from the cell. A nano-fluid used to decrease the temperature of the PV panel and increase its efficiency (Sharifpur et al. 2018). Therefore, the maximum power from the PV curve will vary according to the PV panel temperature and solar irradiation. The main objective of utmost power point operating is to acquire the highest energy from the P-V system regardless of the environmental surroundings (Jordehi et al. 2016). Here, MPPT techniques play a vital role in harnessing the extreme energy output from the P-V system. As a result, the PV arrangements run at their utmost energy point since at the maximum point, a PV panel delivers the greatest electricity and performs most effectively. In the PV arrangement, an utmost power point tracker (Podder et al. 2019; LiuY-H, et al. 2015) typically employed to track the MPP under variable weather conditions.

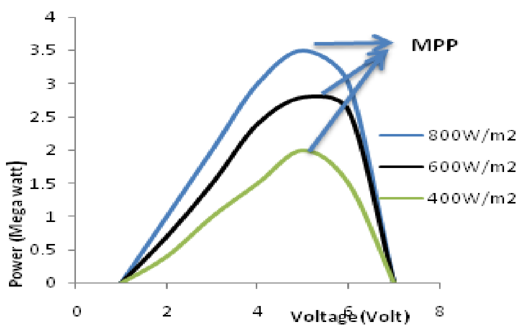

Figure 2. P-V curve of PV cell with variable effect of solar irradiation for T=25°C (Rabia. et al. 2021)

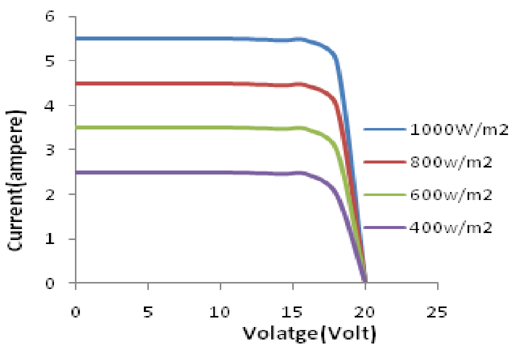

Figure 3. V-I curve of PV cell with effect of variable solar irradiation for T=25°C (Rabia. et al. 2021)

The photovoltaic (PV) system is an excellent source of renewable energy. However, it is not without limitations. The varying nature of PV characteristics means that without an MPPT controller, the PV system offers low output efficacy. Thus, there is a necessity for an MPPT controller to extract the most power possible from a PV system (Jordehi et al. 2016;A. Mohapatra et al. 2017). Many MPPT algorithms are available to find out the peak power point (S. Mahmoudian et al. 2016).Another limitation is the partial shading condition (PSC), where the PV panel is partially covered by hazy skies, animals, trees, or structures. This results in one or more PV cells receiving inadequate solar radiation, leading to a decrement in current. The PV unit also acts as a load and consumes electricity produced by other PV units (Mohapatra et al. 2017).This can result in an incompatible power hammering that is responsible for load and battery damage (LiuY-H et al. 2015) .On a PV curve, PSC can lead to multiple power peaks, with many local maxima and one global maxima (GMPP), as seen in Figure 4. However, several MPPT methods neglect to monitor GMPP under PSC, leading to power losses in the PV system and making it operate inefficiently. As a result, extensive research is underway to find the MPP under PSC (Mohapatra et al. 2017).

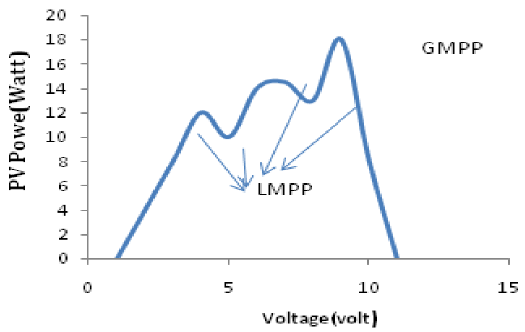

Figure 4. Effect of Partial shading on PV Curve with Major and Local maxima Point

There are several conventional MPPT procedures, including open-circuit potential, short-circuit current, constant voltage, Perturb & Observation (P&O) procedure, H-C, and I-C method. These methods are cost-effective and easy to implement, but they tend to have high oscillation around the maximum power point and steady-state error, and require more tracking time. While P&O method offers high tracking efficiency, it still shows oscillation around MPP and is unable to follow the utmost power point under erratic environmental conditions. The Inc-conductance method overcomes this problem but is not effective under PSC (LiuY-H et al. 2015).

FLC, Gauss Newton tactic (GNT), ANN, Fibonacci Series (FS) based MPPT, and ML-based MPPT (Ahmad R et al. 2022;Mahmoudian et al. 2016;Islam H et al. 2018;BollipoRB et al. 2020) are Artificial Intelligence-based MPPT techniques. These methods are capable of working under partial shading conditions and offer high tracking speed. However, they have high design and computational complexity. Fuzzy logic (P takun et al. 2011;Bounechba et al. 2014) avoids the limitations of less speed and variation around the peak point of the P&O procedure, but the use of machine learning provides more accurate results in a shorter time span. An ANN-based MPPT techniques discussed that offer high convergence speed in tracking, but the design cost is very high due to the large storage of data and the need for periodic tuning for result accuracy. A comparative analysis of GNT and FS-MPPT, which proves that the procedures offer a very complex calculations (Mohapatra et al. 2017;Dogra, et al.2022) Moreover, researchers proposed optimization-based algorithm to enhance the tracking speed but computational complexity is high (Mirhassani et al. 2014;Kermadi M et al. 2015;Sundareswaran et al. 2015;Nugraha D et al. 2019;SundareswaranK et al. 2016).The authors in (Kermadi M et al. 2015)discussed the viability of the particle swarm optimization(PSO) algorithm based on the universal best and local best position. This studies capable to locate the global maximum power point, but the entire process is too complex to implement and takesalongertime to track the GMPP.

A hybrid technique that integrates Ant colony procedure with P&O method is proposed for a swift tracking of maximum power point, but offered thesame tracking efficiency as PSO and ACO did (K Sundareswaran et al. 2016). A novel MPPT algorithm that combines the Cuckoo search algorithm with the proposed golden-section search algorithm to efficiently track the GMPP in PSC. However, this approach has a very high computational complexity and a complex algorithm (Nugraha D et al. 2019) To increase the tracking efficiency an ABC-based MPPT technique proposed and compared the outcome with the results obtained from PSOA and EPSOA. The efficacy of the ABC tactics is almost 99.99%, but efficacy is falling for the variable pattern of shading condition (Sundareshwar K. et al .2016)).

Therefore, most of the MPPT techniques are currently unable to track global maximal power with higher tracking efficiency, shorter tracking time, and less computation complexity. This research compares existing ML-MPPT algorithms employing real-time data under PSC. The basic goal is to gather the best possible energy derived from a PV module using PSC with lower computational complexity and tracking time. The novelty of this paper is outlined below:

(i) A review of ML implemented MPPT procedure aimed at speeding up convergence speed and eliminating mismatching power under PSC.

(ii) This paper addresses a research gap, as previous review papers on the implementation of ML in the field of solar energy forecasting (Yang D. et al. 2019;Ahmad T et al. 2020;Fouilloy A et al 2018;Behera MK et al. 2018) did not cover the study on the application of ML in peak power point tracking under PSC.

(iii) A comparison of the performance of various ML-MPPT approaches is presented in a tabular way, which will be helpful for researchers in selecting the most useful option.

(iv) The paper analyzes the performance of existing ML-MPPT techniques and suggests the optimum ML-MPPT techniques to assist researchers in selecting the optimum algorithm.

(v) The paper identifies research gaps in existing ML-MPPT procedures, highlighting potential future research directions.

Section II details the PV cell modeling; Section III discusses the MPPT techniques; Section IV provides a comparative review of ML algorithm implemented in MPPT techniques; Section V briefly presents the results and discussion; finally, the conclusion of this review paper is presented.

2. PV Cell Modeling discussed the equivalent representation of a solar unit. This type consists of a parallel diode connected to a current generator. In the context of solar cells, the losses incurred by the current flow are known as series resistance (Rs) measured in ohms. To achieve maximum power output, it is important to minimize these losses. Given that the current amount is too small and the resistance amount is too high, the parallel resistance (Rp) in ohms, linked in parallel to the diode responsible for bringing the leakage current loss (Is) in micro-amperes to the ground, should be minimized to ensure optimal power output. Figure 5 (LiuY-H, et al. 2015)shows the corresponding circuit of a PV unit and below are the equations representing the current and voltage of the PV unit. Here, the parameters that change depending on the properties of the PV unit include parallel resistance (Rp), ideality factor (n), and series resistance (Rs) ohm. Boltzman constant K $1.38*10^{-23}$, electron charge q $1.6*10^{-19}$Coulomb, and PV unit temperature (T) in Kelvin are additional variables. IPH, IS, Ipv, and V stand for the photon current (amp), saturation current (micro ampere), PV panel current(ampere), and V panel voltage (Volt), respectively (LiuY-H, et al. 2015).

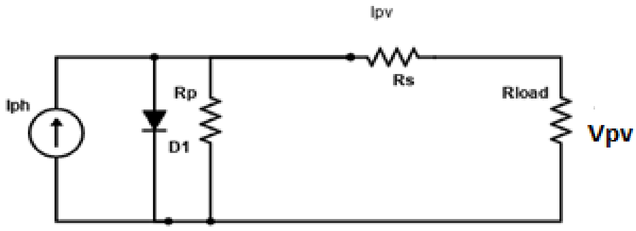

Figure 5. Single PV cell equivalent Model (LiuY-H, et al. 2015)

$$Ipv=Iph–Is[exp(q/nkt(V+IpvRs)-1] –(V+Ipv RS)/Rp \quad (1)$$

$$V=(nkt)/q[ln((Iph+Is-Ipv)/Is)–IpvRs] \quad (2)$$

The optimum value of Rload, at which the highest power is obtained, is Ropt. The utmost power, Pmax, can be expressed as equation 3:

$$Pmax=Vmpp*Impp \quad (3)$$

By harmonizing the V-I operating point with the R_L parameters, the MPPT goal is to maximize PV panel output under all circumstances (Kumar N et al. 2018).Upon controlling the PV panel current or voltage to make the converter run at the MPP, the provided power can be increased. To ensure that the PV structure always performs at utmost point, MPPT is a suitable technology for use. A position on a P-V curvature known as MPP is one where dp/dv= 0. According to the duty cycle, MPPT algorithms determine the corresponding MPP. In the direction of the MPP, the duty ratio either increases or decreases in value. Impedance matching, or matching the output PV resistance to the load resistance, is the primary goal. The MPPT is compelled through impedance matching to derive maximum power from PV setup (BollipoRB et al. 2020).The MPPT offers several benefits, including the reduction of power loss under PSC, minimizing the mismatch between the load and generator, increasing the tracking efficiency, and protecting the load from damage due to load variation.

3. MPPT Techniques

The challenging aspect of this solar power is its dynamic nature, which can result invariable power and voltage levels based on the surrounding conditions (Podder et al. 2019;BollipoRB et al. 2020). To operate PV unit at their highest possible power, a number of MPPT approaches are employed. Therefore, depending on the use of tracking procedures, these strategies are categorized in Figure 6.

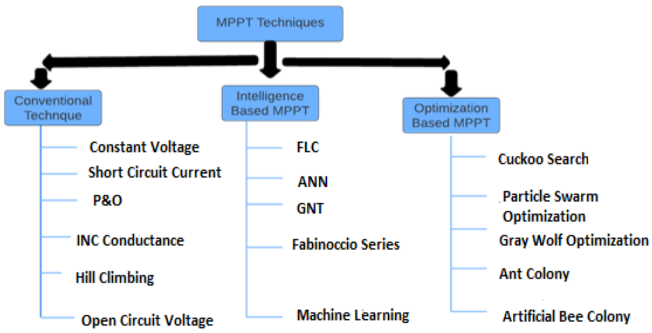

Figure 6. Categorization of MPPT techniques (Yap, 2020)

ML algorithms represent the key division of AI that attempt to analyze the performance of available information, perform logical reasoning, and train the machine without unambiguous instructions (Mohapatra et al. 2017). In recent years, ML algorithms have played a major role in the fields of non-conventional energy resources. Nowadays, the most demanding area of research on solar energy is solar power forecasting and tracking of maximum power point on P-V cell V-I characteristics.

Based on this review, the commonly used ML algorithms for maximum power point tracking are ANN, Random Forest, DT, SVM, WK-NN, ELM, Coarse Tree, regression model, and Q-learning-based model (Keyrouz F et al. 2018;TeyKS et al 2018;Mukherjee et al. 2020;Farayola et al. 2018; Behera MK et al. 2018;DuY et al 2018;Takruri et al. 2020;Nkambule et al. 2021;Memaya et al. 2019;Yung Yap et al. 2020;Sharmin et al. 2021;Kalogerakis et al.2021;Mahesh et al. 2022;A. Rafeeq et al. 2022). Many research papers have calculated the performance parameters of classical MPPT procedures. The main shortcomings of classical techniques are oscillation around the MPP and the inability to track the MPP in PSC (Benbib et al. 2015;Radjai et al. 2014;LiuY-H, et al. 2015;Kumar N et al. 2018;Farayola et al. 2018).A conventional MPPT and ML-MPPT techniques comparison. based on the author's discussions is presented in, a comparison Table 1(Bollipo RB et al 2020). Table 1 is presented to compare the performance parameters of conventional and ML-based MPPT.

Table1. Comparative analysis of conventional and ML-based MPPTs in terms of performance (BollipoRB et al. 2020)

Parameter	Conventional MPPT	ML MPPT
Tracking accuracy	Low	High
Tracking speed	Moderate	High
Convergence speed	slow	Fast
Ability to track under PSC	No	Yes
Steady-state fluctuation	Yes	Less
Fluctuation about MPP	Yes	Less
Settling Duration	High	Less
Intricacy	Low	High
Periodic tuning	Yes	No
Cost	Low	High
Computation time	Less	High
Algorithm complexity	Low	High
System Design	Simple	Complex

4. Comparative Review on ML-based MPPT

The performance parameters used to evaluate the effectiveness of the ML-MPP algorithms include the Mean Squared Error (4), tracking efficiency η (5),and convergence duration. These parameters provide an insight into the abilityof the algorithm to track the utmost power point.

$$MSE = \frac{1}{N}\sum_{K=1}^{N}(PowerMPP - PowerPV)2 \quad (4)$$

$$\eta = \int_0^t PowerPV(t)dt \Big/ \int_0^t \text{Power}MPP(t)dt) * 100 \quad (5)$$

This study provides a review of the ML-implemented MPPT techniques in PV systems in order to yield optimal power from a PV unit under PSC. To this end, different ML-MPPT techniques are compared in terms of the ability to track the utmost power point used in(KeyrouzF et al. 2018; TeyKS et al 2018; Mukherjee et al. 2020; Farayola et al. 2018; Behera MK et al. 2018;DuY et al 2018; Takruri et al. 2020; Nkambule et al. 2021; Memaya et al. 2019; Yung Yap et al. 2020; Sharmin et al. 2021; Kalogerakis et al.2021; Mahesh et al. 2022; A. Rafeeq et al. 2022)A summary of the ML-MPPT techniques is provided based on the result shown in Table 2.Herein, the authors present the evaluating parameters and results computed by the authors (Keyrouz F et al. 2018;TeyKS et al 2018;Mukherjee et al. 2020;Farayola et al. 2018; Behera MK et al. 2018;DuY et al 2018;Takruri et al. 2020;Nkambule et al. 2021;Memaya et al. 2019;Yung Yap et al. 2020;Sharmin et al. 2021;Kalogerakis et al.2021;Mahesh et al. 2022;A.Rafeeq et al. 2022) to compare the algorithm proficiency in a tabular way. Tables 3 and 4 present a comparative analysis of ML-MPPT techniques based on their performance parameters, as well as their advantages and disadvantages.

Table 2. Summary of ML-MPPT techniques based on Evaluating Parameters and Result

MPPT Algorithm	Hardware/Software Simulation	DC-DC Converter	Performance Parameter	Result
Bayesian Neural Network (BNN) (KeyrouzF et al. 2018)	MATLAB/Simulink	PID with Boost	Tracking Average Time, Efficiency	Tracking average Time=1.76s Efficiency=97.89%
SLFFN with MELM Algorithm(Behera MK et al. 2018)	MATLAB/Simulink	Boost	RMSE MAPE MAE	RMSE= 1.4440, MAPE =0.0144 MAE =0.0178
Differential Evolution based MPPT(DE) (Memaya et al. 2019)	PowerSimPVUE125MF5N	SEPIC	Accuracy in tracking; Tracking Time	GMPP in 2 seconds with 99% accuracy and reaction to load changes in 0.1 second
SVM and ELM (DuY et al 2018)	MATLAB/Simulink, SPR-305E-WHT-D	Boost	MPP Ratio	ELM accuracy=94.52% SVM accuracy=92.33%
Support Vector Machine learning (SVM) (Takruri et al. 2020)	MATLAB/Simulink Mitsubishi TD185MF5 panel	PID Controller with Boost	RMSE	RMSE in Vref (V) is 0.0023 RMSE in Pmax (W) is 0.0278.
9 ML-based MPPT techniques (Nkambule et al. 2021)	MATLAB/Simulink Soltech 1STH-215-P	Boost	RMSE and R Squared Error	RMSE, Efficiency % &Train Duration DT =0.420, 90& 0.91s WKNN=0.2977 ,92& 0.78s MLR = 0.440 ,90& 6.17s LDA = 0.480 & 89.6 BT = 0.73 ,88.6& 2.35s GPR = 0.4 ,93.4& 5.04s NBC = 0.51, 88.8& 8.56s SVM = 0.14 ,93.8& 1.1178s RNN = 0.36 , 86.24& 8.9s
Multivariate Linear Regression model withP&Omethod(MLIR)(TeyKS et al 2018)	Python	Buck	Efficiency and Error threshold	Efficiency=99.8% Error Threshold=0.5%
AI,FLC,ANN,SI,ML,GA based controller (Yung Yap et al. 2020)	MATLAB/Simulink (SPR-305E-WHT-D)	Boost	Tracking time, Steady-state oscillation	Tracking time 0.60s Steady-state Oscillation (%)±1.5
Coarse Tree with MPPT Controller & RQGPR without MPP controller (Mukherjee et al. 2020)	MATLAB/Simulink	Boost	RMSE	RMSE1.675 for coarse tree RMSE 1.628 for RQGPR
Bayesian Regularization NN with P&O method (BRNN) (Sharmin et al. 2021)	MATLAB/Simulink ZM-A-M-100	Boost	Efficiency, MSE	Efficiency=99.794% MSE= 2.87*10^-3
Q learning based Algorithm (Kalogerakis et al 2021)	MATLAB/Simulink	Boost	Convergence Time, Efficiency	Convergence time80.5-90.3% reduced, Efficiency=99.3-99.6%
LIR Method (Farayola et al. 2018)	Psim 1STH-215-P module	Cuk	RMSE PV efficiency	RMSE 5.5339e-7 and PV efficiency 73.24%, 102.18% and 100.16% under NOCT, PST and STC.
DT Regression MPPT(DTR) (Mahesh et al. 2022)	MATLAB/Simulink	Boost	Efficiency, Settling Time	Efficiency>93.99% Settling time 0.27 sec,rise time 0.16s
BPNN-DL(A. Rafeeq et al. 2022)	MATLAB/Simulink	Boost	Accuracy	Accuracy 98%

Table 3. Comparative analysis based on performance parameters

MPPT Technique	Track Speed	Complexity	Accuracy	PSC Track	Input	Output	Grid Supported	Cost	Periodic Tuning
Bayesian Neural Network (BNN) (KeyrouzF et al. 2018)	Fast	Less	High	Yes	Voltage, Current	Pmax	Yes		Yes
SLFFN with MELM Algorithm(Behera MK et al. 2018)	-	High	High	Yes	Voltage, Current	Pmax	Yes	High	High
Differential Evolution based MPPT(DE) (Memaya et al. 2019)	Fast	High	High	Yes	Voltage, Current	ΔD,ΔP		Low	Moderate
SVM and ELM (DuY et al 2018)	Fast	High	High	Yes	Voltage	Optimal Step Size	Yes	Low	No
Support Vector Machine learning (SVM) (Takruri et al. 2020)	fast	Less	High	Yes	Voltage, Current	Vref	Yes	High	No
9 ML-based MPPT techniques (Nkambule et al. 2021)	WK-NN is faster	Less	SVM and WK-NN Tracking accuracy > 97%	Yes	Voltage and current	PV efficiency	Yes	Low	No
Multivariate Linear Regression model withP&Omethod(MLIR)(TeyK S et al 2018)	Slow	High	High	Yes	Temperature, Humidity, Solar irradiance	Pref	Yes	Moderate	NO
AI,FLC,ANN,SI,ML,GA based controller (Yung Yap et al. 2020)	Moderate	High	High	Yes	Voltage and current	Pmax	yes	High	NO
Coarse Tree with MPPT Controller & RQGPR without MPP controller (Mukherjee et al. 2020)	Fast	high	high	Yes	Solar insolation, Panel temperature and ambient temperature	Vmax and Imax	yes	High	No
Bayesian Regularization NN with P&O method (BRNN) (Sharmin et al. 2021)		Less	high	Not consider	Temperature and Solar Irradiance, Panel current	Impp	Yes	Low	No
Q learning based Algorithm (Kalogerakis et al 2021)	Fast	Less		yes	Vpv	Duty cycle	yes	High	No
LIR Method (Farayola et al. 2018)	Fast	High	High	Yes	Solar Irradiance and Temperature	Imax	-	Low	No
DT Regression MPPT(DTR) (Mahesh et al. 2022)	Fast	High	Moderate	Yes	Current	Duty cycle and PM	-	High	No
BPNN-DL(A.Rafeeq et al. 2022)	Fast	High	high	yes	ΔT,ΔG	Vref	Yes	Low	No

Table 4. Comparative analysis based on Pros and Cons:

MPPT Technique	Findings	Merits	Demerits
Bayesian Neural Network (BNN) (KeyrouzF et al. 2018)	The controller maintains best possible features to diminish the steady state fluctuation and Tr of the yield power with the help of Bayesian fusion.	Convergence speed for the GMPPT increases.	Temperature variation is not considered.
SLFFN with MELM Algorithm (Behera MK et al. 2018)	The implementation of the modified ELM algorithm; its weights are modified using PSO tactic and their output performance is contrasted with BP model.	Forecast accuracy increased with less mean square error.	Short-term maximum solar power can be tracked. Computational complexity is high. Small dataset is considered.
Differential Evolution based MPPT(DE) (Memaya et al. 2019)	Ability to follow GMPP and react more quickly to changes in load; when an optimization technique is used, it may look for the GMPP across a wider operating zone by employing a single-ended primary-inductor converter.	Less parameters; easy regulation. Faster response against load variation. Algorithm is free from initial point dependency in tracking maximum power point. Evading the recurring track of resolution for identical particles.	Simulation and experiment are performed at constant temperature.
SVM and ELM(DuY et al 2018)	A localized MPPT algorithm proposed for different weather conditions and results are compared with the results of conventional MPPT algorithm.	An automatic location classification system designed to harness maximum power.	Decision of optimal step size depends on the degree of fluctuation of solar irradiance.
Support Vector Machine learning (SVM) (Takruri et al. 2020)	Method is used to predict an ideal reference voltage in all conditions and the result is compared with GRNN implemented networks.	The robustness of the system is offered by using a PID controller.	An accurate data acquisition system required high-quality sensors.
9 ML-based MPPT techniques (Nkambule et al. 2021)	DT, MLR, GPR, WK-NN, LDA,BT, NBC, SVM and RNN are compared in different shading condition and WK-NN perform best.	Fine Tuning of error is obtained by using PID controller. No need of sensor	Small data set is considered.
Multivariate Linear Regression model with P&O method(MLIR) (TeyKS et al 2018)	Hybrid Technique offers better efficiency and lesser time under variable solar irradiance condition.	The proposed model overcomes over fitting. Efficacy and the precision of the projected strategy are not unnatural by the small modification in input parameter.	Training time is very high, approximately 83 hours.
AI,FLC,ANN,SI,ML,GA based controller (Yung Yap et al. 2020)	Comparative analysis is done; good convergence but costly techniques and large data set required.	A comprehensive evaluation of popular smart MPPT tactics for the PV unit is given.	Design Complexity and computational complexity are quite high.
Coarse Tree with MPPT Controller & RQGPR without MPP controller (Mukherjee et al. 2020)	Comparing the RMSE of the proposed algorithm with Bagged Tree, Mattern 5/2 GPR and showing less RMSE	ML algorithm shows the better prediction result of maximum power with the MPPT controller.	Unreal data of sun insolation, PV unit temperature, and environment temperature are used.
Bayesian Regularization NN with P&O method (BRNN) (Sharmin et al. 2021)	Best suited for smaller data and showing improved efficiency, reducing misjudgment, and avoiding power loss at MPP compared to P&O method.	Data set proposed which is free from over fitting problems.	A theoretical result is achieved through simulation.
Q learning based Algorithm (Kalogerakis et al 2021)	Comparing the result with PSO techniques and shows the Lesser convergence time.	Operational characteristics of the PV units are not necessary. Number of search steps reduced after shading pattern learning.	MPPT efficiency is lower than the PSO MPPT efficiency.
LIR Method (Farayola et al 2018)	Comparing the result with ANFIS, Bagged tree, and boost technique and achieved better result using the LIR technique in terms of efficiency and RMSE.	Technique offers better maximum efficiency under diverse weather conditions.	Large and precise training data sets are required.
DT Regression MPPT(DTR) (Mahesh et al. 2022)	Comparing the result with β MPPT, CS, and ANN.	Tracking efficiency>93.93% Tracking time= 0.16 sec.	Partial Shading effect is not considered.
BPNN-DL (A. Rafeeq et al. 2022)	Predicting the optimum reference voltage under variable load and weather conditions.	Whenever the PV units are linked to the boost converter in erratic load situations, which maximizes the yield energy from the solar grids.	Cost of the proposed system is high.

5.RESULT AND DISCUSSION

The authors KeyrouzF et al. 2018;TeyKS et al 2018;Mukherjee et al. 2020;Farayola et al. 2018; Behera MK et al. 2018;DuY et al 2018;Takruri et al. 2020;Nkambule et al. 2021;Memaya et al. 2019;Yung Yap et al. 2020;Sharmin et al. 2021;Kalogerakis et al.2021;Mahesh et al. 2022;Rafeeq et al. 2022). discussed different ML-MPPT techniques and evaluated their performance on the basis of different parameters under PSCs The main quality parameters of the ML algorithm in tracking the utmost power point are tracking efficiency, tracking duration, and error in tracking utmost power point. In this paper, the author technically analyzes the results of all reviewed ML techniques and shows the comparative graph between ML tactics. The graph in Figure 7 shows the comparison of eight ML-MPTT techniques on the basis of tracking time. It is shown that Q learning techniques offer very less tracking time to evaluate the MPP. Figure 8 shows the performance of ML-MPPT on the basis of tracking efficiency. MLIR, BRNN, and Q-Learning techniques exhibit the efficiency greater than 99%under PSC. The graph shown in Figure 9 displays the comparative analysis on the basis of root mean square error in tracking MPP. Here, LIR offers the lowest error in tracking while more error occurs in the case of tracking efficiency.

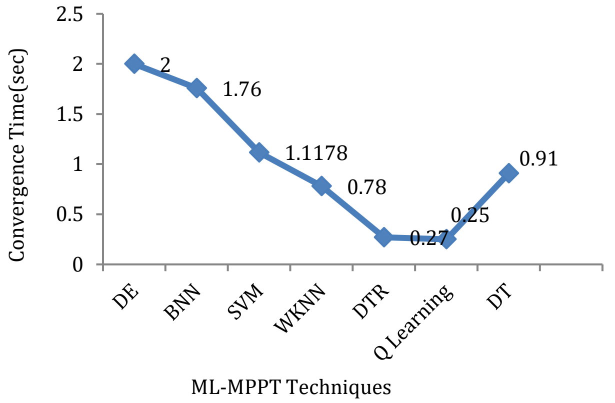

Figure 7. ML-MPPT techniques versus tracking duration (sec)

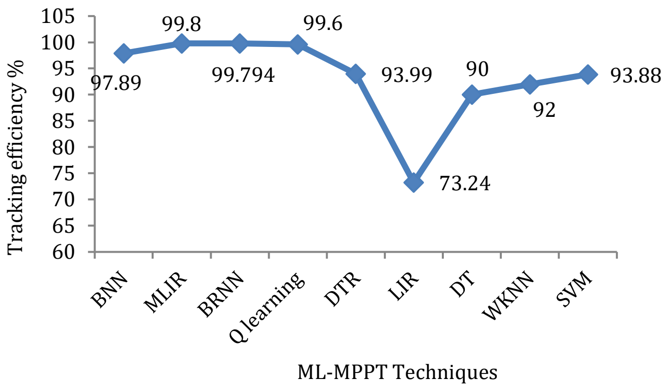

Figure 8. ML-MPPT techniques versus tracking efficiency (%)

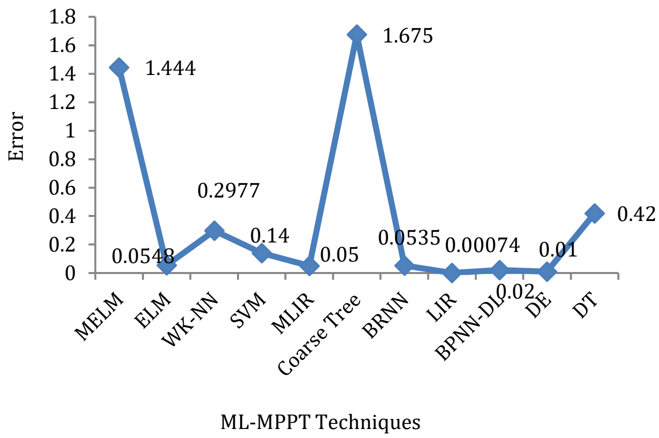

Figure 9. ML-MPPT techniques versus tracking error

According to the literature, selection of ML-MPPT depends on the performance parameter chosen by the researcher under PSC. Based on the graph analysis; Q-learning techniques can give the best optimum result in terms of tracking efficiency, tracking duration, and RMSE. This is while the authorsMahesh et al. 2022 pp. 762-765 discussed only two parameters including efficiency and tracking duration, which is a major research gap. BRNN and MLIR can exhibit more than 95%efficiency, tracking duration less than 1sec, and error less than 0.05 under PSC. Here is also a research gap, that is, authors are considering only two parameters to evaluate the performance. Therefore, the data on all the three parameters should be combined to evaluate the performance of the ML-MPPT so that the optimum result can be obtained.

6. CONCLUSION

One of the current major issues in the field of non-conventional energy research is drawing out maximum power from solar systems to increase its efficiency. In this regard, it is now understood that the idea of the MPPT controller is important given that it maximizes the harvest power supplied by the solar PV system. In order to enhance the potential of the ML to capture the highest solar energy, scientists and engineers may use this review to study the features of various solar MPPT approaches and identify whether ML could enhance their results. This study proposed an optimum ML algorithm to obtain the most optimum performance in ensuring the maximum point tracking of PV cell and a comparative table based on the performance of different ML-MPPT techniques. In summary, this research is helpful for researchers to build a framework for the decision of the ML algorithm to obtain its optimum value of performance parameters. This study reviewed the use of ML-MPPT in-relevant studies and could not prove their optimum suggestion through experimental or simulation work. For future work, the author will propose conducting simulation and experimental work for all the suggested optimum algorithms by considering the performance parameters, i.e., efficiency, tracking, duration and error, to evaluate the performance of the most appropriate algorithm in tracking the MPPT.

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NOMENCLATURE

ANFIS	Adaptive Neuro Fuzzy Inference System
GRNN	Generalized Regression Neural Networks
MAE	Mean absolute error (MJ m2 day -1)
RMSE	Root mean square error (MJ m 2 day -1)
SVR	Support Vector Regression
XG	Boost Extreme Gradient Boosting
ELM	Extreme Learning Machine
SLFN	Single Layer Feed Forward Network
BPANN	Back Propagation Artificial Neural Network
GPR	Gaussian Process Regression
RQGPR	Rational Quadratic Gaussian Process Regression
BANFIS	Bagged ANFIS
BOANFIS	Boosted ANFIS
MNRE	Ministry of New and Renewable Energy
MLR	Multivariate Linear regression
LDA	Linear Discriminant Analysis
BT	Bagged Tree
NBC	Naïve Bayes
RNN	Recurrent Neural Network
LIR	Linear Interaction regression

REFERENCES

1. Ahmad, T., & Chen, H. (2020). A review on machine learning forecasting growth trends and their real-time applications in different energy systems. *Sustainable Cities and Society*, *54*, 102010. https://doi.org/10.1016/j.scs.2019.102010

2. Ahmed, K. Rafeeq., Sayeed, F., Logavani, K., Catherine, T. J., Ralhan, S., Singh, M. K., Prabu, R. T., Subramanian, B., & Kassa, A. (2022). Maximum Power point tracking of PV grids using deep learning. *International Journal of Photoenergy*, *2022*, 1–7. https://doi.org/10.1155/2022/1123251

3. Behera, M. K., Majumder, I., & Nayak, N. (2018). Solar photovoltaic power forecasting using optimized modified extreme learning machine technique. *Engineering Science and Technology, an International Journal*, *21*(3), 428–438. https://doi.org/10.1016/j.jestch.2018.04.013

4. Bendib, B., Belmili, H., & Krim, F. (2015). A survey of the most used MPPT methods: Conventional and advanced algorithms applied for photovoltaic systems. *Renewable & Sustainable Energy Reviews*, *45*, 637–648. https://doi.org/10.1016/j.rser.2015.02.009

5. Bollipo, R. B., Mikkili, S., & Bonthagorla, P. K. (2020). Hybrid, optimization, intelligent and classical PV MPPT techniques: Review. *CSEE Journal of Power and Energy Systems*. https://doi.org/10.17775/cseejpes.2019.02720

6. Bounechba, H., Bouzid, A., Nabti, K., & Benalla, H. (2014). Comparison of Perturb & Observe and Fuzzy Logic in Maximum Power Point Tracker for PV Systems. *Energy Procedia*, *50*, 677–684. https://doi.org/10.1016/j.egypro.2014.06.083

7. D. Mukherjee, S. Chakraborty, P. K. Guchhait & J. Bhunia. (2020). Machine learning based solar power generation forecasting with and without mppt controller, *Int. Conf. for Convergence in Engineering (ICCE), Kolkata,India, vol. 5*, pp. 44–48, https://doi.org/10.1109/ICCE50343.2020.9290685

8. Dogra R, Kumar S & Gupta N (2022). Application of Artificial Neural Network to Solar Potential Estimation in Hilly Region of India. (n.d.), *Journal of Renewable Energy and Environment, Vol.9* issue 3, pp. 10–16. https://doi.org/10.30501/jree.2022.307064.1267

9. Du, Y., Yan, K., Ren, Z., & Xiao, W. (2018). Designing localized MPPT for PV systems using Fuzzy-Weighted Extreme Learning Machine. *Energies*, *11*(10), 2615. https://doi.org/10.3390/en11102615

10. Farayola AM, SunY, Ali (2018) .An Optimization of PV Systems Using Linear Interactions Regression MPPT Techniques. Conference: PowerAfrica 2018 (2018 5th IEEE PES & IAS PowerAfrica Conference) At: Cape Town, South Africa https://doi.org/10.1109/PowerAfrica.2018.8521064

11. Fouilloy, A., Voyant, C., Notton, G., Motte, F., Paoli, C., Nivet, M. L., Guillot, E., & Duchaud, J. (2018). Solar irradiation prediction with machine learning: Forecasting models selection method depending on weather variability. *Energy*, *165*, 620–629. https://doi.org/10.1016/j.energy.2018.09.116

12. Guedri, K., Salem, M., Assad, M. E. H., Rungamornrat, J., Mohsen, F. M., & Buswig, Y. M. (2022). PV/Thermal as Promising Technologies in Buildings: A Comprehensive Review on Exergy analysis. *Sustainability*, *14*(19), 12298. https://doi.org/10.3390/su141912298

13. Hill, J.S.: ' Global solar market demand expected to reach 100 Gigawatts in 2017, says solar power Europe', 2017. Available at https://cleantechnica.com/2017/10/27/global-solar-market-demand-expected-reach-100-gw-2017-solarpower-europe/, accessed 05 November 2017

14. International Energy Agency: ' Snapshot of global photovoltaic markets 2017', 2017. Available at http://www.iea-pvps.org/fileadmin/dam/public/report/statistics/IEA-PVPS-A Snapshot of Global P V-1992-2016-1.pdf, accessed 05 November 2017

15. Ishrat Zaiba, Yadav DK, Dr. Sharma DK & Dr. Nayak S (2022). Review on:challenges solution & scope of iot in solar energy. *J east china univ Sci Technol.*; *65*(4):587-94 http://hdlgdxxb.info/index.php/JE_CUST/article/view/477

16. Islam, H., Mekhilef, S., Shah, N. M., Soon, T. K., Seyedmahmousian, M., Horan, B., & Stojcevski, A. (2018). Performance evaluation of maximum power point tracking approaches and photovoltaic systems. *Energies*, *11*(2), 365. https://doi.org/10.3390/en11020365

17. Jordehi ARjan (2015). Maximum power point tracking in photovoltaic (PV) systems: a review of different approaches. Renew Sustain Energy Rev. 2016;65(65):1127-38. https://doi.org/10.1016/j.rser.2016.07.053. energy system, Volume 64,, Pages 761-770 https://doi.org/10.1016/j.ijepes.2014.07.074

18. Kalogerakis, C., Koutroulis, E., & Lagoudakis, M. G. (2020). Global MPPT Based on Machine-Learning for PV Arrays Operating under Partial Shading Conditions. *Applied Sciences*, *10*(2), 700. https://doi.org/10.3390/app10020700

19. Kamarzaman, N. A., & Tan, C. W. (2014). A comprehensive review of maximum power point tracking algorithms for photovoltaic systems. *Renewable & Sustainable Energy Reviews*, *37*, 585–598. https://doi.org/10.1016/j.rser.2014.05.045

20. Kermadi, M., & Berkouk, E. M. (2015). A maximum power point tracker based on particle swarm optimization for PV-battery energy system under partial shading conditions. *Conference: 3rd International Conference on Control, Engineering & Information Technology CEIT'2015At: Tlemcen, Algeria.* https://doi.org/10.1109/ceit.2015.7233061

21. Keyrouz, F. (2018). Enhanced Bayesian Based MPPT Controller for PV Systems. *IEEE Power and Energy Technology Systems Journal*, *5*(1), 11–17. https://doi.org/10.1109/jpets.2018.2811708

22. Kumar, N., Hussain, I., Singh, B., & Panigrahi, B. K. (2018). Frame work of maximum power extraction from solar PV panel using self-predictive perturb and observe algorithm. *IEEE Transactions on Sustainable Energy*, *9*(2), 895–903. https://doi.org/10.1109/tste.2017.2764266

23. Liu, Y., Chen, J., & Huang, J. (2015). A review of maximum power point tracking techniques for use in partially shaded conditions. *Renewable & Sustainable Energy Reviews*, *41*, 436–453. https://doi.org/10.1016/j.rser.2014.08.038

24. Lorenzo, E. (1994). *Solar electricity: Engineering of Photovoltaic Systems*. Earthscan / James & James. https://www.google.com/books/edition/Solar_Electricity/lYc53xZyxZQC?hl=en&gbpv=0

25. Mahesh, P. V., Meyyappan, S., & Alla, R. R. (2022). Maximum power point tracking using decision-tree machine-learning algorithm for photovoltaic systems. *Clean Energy*, *6*(5), 762–775. https://doi.org/10.1093/ce/zkac057

26. Maleki, A., Haghighi, A., Assad, M. E. H., Mahariq, İ., & Nazari, M. A. (2020). A review on the approaches employed for cooling PV cells. *Solar Energy*, *209*, 170–185. https://doi.org/10.1016/j.solener.2020.08.083

27. Memaya, M., Moorthy, C. B., Tahiliani, S., & Sreeni, S. (2019). Machine learning based maximum power point tracking in solar energy conversion systems. *International Journal of Smart Grid and Clean Energy*, 662–669. https://doi.org/10.12720/sgce.8.6.662-669

28. Mirhassani, S. M., Golroodbari, S. Z. M., Golroodbari, S. M. M., & Mekhilef, S. (2015). An improved particle swarm optimization based maximum power point tracking strategy with variable sampling time. *International Journal of Electrical Power & Energy Systems*, *64*, 761–770. https://doi.org/10.1016/j.ijepes.2014.07.074

29. Mohapatra, A., Nayak, B., Das, P., & Mohanty, K. B. (2017). A review on MPPT techniques of PV system under partial shading condition. *Renewable & Sustainable Energy Reviews*, *80*, 854–867. https://doi.org/10.1016/j.rser.2017.05.083

30. Sharifpur, M., Ahmedi, M. H., Mornrat, J. R. & Malik Mohsein, F. (2022). Thermal Management of Solar Photovoltaic Cell by Using Single Walled Carbon Nanotube (SWCNT)/Water: Numerical Simulation and Sensitivity Analysis, *Journals Sustainability Volume 14* Issue 18 10.3390/su141811523 https://doi.org/10.3390/su141811523

31. Nazari, M. A., Rungamornrat, J., Prokop, L., Blazek, V., Misak, S., Al-Bahrani, M., & Ahmadi, M. H. (2023). An updated review on integration of solar photovoltaic modules and heat pumps towards decarbonization of buildings. *Energy for Sustainable Development*, *72*, 230–242. https://doi.org/10.1016/j.esd.2022.12.018.

32. Nkambule, M. S., Hasan, A. N., Ali, A., Hong, J., & Geem, Z. W. (2020). Comprehensive evaluation of machine learning MPPT algorithms for a PV system under different weather conditions. *Journal of Electrical Engineering & Technology*, *16*(1), 411–427. https://doi.org/10.1007/s42835-020-00598-0

33. Nugraha, D. A. Lian, K.L. & Suwarno,(2020). A Novel MPPT Method Based on Cuckoo Search Algorithm and Golden Section Search Algorithm for Partially Shaded PV System, *Canadian Journal of Electrical and Computer Engineering*, *42*(3):173-182 http://dx.doi.org/10.1109/CJECE.2019.2914723

34. Podder, A. K., Roy, N. K., & Pota, H. R. (2019). MPPT methods for solar PV systems: a critical review based on tracking nature. *Iet Renewable Power Generation*, *13*(10), 1615–1632. https://doi.org/10.1049/iet-rpg.2018.5946

35. Pongsakor Takun et al (2011).Maximum Power Point Tracking using Fuzzy Logic Control for Photovoltaic Systems", *Proc. International Multi conference of Engineers and Computer Scientists (IMECS), Hong Kong, 2011, vol. 2*, pp. 1– 5. https://www.researchgate.net/publication/50864354_Maximum

36. Rabaia, M. K. H., Abdelkareem, M. A., Sayed, E. T., Elsaid, K., Chae, K., Wilberforce, T., & Olabi, A. (2021). Environmental impacts of solar energy systems: A review. *Science of the Total Environment*, *754*, 141989. https://doi.org/10.1016/j.scitotenv.2020.141989

37. Radjai, T., Rahmani, L., Mekhilef, S., & Gaubert, J. (2014). Implementation of a modified incremental conductance MPPT algorithm with direct control based on a fuzzy duty cycle change estimator using dSPACE. *Solar Energy*, *110*, 325–337. https://doi.org/10.1016/j.solener.2014.09.014

38. Riaz, A., Murtaza, A. F., & Sher, H. A. (2019). Power tracking techniques for efficient operation of photovoltaic array in solar applications – A review. *Renewable & Sustainable Energy Reviews*, *101*, 82–102. https://doi.org/10.1016/j.rser.2018.10.015

39. Seyed Mahmoudian, M., Horan, B., Soon, T. K., Rahmani, R., Oo, A. M. T., Mekhilef, S., & Stojcevski, A. (2016). State of the art artificial intelligence-based MPPT techniques for mitigating partial shading effects on PV systems – A review. *Renewable & Sustainable Energy Reviews*, *64*, 435–455. https://doi.org/10.1016/j.rser.2016.06.053

40. Sharmin, R., Chowdhury, S. S., Abedin, F., & Rahman, K. (2022). Implementation of an MPPT technique of a solar module with supervised machine learning. *Frontiers in Energy Research*, *10*. https://doi.org/10.3389/fenrg.2022.932653

41. Soon, T. K., Mekhilef, S., Seyedmahmoudian, M., Horan, B., Oo, A. T., & Stojcevski, A. (2018). Improved differential Evolution-Based MPPT algorithm using SEPIC for PV systems under partial shading conditions and load variation. *IEEE Transactions on Industrial Informatics*, *14*(10), 4322–4333. https://doi.org/10.1109/tii.2018.2793210

42. Sundareswaran, K., Peddapati, S., Nayak, P. S. R., Simon, S. P., & Palani, S. (2015). Enhanced energy output from a PV system under partial shaded conditions through artificial bee colony. *IEEE Transactions on Sustainable Energy*, *6*(1), 198–209. https://doi.org/10.1109/tste.2014.2363521

43. Sundareswaran, K., Vigneshkumar, V., Peddapati, S., Simon, S. P., Nayak, P. S. R., & Palani, S. (2016). Development of an Improved P&O Algorithm Assisted Through a Colony of Foraging Ants for MPPT in PV System. *IEEE Transactions on Industrial Informatics*, *12*(1), 187–200. https://doi.org/10.1109/tii.2015.2502428

44. Takruri M, Farhat M, Barambones O, Ramos-Hernanz JA, TurkiehMJ & BadawiMetal (2020). "Maximum power point tracking of PV system based on machine learning." Energies.2020;13(3):692. https://doi.org/10.3390/en13030692

45. Yagli, G. M., Yang, D., & Srinivasan, D. (2019). Automatic hourly solar forecasting using machine learning models. *Renewable & Sustainable Energy Reviews*, *105*, 487–498. https://doi.org/10.1016/j.rser.2019.02.006

46. Yap, K. Y., Sarimuthu, C. R., & Lim, J. M. (2020). Artificial Intelligence Based MPPT Techniques for Solar Power System: A review. *Journal of Modern Power Systems and Clean Energy*, *8*(6), 1043–1059. https://doi.org/10.35833/mpce.2020.000159