IJRCS
International Journal of Robotics and Control Systems
Vol. 3, No. 4, 2023, pp. 1007-1020
ISSN 2775-2658
http://pubs2.ascee.org/index.php/ijrcs
ASCEE

Optimizing Solar Energy Harvesting: Supervised Machine Learning-Driven Peak Power Point Tracking for Diverse Weather Conditions

Zaiba Ishrat [a,1,*], Kunwar Babar Ali [b,2], Satvik Vats [c,3], Surender Kumar [d,4]

[a] Meerut Institute of Technology, Meerut, Bypass Road Bahgpat Crossing, Meerut, 250005, U.P. India
[b] Meerut Institute of Engineering and Technology, N.H. 58, Delhi Roorkee Highway, Meerut, 250005, U.P. India
[c] Graphic Era Hill University, Road Sociuety Area, Celement Town, Dehradun, 248002, Uttrakhand, India
[d] IIMT College of Engineering, Knowledge Park III, Greater Noida, 201310, U.P, India
[1] zaibaishrat01@gmail.com; [2] kunwarbabrali1@gmail.com; [3] Svats@gehu.ac.in; [4] skladhoura88@gmail.com
* Corresponding Author

ARTICLE INFO

Article history
Received October 03, 2023
Revised November 24, 2023
Accepted December 14, 2023

Keywords
PV System (PVS);
MxPPT;
SGPRA;
Matlab/Simulink

ABSTRACT

Solar Power is one of the significant prevalent forms of clean energy due to its perceived to be pollution-free and easily accessible. The market for renewable energy was established by the rapid development in electrical energy consumption and the diminution of conventional energy resources (CER). Under varying weather condition extracted energy from solar system is not constant and maximum. This study suggests the applicability of machine learning algorithm (MLA) in Peak power point tracking (P3T) methods to maximize power of a PV arrangement under varying weather conditions. Machine learning methods optimize peak power point tracking in solar photovoltaic systems by bringing agility, data-driven decision-making, and increased accuracy. MLAs improve the overall efficiency, stability, and dependability of these systems by handling the unpredictability of solar energy production under varying weather circumstances and PSCs Because MLAs are able to learn and adjust to non-linear relationships between solar intensity and PVS output. In this study, the squared multiple squared exponential Gaussian process regression method SGPRA tested in three rapidly varying ecological conditions. The performance of ML-P3T methods is validated using Matlab/Simulink, and the simulation outcome are compared with one of the most used algorithms, the variable step size incremental conductance algorithm (VINA). The Matlab/Simulink findings show that SGPRA operates significantly better under varying weather circumstances, harnessing more peak power efficiency > 90%, shorter tracking time 0.13 sec, a mean error of 0.042, and superior stability.

1. Introduction

Massive interest in the use of green energy resources (GER) has been sparked by the rise in demand, rising costs of fossil fuels, and concern about environmental issues. Because it is so readily available, solar energy is one of them [1], [2]. It appears encouraging that solar energy power will expand from 227 GW in 2015 to 1362 GW by 2030 [38], [39].

Despite the advantages that a PV system (PVS) can provide, PVS has certain drawbacks; including a high installation cost, poor energy conversion efficiency, and unpredictable power output due to a reliance on constantly shifting climatic circumstances [3], [25]. The most commercial solar panels' efficiency falling between 15% and 22%, a sizable amount of sunshine does not get converted into electrical power. When a solar panel is partially shaded, either the system as a whole or specific sections of it are, resulting in uneven lighting. This may occur as a result of adjacent structures, trees, or even cloud cover. In addition to low ouput power PSCs also responsible for mismatch in power loses. There are several peaks on the P-V characteristics (PVC) curve under Partial shading conditions (PSCs) [31], including a number of local minima and one GP (Global Peak). As a result, some MxPP algorithms must be created that can haul out the utmost amount of power from PVS and transmit it to the load while operating in a variety of environmental conditions [4]. However, under PSCs, several MxPPT strategies were unable to follow GMxPP. As a result, the PVS experienced power losses and operated with low efficiency [4]-[6].

Various approaches to tracking maximum power have been presented, as seen in the literature. Swarm optimization algorithms, artificial intelligence algorithms, and conventional algorithms can all be used to classify these techniques [1], [6], [7], [26]. Hill climbing (HCA), perturb and observe (PnOA), incremental conductance (ICA), open circuit voltage [8], [9], [23], short circuit current method [23], are all straightforward techniques that work well in stable weather conditions. The P&OA exhibit the swinging around the topmost point which is overawed by INCA however, under NUW conditions but INCA is unable to track the MxPP. The author suggests a fixed voltage [7]-[9], open circuit voltage [9], and short circuit current method [8], but they are all offline methods and unrealistic methods because they call for constant solar radiation and temperature.

AI-based strategies like ANN [1], [32], FLC [10], and ANFIS [12] are utilized to get beyond the limitations of classical algorithms. Although they require a significant internal storage area, ANN-based approaches [1], [32] have the advantage of monitoring the GMxPP under PSC. A unique FLC-MxPPT has been proposed that does not require a mathematical model of the PVS but rather a professional with knowledge of the fuzzification process [10]. N. Priyadarshi, et al. [11] employed ANFIS to take advantage of FLC and ANN advantages.

Researchers have employed optimization strategies to track the GMxPP under PSC, such as the CSA with Golden Search Algorithm [17], PSOA [12], [16], ACO [18], [21], GA [13] but the mathematical computational complexity is very high. The efficiency of CSA depends on tuning of parameters i. e. population size and probability of finding new nest which is very difficult to decide in NUW. In PSOA [12], [16] the inertia weight and acceleration coefficients in PSOA are usually static, making it thought-provoking for the algorithm to adjust quickly in NUW. GA comprise functions like crossover and mutation, which are computational complex and like CSA this algorithm is also parameter sensitive. The MLA [15], [19], [20], [24], [30], [33] is used by the researchers. The researcher proposed a multiple linear regression model for forecasting of power under varying weather [24]. The model predict the power with less than 6% error as an actual power. A study is published to propose the systematic literature review of Deep learning in solar power tracking [27]. These techniques give good convergence speed and tracking efficiency, but the computational complexity is quite high for the suggested algorithms.

Squared Gaussian Process Regression algorithm (SGPRA), an enhanced ML-MxPPT technique, is introduced in this study and correlated with variable step size incremental conductance algorithm (VINA) utilizing real-time data under PSC. This study recommended cascading the MxPPT and PID controllers (PIDC) to rectify and optimize the large flaws into smaller flaws. Additionally, it increases the MxPPT algorithm's precision, which ultimately raises the PV panel's effectiveness. This paper's primary contribution is as follows:

(i) Emphasizing the MxPPT controllers' significance within non uniform weather conditions (NUW).

(ii) Harnessing MxPP for real-time data using SGPRA-MxPPT approaches.

(iii) Using a PIDC to lower the inaccuracy and thereby improve MxPPT controller performance.

(iv) Using SGPRA enhance the tracking rate and tracking efficiency under non uniform weather condition (NUW).

(v) Using SGPRA technique decreases the fluctuation around the MxPP therefore negligible power losses.

The outline of this study is organized as follows: Section II discuss the designing of proposed system, segment III explains MLA, flow chart and proposed algorithm under NUW. Section IV discuss the simulation result analysis and finally concludes the research paper.

2. Design and Methodology

The MSX -60W solar panel data set [40] was utilized by the author to test the squared Guassian regression model (SGPRA.The suggested strategy splits the PV panel data set into an 80% and 20% ratio randomly. SGPRA is trained on 80% of the data and tested on 20% of the data. Solar insolation and temperature are employed as key features to train the model, while ref maximum panel current is the desired parameter. “Table 1” shows he MSX-60W solar module's PV model specifications [22].

To obtain the equilibrium PVS and load impedances, the Boost Converter is used. In order to control the transmission of electricity, the duty cycle (Dc) is used to change its ON/OFF condition [25]. The duty ratio, which can be stated as a ratio or percentage, is the percentage of time that an electrical device is used. Using Equation (1), Dc is computed where average output and input voltages of the converter are represented by Vout and Vin. Equations (2), (3), and (4), used to establish the suitable values for inductors and capacitors [35]. Table 2 shows the parameters of designed boost converter.

$$Vo = Vi \div (1 - Dc) \tag{1}$$

$$L = \frac{Dc * Vi}{f * 2 * \mathrm{d}IL} \tag{2}$$

$$C1 = \frac{4ViDc}{\mathrm{d}Vi\, Ri.f} \tag{3}$$

$$C2 = \frac{2Vo\, Dc}{dVoRof} \tag{4}$$

The suggested network is fully depicted in Fig. 1, which includes the PV panel, MxPPT methods, the PID controller [34], the PWM generator, the Boost DC-DC converter, and the 60 Ohms load resistor. PID controller, which is the most popular, is utilized to enhance system capabilities like steadiness, voltage management, swiftness, and precision [34]. For the tuning of PID controller Ziegler-Nichols" approach is used. The parameter of tuned PID controller is given in Table 3.

3. Supervised Machine Learning Algorithm

MLA is a subfield of AI that allows a computer algorithm to anticipate events more precisely without its exclusively designing to do so. In order to anticipate new response values, MLA use chronological data as input. Regression algorithm is a supervised algorithm [36]. Squared Gaussian process regression SGPRA is based on the idea of Gaussian processes, which are a set of haphazard variables with a mutual Gaussian distribution for any finite number of them. A mean function and a covariance function also referred to as a kernel function, describe a Gaussian process [23], [27]-[29]. The squared exponential kernel, also acknowledged as the radial basis function, is the covariance function used in the squared exponential GPR use (5).

$$M((x1, x2), (x1', x2')) = ¥^2 * exp(-0.5 * (||x - x'||^2 / L^2)) \quad (5)$$

Table 1. PV module specification of MSX-60W pv module [22]

PV module specification	Value
Voc open circuit voltage	21.1volt
Isc short circuit current in amp	3.8A
Impp panel maximum current in ampere	3.5A
Vmpp Panel max output voltage in volt	17.1volt
K_s (boltzman constant)	1.38×10^{-23} J/K
N (series cell)	36
q (electron charge)	1.6×10^{-19} coulomb
n is the constant	1.3
Isc short circuit current	3.8A
Tr (reference temperature)	25 °C
Gr (reference Sun radiation)	1000 watt/m^2
Series Resistor Rx	0.00181 ohm
Shunt Resistor Ry	400 ohm
Temperature coefficient of current Ki	.003 mA/°C
Temperature coefficient of voltage Kv	-.08 mA/ °C
Maximum output power	60W

Table 2. Parameters of boost converter

Parameter	Value
Vi (Maximum Panel output voltage)	51.3 volt
Ro	60 ohm
L	29 mH
F (Switching frequency)	25 khz
dI_L (current ripple)	10% of I_L
dV_i (voltage ripple)	1% of Vo
C_2	260 microfarad
C_1	34.11 microfarad

Table 3. Performance & robustness parameter of PID controller

Stability	Rise Time	Overshoot	Settling Time	Peak	Gain margin
Stable	0.0251sec	4.20%	0.0649	1.01	67.5deg

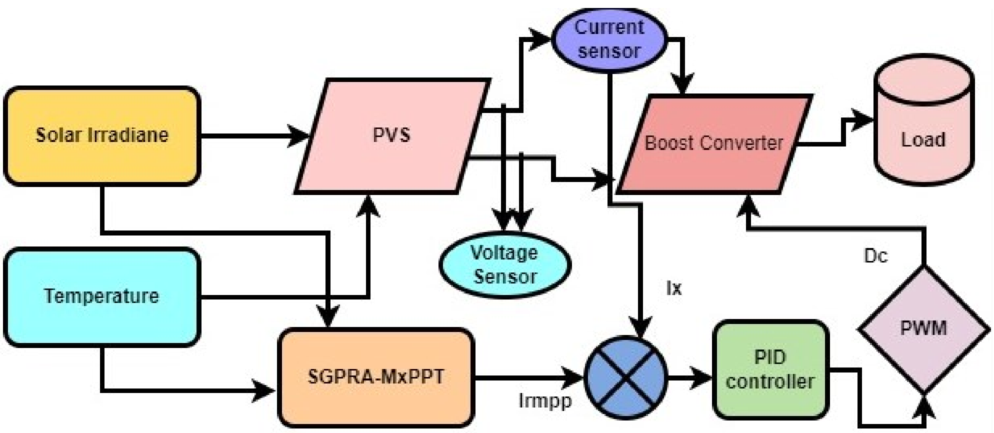


Fig. 1. Proposed block diagram of SGPRA-MxPPT

Here, $(x1, x2)$ and $(x1', x2')$ shows the two points input features in space, $¥^2$ is the variance, $||x - x'||^2$ is the squared Euclidean distance between the points, and L is the length scale. Estimate the parameters of the covariance function ($¥^2$ and L) using techniques like maximum likelihood estimation. To make the predictions for a test input $(x1^*, x2^*)$ compute the covariance vector among the investigation point and the training points: $M\_^* = [M((x1^*, x2^*), (x1, x2))]$ for each training point $(x1, x2)$. Compute the predictive mean $(\text{£}(x^*))$ and predictive variance $(\text{¥}\hat{}2(x^*))$ using equation (6) and (7) [23], [29].

$$\text{£}\,(x^*) = M\_\hat{}T * (M + \text{¥}\hat{}2\_n * L)\hat{}(-1) * y \tag{6}$$

$$\text{¥}\hat{}2(x) = M(x^*, x^*) - M\_\hat{}T * (M + \text{¥}\hat{}2\_n * L)\hat{}(-1) * M\_ \tag{7}$$

Here, $M\,(x^*, x^*)$ represents the covariance between the test point and its self. Proposed model's efficacy is computed by correlated the anticipated values with the actual target values using appropriate evaluation metrics (e.g., MSE, R-squared) for regression tasks [26]-[29]. Fig. 2 displays the flow of SGPRA algorithm.

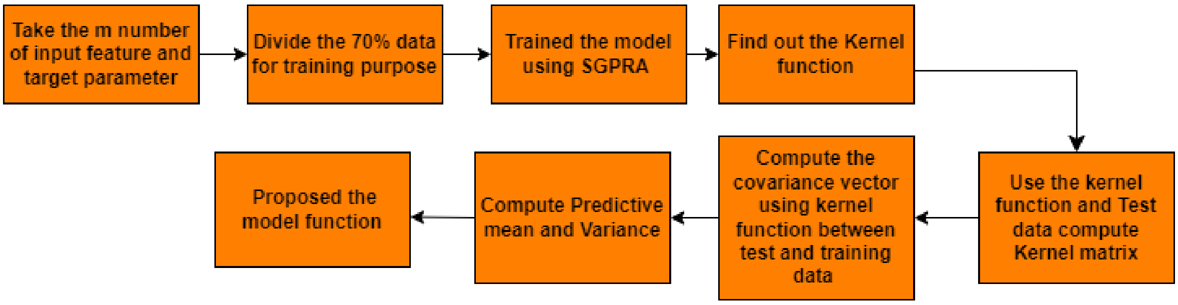
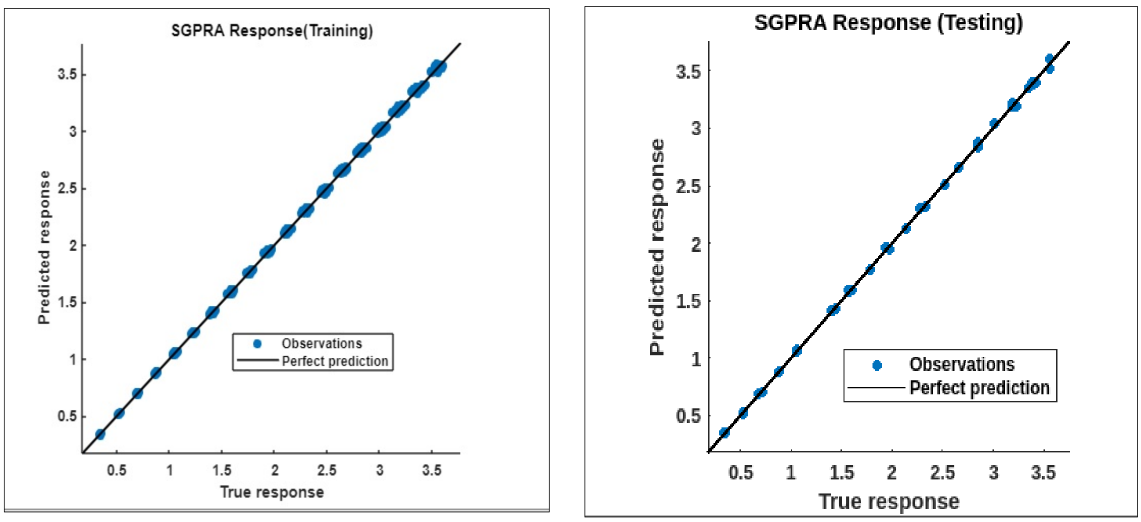


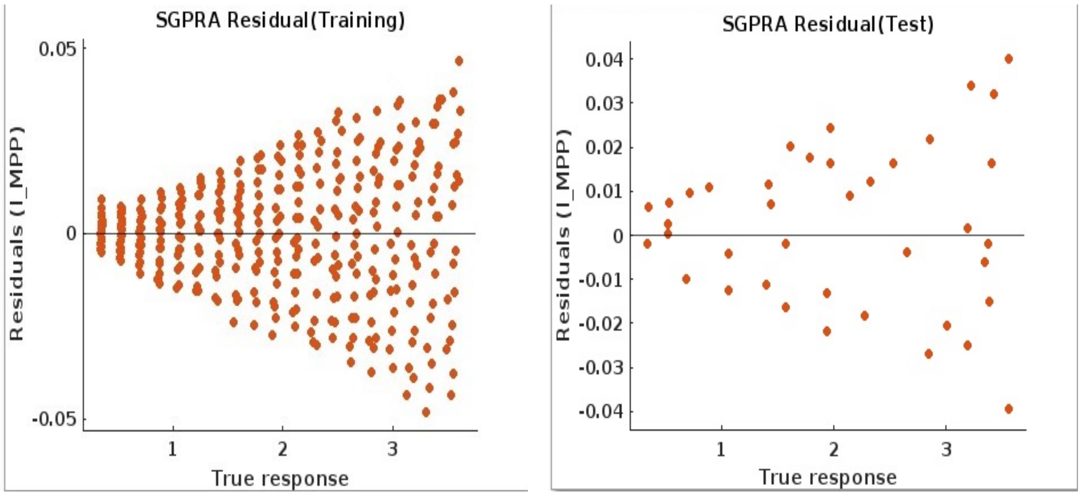
Fig. 2. Flow chart of SGPRA algorithm

The SGPRA used data set of MSX-60W for training and testing purpose. The Table 4 shows the error result during validation and testing duration, Fig 3 (a) and Fig. 3 (b) shows the plot of response of model during training and testing phase and Fig. 4 (a), (b) residual error during training and testing phase. The extracted model for the prediction of new value to unknown input parameter is trainedModel.predictFcn = @(x) gpPredictFcn(predictorExtractionFcn(x));



(a) (b)

Fig. 3. SGPRA Response during training (a), testing (b)



(a) (b)

Fig. 4. Residual during training (a), testing (b)

3.1. Proposed MxPPT Algorithm

Author uses SGPRA model to track MxPP of a PVS using. The proposed MxPPPT algorithms steps are given below. Fig. 5 shows the proposed SGPRA-MxPPT algorithm flow chart.

(i) Measure the panel voltage Vx and current Ix for an incident illumination and temperature value.

(ii) Calculate the panel instantaneous power Px.

(iii) Compute the predicted maximum current Irmpp using the SGPRA model for incident radiation and temperature.

(iv) If measured instantaneous current Ix <Irmpp then increase the Ix by adjusting duty duration Dd.

(v) If measured instantaneous current Ix >Irmpp then decrease the Ix by adjusting duty duration Dd.

(vi) Continue the process until Irmpp=Ix

(vii) Calculate Px at when objective achieved and display maximum power of PVS.

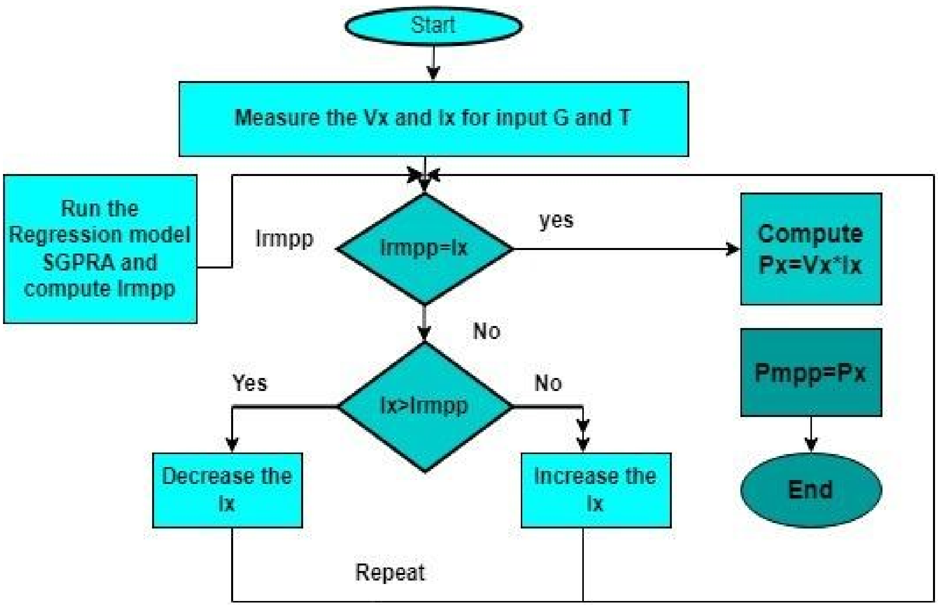


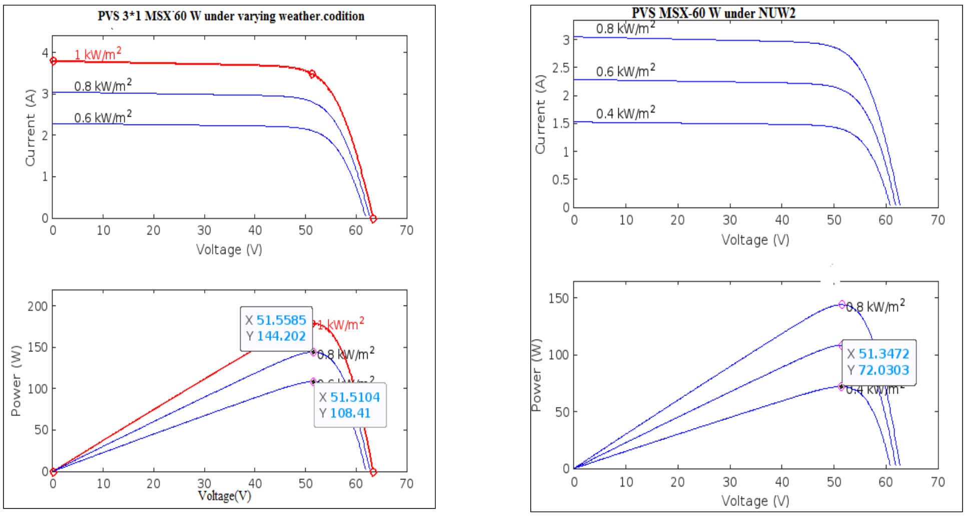
Fig. 5. SGPRA-MxPPT Algorithm flow chart

Table 4. SGPRA Result analysis during training and testing phase

Regression constant	Value	Error	Training Result (Validation)	Error	Testing Result
Variance	1.00	RMSE	0.016791	RMSE	0.01461
Mean	0.00	MSE	0.000281	MSE	0.000213
		MAE	0.013081	MAE	0.0115
Training Time ------------2.35 sec					
Prediction speed-----------19000obs/sec					

4. Result and Discussion

A PVS system of MSX -60W 3×1 photo panel connected in series. Fig. 6 (a) and (b) shows the PVC of PVS under different solar insolation. When array is subjected to UWC (1000w/m^2 solar illumination and 25 °C temperature) than average power (P_a) from the array is 179.5 Watt, if panel is subjected to NUW1 (1000w/m^2 to 800w/m^2 to 600 w/m^2 at 25 °C) than average power (Pa)is 143Watt and under NUW2 (800w/m^2 to 600w/m^2 to 400 w/m^2 at 25 °C) average power is 108 Watt. The simulation of model on Matlab/Simulink under UWC, NUW1 and NUW2 as exposed in Fig. 7 is performed. The Table 5 shows the result of 3×1 MSX-60W PVS under UWC, NUW1 and NUW2 without MxPPT controller. In Table 5 No of peak shows the global and minor peak in variable weather conditions, Vmp is the maximum voltage at global peak, Imp is maximum current at global peak and Pm is the mean power which is the average of total power under the plot. Fig. 8 (a), (b), and (c) demonstrate the result analysis under non uniform weather conditions without MxPPT controller.



(a) (b)

Fig. 6. V-I & P-V curve of array under NUW1 (a), NUW2 (b)

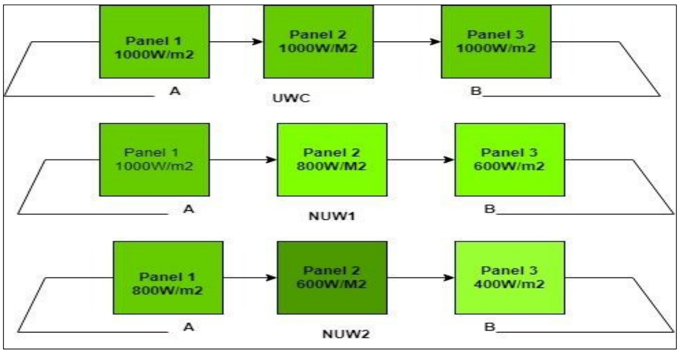
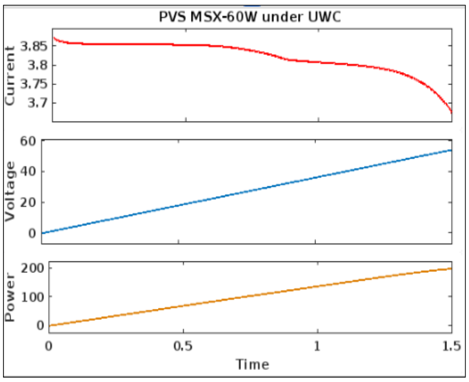


Fig. 7. UWC, NUW1 and NUW2

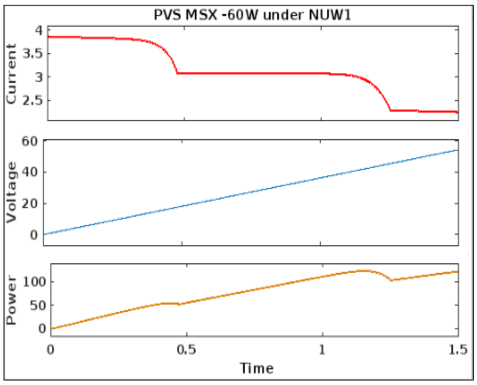
Simulation result analysis of PVS without MxPPT under UWC shows one global peak (GP) at 178.8 watt, NUW1 3 peaks with GP at 126W and in NUW2 3 peaks with GP at 90W. For the same operating conditions Simulation run under UWC, NUW1 and NUW2 using SGPRA controller and VINA-MxPPT controller. The Fig. 9 (a, b & c) displays the results of SGPRA-MxPPT under UWC, NUW1 and NUW2 and Fig. 10 (a, b & c) shows the response of VINA under UWC, NUW1 and NUW2. The time required to stable the algorithm under UWC, NUW1 and NUW2 is 0.13s by SGPRA and 0.26 s by VINA although fluctuation around the stable value using SGPRA algorithm are negligible small as publicized in Fig. 11 a and b. Table 6 shows the response analysis under three operating condition for both the MxPPT Controller.

Table 5. Response analysis of MSX-60W PVS without MxPPT controller

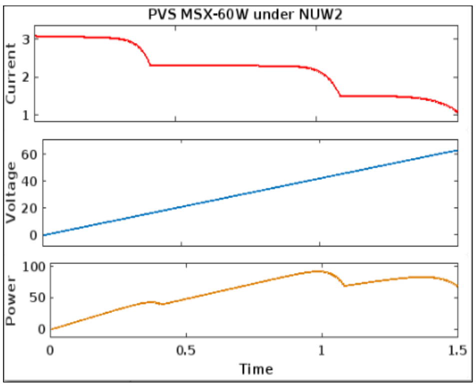
Operating Condition	No of Peak	Maximum Voltage (Vmp)	Maximum Current (Imp)	Max Power (Pmp)	Mean Power (Pm)
UWC	1	51.1	3.50	178.8Watt	83.84W
NUW1	3 (GP, LP1, LP2)	51.20	2.98	126 Watt	64.61W
NUW2	3 (GP, LP1, LP2)	51.19	2.25	90 Watt	46.69W



(a)



(b)

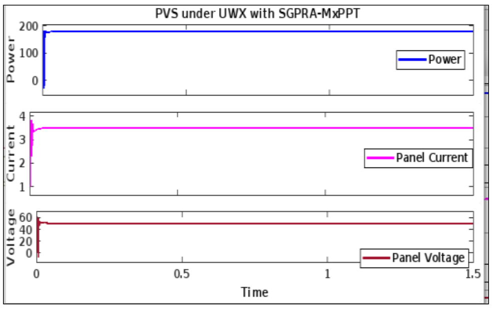


(c)

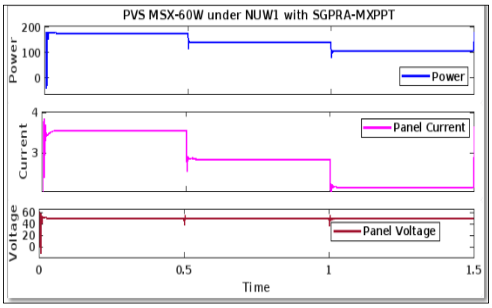
Fig. 8. Response under UWC (a), NUW1 (b), NUW2 (c)

$$Efficiency = (Px/Pa) * 100 \tag{8}$$

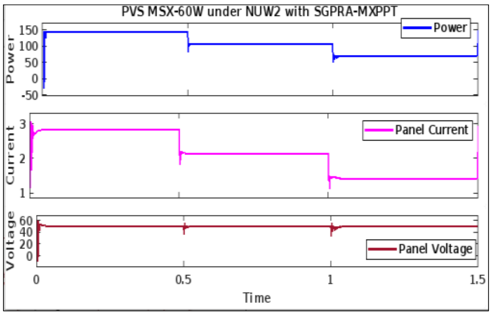
The comparative analysis of simulation result SGPRA-MxPPT and VINA-MxPPT in Table 6 shows that SGPRA controller exhibits improved performance in terms of maximum power, mean power and transit time. The means power efficacy of projected controller can be computed by using equation (8), where Pa is the maximum average power of an actual solar panel in UWC, NUW1 and NUW2 conditions i. e. 179.5W, 143W and 108W and Px is the mean power using MxPPT controllers show in. Fig. 12 shows the mean efficiency of SGPRA-MxPPT, VINA-MxPPT and Fig. 13 shows the tracking duration for proposed MxPPT.



(a)

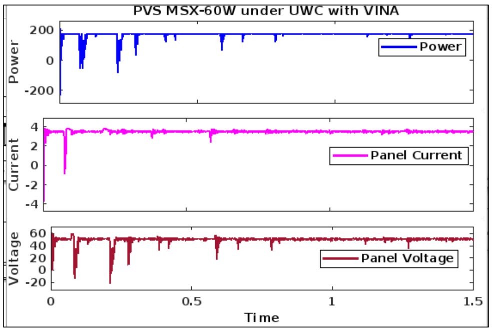


(b)

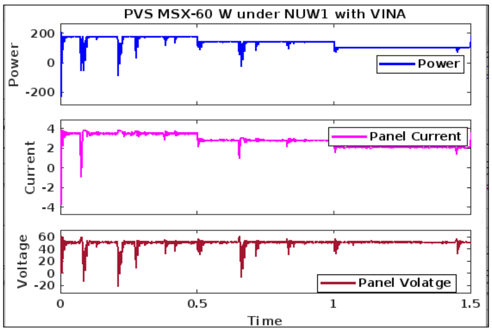


(c)

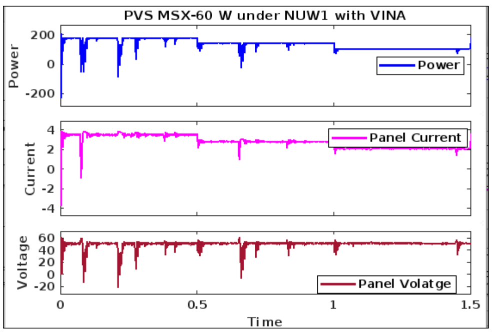
Fig. 9. PVS under UWC with SGPRA-MxPPT (a), PVS under NUW1 with SGPRA-MxPPT (b), PVS under NUW2 with SGPRA-MxPPT (c)



(a)



(b)

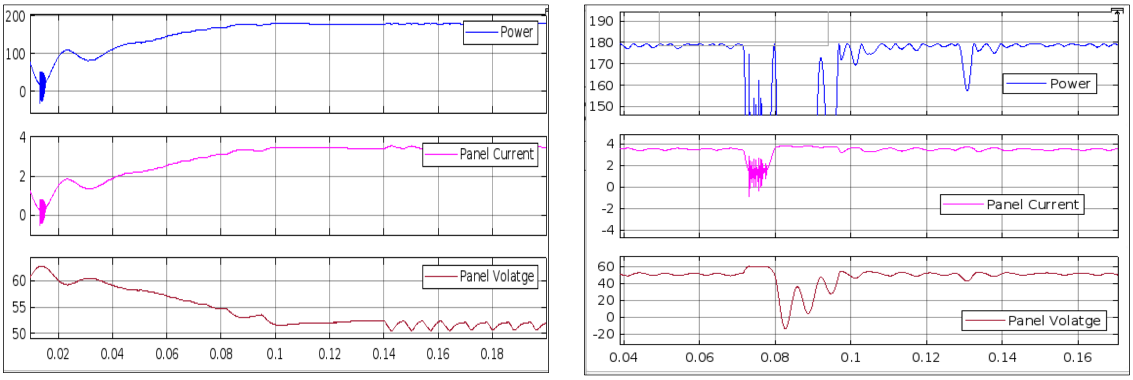


(c)

Fig. 10. PVS under UWC with VINA (a), PVS under NUW1 with VINA (b), PVS under NUW2 with VINA (c)

Vol. 3, No. 4, 2023, pp. 1007-1020

The Table 6 shows that mean power Px using UWC, NUW1 and NUW2 is more than the mean power Pm without using MxPPT controller. The Table 5 and Table 6 demonstrates that maximum tracking power (Pmp) and mean power (Px) by using MxPPT controller is more than the without MxPPT controller. The SGPRA-MxPPT mean Power Px is 179.3W, 143.4W, and 106.6W and VINA Px are 173.7W, 137.6W, and 103.6W.



(a) (b)

Fig. 11. Oscillation for SGPRA-MxPPT (a), Oscillation for VINA-MxPPT (b)

Table 6. Comparative analysis of results with SGPRA-MxPPT and VINA-MxPPT

Environment Condition	MxPPT Controller	Vmax (V)	Imax (A)	Pmax (watt)	Mean Power Px (watt)	Time	Efficiency =(Px/ Pa)*100
UWC (1000w/m^2, 25c)	SGPRA	50.9	3.51	179.3	179.3	0.13s	99.86%
NUW1 (1000, 800, 00W/m^2 25c)		50.29	2.829	158.8	142.4	0.13s	99.58%
NUW2 (800, 600, 400W/m^2 25 c)		50.29	2.136	143.6	106.6	0.16s	99.02%
UWC (1000w/m^2, 25c)	VINA	49.92	3.49	178.8	173.7	0.23s	96.74%
NUWC1 (1000, 800, 600W/m^2 25c)		49.78	2.79	105.09	137.6	0.25s	96.21%
NUWC2 (800, 600, 400W/m^2 25 c)		47.32	2.11	71.07	103.2	0.28s	95.31%

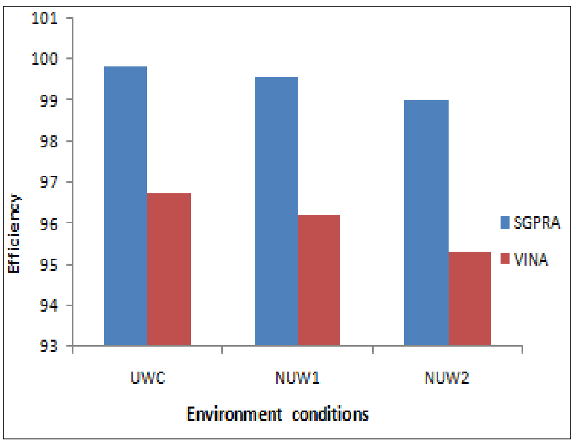


Fig. 12. Means efficiency of MxPPT controller

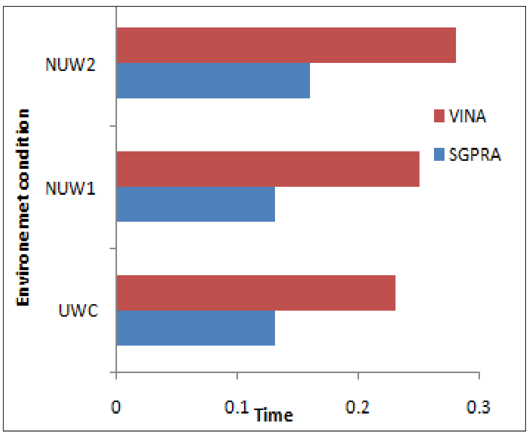


Fig. 13. Tracking duration of MxPPT controller

5. Conclusion

This research introduces a novel regression machine learning-based MxPPT controller. It resolves a number of underlying issues that the bulk of MxPPT algorithms typically have. The primary aim of the MxPPT-Controller is to track the utmost power point with the least variation around steady state power under varying solar illumination in the shortest amount of time. The following conclusions are find out by the authors in presented paper:

- A New ML-MxPPT controller proposed that shows the mean power approximate equals to Solar Panel mean Power.
- Under different environmental conditions, the suggested MxPPT controller's efficiency in MATLAB is greater than 99%, with 0.13 sec tracking time and barely perceptible oscillations around stable maximum power.
- Comparing the SGPRA-MxPPT controller's performance to that of other advanced methods In order to prove its superiority, VINA used a 0.26-second tracking duration with a high tracking efficiency.

Author's intended hardware setup in upcoming works and experimental result to prove the advantage of MLA in the field of MxPPT under varying environment situation.

Data Availability: The statistics utilized to help out the result of this research are integrated in the article and mentioned in reference section.

Acknowledgements: The authors are very grateful to the research department of MIET, Meerut and MIT Meerut, India for offering a good exploration surroundings and facilities.

Conflicts of Interest: The authors declare that they have no conflicts of interest to this work.

References

[1] A. K. Podder, N. K. Roy, and H. R. Pota, "MPPT methods for solar PV systems: a critical review based on tracking nature," *IET Renewable Power Generation*, vol. 13, no. 10, pp. 1615-1632, 2019, https://doi.org/10.1049/iet-rpg.2018.5946.

[2] N. A. Kamarzaman and C. W. Tan, "A comprehensive review of maximum power point tracking algorithms for photovoltaic systems," *Renewable and Sustainable Energy Reviews*, vol. 37, pp. 585–598, 2014, https://doi.org/10.1016/j.rser.2014.05.045.

[3] M. Mosa, M. B. Shadmand, R. S. Balog, and H. A. Rub, "Efficient maximum power point tracking using model predictive control for photovoltaic systems under dynamic weather condition," *IET Renewable Power Generation*, vol. 11, no. 11, pp. 1401-1409, 2017, https://doi.org/10.1049/iet-rpg.2017.0018.

[4] R. J. Mustafa, M. R. Gomaa, M. Al-Dhaifallah, and H. Rezk, "Environmental Impacts on the Performance of Solar Photovoltaic Systems," *Sustainabilty*, vol. 12, no. 2, p. 608, 2020, https://doi.org/10.3390/su12020608.

[5] N. Karami, N. Moubayed, and R. Outbib, "General review and classification of different MPPT Techniques," *Renewable and Sustainable Energy Reviews*, vol. 68, pp. 1–18, 2017, https://doi.org/10.1016/j.rser.2016.09.132.

[6] M. Seyedmahmoudian *et al.,* "State of the art artificial intelligence based MPPT techniques for mitigating partial shading effects on PV systems-A review," *Renewable and Sustainable Energy Reviews*, vol. 64, pp. 435–455, 2016, https://doi.org/10.1016/j.rser.2016.06.053.

[7] A. R. Jordehi, “Maximum power point tracking in photovoltaic (PV) systems: a review of different approaches,” *Renewable and Sustainable Energy Reviews*, vol. 65, pp. 1127-1138, 2016, https://doi.org/10.1016/j.rser.2016.07.053.

[8] R. Ahmad, A. F. Murtaza, and H. A. Sher, “Power tracking techniques for efficient operation of photovoltaic array in solar applications – A Review,” *Renewable and Sustainable Energy Reviews*, vol. 101, pp. 82-102, 2019, https://doi.org/10.1016/j.rser.2018.10.015.

[9] 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, https://doi.org/10.1016/j.rser.2015.02.009.

[10] T. Radjai, L. Rahmani, S. Mekhilef, and J. P. Gaubert, “Implementation of a modified incremental conductance MPPT algorithm with direct control based on a fuzzy duty cycle change estimator using dSPACE,” *Solar Energy*, vol. 110, pp. 325-337, 2014, https://doi.org/10.1016/j.solener.2014.09.014.

[11] N. Priyadarshi, F. Azam, A. K. Sharma, and M. Vardia, “An adaptive neuro- fuzzy inference system-based intelligent grid-connected photo-voltaic power generation,” *Advances in Computational Intelligence*, vol. 988, pp. 3–14, 2020, https://doi.org/10.1007/978-981-13-8222-2_1.

[12] W. Hayder, E. Ogliari, A. Dolara, A. Abid, M. B. Hamed, and L. Sbita, “Improved PSO: A Comparative Study in MPPT Algorithm for PV System Control under Partial Shading Conditions” *Energies*, vol. 13, no. 8, p. 2035, 2020, https://doi.org/10.3390/en13082035.

[13] Y. Shaiek M. B. Smida, A. Sakly, and M. F. Mimouni, “Comparison between conventional methods and GA approach for maximum power point tracking of shaded solar PV generators,” *Solar Energy*, vol. 90, p. 107-122, 2013, https://doi.org/10.1016/j.solener.2013.01.005.

[14] M. K. Behera, I. Majumder, and N. Nayak, “Solar photovoltaic power forecasting using optimized modified extreme learning machine technique,” *Engineering Science and Technology an International Journal*, vol. 21, no. 3, pp. 428-438, https://doi.org/10.1016/j.jestch.2018.04.013.

[15] M. Takruri *et al.,* “Maximum power point tracking of PV system based on machine learning,” *Energies*, vol. 13, no. 3, p. 692, 2020, https://doi.org/10.3390/en13030692.

[16] D. D. Martínez, R. T. Codorniu, R. Giral, and L. V. Seisdedos, “Evaluation of particle swarm optimization techniques applied to maximum power point tracking in photovoltaic systems,” *International Journal Circuit Theory and Applications*, vol. 49, no. 7, pp. 1849-1867, 2021, https://doi.org/10.1002/cta.2978.

[17] D. A. Nugraha, K. L. Lian, and Suwarno, "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*, vol. 42, no. 3, pp. 173-182, 2019, https://doi.org/10.1109/CJECE.2019.2914723.

[18] H. Rezk, A. Fathy, and A. Y. Abdelaziz, “A comparison of different global MPPT techniques based on meta-heuristic algorithms for photovoltaic system subjected to partial shading conditions,” *Renewable and Sustainable Energy Reviews*, vol. 74, pp. 377-386, 2017, https://doi.org/10.1016/j.rser.2017.02.051.

[19] M. S. Nkambule, A. N. Hasan, A. Ali, J. Hong, and Z. W. Geem, “Comprehensive evaluation of machine learning MPPT algorithms for a PV system under different weather conditions,” Journal Electrical Engineering Technology, vol. 16, no. 1, pp. 411-427, 2021, https://doi.org/10.1007/s42835-020-00598-0.

[20] R. Sharmin, S. S. Chowdhury, F. Abedin, and K. M. Rahman, “Implementation of MPPT Technique of Solar Module with Supervised Machine Learning,” *Frontiers in Energy Research*, vol. 10, p. 932653, https://doi.org/10.3389/fenrg.2022.932653.

[21] R. K. Phanden, L. Sharma, J. Chhabra, and H. İ. Demir, “A novel modified ant colony optimization based maximum power point tracking controller for photovoltaic systems,” *Materials Today Proceeding*, https://doi.org/10.1016/j.matpr.2020.06.020.

[22] K. Nallathambi, S. S. Dash, S. Padmanaban, S. Paramasivam, and P. K. Morati, “Maximum Power Point Tracking Implementation by Dspace Controller Integrated Through Z-Source Inverter Using Particle Swarm Optimization Technique for Photovoltaic Applications,” *Applied Sciences*, vol. 8, no. 1, p. 145, 2018, https://doi.org/10.3390/app8010145.

[23] Y. Xie, C. Zhu, W. Jiang, J. Bi, and Z. Zhu, "Analyzing Machine Learning Models with Gaussian Process for the Indoor Positioning System", *Mathematical Problems in Engineering*, vol. 2020, 2020, https://doi.org/10.1155/2020/4696198.

[24] P. Pourmalekia, W. Agutub, A. Rezaei, and N. Pourmaleki, “Techno-Economic Analysis of a 12-kW Photovoltaic System Using an Efficient Multiple Linear Regression Model Prediction,” *IJRCS International Journal of Robotics and Control Systems*, vol. 2, no. 2, pp. 370-378, 2022, https://doi.org/10.31763/ijrcs.v2i2.702.

[25] M. L. Katche, A. B. Makokha, S. O. Zachary, and M. S. Adaramola, “A Comprehensive Review of Maximum Power Point Tracking (MPPT) Techniques Used in Solar PV Systems,” *Energies*, vol. 16, no. 5, p. 2206, 2023, https://doi.org/10.3390/en16052206.

[26] J. P. Ram, N. Rajasekar, and M. Miyatake, “Design and overview of maximum power point tracking techniques in wind and solar photovoltaic systems: A review,” *Renewable and Sustainable Energy Reviews,* vol. 73, pp. 1138-1159, 2017, https://doi.org/10.1016/j.rser.2017.02.009.

[27] M. Phiri, M. Mulenga, A. Zimba, and C. I. Eke, “Deep Learning Techniques for Photovoltaic SolarTracking Systems: A Systematic Literature Review,” *Research Square*, 2023, https://doi.org/10.21203/rs.3.rs-2539961/v1.

[28] F. Lubbe, J. Maritz, and T. Harms, “Evaluating the Potential of Gaussian Process Regression for Solar Radiation Forecasting: A Case Study,” *Energies*, vol. 13, no. 20, p. 5509, 2020, https://doi.org/10.3390/en13205509.

[29] B. Zazoum, “Solar photovoltaic power prediction using different machine learning methods,” *Energy Reports*, vol. 8, pp. 19-25, 2022, https://doi.org/10.1016/j.egyr.2021.11.183.

[30] K. R. Ahmed *et al*, "Application of Hybrid Nanostructure for Photo and Bioenergy Applications,” *International Journal of Photoenergy*, vol. 2022, 2022, https://doi.org/10.1155/2022/1123251.

[31] K. S. Awan, T. Mahmood, M. Shorfuzzaman, R. Ali, and R. M. Mehmood, “A Machine Learning Based Algorithm to Process Partial Shading Effects in PV Arrays,” *Computers, Materials & Continua*, vol. 68, no. 1, pp. 29-43, 2021, https://doi.org/10.32604/cmc.2021.014824.

[32] A. G. Olabi *et al.,* “Artificial neural networks applications in partially shaded PV systems,” *Thermal Science and Engineering Progress*, vol. 37, p. 101612, 2023, https://doi.org/10.1016/j.tsep.2022.101612.

[33] Z. Ishrat, S. Vats, K. B. Ali, O. Ahmad Shah, and T. Ahmed, "A Comprehensive Study on Conventional HPPT Techniques for Solar PV System," *2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN)*, pp. 315-321, 2023, https://doi.org/10.1109/CICTN57981.2023.10140264.

[34] A. Khaled, H. Aboubakeur, B. Mohamed, and A. Nabil, "A Fast MPPT Control Technique Using PID Controller in a Photovoltaic System," *2018 International Conference on Applied Smart Systems (ICASS)*, pp. 1-5, 2018, https://doi.org/10.1109/ICASS.2018.8652062.

[35] X. Wang and F. Blaabjerg, "Harmonic Stability in Power Electronic-Based Power Systems: Concept, Modeling, and Analysis," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 2858-2870, 2019, https://doi.org/10.1109/TSG.2018.2812712.

[36] S. Sun, Z. Cao, H. Zhu, and J. Zhao, "A Survey of Optimization Methods from a Machine Learning Perspective," *IEEE Transactions on Cybernetics*, vol. 50, no. 8, pp. 3668-3681, 2020, https://doi.org/10.1109/TCYB.2019.2950779.

[37] C. E. Rasmussen, "Gaussian Processes in Machine Learning," *Advanced Lectures on Machine Learning*," vol. 3176, pp. 63-71, https://doi.org/10.1007/978-3-540-28650-9_4.

[38] M. S. Raboaca *et al.,* "Concentrating Solar Power Technologies," *Energies*, vol. 12, no. 6, p. 1048, https://doi.org/10.3390/en12061048.

[39] S. Fadhel *et al*., "PV shading fault detection and classification based on I-V curve using principal component analysis: Application to isolated PV system," vol. 179, pp. 1-10, 2019, https://doi.org/10.1016/j.solener.2018.12.048.

[40] N. Al-Rousan, N. A. M. Isa, and M. K. M. Desa, "Advances in solar photovoltaic tracking systems: A review," *Renewable and sustainable energy reviews*, vol. 82, pp. 2548-2569, 2018, https://doi.org/10.1016/j.rser.2017.09.077.