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Optimizing Photovoltaic Arrays: A Novel Approach to Maximize Power Output in Varied Shading Patterns

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ABSTRACT

The rapid rise in electrical energy demand and the depletion of fossil fuels have created a market for renewable energy. Among all the renewable energy resources, the most popular is solar energy, perceived as pollution-free, easily accessible, and low maintenance. In non-uniform solar irradiation or partial shading conditions (PSC), the photovoltaic characteristics (PVC) of a solar panel system (SPS) exhibit multiple minor peaks (MP) with one global peak power point (GPPP). To extract the utmost energy from the SPS, the authors proposed an efficient hybrid algorithm integrating the advantages of machine learning and the classical algorithm fractional open circuit voltage (FOVA) to track the GPPP. To follow the GPPP of SPS under unstable environmental surroundings, this study tests ML-based hybrid MPPT algorithms, specifically squared multiple variable linear regression algorithms (SMVLRA), using Matlab/Simulink. Simulation through Matlab is employed to validate the efficiency of the SMVLRA-MPPT approach compared to existing popular conventional and modern MPPT algorithms, namely the Perturb and Observation algorithm (P&OA), the variable step size incremental conductance (VINC) algorithm, and an intelligent algorithm, Decision Tree Regression Algorithm (DTRA). The simulation results demonstrate that SMVLRA offers higher peak power and mean peak power efficiency in less tracking time, with lower error and almost negligible steady-state fluctuation under PSC. The proposed algorithm achieves 99.99% efficiency under standard test conditions (1000w/m^2, 25°C), 99.95% under PSC1 (1000w/m^2, 800w/m^2, 25°C), and 98.89% under PSC2 (1000w/m^2, 800w/m^2, 600w/m^2, 25°C)

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1. INTRODUCTION

Due to its endless supply and environmentally favorable benefits, solar power, a type of pollution-free energy, has been extensively used in response to the increasingly serious environmental pollution (MKH et al., 2020; Motahir et al., 2019). Due to the constant depletion of conventional energy resources, we need to take action to move away from conventional energy and move closer towards greener energy. We currently rely only on non-renewable energy sources, which seriously jeopardize the possibility of a sustainable future. The most extensively used renewable energy source is solar systems, and due to their use in a variety of fields, both industrial and domestic, solar cells are the most practical among them (Ishrat et al., 2022). Solar energy has significant potential to help meet the global need for electricity, particularly in nations with abundant sun radiation. The projected increase in solar energy power from 227 GW in 2015 to 1362 GW by 2030 seems promising (Harrison 2022; Hill J. et al; IEA 2017).

Despite the benefits the PV system offers, it still has significant limitations. Environmental factors such as solar illumination, temperature, dust, obstruction, partial shading, aging, and noise interference can significantly affect the performance of solar power systems. Therefore, it is essential to track the global peak power point (GPPP) of an SPS under varying environmental situations; hence, a MPPT (Maximum Power Point Tracking) controller is needed. Without an MPPT controller, a PV system performs at very low levels of efficiency. As a result, an MPPT controller is required to extract the maximum achievable energy from an SPS. To track GPPP in a solar system, the majority of MPPT algorithms have been proposed (Verma et al., 2016). However, certain MPPT strategies under PSC were unable to track GPPP. This led to power attenuation in the SPS and consequently low-efficiency operations (Shakthivel 2022;Vincheh et al 2014).

As demonstrated in the literature, diverse ways have been proposed to follow the peak power. These strategies can be divided into three categories: classical algorithms, artificial intelligence algorithms, and swarm optimization algorithms R Murtaza 2019; Bendib 2019; Podder 2019). Hill climbing (HC), P&OA, incremental conductance (INCA), FOVA, and Short circuit current algorithm (ISCA) are traditional techniques used. Although the traditional methods P&OA (Radjai et al.,

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2014) and INCA(Z. Ishrat et al. 2023)) are fairly easy to implement, they have the drawback of not being able to follow the GPPP in a variety of meteorological conditions.

The P&OA displays oscillation around the peak point, which is overcome by INCA under fluctuating weather conditions, but INCA is unable to track the GPPP. The authors suggested a fixed voltage (Bendib 2019; Podder 2019; Radjai et al., 2014), open circuit voltage (Kumar et al., 2018), and short circuit current method (Radjai et al., 2014), but they are all offline methods and unre(Radjai et al., 2014), alistic because they call for constant solar radiation and temperature. The inadequacies of traditional approaches are suggested to be addressed by artificial intelligence-based solutions. These techniques include ANN, FLC, ANFIS, and ML. Temperature, solar radiation, and the state of the PV panel are used in ANN-based methods to adjust the weight of buried layers and predict unknown data. These techniques have the benefit of monitoring the global peak power under PSC and in a range of weather scenarios, but they necessitate a huge internal storage area to handle the enormous volumes of data that must be saved (RaeisiAli et al., 2014). The authors(Radjai et al., 2014; Kumar et al., 2018) published a novel FLC-based peak power point tracking method that does not rely on a mathematical model of the PV system. Since people choose the fuzzy-fiction criteria, the controller design is entirely reliant on their expertise. Modeling of GPPPT controllers under variedweather conditions is made simple by the FLC technique(Nugraha et al., 2019). By merging ANN and FLC to create ANFIS (Artificial Neural Fuzzy Inference System), Priyadarshi, et al., 2020proposed unique strategies by employing the d-space as an interface; this method increases tracking time and efficiency.

X Yang Yap et al(2020) proposed an optimization technique that uses a metaheuristic approach inspired by brood parasitism to find the optimal operating point. D.A. Naguraetal.(2019) created a hybrid system by combining the CS algorithm with the golden search technique, which provides incredibly fast speed and swiftly follows the PPP. H. Rezk, et al. (2017) introduced the TLBO technique, which would alter the duty cycle, to follow the global power point. Hayder et al. (2020)proposed an improved PSO technique that computes duty cycle for every sample time and offers high convergence speed and better accuracy. Phandenetal.(2020) proposed an ACO technique inspired by the way of communication of ants. This technique is fit for linear and nonlinear search both, but the computational complexity is high. Shaiekh et al. (2013) offers a genetic algorithm that is using for natural and unnatural optimization problems based on biology evolution process.

The precision of the training data is a key component of any ML-based technique, which is why authors in (M.K. Behra et al. 2018;Z.Ishrat et al 2023) employed the algorithm to identify the GPPP that delivers extremely fast tracking speed, low tracking error, and high tracking efficiency. A real-time maximum power forecasting model in SLFN was proposed by M.K. Behra et al. (2018); it was trained using a modified extreme learning machine (ELM) technique, and its weights were updated using the PSO technique. Its output indices were compared to an accessible structure similar to the BP fore-see structure. A localized MPPT approach was presented by Du Yan et al. [2018] that uses the SVM and ELM supervised machine learning algorithms to reduce the need for periodic parameter training.

The ideal reference voltage of a PV setup under changeable solar irradiation temperatures and load conditions was also predicted by Takuri et al. (2020) using SVM. In order to improve the efficiency of the hybrid model up to 99.8% and shorten the convergence duration to achieve the PPP in comparison to the conventional technique, Memaya et. all (2020) suggested an ML-based multivariate linear regression algorithm in the pre-existing P&O method. A Decision Tree regression machine learning approach (DTRA) is presented by Mahesh et al. (2022) to determine the MPPT for an isolated PV system. The simulation result is compared to the results of the ANN and CS and exhibits an efficiency of more than 93.99% under conditions of static solar irradiation and temperature, with a swift response in 0.159s and the suggested scheme stable in.269s.

A supervised machine learning approach based on a neural network was proposed by R. sharmin et al. (2021) to determine the GPPP for a smaller data set and support the heterogeneous train data set. Mahesh et al. (2023) predict the maximum power for a given value of solar irradiation and temperature using linear and non-linear regression models. The efficiency of the PV system ranges from 93.34% to 95.34% for both linear and nonlinear regression models. Ishrat et al.(2023) reviewed the comparative analysis and research gap in ML techniques used by different authors to track the maximum power efficiency.

The primary motive of this paper is to propose an effective and optimum MPPT controller under varying atmospheric conditions using the regression ML algorithm i.e. SMVLRA and compare the simulation result with the pre-existing MPPT controller. This MPPT method can track the major peak power point under variable solar irradiation conditions instead of sticking at the local peak point. The novelty of work as follows:

(ii) The proposed system works in a real-time environment due to the use of ML and offers high tracking speed and tracking efficiency with low RMSE and less steady-state fluctuation.

(iii) This hybrid algorithm removes the shortcoming of FOVA. In FOVA, for computing the reference voltage (Vref = K*Voc), accurate selection of K is necessary, which depends upon the environmental situation and solar cell used. Here, the selection of K is not necessary as the reference voltage is predicted by using the regression algorithm.

(iv) A comparative analysis is proposed between regression algorithms on the basis of peak power, tracking duration, and RMSE using Matlab/Simulink with P&OA and VINC and DTRA.

As a result, the authors of this study present an ML approach for SPS reference voltage determination based on regression analysis. The authors suggest thorough research by conducting a comparison analysis of the transient performances of four different MPPT techniques using SMVLRA, P&OA VINC, and DTRA in a real-world setting for MSX-60W 3*1* SPS while taking environmental disturbances into account. Better mean power efficiency, higher power at MPPP, very little transit time, and less constant steady-state error are all features of the proposed approach. The study offers technical information in a real-time condition. It may be useful for new researchers and professionals in the field *of* MPPT research to harness the maximum power. In future work, authors will *propose a*hardware*setup* and experimental result to prove the advantage of MLA in the field of MPPT under varying *environmental situations*. The rest of the paper has the following *sections*: Section 2 discusses the design of solar panels, boost converter, and PID controller, and Section 3 introduces the regression algorithm. The proposed MPPT regression algorithm using SMVLRA for the MSX-60W *3*1 PV panel is explained in

Section 4, than finally a discussion of the simulation results is introduced in Section 5.

2. DESIGING OF SOLAR PANEL SYSTEM(SPS)

2.1 PV Cell modeling:

Whenever photon light incident on a PV cell, the photonic light will be converted into an electrical signal. The analogous model of a photovoltaic cell consists of a constant photocurrent source (Ip), diode (Dx), series and parallel resistances (Rx, Ry, and Rz) (Lorenzo (1994)). Figure 1 represents the equivalent electrical network of a unit photovoltaic cell. Panel current is represented by Equation 1.

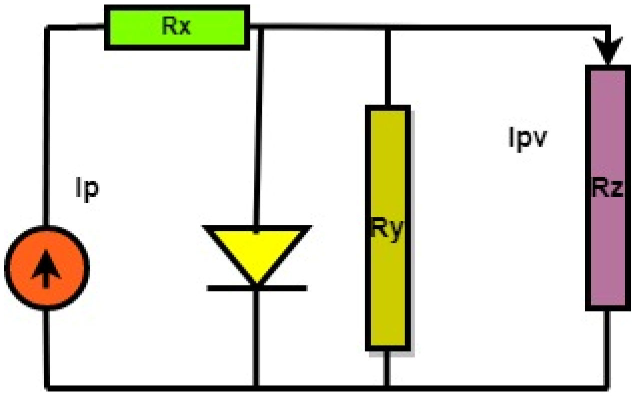


Figure 1. A unit photo cell Modeling (Lorenzo 1994)

$$Ipv = Ip - Is\left(e^{\frac{q(Vpv+IpvNRx)}{nNKsT}} - 1\right) - (Vpv + IpvNRx)/NRy \qquad (1)$$

The photo-generated current Ip is dependent on environmental conditions, namely temperature and solar irradiation, as represented by Equation 3 (Vinodet al 2018).

$$Ip = Isc + Km(Tc - Tr)\frac{Gc}{Gr} \qquad (2)$$

Here, Gc is the current solar radiation, and Gr is the reference solar radiation (1000W/m², 25°C). In this study, the authors use an MSX-60W solar module. Table 1 shows the PV model specifications of the MSX-60W solar module (Padmanaban 2018).

Table 1. PV Module Specification of MSX-60W (Kalaiarasi et al 2018)

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
Ks boltzman constant	1.38*10-23 J/K
N (Total series cell)	36
q (electron charge)	1.6*10-19 coulomb
n(ideal constant)	1.2
Isc short circuit current	3.8A

2.2 Boost Converter:

A PWM control is used to pulse to control the DC-DC boost converter, which is connected to the photovoltaic panel. The duty ratio (D) of the metal-oxide field-effect transistors decides the amount of power that is taken from the solar power system (SPS) to the output. The boost converter enhances the SPS energy to the predicted yield point by employing an inductor (L). The input L and capacitor (C1) work together to lessen the ripple content of the response voltages. When the MOSFET is switched on and the diode is turned off, L's current increases linearly, and when the MOSFET is off, the energy saved in L starts to flow across the output Ro C1 circuit. The capacitive filter offers a DC voltage to the load while smoothing the pulsating current caused by the switching operation .Fig. 2 shows the 3×1 MSX-60W solar panel, whose maximum panel power is 180 watts under standard test conditions. The maximum output voltage for the output load is required to be 17.1 volts, and the current at the load is 3.5 amps for a single PV module. The boost converter for the SPS can be designed using the following equations discussed by (M.H. Rashid 2016).Table 2 shows the parameters of the designed DC-DC boost converter.

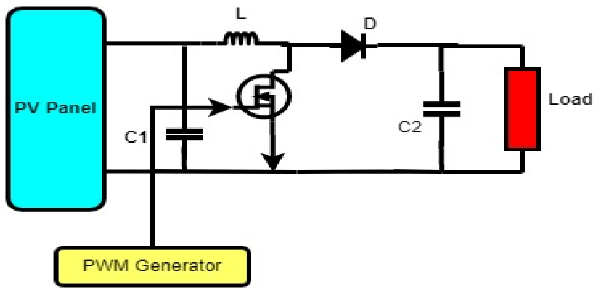


Figure 2. DC-DC Boost Converter (O. Nyrko .et al 2021)

2. EXPERIMENTAL

$$V_o = Vi \div (1-D) \qquad (3)$$

$$I_L = Ii\,(1-D) \qquad (4)$$

$$L = \frac{D*Vi}{f*2*dIL} \qquad (5)$$

$$C_1 = \frac{4ViD}{dViRi.f} \qquad (6)$$

$$R_i = R_o(1-D^2) \qquad (7)$$

$$R_o = 2.5\ Rmp \qquad (8)$$

$$C_2 = \frac{2VoD}{dVoRof} \qquad (9)$$

Table 2. Parameters of Boost Converter

Parameter	Value
Vi (Maximum Panel output voltage)	17.1 volt
Ro	60 ohm
L	29.3mH
F (Switching frequency)	25 khz
dIL(Current ripple)	10% of IL
dVo(Voltage ripple)	1% of Vo
C2	260 microfarad
C1	34.11 microfarad

2.3 PID Controller:

Generally, a boost converter is connected between the SPS and the output load. Both the input and output sides are vulnerable to abrupt changes in value, and delayed transient responses increase system losses and lower efficiency. This study suggests a PID controller for the converter that is MPPT-based. The PID controller, which is the most popular, is utilized to enhance system capabilities like steadiness, voltage management, swiftness, and precision (A Kahled 2018). The transfer function of a PID controller with one pole is in equation 10,and the compensator formula is in equation 11. One of the finest methods for tuning "PID controllers" is the "Ziegler-Nichols" approach. This technique's first step is to array the "I and D" gain up to zero and then increase the P avail until the output exhibits controlled and static swaying. The tuning of PID is done once and does not change according to environmental conditions. The estimated progress result of the PID tuning with the SMVLRA-MPPT controller is shown in Table 3. According to the table, a total of 10 iterations are required for tuning the plant with PID, and during this, eleven transfer functions are computed. As the number of iterations increases, the PID controller cost is reduced, and the compensator becomes more feasible with the simulation set-up. The PID controller, after ten iterations, becomes 94.35% fit to simulated data. Table 4 shows the performance parameters, i.e., rise time, peak time, settling time, and overshoot of the proposed controller. The proposed controller and plant set-up are both stable after the Matlab/Simulink tuning process.

$T(s) = \frac{K}{1+sT}$ where K=-59.93 and T=0.0161 (10)

C(s)= P+ I/s where P= -0.002 & I= -1.016 (11)

Table 3. Tuning Estimation Progress of PID Controller

Iteration	Cost	Number of Steps	First-order Optimality	Expected Improvement %	Achieved Improvement%
0	417.897		100	0.103	
1	245.773	1.73	19	0.103	41.2
2	167.636	4.09	18.6	0.116	31.8
3	84.3913	10.9	26	0.28	49.7
4	6.67937	36.8	101	1.01	92.1
5	0.569014	25.2	266	14.6	91.5
6	0.265346	5.38	145	103	53.4
7	0.253223	0.128	9.9	20	4.89
8	0.252323	0.0114	0.79	0.0995	0.0232
9	0.252323	0.00349	0.0637	0.000666	0.000157
10	0.252323	0.000741	0.00486	$5.73e^{-6}$	$1.4e^{-6}$
Number of evaluated functions ……………………..11					
Fit with the estimation data ……………………94.35%					

Table 4. Performance & Robustness Parameter of PID Controller

Stability	Rise Time	Overshoot	Settling Time	Peak	Gain margin
Stable	0.0275sec	4.28%	0.0749	1.04	67.5deg

3. MACHINE LEARNING ALGORITHM

3.1 Supervised machine Learning algorithm

Linear Regression Algorithm: MLA is a subfield of AI that enables computer programs to forecast events more accurately without being exclusively premeditated to do so (Nakumble et al 2021). The forecasting of new output values is done by using historical data. Reinforcement learning, unsupervised learning, and supervised learning are the three key tactics. The type of methodology that data miners use depends on the type of data they are attempting to predict (Mahdi et al., 2014). A regression algorithm is a supervised algorithm. This technique is employed for the modeling and analysis of numerical data and response data where the output and input variables are linearly related. Regression can be used for causal connection modeling, estimation, hypothesis testing, and prediction. In order to learn more about one variable by understanding the values of another, the linear regression approach takes advantage of the relationship between two or more variables. The best fit line for the correlation between y (the dependent variable) and x (the autonomous variable) is indicated by the mathematical formula y = mx + c, which is utilized in linear regression analysis and is shown in Figure 3. The r2 regression coefficient indicates how erratic the relationship between y and x is. Predictors are used in linear regression to estimate the significant risk variables that have an effect on the dependent variable. The main goal is to find the best-fit line equation (12) with the least amount of error (E. Alphydin 2014).

$$Y = \alpha o + \alpha 1 + £ \quad (12)$$

where x is the independent variable, Y the response or target variable, £ the random error, and α_0 the intercept ofthe true regression line. This value can be obtained by putting x=0 and £=0; then, Y= α_0. $\alpha_1$is the slope of the predicted line; thisis the average change in Y value per unit change in x value. Fig. 4 shows the plot of the true regression line with coefficients.

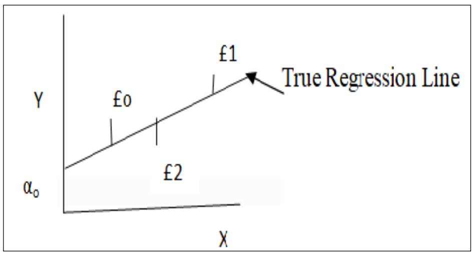


Figure 3. Regression line Estimation

If the number of independent variables is more than the multiple linear regression model is used, then the dependent variable model equation is as follows:

$$Y=\alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \ldots\ldots\ldots\ldots + \alpha_n x_n + £ \quad (13)$$

For the best-fit line, the distance between the predicted value and the actual value should be minimized, as defined by the cost function in Equation 14.

$$J(\alpha_0, \alpha_1)= \sum_{i=1}^{m} \frac{1}{2m}[Y_\alpha(x)^i - A^i]^2 \quad (14)$$

where Y is the hypothesis, which is our predicted value, and A is the actual value of output. Therefore, the main aim of this model is to change the value of α_0, α_1 until the minimum error is obtained (E. Alphydin 2014)

The value of the initial intercepts and slope parameters for the given dataset are determined by the above equation. To update the value of the initialized parameter, the convergence theorem is necessary to achieve the global minima. The convergence theorem is represented in Equation (15) as follows:

$$\alpha_i = \alpha_i - \mu \frac{\partial}{\partial \alpha J} J(\alpha i) \quad (15)$$

where μ is the learning rate and the value is 0.01. This study employs regression algorithm, namely SMVLRA.

3.2 SMVLRA

The authors predict the maximum power point of an SPS using a step-wise linear regression model. With stepwise regression, the most pertinent variables are chosen while preventing over-fitting, aiming to balance model complexity and prediction performance. An automated method for choosing a subset of independent variables from a wider pool of prospective variables to construct a regression model is known as stepwise linear regression. This method combines backward elimination with forward selection. In this case, start with an empty model and take into account all independent variables. At each step, add the variable that provides the best improvement or remove the variable that contributes the least, based on a predefined criterion. Continue this process until no more variables meet the criteria for inclusion or exclusion. Fig. 4 shows the flow chart of the SMVLRA algorithm (E. Alphydin 2014). The proposed model considers the effect of solar irradiation (dependent parameter X1) to be more important in comparison to temperature.

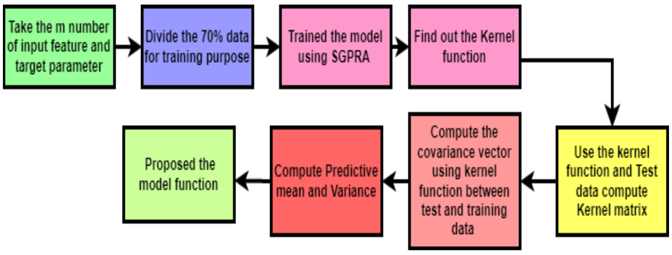


Figure 4. Flow Chart of SMVLRA

4 DESIGN & METHODOLOGY

The SMVLRA exhibits robustness, considerable analytical capabilities, and the ability to find optimal solutions for complex issues. In this study, we resolve the optimal PV operation based on the SMVLRA for GPPP tracking under PSC. We propose the use of a new intelligent ML algorithm capable of locating the GPPP while ensuring maximum power transfer. Employing the SMVLRA-MPPT technique, we control a Solar Power System (SPS) equipped with three MSX-60 W photovoltaic modules. The core component of the SPS is the DC-DC converter, where the duty cycle (D_C) related to the GPPP is determined by manipulating the gate pulses across the switch from the MPPT technique to the switching frequency of the converter. The authors utilized a regression algorithm, specifically the stepwise multiple linear regression model (SMVLR), on the data set of MPPT for the MSX-60W solar panel(Harrison et al 2022). Figure 5 illustrates the block diagram of the SMVLRA-MPPT controller. The proposed method involves dividing the data set received from the PV panel into a 70% and 30% ratio. The 70% of data is used for training the multiple variable linear regression algorithm, while the remaining 30% is employed for testing the model. The input features for training the model are solar irradiance (x1) and temperature (x2). Here, the independent parameters are solar irradiance and solar panel temperature, while the dependent or target parameter is the panel's maximum voltage.

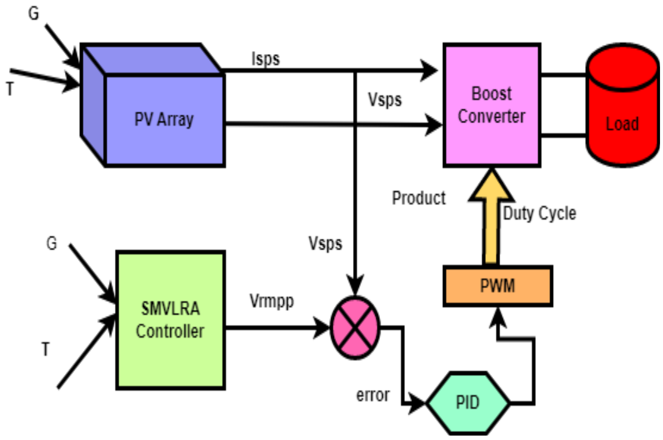


Figure 5. Block diagram of SMVLRA-MPPPT Controller set up

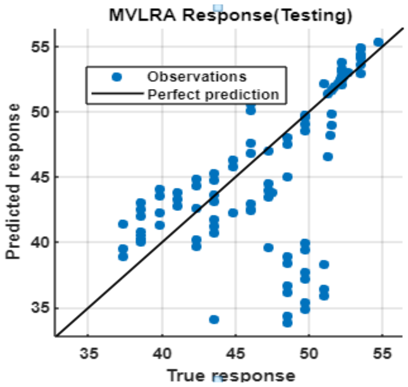
The stepwise multiple-variable linear regression model predicts the reference maximum power for a selected value of α_o α_1 $\alpha_2$parameters. The model function is given by Equation 16.

$$Vrmpp=49.9490+0.00809x1-0.2620x2 \quad (16)$$

The error estimation for the validation and testing of SMVLRA is provided in Table 5, while Fig. 6(a) and Fig. 6(b) depict the actual and predicted power for the validation and testing phases of the algorithm using the provided dataset. Additionally, Fig. 7(a) and Fig. 7(b) illustrate the residual error, representing the difference between the predicted values and the actual values, for both the validation and testing phases.

Table 5. Error estimation result for training and testing phases

Regression constant	Value	Error	Training Result(Validation)	Error	Testing Result
α_o (Intercept)	49.9490	RMSE	0.042706	RMSE	0.53
α_1(Predictor)	0.00809	MSE	0.4000	MSE	0.070001
α_2(Predictor)	-0.2620	MAE	0.004	MAE	0.66136
Training Time -------------3.9184 sec Prediction speed-----------11000obs/sec					



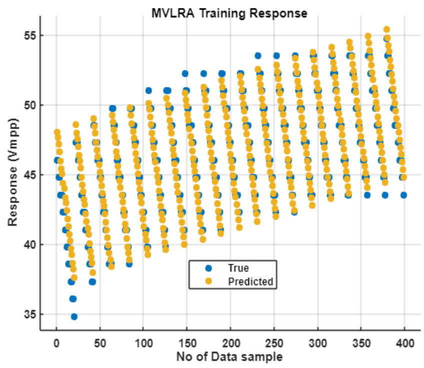
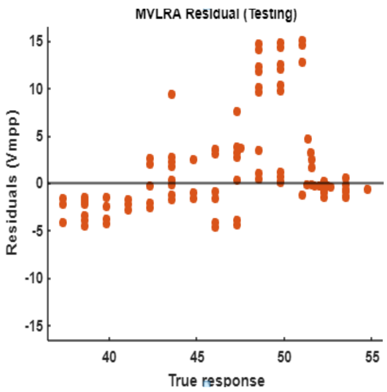


Figure 6 (a). SMVLRA Training Response **Figure 6 (b).** SMVLRA Testing Response



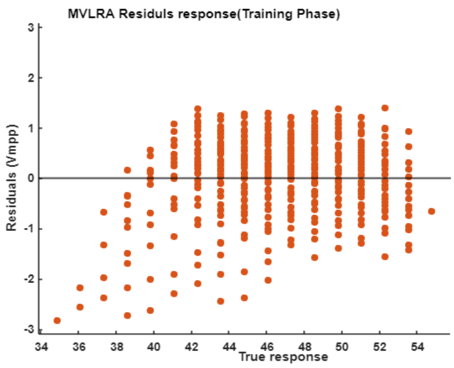


Figure 7 (a). SMVLRA Residual Error(Training) **Figure 7 (b).** SMVLRA Residual error(Testing)

4.2 Proposed MPPT Algorithm:

Authors use the regression model to track the peak power point of an SPS using SMVLRA. The steps to implement the proposed MPPT algorithms, as shown in Fig. 8, are as follows:

(i) Measure the panel voltage (Vsps) and current (Isps) for incident illumination and temperature value. Calculate the panel power, Psps.

(ii) Compute the predicted maximum voltage Vrmpp using SMVLRA model for an incident radiation and temperature.

(iii) Compare the Vsps with Vrmpp and generate error signal.

(iv) If Vrmpp=Vsps, then maximum power is achieved.

(v) If Vsps>Vrmpp, then reduce the value of Vsps by decreasing the D_C of boost converter by using PI controller.

(vi) If Vsps<Vrmpp, then increase the Vsps and the D_C of Boost converter by PI controller.

(vii) Repeat the Step until Vrmpp= Vsps

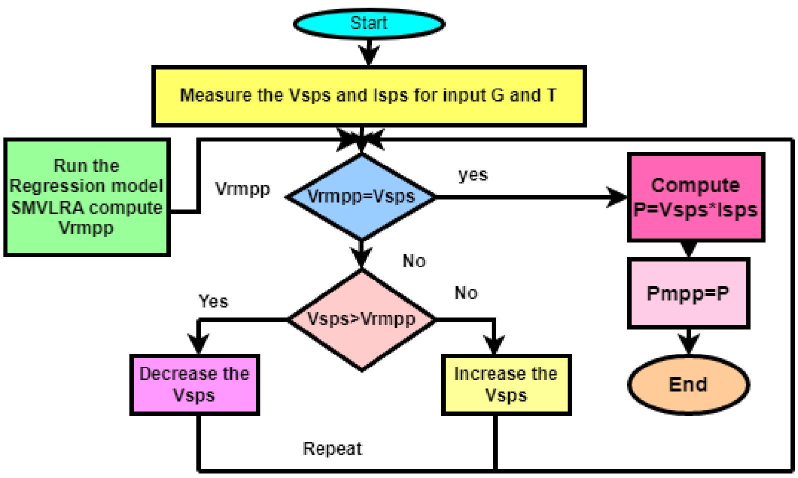


Figure 8. Flowchart of the SMVLRA-MPPT algorithm

4.3 Simulation & Result:

The proposed SPS dynamic properties are investigated under various Weather situations are analyzed using the MATLAB/Simulink tool. The complete setup, consisting of an SPS, MPPT controller, PID controller, PWM generator, and Boost converter, is shown in Figure 12. The SPS comprises three modules connected in series to increase the photo output voltage. The detailed specification of the single module utilized in the simulation is listed in Table 1. Fig. 8 illustrates how the SMVLRA-MPPT algorithm and boost converter are utilized to extract GPPP from an SPS. The SPS power received is inversely correlated to temperature and directly correlated to the quantity of photo insolation incident upon it ([A. Murtza et al., 2019).](#) Each photocell has a distinct utmost power at a particular light illumination. The MPP varies along with changes in atmospheric conditions. Fig. 9 displays the P-V and I-V plots of an SPS under conditions of fixed temperature and fluctuating irradiation. Fig. 9 displays GPPP will vary as the solar insolation increases. To increase the output power from a PV module, multiple modules are connected in series-parallel to build an SPS. The MSX-60W (3*1) SPS is simulated under STC (1000w/m^2 solar illumination and 25°C temperature), PSC1 (1000W/m^2, 1000W/m^2, and 800 W/m^2 at 25°C), and PSC2 (1000W/m^2, 800W/m^2, and 600 W/m^2 at 25°C) on MATLAB/Simulink, as shown in figures 10(A), 10(B), and 10(C) respectively. Here the temperature is kept constant as the effect of temperature on panel power is small, so it is neglected. Simulation results in all three conditions are measured and analyze the effect of PSC on SPS maximum power, maximum voltage, and maximum current, as shown in figures 11(a), 11(b), and 11(c) respectively. Table 6 shows the results of the 3×1 SPS under STC, PSC1, and PSC2. There will be one global peak, in PSC1 one local and one global peak, and in PSC, there are two local and one global peak that exists. Under PSC when solar illumination varies, the current is decreasing by approximately 0.2 amps.

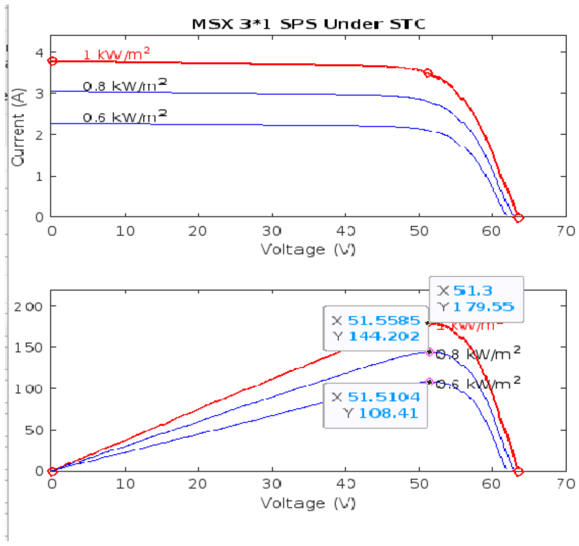


Figure 9. P-V&V-I curve of 3*1 MSX -60W PV array

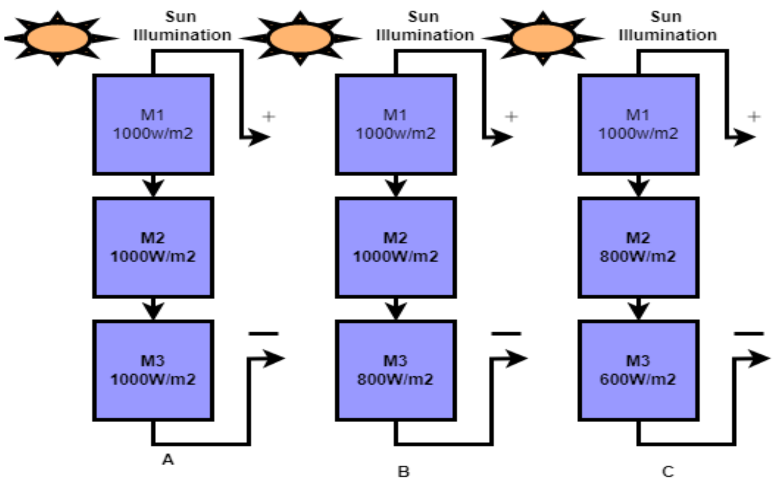


Figure 10. (3*1)MSX-60W SPS under STC(A) PSC1(B) and PSc2(C)

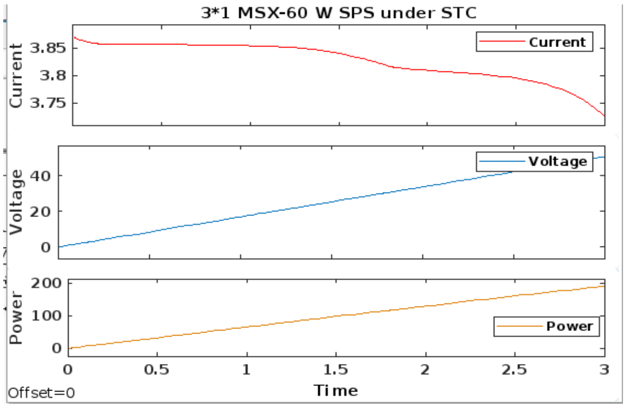


Figure 11 (a). STC (1000w/m^2 &25 °C)

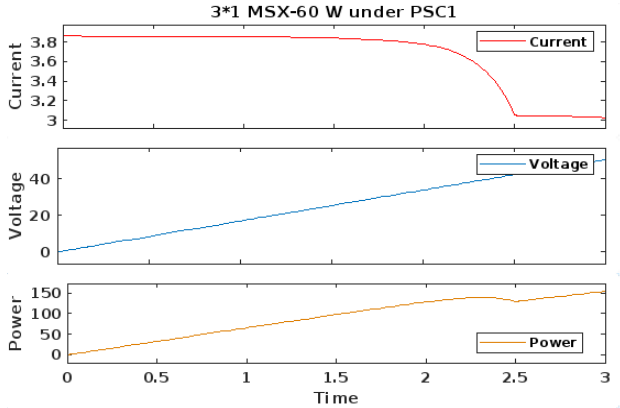


Figure 11 (b). PSC1(1000W/m^2,1000W/m^2,800 W/m^2 at 25°C)

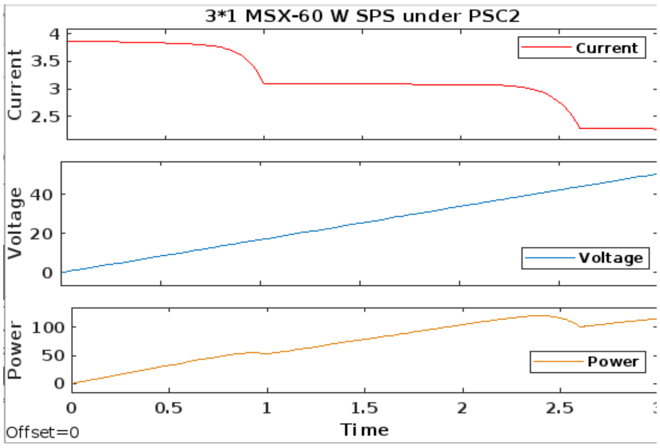


Figure 11 (c).·(1000W/m^2,800W/m^2,600 W/m^2 at 25°C)

Table 6. 3*1 MSX-60W SPS Response in different solar illumination

Operating Condition	No of Peak	Voltage(Volt)	Current (amp)	Power(Watt)	Time(sec)	Mean Power
STC	1	51.0	3.49	179.30	1.2s	113W
PSC1	2(GP,LP)	47.22 38.80	3.04 3.6	LP=128W GP=145 W	0.9s 1.2s	101.9W
PSC2	3(GP,LP1,LP2)	15.3 40.24 50.26	3.5 2.40 2.12	LP1=54W LP2=98W GP=106.5W	0.3s 1.1s 1.4s	82.39W

4.4 Simulation Setup and Result Analysis of SMVLRA-MPPT Controller

The proposed SMVLRA-MPPT with the boost converter has been demonstrated for a 3*1 configuration under STC and varying irradiance situations. The MPPT process is confirmed under two dissimilar PSCs. The complete simulation setup of MPPT using regression algorithms is shown in Figure 12. Simulations run under STC (1000W/m^2, 25°C), PSC1 (1000W/m^2, 1000W/m^2, 800W/m^2, 25°C), and PSC2 (1000W/m^2, 800W/m^2, 600W/m^2, 25°C) using the SMVLRA controller, traditional P&OA, a modern technique, step size variable incremental conductance (VINC) (Owusu et al., 2019), and a smart technique, i.e., Decision Tree regression algorithm (DTRA) by Mahesh et al. (2022). As per Figures 13(a), 13(b) and13(c) the time required to stabilize the peak power using SMVLRA is 0.1 seconds, whereas using P&OA, VINC, and DTRA, the time required to stabilize the algorithm is 0.39s, 0.19s, and 0.15s, respectively. The MPPT observed in STC, PSC1, and PSC2 using SMVLRA is higher than using P&OA, VINC, and DTRA. It is evident from Figures 13(a, b, & c) that under STC, the GPPP is 179.40; PSC1 GPPP is 144.9W, and under PSC2, GPPP is 106W using SMVLRA. Figures 14, 15, and 16 exhibit the simulation outcomes for three situations (STC, PSC1, and PSC2) for P&OA, VINC, and DTRA. The simulation analysis for the proposed tactic and the pre-existing technique shown in Table 7 proves the superiority of the proposed SMVLRA-MPPT controller. The fluctuation around the steady state is negligible in SMVLRA and DTRA for the same simulation duration compared to P&OA and VINC, as shown in Fig. 17 (a, b, c, & d).

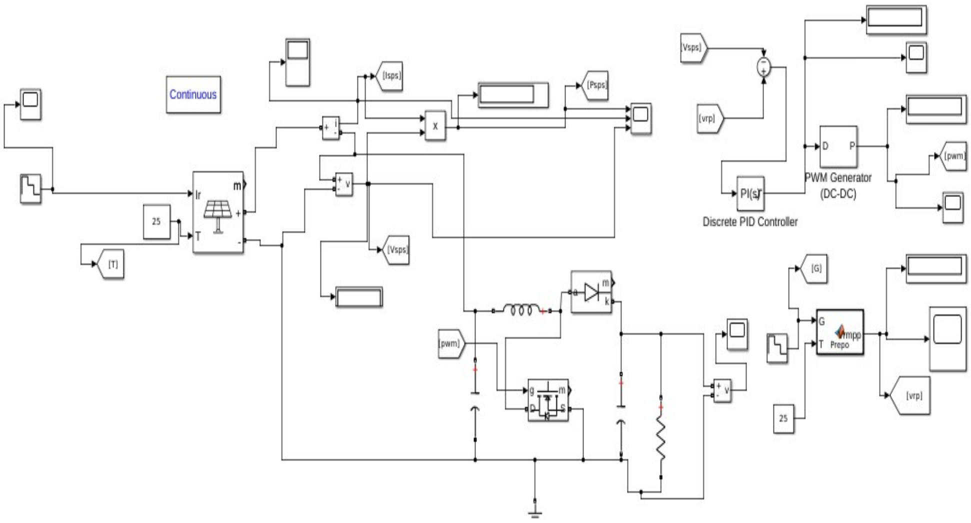


Figure 12. SMVLRA-MPPPT Simulation Set-UP

The efficiency of the SMVLRA-MPPT controller is analyzed by computing the mean power efficiency of the proposed and competitive controllers using Equation 18.

$$Efficiency = \frac{P1}{P2} * 100 \quad (19)$$

where P1 is the stable mean output power using a different MPPT controller and P2 is the mean power output power of an SPS in all operating conditions. The comparison chart of tracking efficiency is shown in Fig.18 (a,b&c).

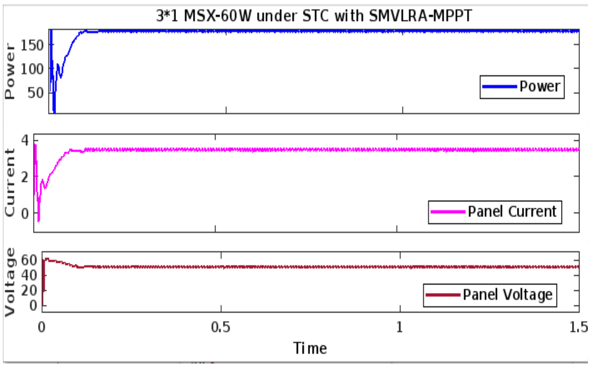


Figure 13 (a). Response under STC with SMVLRA

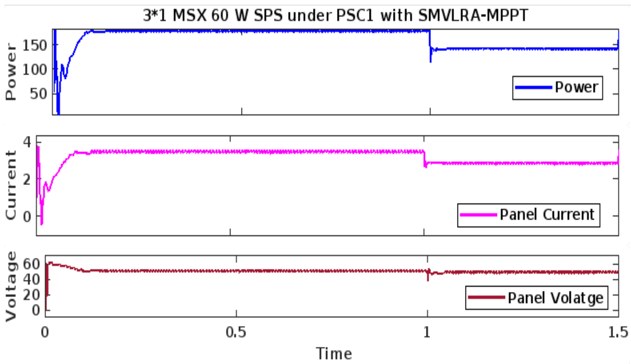


Figure 13 (b). Response under PSC1 with SMVLRA

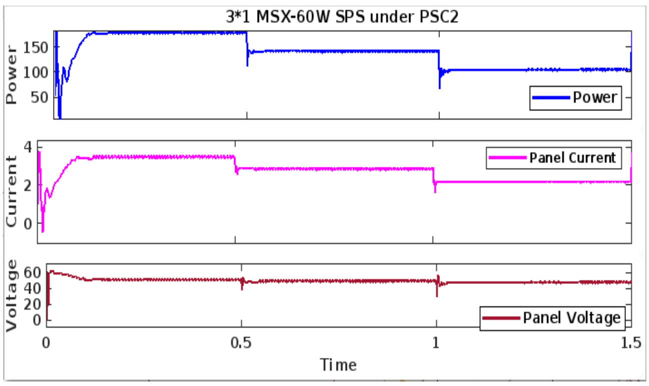


Figure 13 (c). Response under PSC2 with SMVLRA

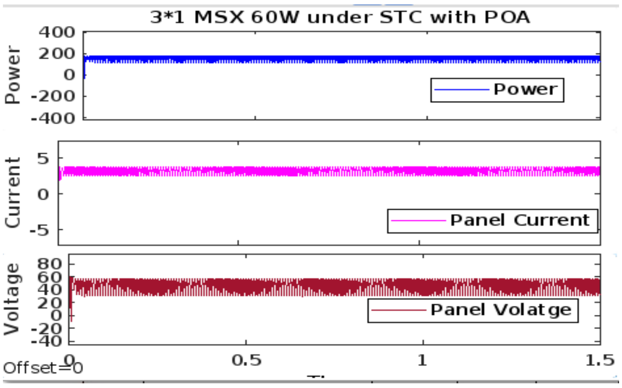


Figure 14 (a). Response under STC with P&OA

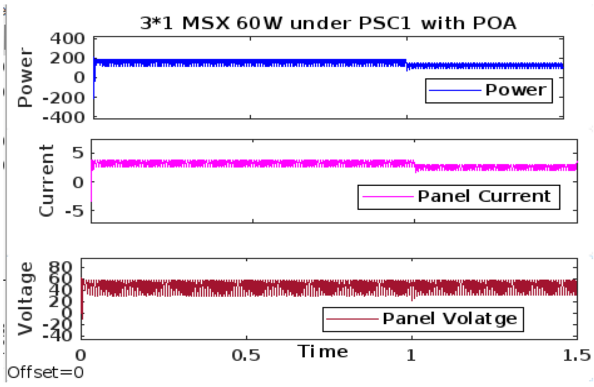


Figure 14 (b). Response under PSC1 with P&OA

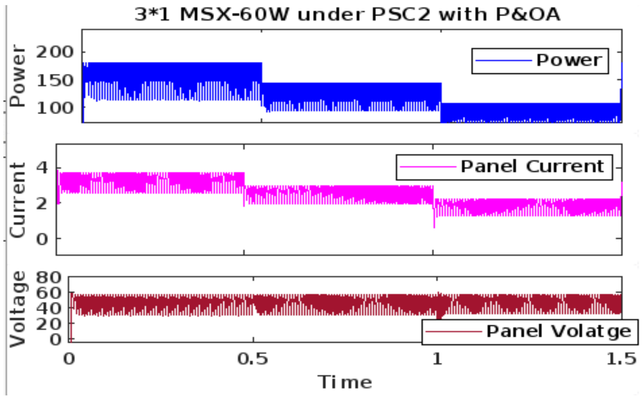


Figure 14 (c). Response under PSC2 with P&OA

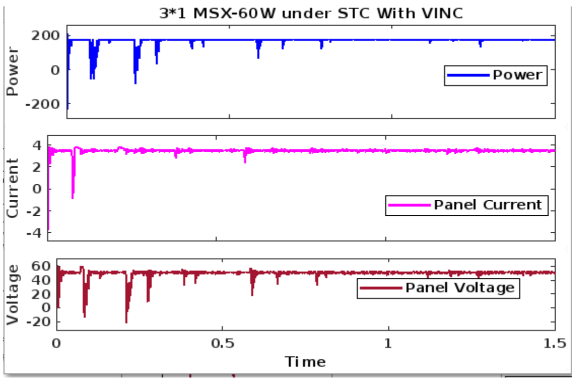


Figure 15 (a). Response under STC with VINC

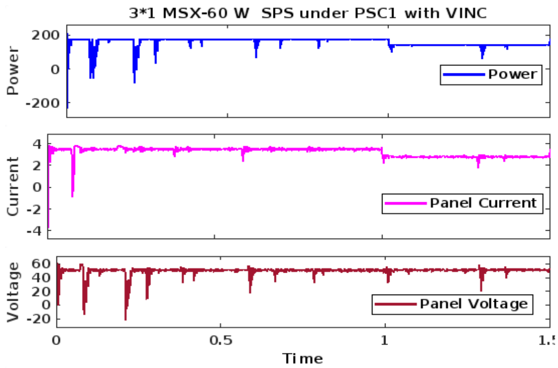


Figure 15 (b). Response under PSC1 with PSC1

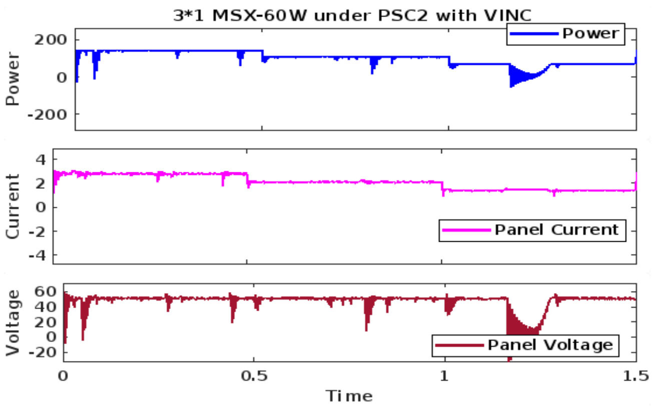


Figure 15 (c). Response under PSC2 with VINC

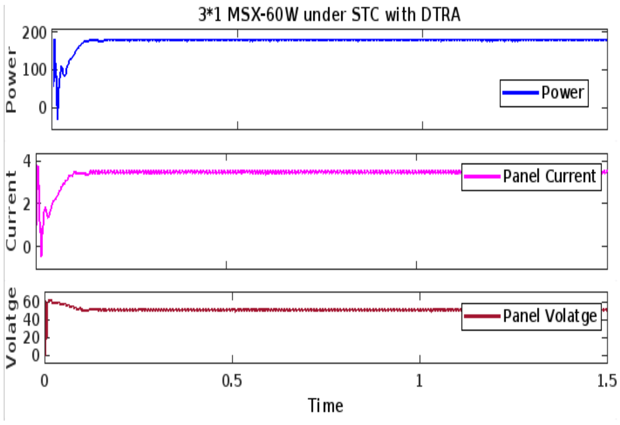


Figure 16 (a). Response under STC with DTRA

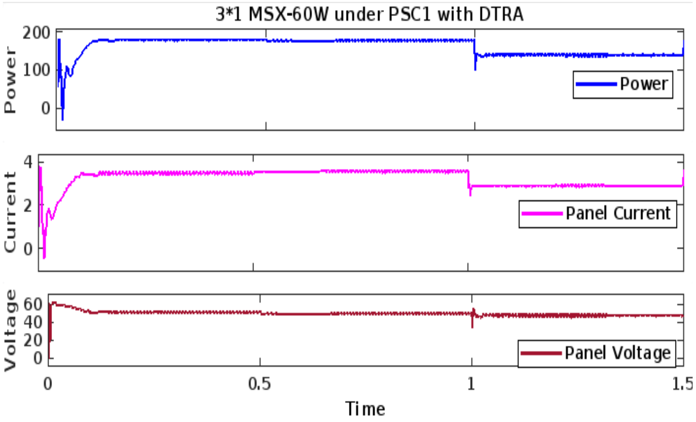


Figure 16 (b). Response under PSC1 with DTRA

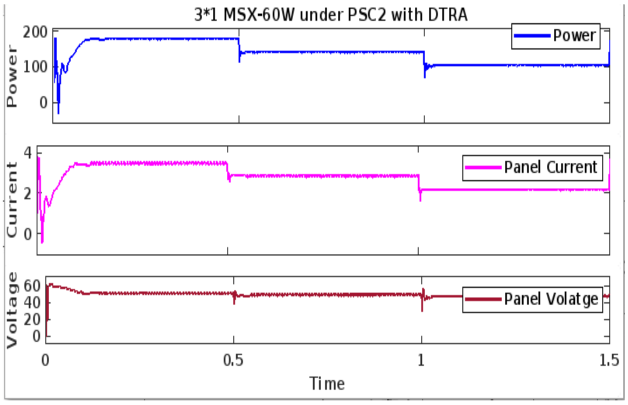


Figure 16 (c). Response under PSC2 with DTRA

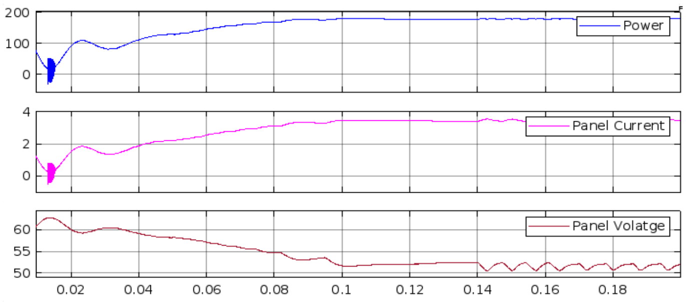


Figure 17 (a). Fluctuation in SMVLRA

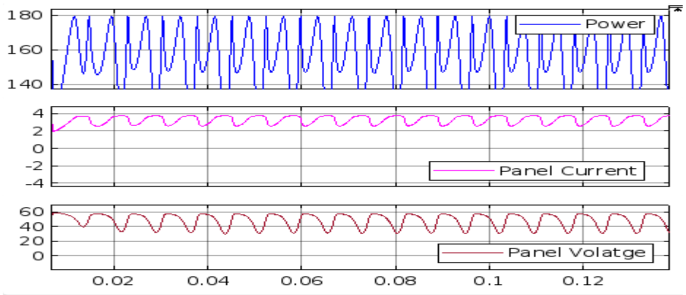


Figure 17 (b). Fluctuation in P&OA

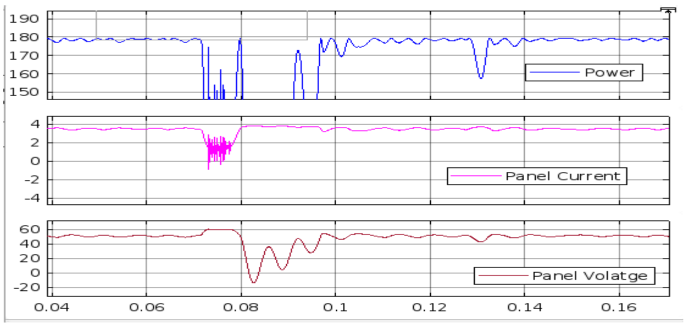


Figure 17 (c). Fluctuation in VINC

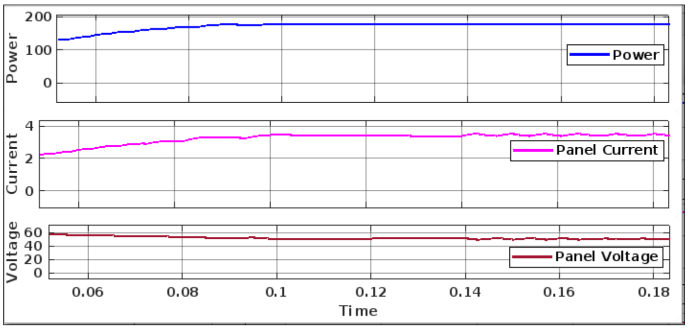


Figure 17 (d). Fluctuation in DTRA

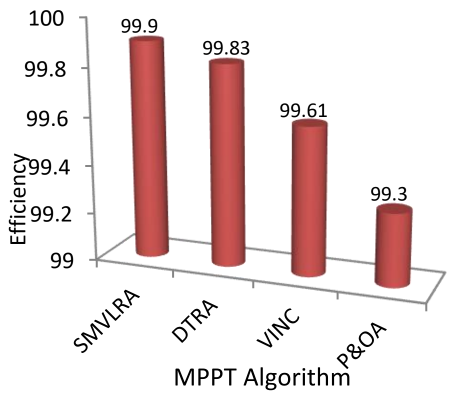


Figure18 (a). Efficiency under STC

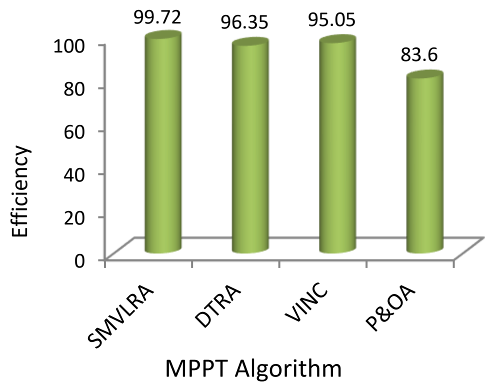


Figure 18 (b). Efficiency under PSC1

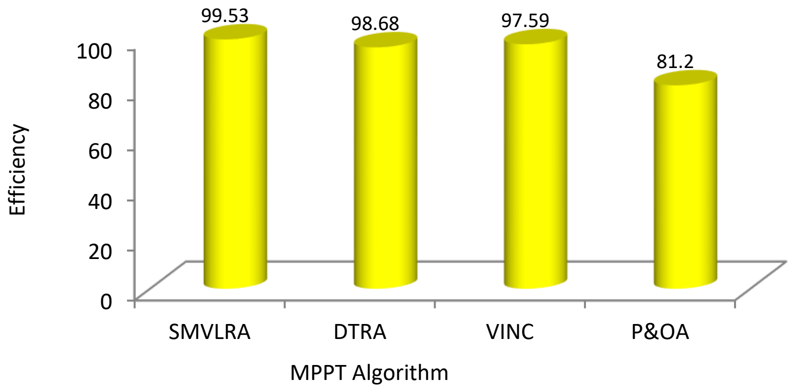


Figure 18 (c). Efficiency under PSC2

Table 7. Simulation analysis of SMVLRA, P&OA, and VINC MPPT Controller

Environment Condition	3*1 MSX-60W value	SMVLRA	DTRA	P&OA	VINC	Power efficiency%
STC(1000w/m^2 at 25c)	Vmax=51.0v Imax=3.49A GP=179.3W T=1.2s Pm=113W	51.0v 3.51A 179.4 0.1s 175.6W	50.25v 3.20A 179 0.15s 174.1W	49.91v 3.57A 178.2W 0.38s 151.9W	50.1v 3.56A 178.8W 0.19s 173.7W	SMVLRA=99.90 P&OA=99.3 VINC=99.61 DTRA=99.83
PSC1(1000,1000, 800W/m^2 at 25c)	Vmax=38.80v Imax=3.6A GP=145.3W T=1.2s Pm=101.9W	50.68v 2.8A 144.9 0.1s 163.5W	50.25v 3.23A 140W 0.15s 162.3	57.28v 2.009A 122W 0.39s 141.4W	52.77v 2.71A 138.1W 0.19s 161.8W	SMVLRA=99.72 P&OA=83.6 VINC=95.05 DTRA=96.35

5. CONCLUSION

This paper introduces a novel MPPT controller constructed using regression machine learning, which possesses the following key features:

- It addresses various inherent issues present in the majority of currently used MPPT algorithms.
- The algorithm's primary objective is to monitor the maximum power point with minimal fluctuation around steady-state power under varying solar illumination.
- In MATLAB, the proposed MPPT controller exhibits a mean power efficacy exceeding 99%.
- The tracking time for the proposed algorithm is exceptionally low, at 0.1 seconds. The performance of the SMVLRA-MPPT controller is compared to other advanced techniques (DTRA, VINC, and P&OA) to highlight its superiority, thereby demonstrating the effectiveness of the SMVLRA-MPPT controller

Data Availability:

The data used to support the findings of this study are included in the article and mentioned in the reference section.

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Conflicts of Interest:

The authors declare that they have no conflicts of interest in this work.

REFERENCES

1. Alpaydin, E. (2013). Introduction to Machine Learning. MIT press. https://dl.matlabyar.com/siavash/ML/Book/Ethem%20Alpaydin-Introduction%20to%20Machine%20Learning-The%20MIT%20Press%20(2014).pdf

2. Ameur, K., Hadjaissa, A., Boutoubat, M., &Abouchabana, N. (2018). A fast MPPT control technique using PID controller in a photovoltaic system. *2018 International Conference on Applied Smart Systems (ICASS)*. https://doi.org/10.1109/icass.2018.8652062

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. 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

6. Harrison, Ambe, &Alombah, H. (2022). *Solar PV data: (A-M) piecewise segmentation of the I-V curve.*https://doi.org/10.6084/m9.figshare.21677555.v

7. Hayder, W., Ogliari, E., Dolara, A., Abid, A., Hamed, M. B., &Sbita, L. (2020). Improved PSO: A Comparative Study in MPPT Algorithm for PV System Control under Partial Shading Conditions. *Energies*, *13*(8), 2035. https://doi.org/10.3390/en13082035

8. Hill, J. S. (n.d.). Global solar market demand expected to reach 100 Gigawatts in 2017, says solarpower Europe', (2017).https://cleantechnica.com/2017/10/27/global-solar-market-demand-expected-reach-100-gw-2017-solarpower-europe/

9. International Energy Agency: ' Snapshot of Global Photovoltaic Markets 2017', (2017). (n.d.).http://www.ieapvps.org/fileadmin/dam/public/report/statistics/IEA-PVPS-A.

10. Ishrat, Z., Nayak, S., & Gupta, A. (2023). Journal Of Renewable Energy and Environment. *A Comprehensive Review of MPPT Techniques Based on ML Applicable for Maximum Power in Solar Power Systems*.https://doi.org/10.30501/jree.2023.385661.1556

11. Ishrat, Z., Yadav, D. K., Sharma, D. K., & Nayak, S. (2022). Review on:Challenges Solution & Scope of IOT in Solar Energy. *J East China Univ Sci Technology*, *65*(4), 587–594. http://hdlgdxxb.info/index.php/JE_CUST/article/view/477

12. Kalaiarasi, N., Dash, S. S., Padmanaban, S., Paramasivam, S., &Morati, P. K. (2018). Maximum Power Point Tracking Implementation by Dspace Controller Integrated Through Z-Source Inverter Using Particle Swarm Optimization Technique for Photovoltaic Applications. *Applied Sciences*, *8*(1), 145. https://doi.org/10.3390/app8010145

13. 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

14. Kumar, N., Hussain, I., Singh, B., &Panigrahi, B. K. (2018). Framework 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

15. Lorenzo, E. (1994). *Solar Electricity: Engineering of photovoltaic systems: Vol. Chapter 3*. 7.6. , Progensa, Earthscan Publications Ltd.,https://ccl.northwestern.edu/2016/Opiyo.pdf

16. 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

17. Mahesh V. (2023) Maximum Power Point Tracking with Regression Machine Learning Algorithms for Solar PV systems. (2023). *International Journal of Renewable Energy Research*, *Vol12i3*. https://doi.org/10.20508/ijrer.v12i3.13249.g8517

18. Memayaa, M., &Moorthyb, C. Balakrishna. (2019). Machine learning based maximum power point tracking in solar energy conversion systems. *International Journal of Smart Grid and Clean Energy*. https://www.ijsgce.com/uploadfile/2019/0910/20190910030832865.pdf

19. Rashid, M. H. (2016), Power Electronics: Devices, Circuits, and Applications. (n.d.).https://powerunit-ju.com/wp-content/uploads/2016/11/Book-Power_Electronics_Handbook_3rd_Edition_M_Rashid.pdf

20. Motahhir, S., Hammoumi, A. E., &Ghzizal, A. E. (2020). The most used MPPT algorithms: Review and the suitable low-cost embedded board for each algorithm. *Journal of Cleaner Production*, *246*, 118983. https://doi.org/10.1016/j.jclepro.2019.118983

21. 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

22. Nugraha, D. A., Lian, K. L., &Suwarno. (2019). 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. https://doi.org/10.1109/cjece.2019.2914723

23. Owusu-Nyarko, I., Elgenedy, M. A., Abdelsalam, I., & Ahmed, K. (2021). Modified Variable Step-Size Incremental Conductance MPPT technique for photovoltaic systems. *Electronics*, *10*(19), 2331. https://doi.org/10.3390/electronics10192331

24. Phanden, R. K., Sharma, L. K., Chhabra, J., & Demir, H. İ. (2021). A novel modified ant colony optimization based maximum power point tracking controller for photovoltaic systems. *Materials Today: Proceedings*, *38*, 89–93. https://doi.org/10.1016/j.matpr.2020.06.020

25. 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

26. Priyadarshi, N., Azam, F., Sharma, A. K., &Vardia, M. (2019). An adaptive Neuro-Fuzzy inference System-Based intelligent Grid-Connected photovoltaic power generation. In *Advances in intelligent systems and computing* (pp. 3–14). https://doi.org/10.1007/978-981-13-8222-2_1

27. 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

28. Radjai, T., Rahmani, L., Mekhilef, S., &Gaubert, J. (2014a). 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

29. Reisi, A. R., Moradi, M. H., &Jamasb, S. (2013). Classification and comparison of maximum power point tracking techniques for photovoltaic system: A review. *Renewable & Sustainable Energy Reviews*, *19*, 433–443. https://doi.org/10.1016/j.rser.2012.11.052

30. Rezk, H., & Fathy, A. (2016). Simulation of global MPPT based on teaching–learning-based optimization technique for partially shaded PV system. *Electrical Engineering*, *99*(3), 847–859. https://doi.org/10.1007/s00202-016-0449-3

31. 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

32. Sakthivel, S. S., & Arunachalam, V. (2022). Artificial Neural Network Assisted P &O-Based MPPT Controller for a Partially Shaded Grid-Connected Solar PV Panel. *Arabian Journal for Science and Engineering*, *48*(11), 14333–14344. https://doi.org/10.1007/s13369-022-07566-y

33. Shaiek MB, Smida AS, Mimouni MF. (2012). Comparison between conventional methods and {GA} approach for maximum power point tracking of shaded solar{PV}generators. *Solar Energy*. https://www.sciencedirect.com/science/article/PII/S0038092X1300009.

34. 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

35. Takruri, M., Farhat, M., Barambones, Ó., Ramos-Hernanz, J. A., Turkieh, M. J., Badawi, M., AlZoubi, H., &Sakur, M. A. (2020). Maximum power point tracking of PV system based on machine learning. *Energies*, *13*(3), 692. https://doi.org/10.3390/en13030692

36. Verma, D., Nema, S., Shandilya, A., & Dash, S. K. (2016). Maximum power point tracking (MPPT) techniques: Recapitulation in solar photovoltaic systems. *Renewable & Sustainable Energy Reviews*, *54*, 1018–1034. https://doi.org/10.1016/j.rser.2015.10.068

37. Vincheh, M. R., Kargar, A., &Markadeh, G. A. (2014). A hybrid control method for maximum power point tracking (MPPT) in photovoltaic systems. *Arabian Journal for Science and Engineering*, *39*(6), 4715–4725. https://doi.org/10.1007/s13369-014-1056-0

38. Vinod, Kumar, R., & Singh, S. (2018). Solar photovoltaic modeling and simulation: As a renewable energy solution. *Energy Reports*, *4*, 701–712. https://doi.org/10.1016/j.egyr.2018.09.008

39. 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

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

41. Z. Ishrat., Babar Ali, K., Vats, S., & Kumar, S. (2023). Optimizing Solar Energy Harvesting: Supervised Machine Learning-Driven Peak Power Point Tracking for Diverse Weather Conditions. *InternationalJournal of Robotics and Control Systems*, *3*(4), 1007-1020. https://doi.org/10.31763/ijrcs.v3i4.1176