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Maximizing solar photovoltaic system efficiency by multivariate linear regression based maximum power point tracking using machine learning

Introduction. *In recent times, there has been a growing popularity of photovoltaic (PV) systems, primarily due to their numerous advantages in the field of renewable energy. One crucial and challenging task in PV systems is tracking the maximum power point (MPP), which is essential for enhancing their efficiency.* ***Aim.*** *PV systems face two main challenges. Firstly, they exhibit low efficiency in generating electric power, particularly in situations of low irradiation. Secondly, there is a strong connection between the power output of solar arrays and the constantly changing weather conditions. This interdependence can lead to load mismatch, where the maximum power is not effectively extracted and delivered to the load. This problem is commonly referred to as the maximum power point tracking (MPPT) problem various control methods for MPPT have been suggested to optimize the peak power output and overall generation efficiency of PV systems.* ***Methodology.*** *This article presents a novel approach to maximize the efficiency of solar PV systems by tracking the MPP and dynamic response of the system is investigated.* ***Originality.*** *The technique involves a multivariate linear regression (MLR) machine learning algorithm to predict the MPP for any value of irradiance level and temperature, based on data collected from the solar PV generator specifications. This information is then used to calculate the duty ratio for the boost converter.* ***Results.*** *MATLAB/Simulink simulations and experimental results demonstrate that this approach consistently achieves a mean efficiency of over 96 % in the steady-state operation of the PV system, even under variable irradiance level and temperature.* ***Practical value.*** *The improved efficiency of 96 % of the proposed MLR based MPP in the steady-state operation extracting maximum from PV system, adds more value. The same is evidently proved by the hardware results.* References 24, table 4, figures 14.

Key words: **machine learning, maximum power point trackers, solar photovoltaic systems.**

Вступ. *Останнім часом зростає популярність фотоелектричних (ФЕ) систем, насамперед через їх численні переваги в галузі відновлюваної енергетики. Однією з найважливіших і складних завдань у ФЕ системах є відстеження точки максимальної потужності (МРР), яка необхідна для підвищення їх ефективності.* ***Мета***. *ФЕ системи стикаються із двома основними проблемами. По-перше, вони демонструють низьку ефективність вироблення електроенергії, особливо в умовах низького випромінювання. По-друге, існує сильний зв'язок між вихідною потужністю сонячних батарей і погодними умовами, що постійно змінюються. Ця взаємозалежність може призвести до невідповідності навантаження, коли максимальна потужність не ефективно відбиратиметься і передаватиметься в навантаження. Цю проблему зазвичай називають проблемою відстеження точки максимальної потужності (МРРТ). Для оптимізації пікової вихідної потужності та загальної ефективності генерації ФЕ систем було запропоновано різні методи керування МРРТ.* ***Методологія***. *У цій статті представлено новий підхід до максимізації ефективності сонячних ФЕ систем шляхом відстеження МРР та дослідження динамічної реакції системи.* ***Оригінальність***. *Цей метод включає алгоритм машинного навчання багатовимірної лінійної регресії (MLR) для прогнозування МРР для будь-якого рівня освітленості і температури на основі даних, зібраних зі специфікацій сонячних ФЕ генераторів. Ця інформація потім використовується для розрахунку коефіцієнта заповнення перетворювача, що підвищує.* ***Результати***. *Моделювання MATLAB/Simulink та експериментальні результати показують, що цей підхід послідовно забезпечує середню ефективність понад 96 % в режимі роботи ФЕ системи, що встановився, навіть при змінних рівнях освітленості і температурі.* ***Практична цінність***. *Підвищена ефективність 96 % пропонованого МРР на основі MLR в режимі роботи, що вистачає максимум з ФЕ системи, підвищує цінність. Те саме, очевидно, підтверджують і апаратні результати.* Бібл. 24, табл. 4, рис. 14.

Ключові слова: **машинне навчання, відстежувачі максимальної потужності, сонячні фотоелектричні системи.**

Introduction. Solar photovoltaic (PV) generator energy systems have become increasingly popular as a source of renewable energy. However, one of the main challenges is, achieving maximum power extraction from the PV generator as it is typically not operated at its optimal point for specific levels of irradiance (I_r) and temperature (T). To address this challenge, various techniques have been developed for tracking the maximum power point (MPP) known as MPP tracking (MPPT) techniques, which aim to improve the efficiency of PV generator. The most common conventional methods for MPPT of a PV generator are Perturb & Observe (P&O) and Incremental Conductance (IC) algorithms. These methods involve adjusting the voltage of the PV generator [1-3] to calculate the required change in voltage for maximum power extraction. Other methods include mathematical-based approaches like the curve-fitting algorithm, which indirectly tracks the MPP using the power-voltage curve of the panel. Constant-parameter algorithms like fractional open-circuit voltage require periodic measurement of the open-circuit voltage, while the fractional short-circuit current algorithm requires periodic measurement of the short-circuit current. Trial-and-error-based methods like gradient descent calculate the adjacent local MPP using the gradient function. Intelligent prediction algorithms like fuzzy logic control (FLC) and artificial neural networks (ANN) can predict MPP by adjusting the weights of different layers through a training process [4, 5]. Optimization methods like ant colony optimization, firefly algorithm, genetic algorithm, and grey wolf optimization attempt to optimize functions or variables to achieve maximum power extraction from the PV generator.

These algorithms are designed to operate the PV generator at the MPP to extract the maximum available power for delivery to the load.

Machine learning (ML) algorithms can predict unknown data with a high degree of accuracy by learning from known data. By training a ML algorithm [6] with existing data and testing it with new data, a ML model is created. Typically, 75 % of the data is used for training, and the remaining 25 % for testing the model. Image-based ML and reinforcement learning algorithms have been used for MPPT in PV generator. To operate the PV generator at the MPP, a converter is required.

The literature reports the use of various types of converters, including DC-DC buck converters, boost converters, buck-boost converters, single-ended primary inductor converters, and controlled inverters.

Although the conventional P&O and IC methods are simple and require fewer sensing elements, they have a low MPPT speed for rapid changes in irradiances. Intelligent prediction algorithms like ANN and FLC can address this issue. The performance of the ANN model depends on the correlation between the training and validation data, the number of iterations used for training, and the number of layers and neurons. The accuracy of the FLC is dependent on the rule-based design, which requires human expertise and experience. The Cuckoo Search (CS) technique is considered one of the fastest and most reliable optimization techniques but has a high failure rate and high oscillations in the steady state.

Achieving fast-tracking of the MPP is crucial for efficient solar PV generator, as irradiance and temperature change rapidly. ML algorithms offer a promising solution to improve MPPT speed without requiring an iterative approach or controller. To evaluate this approach, a new multivariate linear regression (MLR) algorithm is proposed in this study, and its performance is compared to conventional techniques like P&O and IC, intelligent methods like ANN and FLC, and optimization algorithms.

The block diagram shown in Fig. 1 for a complete system, where P_{mp} is maximum power available at MPP, V_{mp} is the voltage of the solar PV generator at MPP, I_{mp} is the current through the solar PV generator at MPP, D is duty cycle, R_{mp} is the resistance at MPP and R_0 is the load resistance. The mean efficiency is calculated under different irradiance level (IL) and temperature T to validate the effectiveness of the MLR method.

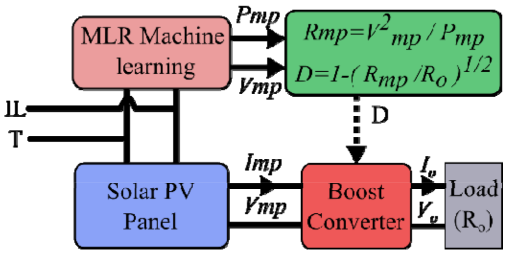

Fig. 1. System block diagram

System description. Characteristics of PV generator and DC-DC boost converter. Solar PV generator convert sunlight into electricity, and several cells are connected to form a PV generator. The one-diode equivalent circuit [7-11] of a PV generator is depicted in Fig. 2 and represented mathematically in (1). The number of solar PV generator in a panel determines the specifications for voltage, current, and power.

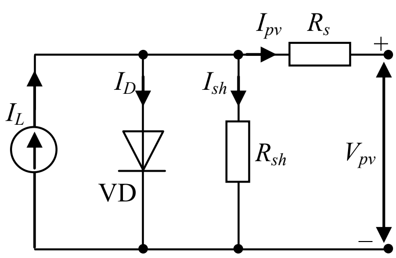

Fig. 2. The one-diode equivalent circuit of a PV generator

$$I_{pv} = I_L - I_D\left(e^{\frac{V+IR_s}{nV_T}} - 1\right) - \frac{V + I_{pv}R_s}{R_{sh}}, \qquad (1)$$

where I_{pv} is the solar PV generator current; I_L is the photocurrent as a function of IL and T; I_D is the diode saturation current; V is the solar PV generator voltage; R_s is the series resistance; n is the diode ideal factor ($1 \le n \le 2$); V_T is the thermal voltage equivalent; R_{sh} is the shunt resistance.

Figure 3 illustrates a boost converter with pulse width modulation control, which is powered by a solar PV generator. The MOSFET switch and duty cycle (D) is responsible for controlling the amount of power that is delivered to the load from the solar PV generator. The inductor L present in the circuit boosts the solar PV generator voltage to the required output voltage level. Additionally, the load current I_o flow through the load and input and output capacitors C_i and C_o are utilized to minimize the ripple content in the voltages [8-10].

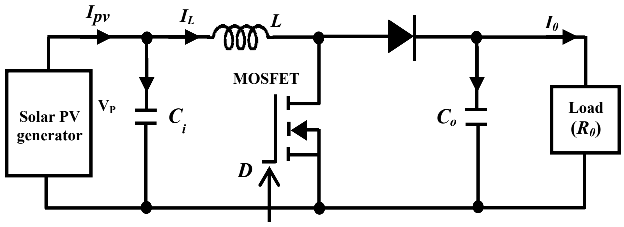

Fig. 3. Boost converter with solar PV generator

The solar panel specifications used for the simulation include a maximum power of 250 W, short-circuit current of 9.38 A, open-circuit voltage of 36 V, voltage at MPP of 28.8 V, and current at MPP of 8.68 A. The current-voltage and power-voltage characteristics of the solar PV generator under different temperature and irradiances are illustrated in Fig. 4.

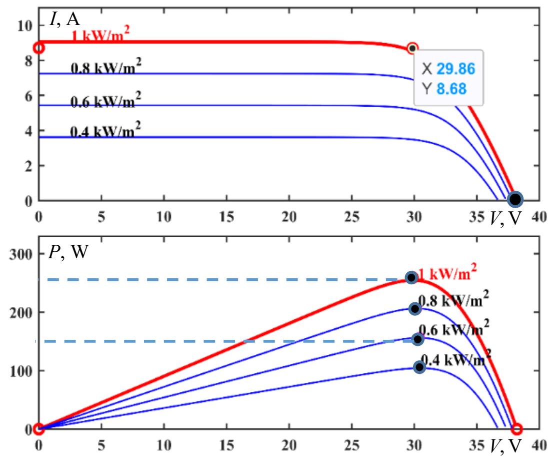

Fig. 4. The current-voltage and power-voltage characteristic curves of solar PV generator

Multivariate linear regression. The linear regression method is a simple ML technique that is suitable for predicting real numbers from available data. It works by predicting unknown data, which is also known as dependent data, from the features, which are referred to as independent data [12, 13]. If the data has a single feature, then the univariate linear regression algorithm gives a straight line that predicts the data in a two-dimensional space. On the other hand, if there are multiple features, the MLR algorithm provides a plane in multidimensional space. The general form of the multiple linear regression planes [12] can be expressed as:

$$y = \beta_0 + \beta_0 \cdot x_1 + \ldots + \beta_{n-1} \cdot x_{n-1} + \beta_n \cdot x_n, \qquad (2)$$

where y is the data to be predicted in a n-dimensional space $x_1, x_2, \ldots, x_{n-1}, x_n$ are the feature with $\beta_0, \beta_0, \ldots, \beta_{n-1}, \beta_{n-1}$ as regression coefficients.

ANN-based MPP [14-18] is shown in Fig. 5 for an example of finding the duty at MPP (D_{mpp}) based on the training provided for the ANN. The results of D_{mpp} are taken as output and are used for comparisons.

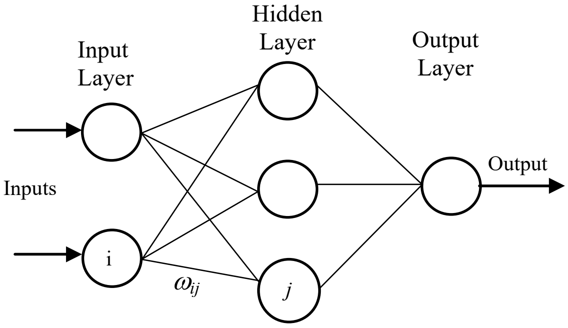

Fig. 5. Neural network example

Data in linear regression. ML algorithms acquire knowledge by analyzing data, allowing them to identify patterns, make informed decisions, and assess their level of certainty based on the information provided. The quality of the training data plays a critical role in determining the effectiveness of the model. Figure 6 indicates the learning model. Three-dimensional MLR model is shown in Fig. 7.

Fig. 6. Learning model

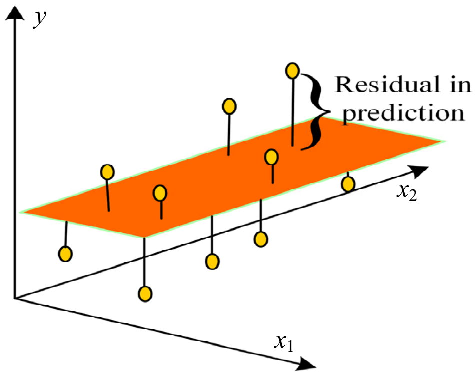

Fig. 7. MLR model in a three-dimensional space

Learning is data refers to raw and unprocessed facts, values, texts, sounds, or images that are yet to be analyzed. It is a crucial component in the fields of ML and artificial intelligence, and without it, cannot train any models. Information, on the other hand, is data that has been interpreted and manipulated to provide final results. Knowledge is a combination of inferred information, experiences, learning, and insights that result in awareness.

Data preprocessing. Training data. The part of data used to train the model. This is the data that the MLR model sees (both input and output) and learns from this data. In the proposed work, 70 % of data is given for training purpose and the records were chosen randomly (Fig. 8).

Validation data. The part of data that is used to do a frequent evaluation of the model, fits on the training dataset along with improving involved hyper parameters (initially set parameters before the model begins learning). This data plays its part when the model is training. For validation of data, only 20 % of the data is given and the records were random.

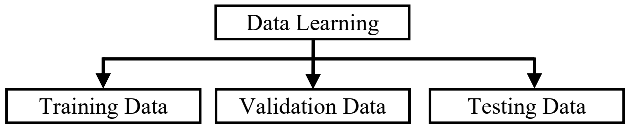

Fig. 8. Data preprocessing

Testing data. Once the model is completely trained, testing data provides an unbiased evaluation. When the inputs of testing data are fed, the trained model will predict some values (without seeing actual output). After prediction, to evaluate the model by comparing it with the actual output present in the testing data.

This is how the evaluation and performance model has learned from the experiences feed in as training data, set at the time of training. The remaining data i.e., 10 % of data is fed to the trained and validated model to evaluate performance.

Methodology. The methodology used in this study is divided into 4 stages, as the flowchart shown in Fig. 9. The first stage involves collecting and processing raw data from the solar PV generator specifications using MATLAB/Simulink. After collecting the data, an analysis is performed to remove any outliers. The second stage focuses on developing the MLR model through training, validation, and testing using the prepared data. The performance of the model is evaluated using metrics such as sum squared error (SSE), R^2, and root mean square error (RMSE). The formula to calculate these measures are provided below.

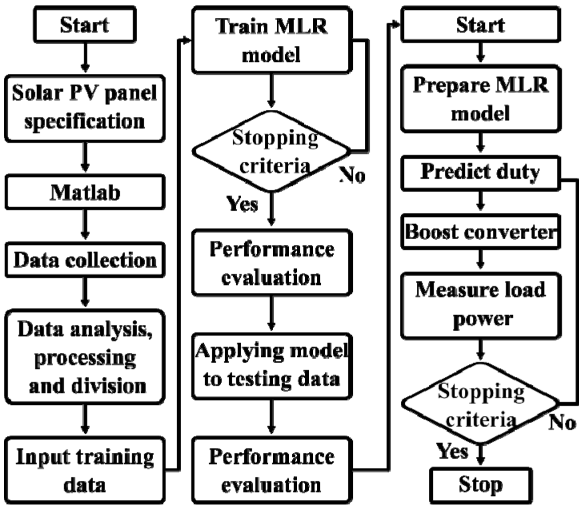

Fig. 9. Flowchart for the proposed MMPT using MLR

$$SSE = \sum_{K=1}^{n_s} \left(Y_{A,K} - Y_{P,K}\right)^2; \qquad (3)$$

$$R^2 = 1 - \frac{\sum_{K=1}^{n_s} \left(Y_{A,K} - Y_{P,K}\right)^2}{\sum_{K=1}^{n_s} \left(Y_{A,K} - Y_{P,Avg}\right)^2}; \qquad (4)$$

$$RMSE = \sqrt{\left[\frac{1}{n_s} \sum_{K=1}^{n_s} \left(Y_{A,K} - Y_{P,K}\right)^2\right]}, \qquad (5)$$

where Y_A represents the actual data; Y_P is the predicted data; n_s is the number of samples; Y_{Avg} is the average values of Y_A. The value of $R^2 \in [0, 1]$ specifies the prediction strength of models, and an R^2 value closer to 1 ensures the best fit of the model. Likewise, the SSE and RMSE values measure the residual or error among Y_A and Y_P. Therefore, SSE and RMSE values closer to 0 represent the models' superior prediction.

In the proposed methodology, the third stage involved using the MLR model to perform MPPT. The MLR model predicted the maximum power available at MPP (P_{mp}) and the voltage of the solar PV generator at MPP (V_{mp}) for a given IL and temperature T. The predictions were used to determine the required D for the boost converter to operate the PV generator at MPP. The corresponding resistance at MPP (R_{mp}) was computed using these predicted values as in (6). The R_{mp} was reflected between nodes of boost converter by controlling the D of the boost converter. The D in terms of R_{mp} and load resistance R_0 is given in (7):

$$R_{mp} = V_{mp}^2 / P_{mp}\ ; \qquad (6)$$

$$D = 1 - \sqrt{\left(R_{mp} / R_0\right)}. \qquad (7)$$

The maximum and minimum values of the load resistance were determined using the method proposed in [8]. The boost converter is designed using the procedure explained in [7]. The required boost converter inductance L and capacitance C are as follows:

$$L = V_{inp} \cdot \left(V_{out} - V_{inp}\right) / f_{sw} \cdot \Delta I \cdot V_{out}\ ; \qquad (8)$$

$$C = I_{out} \cdot \left(V_{out} - V_{inp}\right) / f_{sw} \cdot \Delta V \cdot V_{out}\ , \qquad (9)$$

where V_{inp} is the input voltage; V_{out} is the output voltage; f_{sw} is the switching frequency; ΔI is the current ripple; I_{out} is the output current; ΔV is the voltage ripple.

The fourth stage of the methodology involved a comparative analysis of the MLR methodology with existing conventional, intelligent, and optimization MPPT methods.

Simulation results and discussion. Data collection. The simulated dynamic result for the IL changed from 900 to 500 W/m^2 is shown in Fig. 10. In that corresponding solar power, voltage, and current were demonstrated that the maximum power can track using the proposed method.

The data collected for this study includes four variables: I_r, T, P_{mp} and V_{mp}. The values of P_{mp} and V_{mp} depend on I_r and T.

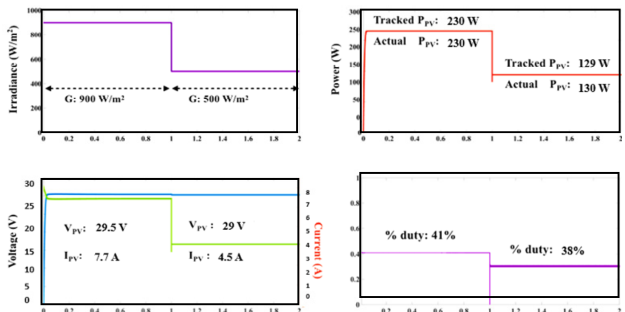

Fig. 10. Simulation results of V_{pv}, I_{pv}, P_{pv} and D for change in I_r from 900 to 500 W/m^2, T = 25 °C

To predict P_{mp} and V_{mp}, I_r and T are used as features. The MPP of changes in variables for the installed roof solar PV generator and its specification of 250 W Zy-TECH 250P [19-21] are given in Table 1.

Table 1
Specification of solar PV generator

Specification	Value
Rated power, W	250
Voltage at maximum power, V	28.8
Current at maximum power, A	8.68
Open circuit voltage, V	36
Short-circuit current, A	9.38
Voltage temperature coefficient	–0.36901
Current temperature coefficient	0.086988

Performance of the proposed MLR model. The MLR machine learning models created using MATLAB/Simulink involves two independent and one dependent variable. These models can predict the values of P_{mp} and V_{mp} based on specific values of I_r and T. The data were collected as described earlier, based on the specification of the PV generator. The MLR model developed is presented mathematically in (10) and (11):

$$P_{mp} = 0.8994 + 0.01001 \cdot I_r - 0.03685 \cdot T; \qquad (10)$$

$$V_{mp} = 19.21 + 0.0007073 \cdot I_r - 0.08946 \cdot T. \qquad (11)$$

The developed MATLAB MLR machine learning technique consists of two input variables and one output variable. These techniques can predict P_{mp} and V_{mp} at various irradiance I_r and temperature T.

The regression coefficients of (10) define a plane in I_r, T and P_{mp} as shown in Fig. 11,*a*. The residuals in the prediction for these parameters are shown in Fig. 11,*b*. The numerical analysis of SSE, R^2, and RMSE are 0.0197, 0.9999 and 0.0405, respectively. The SSE and RMSE values are close to 0, and the R^2 value is close to 1, indicating the best prediction of the models and the results given in Table 2, 3.

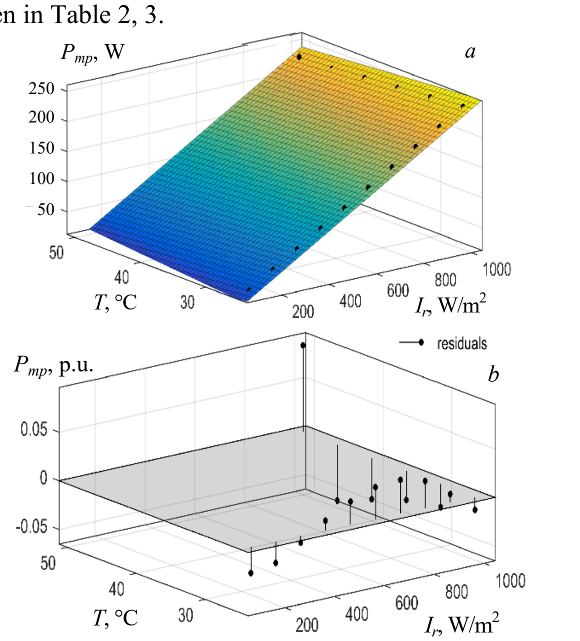

Fig. 11. *a* – P_{mp} plane defined by regression coefficients; *b* – residuals in prediction

Table 2
Training results

Metric	Value
RMSE	$1.0347 \cdot 10^{-14}$
R^2	1
MSE	$1.0762 \cdot 10^{-28}$
Prediction speed	9800 obs/s*
Training time	4.9252 s

*obs/s – refers to number of observations processed per second.

Table 3
Testing results

Metric	Value
RMSE	$3.6016 \cdot 10^{-14}$
R^2	1
MSE	$1.2972 \cdot 10^{-27}$

Performance comparison of various methods. The performance of the MLR model was compared to other models, and the results were summarized in Table 4 for the time range of 0 to 0.5 s. The comparison indicated that the P&O and IC methods exhibited oscillations in steady-state, while the other models did not [22-24]. According to Table 4 the MLR model settled in less than half the time with a high steady-state value of 230 W and almost zero overshoot compared to the P&O method. Similarly, the MLR model settled in less than half the time with a high steady-state value and nearly zero overshoot compared to the IC method. Overall, the MLR model outperformed the P&O and IC algorithms in terms of settling time, steady-state value, and overshoot.

Table 4
Comparison of the MPPT response characteristics for various methods

Parameter	MLR	P&O	IC	ANN
Rise time, s	0.1409	0.0463	0.0352	0.1314
Settling time, s	0.2410	0.5000	0.4994	0.2144
Overshoot, %	0.0023	9.2364	39.294	0
Peak time, s	0.4999	0.0829	0.2300	0.5

According to the power response numerical values, the MLR model's performance is comparable to that of the intelligent methods, such as ANN and FLC, while the CS method exhibits an undesirable undershoot. Moreover, the MLR model outperforms the CS optimization method in terms of rise time and overshoot. Based on this analysis, it can be concluded that the MLR control method is suitable for MPPT in PV generator, as it can track the MPP under varying I_r and T conditions in a stable state and ensure that the PV generator operate at the MPP.

Experimental results and discussion. To further substantiate the dynamic performance, the experiments have been conducted using the solar PV generator of 250 W Zy-TECH 250P where considered for this work shown in Fig. 12. Under standard test conditions of I_r = 1000 W/m^2 and T = 25 °C solar PV generator produce power of 250 W. MLR algorithm tested for solar PV generator under various algorithm is tested for solar PV generator under various I_r and T profiles.

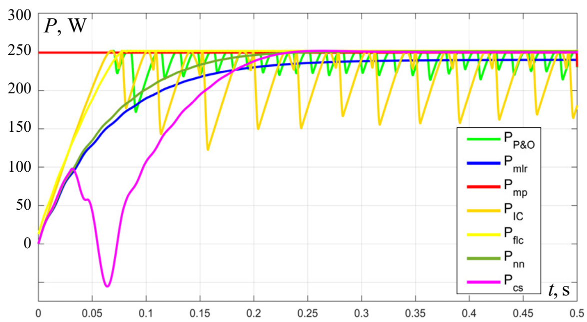

Fig. 12. Solar PV panel power comparison for various methods

The experimental setup shown in Fig. 13 consists of a solar PV panel, a designed boost converter and a program kit ESP-32. The IL is changed from 900 W/m^2 to 500 W/m^2 at t_{IL} result shown in Fig. 14.

Fig. 13. Experimental setup

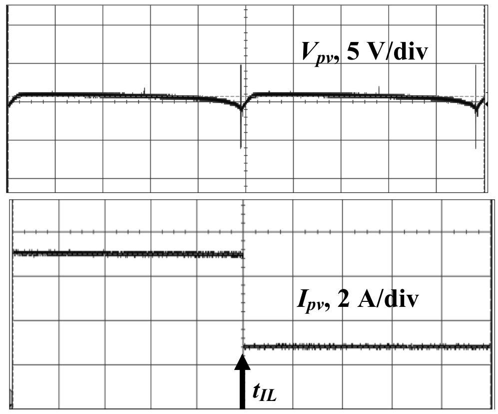

Fig. 14. Dynamic performance of proposed MPPT controller. IL changed from 900 W/m^2 to 500 W/m^2
Note. T = 25 °C, V_{pv} = 29 V, time axis: 20 ms/div, and t_{IL} is the instant at which step change in I_r of solar PV generator initiated

Conclusions. A new approach based on multivariate linear regression machine learning was implemented in this study to achieve high accuracy in tracking the maximum power point of a solar photovoltaic generator using a pulse width modulation control boost converter. The mean efficiency was found to be over 96.18 % in steady-state, which validates the effectiveness of the multivariate linear regression algorithm. Simulation with experimental hardware results showed that the multivariate linear regression algorithm had a high level of accuracy in maximum power point tracking in steady-state compared to conventional perturb & observe, incremental conductance algorithms, intelligent prediction artificial neural networks algorithm, and cuckoo search optimization method. Moreover, the multivariate linear regression algorithm proved to be effective even in the presence of varying irradiance and temperature.

As a part of future work, the effect of partial shading on photovoltaic generator will be analyzed with the help of hardware implementation.

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Conflict of interest. The authors declare that they have no conflicts of interest.

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