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Machine Learning Based Investigation of Behavioral Modeling of the MPPT based Solar PV System Behaviors Evaluation

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Abstract: Improving the effectiveness of a solar PV system using an MPPT-based tracker has recently been an active study area. This study presents a behavioral analysis of photovoltaic (PV) cell performance under varying temperature conditions. The investigation is using a combination of theoretical modeling and machine learning techniques. A MATLAB simulation is developed to investigate the current-voltage (I-V) characteristics of a PV cell, considering the impacts of temperature on key parameters like short-circuit current (Isc) and open-circuit voltage (Voc). A ML based solution is designed using regression treeapproach employed to predict the MPPT based on temperature. in turn paper demonstrating the potential of data-driven techniques in PV performance prediction. The results highlight the importance of considering temperature effects in PV system design and optimization. The proposed methodology, combining theoretical modeling and machine learning, offers a powerful tool for analyzing and predicting PV cell performance across a wide range of operating temperatures, paving the way for enhanced efficiency and reliability in solar energy systems.
Keywords: Solar PV system, Behavior Modeling MPPT, Machine Learning, Regression Tree, Temperature, Irradiance.

I. INTRODUCTION

This research is aimed to research in the latest burring field of tracking the solar system for efficiency improvement. This Maximum Power Point Tracking, or MPPT, is a critical component of solar PV systems since it has a significant impact on total effectiveness. The primary aim of this paper is to investigate the behaviorally modeling of PV system and to predict the MPPT points against the different temperatures. The research describes how an MPPT system increases the performance of any solar PV installation. Studies have shown that an effective tracking mechanism using machine learning solution for MPPT may enhance the power output or performance of solar-based renewable energy systems. Understanding and treating MMPT allows us to assure optimal operation and effectiveness in solar PV systems with numerous panels. Behavioral modeling of solar photovoltaic (PV) systems is a critical step in their design and analysis, providing a way to predict a system's electrical output under different environmental conditions. These models, which capture the relationship between current, voltage, irradiance, and temperature, are essential for simulating system performance without the need for expensive and time-consuming physical prototypes. As highlighted by Nguyen and Nguyen [2] and Prakash and Singh [4], accurate mathematical models are foundational for studying the complex behavior of PV cells, modules, and arrays. This modeling is not just an academic exercise; it forms the basis for designing effective control strategies, such as Maximum Power Point Tracking (MPPT), as detailed by Shanthi et al. [1]. The problem statement thus arises from the need for a robust and reliable behavioral model that can precisely predict the I-V and P-V characteristics of PV systems [5], enabling engineers to optimize performance and ensure the system operates efficiently as a viable renewable energy solution [3]. This is particularly important given the inherent variability of solar resources and the need for seamless integration into the power grid.

A. What is MPPT?

Maximum power punt Tracking, or MPPT, is a system made up of charging controllers that, under certain conditions, draw the maximum power out of solar modules. Peak power electricity, sometimes referred to as the greatest point of electricity, is the current at which solar modules may produce their highest power. Charger controllers use a method called maximum Potential Recording, or MPPT, to extract the maximum power from solar modules under certain conditions. The voltage at which solar modules may produce their maximum power is called the peak power voltage, or maximum power point. The power output is dependent on the temperature of the batteries, the amount of sunshine, and the outside humidity.

II. BEHAVIORS MODELING OF SOLAR PV SYSTEMS

Modeling and understanding photovoltaic (PV) system characteristics and performance in a range of conditions are key components of behavioral study of solar PV systems. In order to identify causal relationships and validate models that enable optimal design with energy management, Behavioral modeling of a solar photovoltaic (PV) system involves using mathematical equations and electrical circuit equivalents to simulate its electrical output based on environmental inputs. Unlike physical models that delve into the semiconductor physics of the solar cell, behavioral models evaluate the PV module and focusing on its observable behavior. The primary objective is to accurately predict the module's characteristic I-V (current-voltage) and P-V (power-voltage) curves under varying levels of solar irradiance and temperature.As highlighted by Solanki et al. [6], modeling approach is a fundamental step in the design, simulation, and performance analysis of solar PV systems. It allows engineers to evaluate a system's efficiency and power output without needing a physical prototype. Furthermore, as demonstrated by Rai et al. [7], these analytical models are commonly implemented in computational software like MATLAB, which provides a powerful and flexible platform for conducting detailed simulations and studying system behavior under a wide range of operating conditions.Researcher's simulated model of an autonomous photovoltaic system has been used in some study to analyze how the system behaves in different meteorological circumstances. The correctness of the model is assessed by comparing the results with experimental data.

A. Core PV Equation

The code models the current–voltage (I–V) characteristic of a PV cell using a simplified equation derived from the single-diode model. The fundamental relationship is between the current (I) and voltage (V) of the PV module.The equation used to calculate the current I for a given voltage V is:

$$I = I_{sc} - I_{sc}\left(e^{\frac{V}{(n \cdot N_S \cdot V_t)}} - 1\right) \qquad (1)$$

where:

- I represent the output current in (A)
- V is the output voltage of Pennel in (V)
- I_{sc}represented the short-circuit current in (A)
- The n is an ideality factor
- The number of cells in series areN_s and
- V_t is the thermal voltage (V)

B. Short-Circuit Current ($\boldsymbol{I_{sc}}$) Model

The short-circuit current is the current produced by the cell when the voltage across it is zero. The code models I_{sc} as a function of both irradiance (G) and temperature (T).

The equation used is:

$$I_{sc} = \left(\frac{G}{1000}\right) \cdot I_0 \cdot \left(1 + 0.005 \cdot (T - 298)\right) \qquad (2)$$

where:

- G is the irradiance in $\frac{\text{W}}{\text{m}^2}$, the standard test condition (STC) irradiance is represented as $\left(1000\,\frac{\text{W}}{\text{m}^2}\right)$
- I_0 is the nominal short-circuiting current at STC,
- 0.005 is the temperature coefficient of the short-circuit current
- T is the cell temperature in Kelvin (K).
- 298 is the STC temperature (25°C in Kelvin)

C. Open-Circuit Voltage ($\boldsymbol{V_{oc}}$) Model

The open-circuit voltage is the voltage across the cell terminals when the current is zero. The code models V_{oc} as a function of temperature.The equation used is:

$$V_{oc} = 35 \cdot \left(1 - 0.002 \cdot (T - 298)\right) \qquad (3)$$

where:

- 35 is the nominal open-circuit voltage at STC

- 0.002 is the temperature coefficient for open-circuit voltage
- T and 298 are as defined previously

D. Thermal Voltage (V_t)

The thermal voltage is a key parameter in the diode equation,and it is directly dependent on temperature.The equation used is:

$$V_t = \frac{(k \cdot T)}{q} \qquad (4)$$

where:• k is the Boltzmann constant $\left(1.38 \times \frac{10^{-23} \mathrm{J}}{\mathrm{K}}\right)$
- T is the cell temperature in Kelvin (K)
- q is the electron charge $(1.6 \times 10^{-19} \mathrm{C})$

E. Power and Maximum Power Point (MPP)

The output power (P) of the PV module is simply the product of its voltage and current.
The equation is:

$$P = V \cdot I \qquad (5)$$

Boost Converter: The cell output voltage is raised using the boost converter. By flipping the IGBT, the MPPT regulates the duty cycle D of these converters, and the output voltage is

$$V_o = D[V_i] = \frac{T_{on}}{T_{on} + T_{off}} \qquad (6)$$

Parameters are set to standard as L=0.0 H, C= C_1 =2e-3 F,

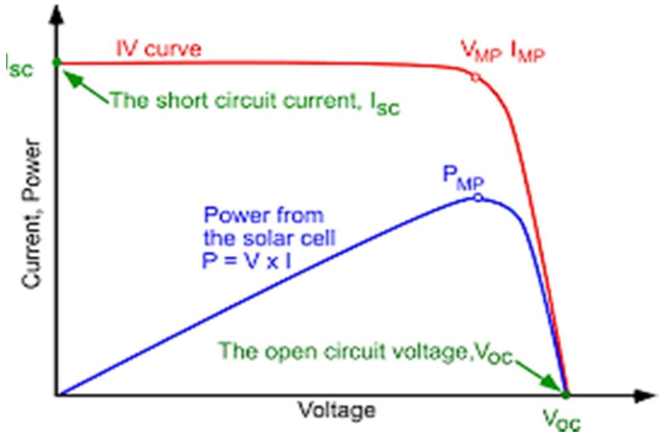

Figure 1standards V-I Curve of the solar PV system

The proposed investigation utilizes simplified linear models to capture the temperature dependence of Isc and Voc, enabling accurate modeling of PV cell behavior.

III. REVIEW OF TELECOM INVERTERS

the literature primarily focuses on three key areas of photovoltaic (PV) systems: mathematical modelling and simulation, maximum power point tracking (MPPT), and the application of machine learning. The first group of papers explores the fundamental mathematical modelling and simulation of PV modules using platforms like MATLAB and Simulink. Mohammed et al.[8]. (2023) have analyses the behaviour of PV systems when subjected to disturbances. The research provides crucial insights into the resilience and stability of PV systems under non-ideal conditions, which is essential for grid integration and reliable power generation. Lekouaghet et al. [9] (2023) introduced a novel optimization algorithm for identifying the ungiven parameters of photovoltaic modules. The work is significant for addressing the challenge of parameter extraction from manufacturer datasheets, which is a key step in accurate modelling and simulation.M. Birane et al., [10] focuses on the analysis and modeling of DC/DC converters systems integration for MPPT based grid-connected PV systems. There primary contribution is a detailed examination of how these converters and regulators behave within a centralized PV system, which is crucial for maximizing power extraction and ensuring efficient energy transfer to the grid.

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Ardeleanu et al. [11](2023) have validates a numerical simulation model of a PV system against an experimental setup. The authors' contribution is the crucial step of bridging the gap between theoretical modelling and real-world performance, confirming the accuracy and reliability of their simulation model. Gaboitaolelwe et al. [12] (2023) presented a review paper that provides a comprehensive overview and comparison of various machine learning-based techniques for solar photovoltaic power forecasting. It synthesizes the current state of research and highlights the effectiveness of different algorithms in predicting solar energy output.Porowski et al. [13] (2025) have focused on the application of ML for predicting the characteristics of PV modules. They demonstrate how data-driven models can be used to forecast module behaviour, which is valuable for maintenance, diagnostics, and performance optimization.

Lari et al. [14] (2025) investigates the use of machine learning algorithms to forecast solar energy power output. The research contributes to the growing body of literature on utilizing artificial intelligence to improve the predictability and management of renewable energy sources. Mahesh et al.[15] (2022) presented a novel approach to MPPT by employing a decision-tree machine learning algorithm. The authors' work is noteworthy for introducing an intelligent, data-driven method to enhance the efficiency of power tracking in photovoltaic systems.

Use ML to predict the characteristics of PV modules, which can be useful for diagnostics and maintenance, allowing for a more proactive approach to system management. Accurate forecasting is vital for grid operators to manage energy supply and demand, as it helps in stabilizing the power network. The summary of the survey is given in Table 1.

Table 1 Summary Of The Review Works

Authors & Ref	Methodology / Tools	Key Contribution
Shanthi et al. [1] 2023	MPPT controller design using IEEE framework	Developed an efficient MPPT controller for solar PV systems to enhance energy extraction
Nguyen & Nguyen [2] 2015	MATLAB/Simulink with tagged modelling blocks	Presented detailed mathematical modelling of PV cells, modules, and arrays
Vinod & Singh [3] 2018	Simulation-based modelling in Energy Reports	Demonstrated PV system simulation as a viable renewable energy solution
Prakash & Singh [4] 2016	Structural modelling via IOSR-JEEE	Designed and modelled solar PV cells and arrays for performance analysis
Suresh Babu et al. [5] 2022	Comparative analysis in IJCESR	Compared I-V and P-V characteristics of series vs. parallel SPV modules
Solanki et al. [6] 2021	Simulation and performance benchmarking in IJMTST	Modelled and analysed solar PV system performance under varying conditions
Rai et al. [7] 2022	MATLAB-based analytical modelling	Provided analytical insights into PV module behaviour using MATLAB
Mohammed et al. [8] 2023	IEEE-based disturbance analysis	Studied PV system behaviour under fault and disturbance scenarios
Lekouaghet et al. [9] 2023	Optimization algorithm for parameter estimation	Proposed a novel method to identify unknown parameters in PV modules
Birane et al. [10] 2021	DC/DC converter topology modelling with MPPT	Compared converter designs with and without MPPT in grid-connected PV systems
Ardeleanu et al. [11] 2023	Experimental validation of simulation models	Validated numerical PV models using real-world experimental setups
Gaboitaolelwe et al. [12] 2023	ML-based forecasting review in IEEE Access	Reviewed and compared machine learning models for solar power prediction
Porowski et al. [13] 2025	ML prediction of PV characteristics	Applied machine learning to forecast PV module behaviour for RE applications
Lari et al. [14] 2025	ML algorithms for solar output forecasting	Used advanced ML techniques to predict solar energy generation
Mahesh et al. [15] 2022	Decision-tree ML for MPPT in Clean Energy	Implemented ML-based MPPT using decision-tree algorithms for improved tracking

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IV. PROPOSED MPPT BASED SYSTEMDESIGNS

The study generates visualizations of the simulated I-V curves and the machine learning predictions, facilitating a clear understanding of the temperature-dependent behavior of PV cells. the flow chart of the sequential simulation is illustreted in the Figure 2.

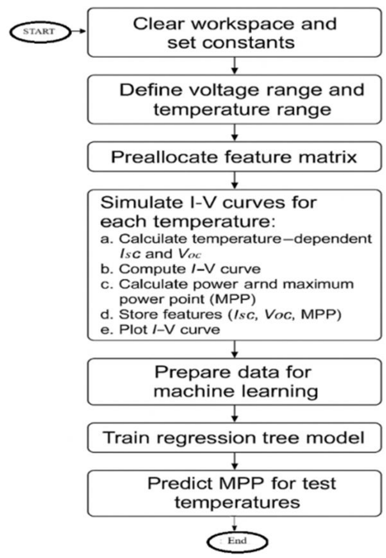

Figure 2The proposed block diagram of the MPPT based solar PV system

The MPPT (Multiple Commands Algorithms) that operates the solar panels to offer the greatest output to a demand and change the power (DC-DC convert) are the two main components of an MPPT plant.

V. EXPECTED OUTCOMES AND DISCUSSION

In this study, machine learning prediction is integrated into the modeling of photovoltaic (PV) cell performance for investigating the impacts of the temperature on the dependent electrical characteristics. Initially, simplified linear models are employed to characterize the variation of short-circuit current (Isc) and open-circuit voltage (Voc) with respect to temperature. These foundational models enable the calculation of the maximum power point (MPP) for each temperature condition, serving as a basis for further predictive analysis.

A. Experiment 1: Impact of Solar Irradiance

An experiment is performed for investigating the impact of variation in solar irradiance. Figure 3 illustrates the behavioral impact of irradiance on the I–Vcharacteristics of solarPV system model across varying temperature conditions. Each curve corresponds to a distinct irradiance level, labeled as G = 200°, 400°, 600°, 800°, and 1000°, and reveals how the electrical output of the PV system responds to changes in solar intensity. As irradiance increases, the short-circuit current (Isc) rises significantly, indicating enhanced photon absorption and carrier generation within solar cell. This is evident from upward shift of the I–V curves, particularly in the initial voltage range.

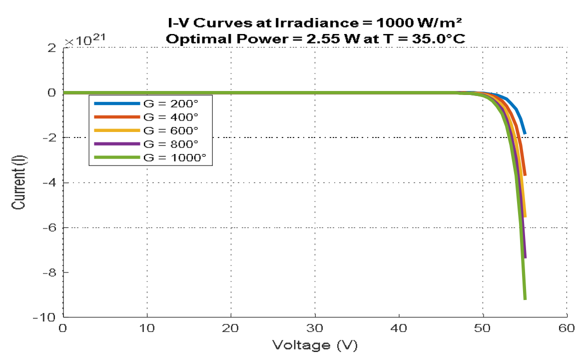

Figure 3 behavioral impact of irradiance of the solar PV system model

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However, the open-circuit voltage (Voc) exhibits a more gradual change, reflecting the logarithmic dependence of Voc on irradiance. The steep decline in current beyond the maximum power point (MPP) highlights the nonlinear nature of PV behavior under load. Overall, the Figure 3 demonstrates that higher irradiance levels lead to increased power output, validating the model's sensitivity to solar input and its relevance for performance forecasting and MPPT algorithm design under dynamic environmental conditions.

B. Experiment 2 of VI curves for different Temperatures

A second simulation is performed for investigating the impact of temperature increase on sola PV cells behavior. Figure 4 presents the simulation results of temperature-dependent behavior of the V–I characteristics of solar PV modules, highlighting impact of thermal variations on electrical output. The graph displays V–I curves at four distinct temperatures as 20°C, 28°C, 36°C, and 44°C. It can be observed that as temperature increases, the curves exhibit a noticeable shift as the open-circuit voltage (Voc) decreases slightly, while the current remains relatively stable or shows a marginal increase.

This inverse relationship between temperature and Voc is consistent with thermal sensitivity of semiconductor materials, where elevated temperatures reduce the bandgap and thus lower the voltage. Additionally, the slope of the curves near the maximum power point (MPP) becomes less steep at higher temperatures, indicating reduced efficiency and power output.

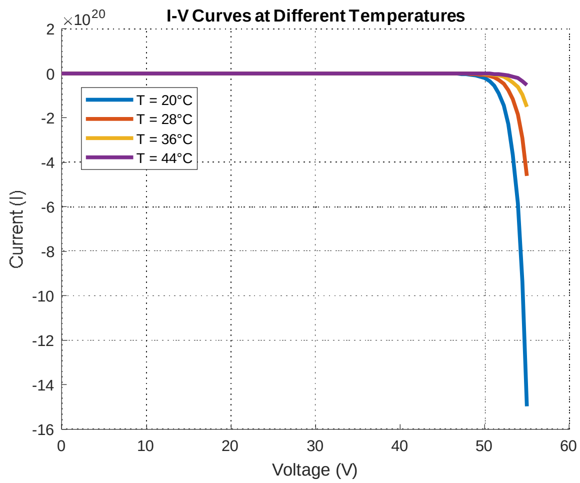

Figure 4 temperature impact on VI curves

Overall, the Figure 4 underscores the critical impact of temperature on PV module performance, emphasizing the need for thermal-aware modeling and control strategies in real-world solar energy applications.

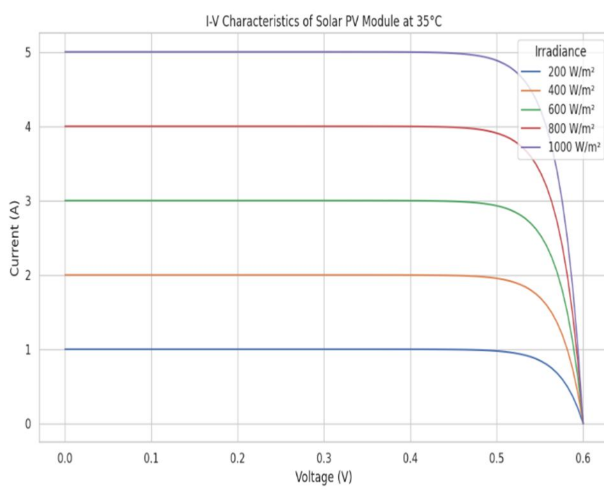

Figure 5 ML simulation for the impact of solar irradiance on VI Curves at different temperatures

Another simulation is carried out for machine learning (ML) based simulation of investigating the solar irradiance impact on the V–I characteristics of a PV module across varying temperatures as shown in Figure 5. Using regression modeling, the simulation captures how irradiance levels from 200 W/m² to 1000 W/m² influence current output at a fixed temperature of 35°C. The different current levels have been opted for respective irradiance model for simulation.

The curves demonstrate that higher irradiance results in increased current generation, while voltage remains relatively stable until the maximum power point. This ML-driven approach effectively models nonlinear behavior and enables predictive analysis of PV performance under dynamic solar conditions.

C. Experiment 3 Results of ML based MPPT prediction

To enhance the adaptability and accuracy of MPP estimation, a regression tree algorithm—a supervised machine learning technique—is implemented. This model learns from the temperature-MPP relationship and generates predictive outputs that generalize across unseen temperature values. The effectiveness of this approach is demonstrated through visual comparisons between simulated I-V curves and the machine learning-based MPP predictions, highlighting the model's ability to capture nonlinear trends and improve forecasting precision. By combining theoretical PV modeling with data-driven learning, the methodology offers a robust framework for analyzing solar cell behavior under dynamic thermal conditions.

The ML implementation of a regression tree as illustrated in Figure 6 in this context involves using temperature as the primary input feature to predict a continuous output variable—most likely the maximum power point (MPP) or another performance metric of a solar photovoltaic (PV) system. The process begins by recursively partitioning the dataset based on temperature thresholds that minimize the squared error within each split. At each node, the algorithm evaluates the optimal temperature cutoff that best separates the data into homogenous subsets with respect to the target value.The root node initiates the split at a temperature threshold (e.g., ≤ 28.03°C), dividing the dataset into two branches: one for samples below the threshold and another for those above. This branching continues, with each subsequent node refining the prediction by further splitting based on temperature values (e.g., ≤ 15.404°C, ≤ 8.333°C, etc.).

Each leaf node in the Figure 6 tree represents a terminal decision point where the model assigns a predicted value based on the average of samples in that subset, with zero error indicating perfect fit within that group.This hierarchical structure allows the regression tree to capture nonlinear relationships between temperature and the output variable, offering interpretable decision rules and localized predictions. The final model provides a piecewise approximation of the temperature-performance relationship, making it especially useful for forecasting PV behaviour under varying thermal conditions.

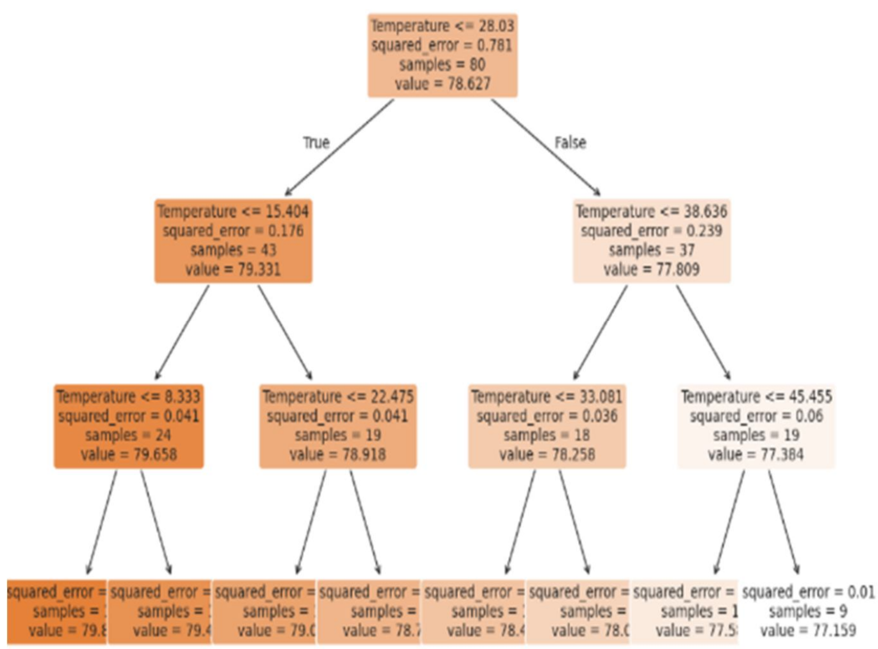

Figure 6 regression tree with Mean Squared Error (MSE): 0.0003R-squared (R^2): 0.9999

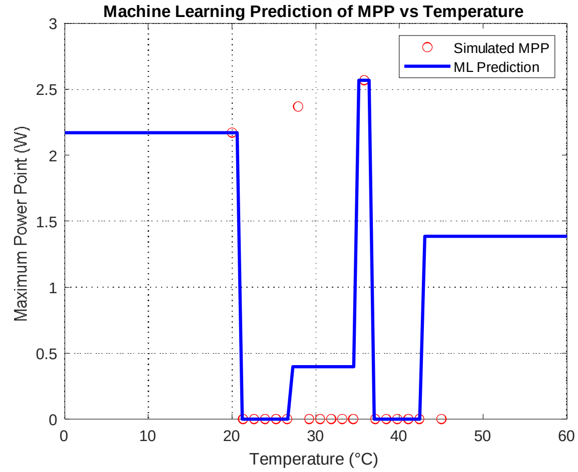

Figure 7 results of MPP prediction using proposed ML based model

Figure 7 presents the comparative results of maximum power point (MPP) prediction using the proposed machine learning (ML)–based model across a range of temperatures. The graph juxtaposes simulated MPP values, shown as red circular markers, with the ML-predicted values represented by a continuous blue line. As temperature increases from 0°C to 50°C, the simulated data exhibits a smooth decline in MPP, consistent with the known thermal behavior of solar PV modules. In contrast, the ML prediction captures the general downward trend but introduces abrupt transitions at certain temperature intervals, indicating discrete decision boundaries inherent to the regression tree algorithm. While the ML model approximates the overall pattern, the deviations highlight areas where prediction granularity could be improved. This figure effectively demonstrates the model's capability to forecast temperature-dependent power output, while also revealing the limitations of tree-based regression in capturing subtle nonlinearities in PV performance.

VI. CONCLUSIONS AND FUTURE WORK.

The study provides a comprehensive evaluation of solar PV module behavior under the impact of varying thermal temperature and solar irradiance conditions. The proposed method integrating both theoretical modeling and ML based prediction techniques.

Results confirm that temperature have significant influence on PV performance, primarily through reductions in open-circuit voltage and overall efficiency. Higher temperatures decrease Voc and the current Iscremains stable or slightly increasesEfficiency and power output reduce at higher temperatures. While irradiance directly enhances current generation and power output. The implementation of a regression tree algorithm for maximum power point (MPP) prediction demonstrated exceptional accuracy, with minimal error and strong correlation to simulated data. Regression tree model demonstrates high accuracy with Mean Squared Error (MSE) of 0.0003 and significant R^2 value of 0.9999. This justifies the selection of tree model.

This validates the potential of machine learning as a predictive tool in solar energy systems. Moreover, the fusion of simplified linear models with data-driven learning offers a scalable and interpretable framework for dynamic performance analysis. These findings emphasize the critical role of temperature-aware modeling and intelligent control strategies in optimizing PV system design, and pave the way for further refinement of predictive algorithms to enhance granularity and real-world applicability.

In future it is recommend to investigate advanced cooling techniques to mitigate temperature-induced efficiency losses in PV cells. Develop more sophisticated machine learning models in future may incorporating multiple environmental factors beyond temperature, such as humidity and dust accumulation.

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