



Analysis of Novel Smart MPPT Approaches Based on M5-Pruned and REPTree Algorithms for Photovoltaic Systems

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Abstract: This paper presents three novel smart MPPT methods that combine a decision tree with a modified incremental conductance and a perturb-and-observe technique to improve the efficiency of solar photovoltaic systems while reducing power ripples in both the photovoltaic system and the associated boost converter during fluctuations in the weather, especially changes in solar irradiation and temperature. Initially, we constructed a mathematical model for solar panels. Subsequently, we developed three innovative smart MPPT techniques utilizing M5-Pruned and REPTree through Weka software, conducted simulations by using MATLAB/SIMULINK, and compared the outcomes with those derived from modified incremental conductance (MINC) and perturb and observe (P&O) MPPT approaches. The simulation results under various conditions indicated that the three innovative smart methods, which utilize M5-Pruned and REPTree, effectively track the maximum power point (MPPT), reduce power ripples in photovoltaic systems and the output ripple of the associated boost converter to it, and enhance the efficiency of solar systems compared to MINC and P&O. Novel approaches exhibit efficiency above 99.77% in comparison to MINC and P&O methods, with an efficiency of 98.88% and 98.83%, respectively. These methods exemplify robust artificial intelligence algorithms for maximum power point tracking (MPPT) due to their efficacy, simplicity in learning and design, and low complexity.

Keywords: *photovoltaic panel; boost converter; modified incremental conductance; M5-Pruned; REPTree.*

Mathematics Subject Classification (2020): 03B52, 93C42, 94D05.

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List of Abbreviations

MPPT	Maximum Power Point Tracking
MINC	Modified Incremental Conductance
P&O	Perturb and Observe
PV	Photovoltaic
M5P	M5-Pruned
REPTree	Reduced Error Pruning Tree
PSO	Particle Swarm Optimization
FLC	Fuzzy Logic Control
ACO	Ant Colony Optimization
ANN	Artificial Neural Network
ANFIS	Adaptive Neuro-Fuzzy Inference System
CS	Cuckoo Search
ABC	Artificial Bee Colony
GWO-INC	Grey Wolf Optimization – Incremental Conductance
PSO-INC	Particle Swarm Optimization – Incremental Conductance
GWO-P&O	Grey Wolf Optimization – Perturb and Observe
INC	Incremental Conductance
HC	Hill Climbing
FOCV	Fractional Open Circuit Voltage
FSCC	Fractional Short Circuit Current
VSSP&O	Improved Variable Step Size Perturb and Observe
THD	Total Harmonic Distortion
M5P-MINC	M5-Pruned – Modified Incremental Conductance
DC–DC	Direct Current to Direct Current

1 Introduction

The photovoltaic solar system is a complicated nonlinear dynamical system, with its output exhibiting nonlinear behavior greatly influenced by external factors such as irradiance levels (G) and temperature (T), as illustrated in Figures 3-4 and equation 1. This nonlinearity engenders a complex, frequently multimodal, non-convex power surface, particularly under partial shade, while the rapidly fluctuating levels of solar irradiation and temperature pose a substantial control and tracking issue within the context of systems theory. Selecting the ideal Maximum Power Point Tracking (MPPT) controller is essential for optimizing power extraction and reducing power loss from the solar panel to DC-DC converters. The MPPT technique's effectiveness is evaluated based on its ability to maintain stability, withstand parametric uncertainty, and achieve rapid convergence — all essential criteria in nonlinear control theory.

Thus, the execution of artificial intelligence (AI) in this field is essential, as conventional MPPT methods often fail to efficiently handle the complex dynamic landscape of the PV system. Papers [1–6] delineate various strategies of AI-based MPPT for optimizing power extraction under both uniform irradiation and partial shading conditions. These methods include the Particle Swarm Optimization (PSO) algorithm, Fuzzy Logic Control (FLC), Ant Colony Optimization (ACO), ANN algorithm [1], Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm [2], Cuckoo Search Colony (ABC) [3], the Grey Wolf Optimization and Incremental Conductance-Based Hybrid MPPT method

(GWO-INC) [4], Hybrid PSO-INC MPPT [5], GWO-P&O algorithm, and other methods based on M5-Purbed [6].

These methods efficiently extract MPPT and minimize power loss during the adaptation phase, however, they are complex and costly to design and implement in practice. Consequently, this has led to enhancements in certain conventional techniques such as the Perturb and Observe (P&O) method, the Incremental Conductance (INC), and Hill Climbing (HC), which are commonly used. Techniques such as Fractional Open Circuit Voltage (FOCV) [8] and Fractional Short Circuit Current (FSCC), and improved Variable Step Size Perturb and Observe (VSSP&O) and modified incremental conductance [9] are used for their simplicity and efficiency in extracting the MPPT under different conditions. Abdelkhalek Chellakhi and his team [9] proposed a unique upgraded Perturb and Observe (P&O) algorithm that integrates an adjustable step-size mechanism, which was implemented using an Arduino board. The new method demonstrates superior performance compared to PSO, FLC, ZV, and traditional P&O algorithms.

M. Sacid Endiz [20] exhibited the effectiveness of the modified incremental conductance method for MPPT extraction using both simulation and empirical findings. The suggested incremental conductance method more accurately identifies the maximum power point and provides optimal power for battery charging under fluctuating solar irradiation conditions, unlike the traditional incremental conductance method. The proposed system can function as a charging infrastructure solution for low-powered electric devices. A. Bouhouta and his team [10] developed a mixed control strategy using pruned model tree (M5P) and fuzzy logic controller datasets. The system effectively detects harmonic currents in active power filter systems, achieving a power factor of 0.99, a minimal THD of 3.07%, and a rapid response time of 100 ms. see [6, 10, 11, 16]. We have conducted extensive research on decision tree-based approaches. We have noticed that these approaches give better results than other methods, and display efficiency across various sectors including electrical, biomedical, and photovoltaic systems, wind energy, agronomy, and the identification of DDoS attacks in software-defined networks. Remaining with this aim to enhance the maximum power point tracking system (Figure 1), we proposed three unique mixed control strategies employing the pruned model tree (M5P), REPTree, and collected datasets from a modified incremental conductance controller and perturb and observe methods.

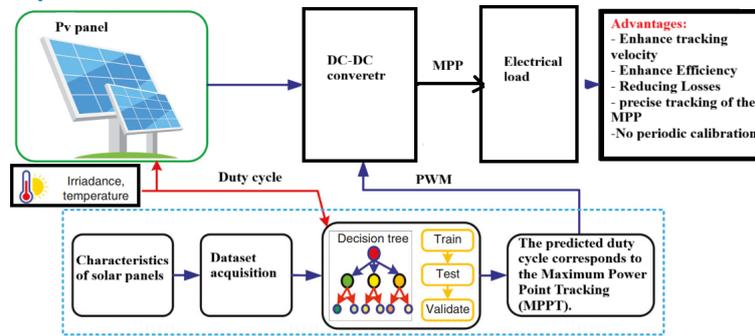


Figure 1: PV panel connected with MPPT [9].

The first approach is M5P-MINC, the second is M5P-P&O, and the third is REPTree-

MINC. This combination aims to leverage the rapid decision-making capabilities of decision trees in conjunction with the advantages of the modified incremental conductance and perturb and observe methods in fluctuating weather conditions such as rapid variations in solar irradiance and temperature. The simulation using MATLAB/SIMULINK under various dynamic settings demonstrated the effectiveness of this combination.

This paper is structured as follows. Section 2 offers a comprehensive explanation of the modeling of the photovoltaic panel and boost converter, whereas Section 3 delineates the proposed methodologies. Section 4 subsequently shows the simulation findings. In conclusion, Section 5 finalizes the paper.

2 Pv Panel, Boost Converter Modelling

2.1 Pv panel modelling

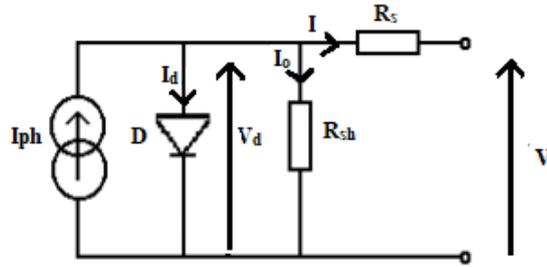


Figure 2: Equivalent electrical circuit to a photovoltaic cell [21].

A solar photovoltaic panel comprises several cells linked in series, parallel, or mixed. Each cell (panel) can be shown by an equivalent circuit, see Figure 2, which consists of a current source (I_{ph}), a single diode (D), a series resistance (R_s), and a parallel resistance (R_p). The correlation between voltage V and current I in a solar cell is articulated by the equation (1):

$$I = I_{ph} - I_0 \left[\exp \left(\frac{V + R_s \cdot I}{U_T \cdot A} \right) - 1 \right] - \frac{V + R_s \cdot I}{R_{sh}}. \quad (1)$$

U_T signifies the thermal voltage of the panel, whereas A indicates the diode ideality index. Figures 3-4 illustrate the distinct characteristic P-V and I-V curves of the solar panel utilized in this study.

2.2 DC-DC boost converter

The employed DC-DC converter is a boost converter. The principal function is to modify the voltage or current levels from an input source to a specified output. This type of switched-mode power supply has two semiconductor components (transistors and diodes) in conjunction with an energy storage element. To ensure a more stable voltage, it is customary to incorporate capacitor-based filters at the input and output terminals of the converter. Figure 5 illustrates the fundamental architecture of the boost converter. The output voltage is elevated with respect to the input voltage. The input power (P_{in})

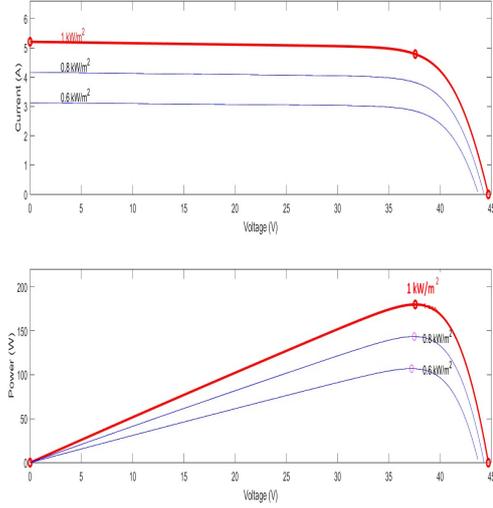


Figure 3: P-V and I-V curves with T constant and G variable.

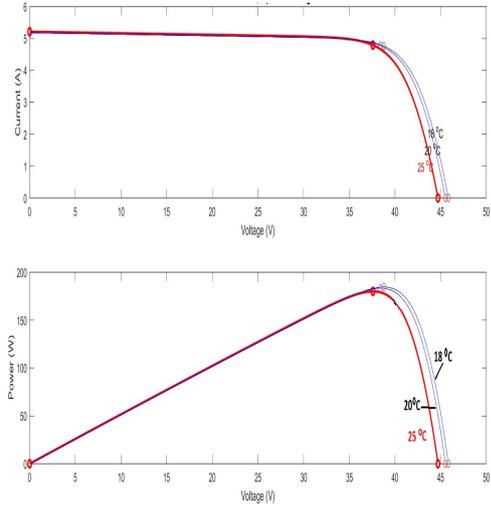


Figure 4: P-V and I-V curves when T is variable and G is fixed.

and output power (P_{out}) are commensurate in accordance with the principle of energy conservation [17],

$$P_{in} = P_{out}. \quad (2)$$

The relation between the input and output voltage is represented by

$$V_{out} = \frac{V}{1 - \alpha}, \quad (3)$$

where V_{out} and V represent the output voltage and input voltage, respectively, while α represents the duty cycle.

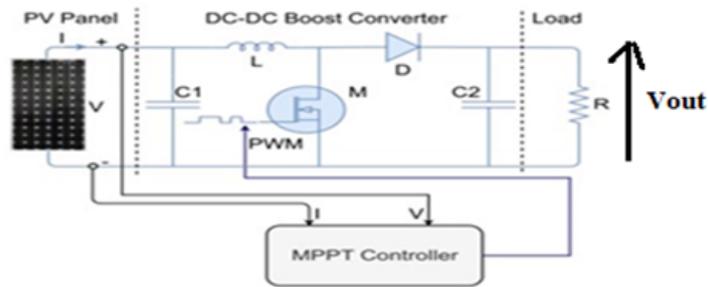


Figure 5: Electrical circuit of boost converter [18].

3 MPPT Approaches

3.1 M5P decision tree

Decision tree algorithms are regarded as the most robust and effective supervised machine learning methods in control applications. Its swift modelling techniques are useful across several engineering domains for regression and classification objectives. DT employs a statistical methodology to classify input data, referred to as “attributes”, into several segments via a tree structure. Pruned M5 (M5P) is an improved variant of the M5 tree [19]. The pruned M5P model tree algorithm partitions training data into subsets, combining traditional model trees with linear regression, resulting in intuitive, comprehensible, and interpretable tree models for accurate class label prediction. R. Quinlan [10] improved the original M5 model by creating an extended version that facilitates tree generation without requiring alterations to system parameters or domain expertise. Numerous studies indicate that the M5P approach is remarkably stable and achieves prediction accuracy akin to that of an artificial neural network (ANN) when utilizing identical data sets. The integration of fuzzy logic with decision tree algorithms can yield improved efficiency.

3.2 REPTree decision tree

REPTree generates several trees across various iterations employing the regression tree framework. The REPTree function constructs a decision tree using a specified data set. It is considered an extension of C45 because it employs Reduced Error Pruning (REP) to improve the pruning process. The C4.5 algorithm is a proficient decision tree learner that generates classification trees for discrete results and regression trees for continuous results. Reduced-error pruning, which includes backfitting, is utilized to determine the requisite pruning cuts following the development of a regression or decision tree utilizing information gain or variance.

3.3 Description of MPPT methods

3.3.1 Perturb and Observe MPPT method

This is the primary method employed in commercial applications. P&O is the favored choice for most practical photovoltaic systems because of their remarkable reliability, simplicity, and efficiency. The process is essentially one of experimentation and correction. This method depends on determining the power output of the photovoltaic (PV) system and the fluctuations in power by quantifying the current and voltage of the photovoltaic array. It functions by adjusting the PV array voltage upward or downward. Assume that a specific disturbance causes a fluctuation in PV power levels. The duty ratio of the boost converter is continually modified and repeated until the MPPT is achieved. A subsequent disturbance should be produced in a comparable or contrasting manner. The oscillations can be diminished by decreasing the intensity of the perturbation step. However, the principal disadvantage of this approach is its effect on the speed of the MPP tracking in smaller increments while the system functions at peak power [8], for a simple implementation, see Figure 6.

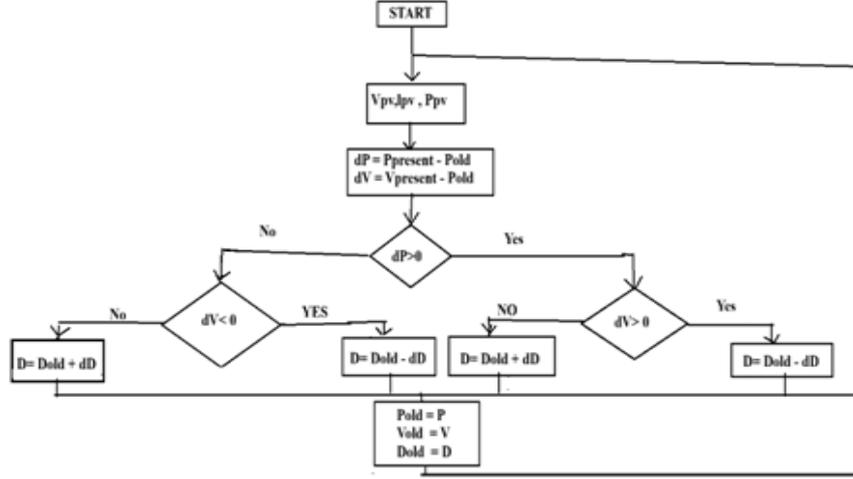


Figure 6: Flowchart of P&O algorithm.

3.3.2 Modified Incremental Conductance (MINC)

The Modified Incremental Conductance technique (MINC) provides enhanced tracking efficiency and usability compared to traditional Incremental Conductance (INC). It employs an optimized computational method to calculate the sum of 'I/V' and 'dI/dV' values to sustain the solar module at the Maximum Power Point (MPP). The MINC employs fewer decision blocks and reduced code, leading to improved algorithm efficacy [19].

3.3.3 Smart MPPT proposed

A distinctive combination of decision trees, M5P and REPTree, together with modified incremental conductance (MINC) and perturb and observe (P&O) methods, is proposed for maximum power point tracking (MPPT). The first method, M5P-MINC, the second, REPTree-MINC, and the third, M5P-P&O, demonstrate swift and dependable tracking skills. The suggested non-parametric MPPT model is developed using input and output data derived from MINC and P&O MPPT approaches. A dataset has been methodically created for the MINC and P&O techniques, leveraging simulated data collected over 100 milliseconds. The chosen MINC and P&O input and output characteristics pertain to the voltage of the solar panel (V_{pv}), the current of the photovoltaic panel (I_{pv}), and the outputs of MINC and P&O, which represent the duty cycle, are enumerated accordingly. A data set of 100,000 samples is employed to develop the proposed M5P and REPTree model-tree-based MPPT, with 66% allocated for training and the remaining portion for testing. Figure 8 succinctly illustrates the data acquisition and training methodologies. Figure 9 delineates a comprehensive analysis of data flow, incorporating WEKA and simulation specifics, and elucidates the principal phases in the formulation of three proposed methodologies.

1. Data collection: The initial phase entails gathering data from the solar panel's V_{pv} and I_{pv} voltage sensors, along with the modifier incremental conductance controller

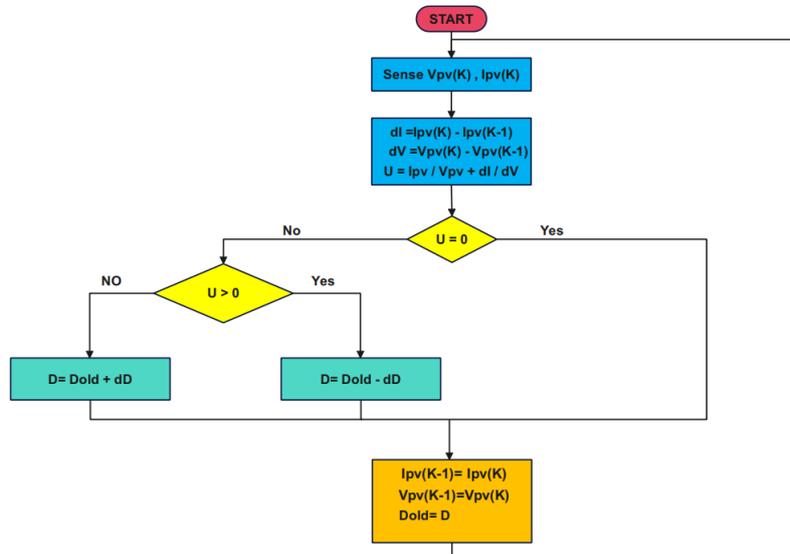


Figure 7: Flow chart of modified incremental conductance.

(MINC) and perturb and observe (P&O), to acquire accurate readings for analysis and regulation.

2. Preprocessing: The step encompasses normalization, data imputation, or filtering approaches to ensure data is organized and prepared for feature extraction and modelling, removing noise, and missing values.
3. Feature extraction (WEKA): During this step, WEKA, a machine learning tool, is utilised to extract some of the pertinent features from the previously processed data. This process entails the selection or modification of the most pertinent variables for the development of the M5-Pruned and REPTree models. This step seeks to diminish data dimensionality and concentrate on critical inputs that affect the system’s performance.
4. M5-Pruned and REPTree model training (WEKA): WEKA employs the extracted features to train the M5-Pruned and REPTree algorithms. These methods create a decision tree, where the leaves represent linear regression models that forecast output variables. The predictive model enables immediate decision-making within the control system.

4 Results and Discussion

Figure 13 depicts the model employed for simulation. This system has five solar panels (Zytech 180s type), linked with boost converters that are controlled by various MPPT algorithms. Figure 14 illustrates the multiple conditions implemented for the validation and assessment of the efficacy of the proposed approaches. The simulation duration

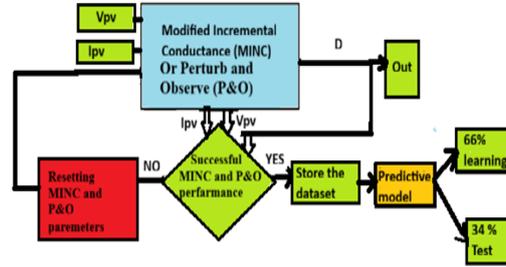


Figure 8: Dataset extraction methodology via MINC and P&O.

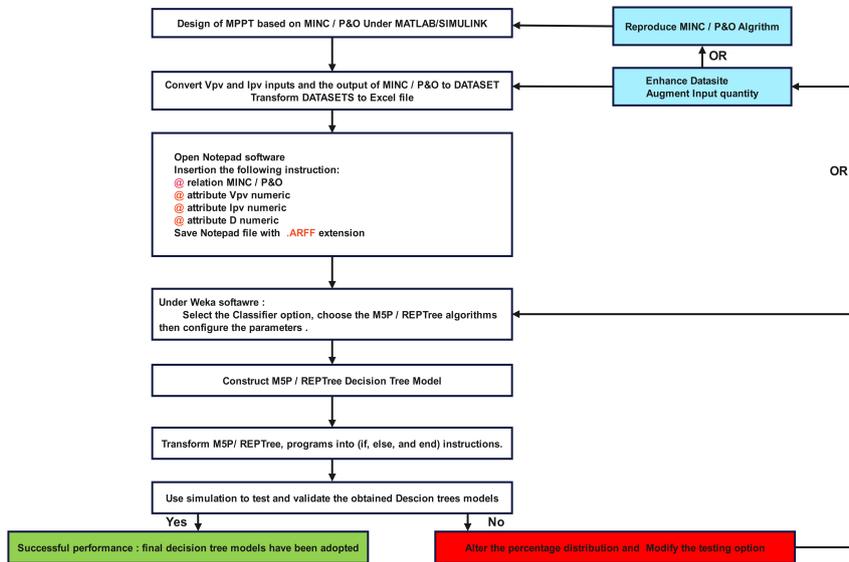


Figure 9: Dataset management process.

in this study was set at 100 milliseconds (ms). During the interval from 0 ms to 30 ms, the temperature and solar irradiation levels are 20° and 800 W m^{-2} , respectively. In the subsequent interval from 30 ms to 40 ms, the temperature and solar irradiation decline to 18° and 600 W m^{-2} , respectively. Subsequently, between 40 ms and 53 ms, the temperature and solar irradiation levels are recorded at 18° and 600 W m^{-2} , respectively. During the ensuing interval from 53 ms to 70 ms, these levels rise to 25° and 1000 W m^{-2} , respectively. In the span of 70 ms to 100 ms, the temperature is 25° and the solar irradiation is 1000 W m^{-2} .

Figures 15 and 16 depict the simulation outcomes for the power delivered by the solar photovoltaic system and the output power of the boost converter linked to the photovoltaic panel (Pload), regulated by various MPPT methodologies, all inside the simulation framework. Table 4 presents a summary of these findings.

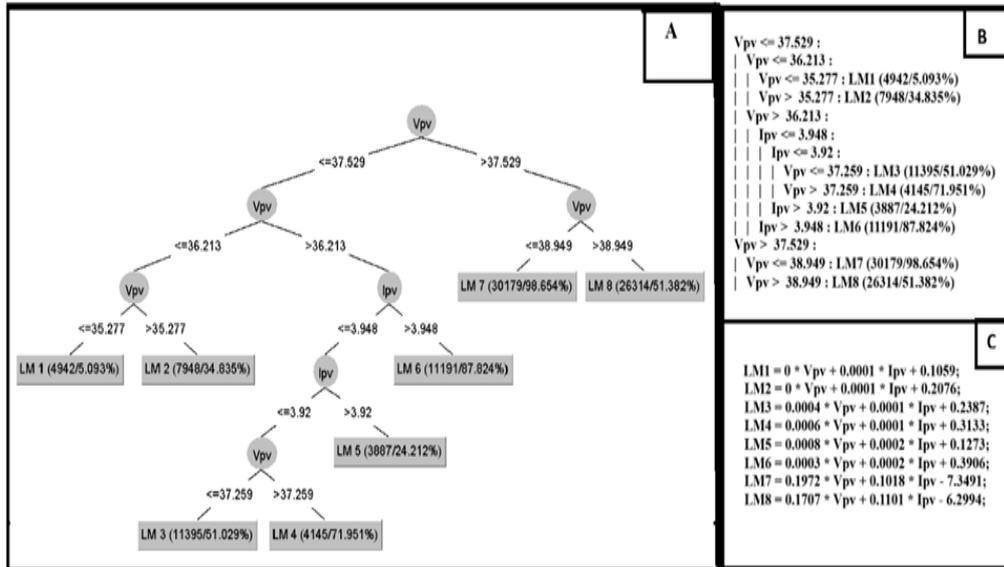


Figure 10: Results of Training Process of M5P-MINC Control via WEKA Software. (A) : Printed flowchart of the M5P-MINC Decision Tree. (B): Predictive Rules of Decision Tree. (C): Attribute Target Weights.

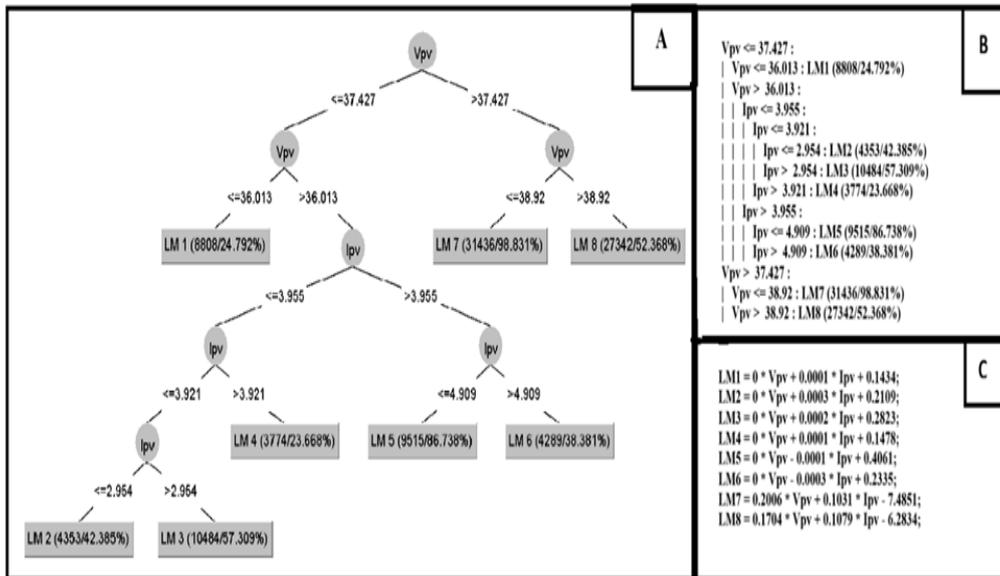


Figure 11: Results of Training Process of M5P-P&O Control via WEKA Software. (A) : Printed flowchart of the M5P-P&O Decision Tree. (B): Predictive Rules of Decision Tree. (C): Attribute Target Weights.

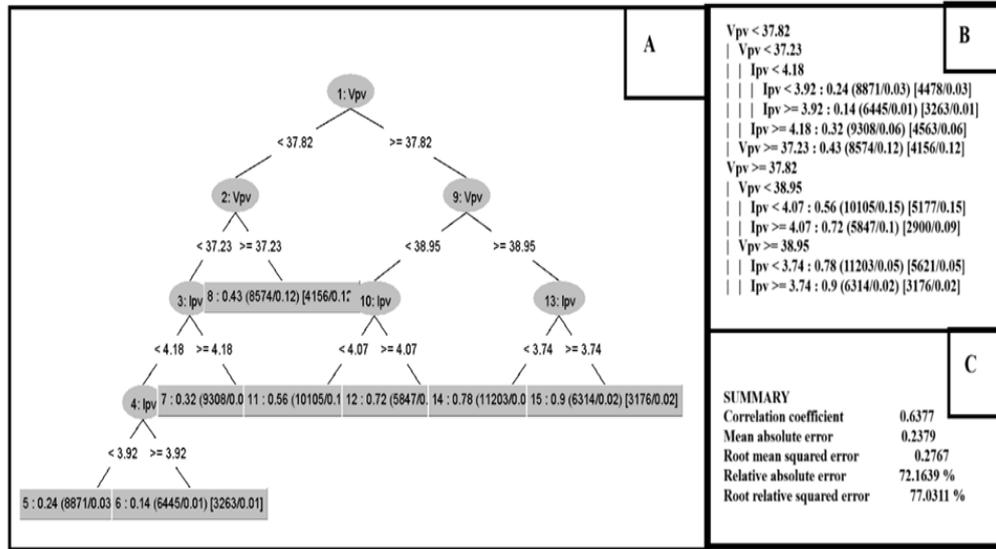


Figure 12: Results of Training Process of REPTree-MINC Control via WEKA Software. (A) : Printed flowchart of the REPTree-MINC Decision Tree. (B): Predictive Rules of Decision Tree. (C): Summary of Process.

The effectiveness of the innovative methods, which combine decision tree (DT) algorithms with modified incremental conductance and perturb and observe, was evaluated under variable weather circumstances. The initial method is M5P-MINC, the subsequent method is REPTree-MINC, and the final method is M5P-P&O. These methods are compared to the MINC and P&O methods. The assessment focused on the accuracy of MPPT tracking, the speed of tracking to MPPT, and the power ripples of both the PV panel and the Pload, in addition to the overall conversion efficiency and the efficiency of MPPT, utilizing MATLAB/SIMULINK.

All evaluated methods effectively extract the MPP and demonstrate swift convergence to the MPPT under various fluctuation conditions. However, as concerning the reduction of the ripple of power for photovoltaic systems and the output ripple of the boost converter linked to the photovoltaic system, the proposed smart algorithms attain minimal ripple levels in contrast to the modified incremental conductance and perturb and observe approaches, which exhibit elevated ripples. The proposed methods demonstrate superior efficiency in the tracking of the maximum power point compared to MINC and P&O, achieving an efficiency exceeding 99.77% versus to 98.88% and 98.83% for MINC and P&O, respectively. Furthermore, the overall conversion efficiency surpasses 88.3% for smart approaches, in contrast to that of MINC and P&O, which is equal to 85.61% and 85.72%, respectively, while the proposed approaches exhibit reduced computational complexity.

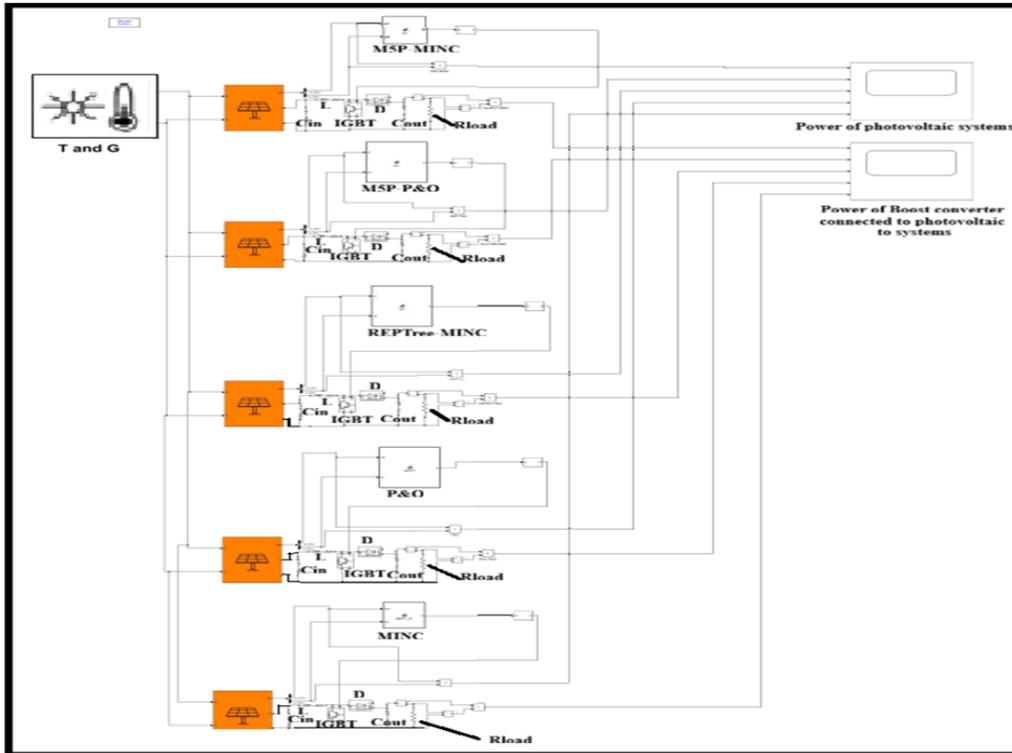


Figure 13: Simulation Model.

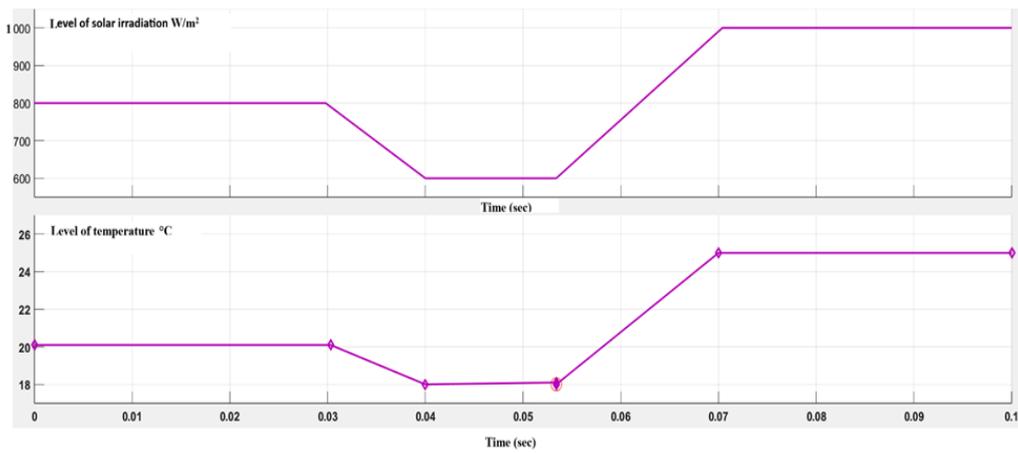


Figure 14: The variation of temperature and solar irradiation over time.

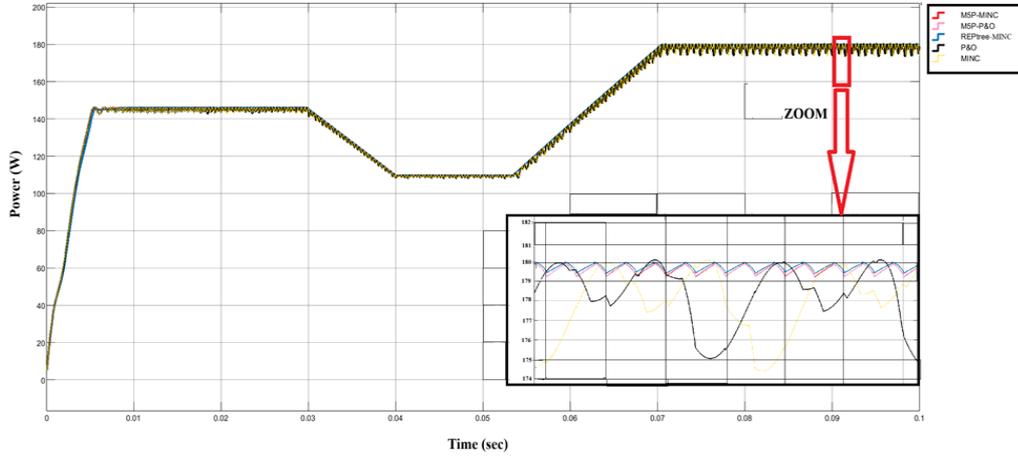


Figure 15: The simulation outcomes for the power delivered by Photovoltaic panel by using the various MPPT approaches.

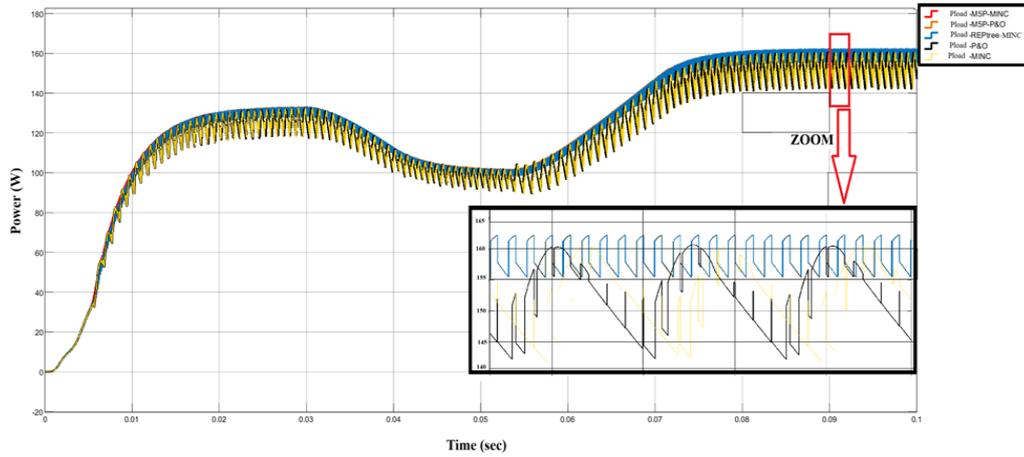


Figure 16: The simulation outcomes for the power of the boost converter connected to the Photovoltaic panel by using the various MPPT approaches.

	Tracking of MPPT	Fast of conversion to MPPT	Ripple of power of PV panel	Ripple of output Boost	Efficiency of tracking MPPT ($\frac{P_{out}}{P_{in}}$)	Complexity	Efficiency of conversion ($\frac{P_{out}}{P_{in}}$)
MINC	YES	HIGH	HIGH (3.68%)	HIGH (12.51%)	98.88%	LOW	Medium (85.61%)
P&O	YES	HIGH	HIGH (3.63%)	HIGH (12.48%)	98.83%	LOW	Medium (85.72%)
M5P-MINC	YES	HIGH	Small (0.39%)	Small (4.36%)	99.77%	LOW	HIGH (88.3%)
M5P-P&O	YES	HIGH	Small (0.40%)	Small (4.37%)	99.77%	LOW	HIGH (88.3%)
REPTree-MINC	YES	HIGH	Small (0.33%)	Small (4.37%)	99.83%	LOW	HIGH (88.31%)

Table 1: The Simulation Results.

5 Conclusion

This paper evaluates three distinct artificial intelligence-based maximum power point tracking (MPPT) methods that combine a modified incremental conductance (MINC)

and perturb and observe (P&O) strategies with M5-Pruned (M5P) and REPTree decision tree techniques. The effectiveness of the proposed techniques was assessed in various dynamic conditions, specifically with variations in temperature and solar radiation levels. The aim is to evaluate the suggested M5P-MINC, REPTree-MINC, and M5P-P&O methodologies against the MINC and P&O methods. Comparative simulations were performed. The main factors for comparison included MPPT efficiency, convergence speed, power ripple reduction in the photovoltaic (PV) system and its corresponding boost converter, as well as the overall conversion efficiency. All assessed approaches efficiently extract the MPP and exhibit rapid convergence to the MPPT over diverse fluctuation situations. However, in terms of the attenuation of power ripple in photovoltaic systems and the output ripple of the boost converter associated with the solar system, the suggested smart algorithms achieve minimal ripple levels compared to the modified incremental conductance and perturb and observe methods, which display higher ripples. The proposed methods exhibit greater efficiency in maximum power point tracking than MINC and P&O, attaining an efficiency of over 99.77% compared to 98.88% and 98.83% for MINC and P&O, respectively. The overall conversion efficiency surpasses 88.3% for the proposed smart approaches, whereas that of MINC and P&O is 85.61% and 85.72%, respectively. The proposed methods exhibit reduced computational complexity. Our findings indicate that the proposed strategies are efficacious for MPPT and ripple reduction in solar systems. These methodologies provide a pragmatic and efficient AI-driven solution, enabling seamless data collection, adaptive system learning, and real-time implementation with little cost.

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