

Enhanced MPPT approach for grid-integrated solar PV system: Simulation and experimental study

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ABSTRACT

The global solar energy utilization has significantly risen, mostly due to the technological, economic, and environmental advantages it offers, particularly through the implementation of photovoltaic (PV) systems. The energy output of PV systems is contingent upon climate conditions. A new hybrid two-stage maximum power point tracking (MPPT) system developed to optimize power extraction and increase efficiency in PV systems. The system consists of two stages: a perturb and observe (P&O) MPPT for regulating the reference voltage in the first stage, and an enhanced model reference adaptive controller (EMRAC) for adjusting the DC-DC converter duty cycle in second stage. This system is designed primarily for 100.7 kW three-phase grid-integrated PV systems operating in environments with rapidly changing solar irradiation and temperature levels. In order to demonstrate efficacy of the suggested approach, a probabilistic evaluation is conducted across three levels of uncertain scenarios, namely ropp, step irradiance profile, and rapid changing irradiation and temperature profile. The proposed approach attained maximum power point (MPP) in 0.11 s and had an average tracking efficiency of 98.28 %. Quantitative, statistical, comparative and experimental analyses utilizing the dSPACE 1202 reveal the effectiveness of the proposed control strategy and demonstrate the superior performance over P&O, INC and ANN based on the power output, response time, power loss, efficiency, and error rates.

1. Introduction

The escalating need for energy, driven by population increase and industrialization, has raised significant concerns about energy consumption recently. Despite growing demand, there is insufficient supply of energy, prompting the exploration of alternative energy resources. Additionally, the exhaustion of fossil fuels, escalating oil costs, environmental concerns associated with traditional energy sources including climate change, the effects of emissions of carbon from burning fossil fuels, and pollution all lead us to consider alternate sources of energy (Zhang et al., 2020). Due to plentiful and enduring nature of sun, solar energy is considered a significant and sustainable renewable energy resource for both the present and the future (Singh et al., 2022). In addition to several benefits such as easy installation, noiselessness, little maintenance requirements, unlimited availability, and environmental friendliness, PV systems (PVS) are hindered by the upfront expenses

associated with acquiring and installing PV panels. Due to the fact that solar panels do not capture all of the sunlight, most PV panels have an efficiency range of 15–18 % (Renewable capacity statistics, 2021). Despite the substantial research conducted on enhancing the efficiency of PV cells, the rates of growth still aren't where they need to be. However, expanding a PV system's power production by improving its MPPT capabilities is equally important. Power converters are necessary for transferring PV panel power to the grid in advanced applications. The primary function of such converters is to regulate the current and voltage at load, controlling power flow in grid integrated and stand-alone PV systems, and primarily follow MPP of device. Consequently, it optimizes the PV system's efficiency in the most economical and efficient way (Alsharif, 2017; Manna et al., 2023).

The MPPT controller's principal function is to maximize PV modules output power in the presence of environmental constraints like as temperature and sun irradiation (Mao et al., 2020). MPPT controllers

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optimize power delivery, resulting in increased power output and improved cost efficiency per watt. There are several controllers documented in literature that are capable of effectively MPPT during operation. Most MPPT approaches calculate power by adjusting the converter's duty cycle in response to changes in PV array's measured current and voltage. Although MPPT approaches have the same aims, they differ in areas such as complexity, cost, control variable, fluctuation at MPP, applications, and tracking speed (Wasim et al., 2022).

Since the inception of the MPPT idea, there have been many different approaches suggested, including INC (Alsharif et al.), P&O (Ge et al., 2020), extreme seeking control (Singh and Pal, 2021), short-circuit current (SCC) (Farajdadian and Hosseini, 2019), ripple correlation control (Pilakkat and Kanthalakshmi, 2020), and fuzzy logic control (FLC) (Mirza et al., 2020) which have gained significant recognition. Solar PV production systems have made extensive use of the P&O strategy. This strategy is based on perturbing voltage using the current power value and its previous value (Fathi and Parian, 2021). Despite the strategy's apparent simplicity, its success is highly dependent on the occurrence of rapid changes and fluctuations. A faster response rate would reduce precision and increase oscillations. Consequently, it is of the utmost importance to adjust the approach's parameters such that the oscillations and convergence rate are balanced (Mathi and Chinthamala, 2020). The abrupt fluctuations in sun irradiation can cause deviations from MPP direction in P&O. Regarding this matter, the INC technique has demonstrated exceptional outcomes when compared to P&O approach in situations involving a variable step increment. However, it is possible that it might cause fluctuations in the output power close to MPP (Farajdadian and Hosseini, 2019).

A new MPPT is suggested for grid integrated PV systems (GIPVS), which integrates the golden section search (GSS), INC and P&O techniques. This combination allows for faster convergence and reduced oscillation, reaching MPP by progressively narrowing the interval width at the golden ratio rate. The suggested approach is capable of identifying MPP within 36 ms and recovering a drifting MPP in about 30 ms. The efficiency of this approach is 98.99 %. However, the method's robustness does not validate for unforeseen atmospheric disruptions (Xu et al., 2021). A novel approach for MPPT of PV modules is suggested that use an inverter's finite control set model predictive current control (FCS-MPCC) in conjunction with model predictive control (MPC). The results indicate that MPC has superior tracking performance while operating within restrictions. Additionally, the system demonstrates faster and more precise dynamic response and greater flexibility compared to traditional Proportional-Integral (PI) control. However, the robustness of the approaches does not account for unforeseen atmospheric disturbances, and the suggested algorithm is merely compared to a traditional algorithm. It does not address the efficacy and time tracking (Zhao et al., 2021). A novel adaptive FLC is proposed, which utilizes the modified krill herd (MKH) algorithm. To compensate for temperature and irradiance uncertainty, the MKH method is used to calibrate FLC's membership functions (MFs). It just takes 0.15 s to follow the MPPT, and the suggested method has an efficiency of 99.32 %. Nevertheless, the implementation of this approach is complicated (Hu et al., 2022). A new hybrid INC-PSO-MPC MPPT approach is developed for GIPVS. The suggested method tracks the MPPT in under 0.05 s and has an efficiency of 99 %. Nevertheless, the method's strength is not tested when exposed to unexpected irradiation profiles, such as sine and ropp test (Kacimi et al., 2023).

The FLC-based MPPT approach has been demonstrated to be a highly efficient method that can be applied to PV systems. A rapid convergence rate and minimal oscillations are guaranteed by this MPPT technology (Díaz Martínez et al., 2021; Gali et al., 2023). It is important to acknowledge that this strategy has a drawback caused by inaccurate membership functions (MFs) when encountering rapid variation in temperature and irradiance. Consequently, AI-based strategies were proposed to resolve the issues. In addition, these strategies do not need exact parameters or a deep understanding of the system (Babes et al.,

2021; Bhukya et al., 2021). Artificial neural networks (ANNs) were developed to deal with highly non-linear systems. Nevertheless, ANN necessitates a large dataset in order to facilitate the training process. The ANFIS, a combinatorial approach that brings together the best features of ANN and FLC, may be efficiently utilized for many problems, including PV system with MPPT. This approach is effective for PV systems when dealing with inaccurate weather data. Unlike the FLC, the ANFIS allows for the utilization of historical data for training purposes (Farayola et al., 2018). In addition, the training data will be acquired through the simulation of the PV model, where ANFIS-MPPT algorithm has been specifically developed for a converter with a single-stage architecture (Aldair et al., 2018). The ANFIS-MPPT method utilized the SCC and open-circuit voltage (OCV). However, this approach resulted in inaccurate MPPT because to the inherent approximations (Priyadarshi et al., 2019). In references (Javed et al., 2020; Al-Majidi et al., 2019) utilized the output current and voltage of PV, as well as irradiance and temperature, to train the ANFIS. However, the dataset's short size will lead to a significant training error, as mentioned in (Lasheen and Abdel-Salam, 2018). Furthermore, no experimental validation has been conducted.

Heuristic techniques, including neural networks (NN) (Kharb et al., 2014), genetic algorithm (GA) (Daraban et al., 2014), and PSO (Soufi et al., 2017), have been implemented in literature as ways to improve the parameters of FLC. NN-based solutions need a substantial quantity of past data in order to adequately train the network and get satisfactory outcomes. Given its stochastic nature, GA is unable to yield a singular and precise solution for the problem. Additionally, it needs complicated and laborious computations to achieve convergence. PSO is more straightforward to adopt and has a lower reliance on the initial population compared to GA. Nevertheless, it is prone to being trapped in local optima when dealing with high-dimensional space and exhibits a slow convergence rate during iterative process.

The author conducted a study on a control mechanism for MPPT based on Prairie dog optimization (PDO) algorithm. The incorporation of PDO will enhance PV output, resulting in improved stability and efficiency of the refrigeration system (Marlin and Jebaseelan, 2023). The Genghis Khan shark optimizer draws inspiration from the hunting abilities employed by sharks and the leadership attributes demonstrated by Genghis Khan. It merges the hunting habit of sharks with Genghis Khan's methods of strategy, leadership and organization (Teklehaimanot et al., 2024). The Geyser Inspired Algorithm emulates the alternating eruption and quiet phases of geysers, making it a meta-heuristic optimization approach. By harnessing the natural occurrence of geyser eruptions, it effectively maintains a balance between exploitation and exploration in the pursuit of optimal solutions (Ghasemi et al., 2023). The Dwarf Mongoose Optimization method is a metaheuristic approach used for optimization and parameter extraction. It is inspired by the unique hunting tactic employed by the dwarf mongoose animal community (Moustafa et al., 2023). Gazelles are renowned for their adeptness at evading predators through agile maneuvers and quick decision-making. This optimizer is renowned for its ability to adjust and perform effectively in changing and challenging conditions (Hasanien et al., 2023). Lungs performance optimization is derived from the respiratory mechanism of our lungs. The model constantly adapts parameters such as carbon dioxide and oxygen levels in the alveoli and improves the process of finding a balance between exploring many options and exploiting the best solution (Ghasemi et al., 2024). The optimization method of the Greater Cane Rat Algorithm is derived from the clever foraging activities exhibited by greater cane rats both within and outside of the breeding season (Agushaka et al., 2024).

Although both the INC and P&O techniques are well-liked and work well when exposed to uniform radiation, they are unable to keep up with the MPPT when the sun's intensity changes suddenly. Another issue with these approaches is that they have a slow tracking speed and a lot of steady-state oscillations, which are their principal drawbacks. To counteract these issues, soft computing based MPPT approaches like

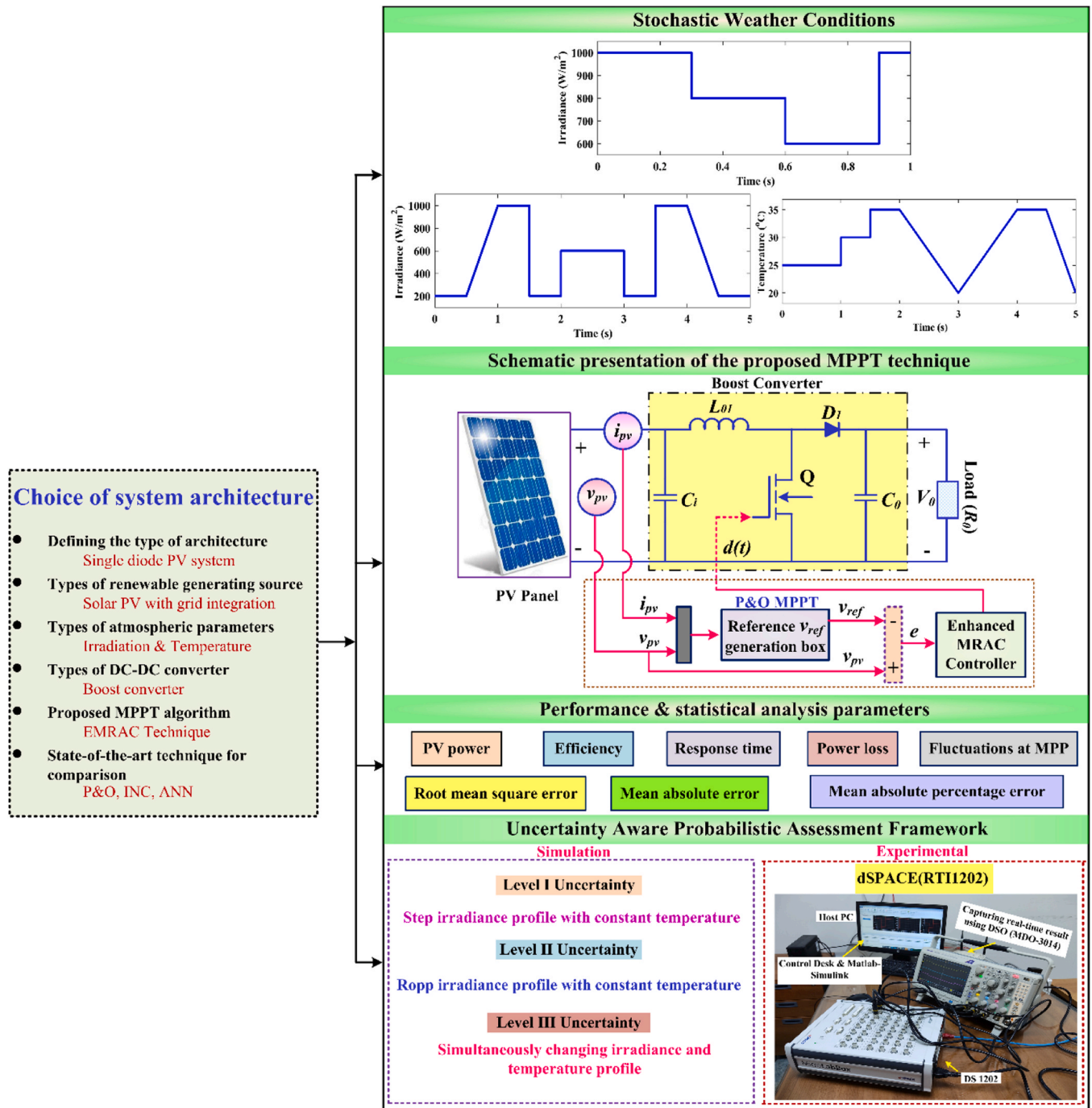


Fig. 1. Methodology for the suggested MPPT approach depicted schematically.

FLC, SMC, ANN, and metaheuristic-based techniques like GA and PSO were developed. When confronted with sudden changes in the values of temperature and irradiance, the FLC technique fails because of its inaccurate membership functions. FLC design is mostly hindered by a lack of expert knowledge and a lack of proper rule base system design. When training an ANN, a large data set is necessary. Negative aspects of ANNs include the need for data about PV systems for training, the high expense of storing massive amounts of data, and the need to fine-tune the parameters. Selecting an appropriate sliding surface has a significant impact on the SMC's performance. One drawback of PSO is the complexity of the objective function, which is affected by the particle's velocity. The huge search space is the GWO's detriment, leading to increased computing time and expense. Complex and time-consuming

computations are required for the hybrid MPPT method, such as ANFIS. Therefore, developing a solar MPPT controller that is effective, simpler, and robust is the primary objective of this research.

In light of the aforementioned limitations, the research presents a new EMRAC MPPT approach for a three-phase GIPVS operating under rapidly changing temperature and irradiance conditions. The EMRAC MPPT control scheme will be based on the MIT rule and aim to achieve rapid tracking speed, minimal oscillation near MPP, high efficiency, and minimum power loss. The suggested MPPT methodology utilizes a sequential two-level hybrid strategy. The first level consists of a reference voltage generating block, while the second level involves an EMRAC. Simulink is utilized for the development and execution of the suggested EMRAC strategy. Probabilistic assessments involve the use of

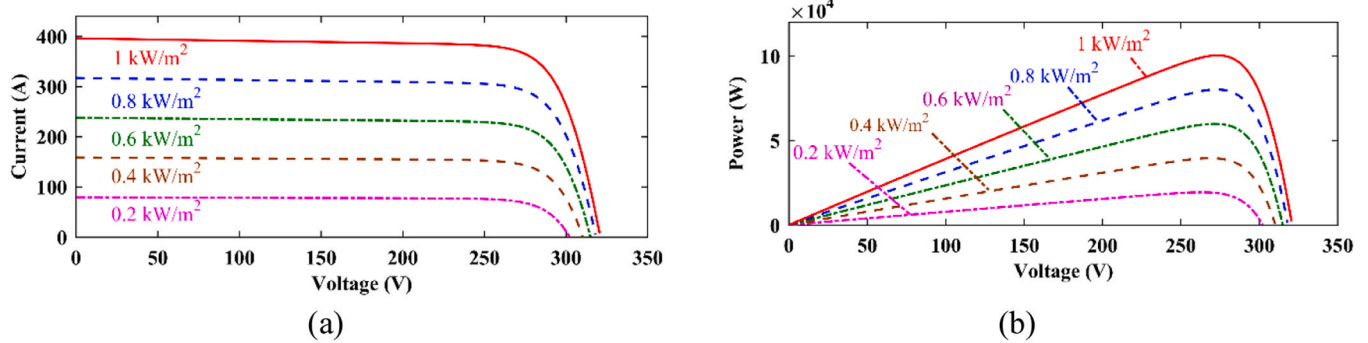


Fig. 2. (a) I-V and (b) P-V characteristics at different irradiances and uniform temperature levels.

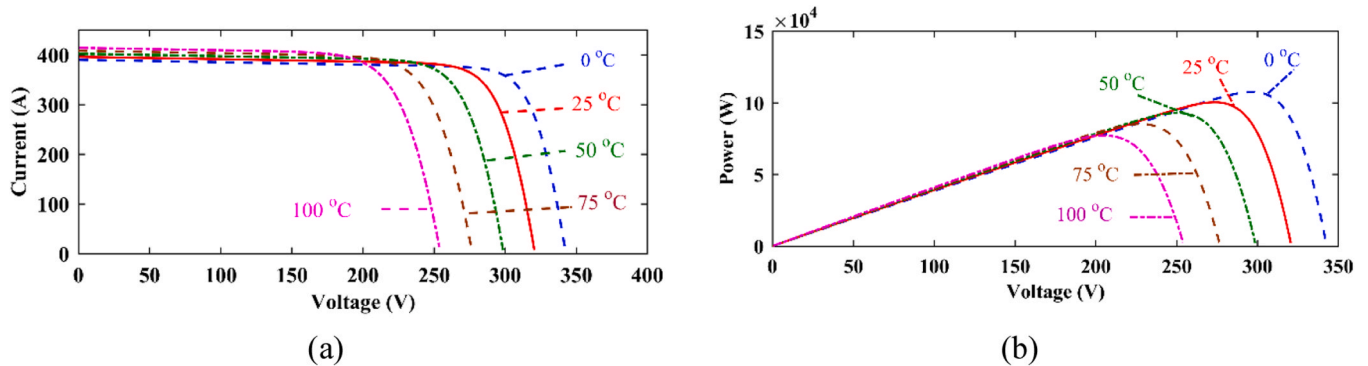


Fig. 3. (a) I-V and (b) P-V characteristics at different temperatures and uniform irradiance levels.

simulation and experimental validation to test the efficacy of proposed strategy under distinct levels of uncertainty. These levels are categorized as follows: Level-I: Step irradiance profile; Level-II: Ropp irradiance profile; Level-III: highly fluctuating irradiance and temperature profile. The research has identified these findings as its primary contributions:

- A novel EMRAC controller based on MIT rule is devised for the first time for three phase grid-connected PV system featuring simple design, easy implementation, higher accuracy, and fast-tracking capabilities.
- The suggested controller's robustness is confirmed through the probabilistic assessment, which employs three distinct levels of uncertainty.
- A thorough comparison of conventional and advanced MPPT strategies, such as P&O, ANN, and INC-MPPT technique, is conducted to verify the superiority of the recommended algorithm.
- The feasibility of the suggested approach is proven by conducting experimental verification utilizing the dSPACE 1202 under different irradiation profile.

Fig. 1. illustrates a systematic approach based on the previously discussed notion to develop a robust MPPT controller for PVS. The following is the organizational scheme for the sections that follow in this paper. The characteristics of PVS is explained in Section 2. Again, P&O, ANN, and INC are some of the MPPT strategies discussed in Section 3. Using a boost converter and the MPPT technique, Section 4 explains PVS modelling. Section 6 focuses into the discussion of the simulation findings. The experimental verifications are implemented in Section 7, followed by conclusion in Section 8.

2. Photovoltaic system characteristics

Solar PV cells are an integral part of solar power plants, which are

responsible for transforming the energy from the sun into electricity. A PV cell is represented by single diode equivalent circuit. The short circuit current and open circuit voltage are two crucial elements in this model. While the temperature and specific characteristics of the cell material affect the open-circuit voltage, the short-circuit current magnitude is affected by level of irradiance. Additional information on the single-diode equivalent circuit of a PV cell and its corresponding equations may be found in (Bollipo et al., 2020; Singh et al., 2023).

3. MPPT techniques

Figs. 2 and 3 depict the attributes of a PV system at varying levels of irradiance and temperature, respectively. Both temperature and irradiation affect MPP of a PV module. Due to the dynamic nature of environmental variables and the nonlinear properties of P-V curve, an MPPT controller is necessary to accurately track the changed MPP whenever there is a change in irradiance and/or temperature (Wasim et al., 2022). Various MPPT techniques, including P&O, ANN and INC are employed to accurately follow MPP. The manuscript implements P&O, INC, and ANN approaches to compare with the EMRAC MPPT approach. P&O and INC offer basic, commonly used MPPT approaches, whereas ANN represents more sophisticated, data-driven strategies. As a result, it becomes a benchmark for assessing the usefulness of proposed MPPT strategies. By comparing existing approaches with the suggested approach, a thorough assessment can be made of the performance of traditional, sophisticated and proposed algorithms under different scenarios. The comparison emphasizes the differences between the complexity of algorithms, the simplicity of implementation, and the performance evaluation. This part offers a succinct overview of these strategies.

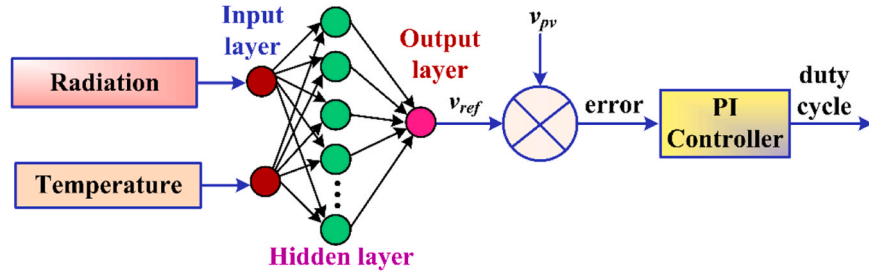


Fig. 4. ANN-MPPT block diagram.

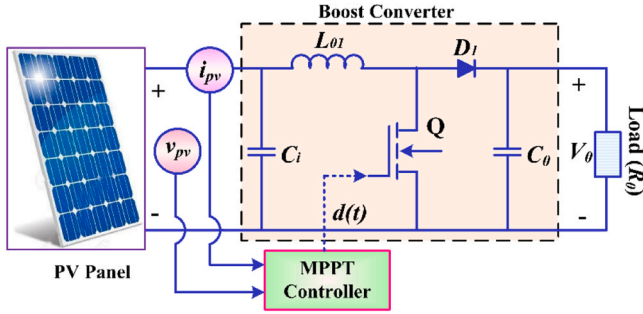


Fig. 5. PV system equipped with boost converter and MPPT controller.

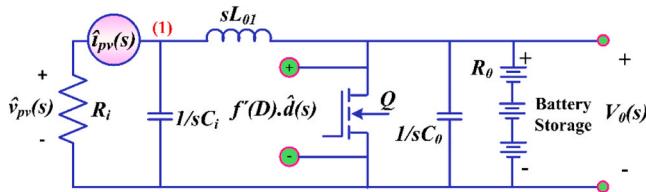


Fig. 6. Model for PV system with small signal equivalent (Khanna et al., 2014).

3.1. P&O approach

To determine P&O strategy, one must first compare the voltage locations and the power acquired at two points on a P-V curve. The voltage is then fine-tuned to follow the MPP precisely by moving it to the right or left of the P-V curve. Essentially, this technique examines the variation in power output of the PV cell (dp), followed by an assessment of the sign of PV voltage (dv). Based on the acquired data, duty cycle is perturbed. P-V curve data is utilized for the analysis of the real-time displacement of the operating point. If dp/dv is positive, then corresponding point is located in left side of MPP. Otherwise, it is located in the negative half. Furthermore, this process continues until dp/dv , reaches zero (Manna et al., 2023).

3.2. INC method

To overcome the drawbacks of P&O, an alternate iterative online MPPT strategy called INC was developed. When comparing accuracy, tracking speed and efficiency, the INC approach is much superior than the P&O. However, there is a higher degree of complexity and sensitivity to errors and disturbance in measured control values using this approach. The fundamental principle of this approach is to determine the rate of change of PV output power in relation to its voltage (Hu et al., 2022). The Eq. (1) that represents PV system output power is discussed as:

$$P_{pv} = v_{pv} i_{pv} \quad (1)$$

Thus, the fundamental equations of this approach may be expressed

as

$$\left\{ \begin{array}{l} \frac{dp_{pv}}{dv_{pv}} = 0 \rightarrow \frac{\Delta i_{pv}}{\Delta v_{pv}} = -\frac{i_{pv}}{v_{pv}} \rightarrow \text{operating point is at MPP} \\ \frac{dp_{pv}}{dv_{pv}} > 0 \rightarrow \frac{\Delta i_{pv}}{\Delta v_{pv}} > -\frac{i_{pv}}{v_{pv}} \rightarrow \text{Operating point is at left side of MPP} \\ \frac{dp_{pv}}{dv_{pv}} < 0 \rightarrow \frac{\Delta i_{pv}}{\Delta v_{pv}} < -\frac{i_{pv}}{v_{pv}} \rightarrow \text{Operating point is at right side of MPP} \end{array} \right\} \quad (2)$$

3.3. Artificial neural networks (ANN)

ANNs are very effective intelligent systems used to handle complex issues in several domains, including pattern classification, identification, recognition and control systems. These applications of ANN will not necessitate much knowledge about the system or mathematical modelling. They may effectively address complicated challenges by accurately mapping the system input-output. The ANN is a sophisticated MPPT technology that utilizes intelligence and is characterized by its ability to learn and its similarity to organic neurons. Essentially, the ANN may be shown as a directed graph, with the neurons represented as nodes and the synapses as edges (Bollipo et al., 2020). In this study, an ANN-MPPT algorithm is constructed utilizing the MATLAB program. The ANN consists of two inputs: temperature and solar radiation. It has one output which is reference voltage. The process occurs within the crucial hidden layer, where it fine-tunes the bias and weights to estimate the optimal value, namely reference voltage for each MPP, using the given input datasets. An error is generated by comparing the reference voltage, which is the ANN's output, to the real PV voltage. A PI controller handles the resultant error to adjust the duty cycle. Fig. 4. shows the ANN-MPPT approach's block diagram.

4. Modelling of PV system using boost converter & MPPT

4.1. Boost converter dynamics

A dc-dc converter coupled to MPPT controls the voltage or current in a standard PV system. This setup is designed to optimize electricity generation, as seen in Fig. 5. The MPPT controller converts the PV panel's current (i_{pv}) and voltage (v_{pv}) into duty cycle ($d(t)$) that regulates the switching (Q) of converter. Total PV current and voltage are a function of both ripple and direct current. The objective of MPPT strategy is to optimize the collection and transmission of solar energy to load by ensuring that v_{pv} and i_{pv} follow MPP as seen in Fig. 2.

The steady-state correlation between the $d(t)$, i_{pv} , and v_{pv} may be expressed as (Dadkhah Tehrani and Shabaninia, 2017):

$$v_{pv} = i_{pv} R_0 (1 - d)^2 \quad (3)$$

with $i_{pv} = I_{pv} + \hat{i}_{pv}$ and $v_{pv} = V_{pv} + \hat{v}_{pv}$. Here, I_{pv} and $\hat{i}_{pv}$ represent the DC and ripple terms of PV current. V_{pv} and $\hat{v}_{pv}$ represent the DC and ripple terms of PV voltage.

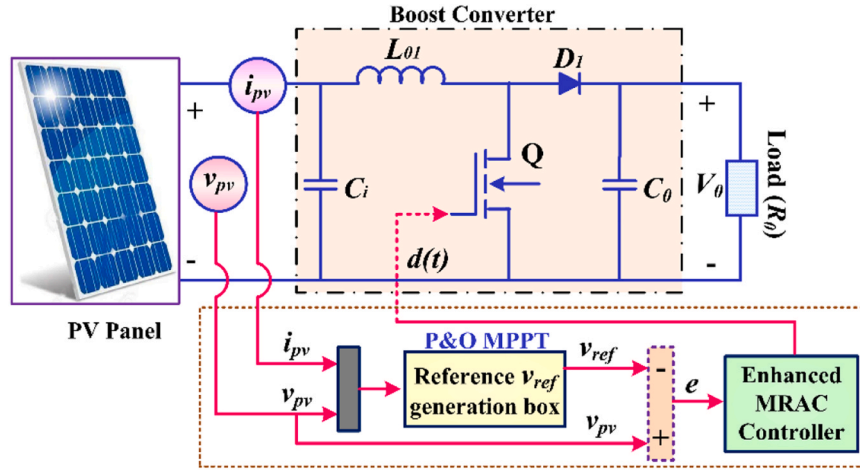


Fig. 7. Illustration of the MPPT control architecture.

4.2. Power conversion step of a PV system: small-signal analysis

Eq. (3) demonstrates the correlation among duty cycle of converter and array voltage in a steady state. Hence, in order to enhance the transient responsiveness, MPPT control must take into account the correlation among array voltage and duty cycle. In order to enhance clarity in the transient analysis, Fig. 6 presents a small-scale representation that is identical to Fig. 5 (Dadkhah Tehrani and Shabaninia, 2017).

R_i , $\hat{v}_{pv}(s)$, and $\hat{i}_{pv}(s)$ represent small signal PV resistance, voltage and current, respectively as demonstrating in Fig. 6. The transfer function that relates array voltage to duty cycle is calculated in small signal operation around a certain operational point. This calculation ignores the effects of the load's dynamics, namely the battery in this case. On node (1), the KCL approach is used to compute the frequency domain relationship among $\hat{v}_{pv}(s)$ and $\hat{d}(s)$.

$$\frac{\hat{v}_{pv}(s)}{R_i} + s\hat{v}_{pv}(s)C_i = \frac{f'(D)\hat{d}(s) - \hat{v}_{pv}(s)}{sL_{01}} \quad (4)$$

The symbol $\hat{d}$ denotes small signal oscillation around the duty cycle D . The Laplace transforms of $\hat{d}(t)$ and $\hat{v}_{pv}(t)$ are denoted as $\hat{d}(s)$ and $\hat{v}_{pv}(s)$ correspondingly. The steady-state output voltage (V_0) and input voltage (V_{pv}) of boost converter are directly connected to the duty cycle (D), which is represented by the function $f(D)$. The derivatives of $f(D)$ at operating point D is represented by $f'(D)$. Upon reordering the aforementioned equation, we obtain

$$\frac{\hat{v}_{pv}(s)}{\hat{d}(s)} = \frac{f'(D)}{L_{01}C_i s^2 + \frac{L_{01}}{R_i} s + 1} \quad (5)$$

It's well-known that

$$f(D) = V_{pv} = (1 - D)V_0 \quad (6)$$

It is assumed that Eq. (6) remains unchanged during the transient response in this scenario. In relation to Eq. (6), we now possess

$$f'(D) = -V_0 \quad (7)$$

By substituting value of $f'(D)$ from Eq. (7) into Eq. (5), we get

$$\frac{\hat{v}_{pv}(s)}{\hat{d}(s)} = \frac{-\frac{V_0}{L_{01}C_i}}{s^2 + \frac{1}{R_i C_i} s + \frac{1}{L_{01} C_i}} \quad (8)$$

Eq. (8), which has a negative sign, indicates that the panel voltage increases as the duty ratio drops. An approximation of the transfer function described by Eq. (8) was approximated by linearizing nonlinear system depicted in Fig. 5 at a certain operating point, as illustrated in

Fig. 6. Whenever the irradiance level varies, the system's operational location likewise changes, and this leads to a corresponding change in the value of Eq. (8), with R_i being the component that is most impacted. The impact R_i of on the system may be assessed by examining the denominator portion of Eq. (8).

$$s^2 + 2\xi\omega_n s + \omega_n^2 \quad (9)$$

The symbols ω_n represent natural frequency and ξ represents the damping ratio. Upon comparing denominator of Eq. (8) with Eq. (9), it becomes evident that

$$\xi = \frac{1}{2R_i} \sqrt{\frac{L_{01}}{C_i}}; \omega_n = \frac{1}{\sqrt{C_i L_{01}}} \quad (10)$$

Systems with a damping ratio (ξ) less than 1, known as underdamped systems, display fluctuations in their response. Employing adaptive strategy to govern the dynamics of a controlled plant can effectively mitigate under-damped oscillations and undesirable behaviours. Controlled plants should be operated as critically damped system (CDS), with a damping ratio (ξ) of 1. It is feasible to get a critically damped system at a specific operating point by adjusting R_i , but maintaining critical damping across all operating points is not practicable with a constant R_i . Therefore, this research proposes a new EMRAC approach to follow MPP. The proposed technique is expected to efficiently accomplish a CDS and optimizing the converter dynamics.

5. Design of proposed EMRAC technique

The reference generating box functions as the initial control level in proposed MPPT approach, as displayed in Fig. 7. For each voltage in the MPP, this block produces a reference voltage, abbreviated as v_{ref} . The second stage involves implementing the EMRAC-MPPT strategy. The v_{pv} and v_{ref} are compared, and resultant error ($v_{pv} - v_{ref}$) is subsequently input into EMRAC. By controlling the duty cycle, the EMRAC ensures that PV panel operates constantly at its MPP. As part of EMRAC, a reference model is developed to depict the optimal behaviour of boost converter and PV system. The reference model establishes a benchmark for the system's performance, outlining the desired response of the converter to maximize power generation from PV array. The EMRAC system constantly examines the discrepancy between the actual output of the system and the output that is expected by reference model. The EMRAC controller responds by modifying its parameters in order to reduce the performance error. It utilizes the gradient-based MIT rule to update the control parameters in the adaptation laws. These rules dynamically modify the controller's configurations to reduce the discrepancy between the desired and actual outputs in real-time. PV

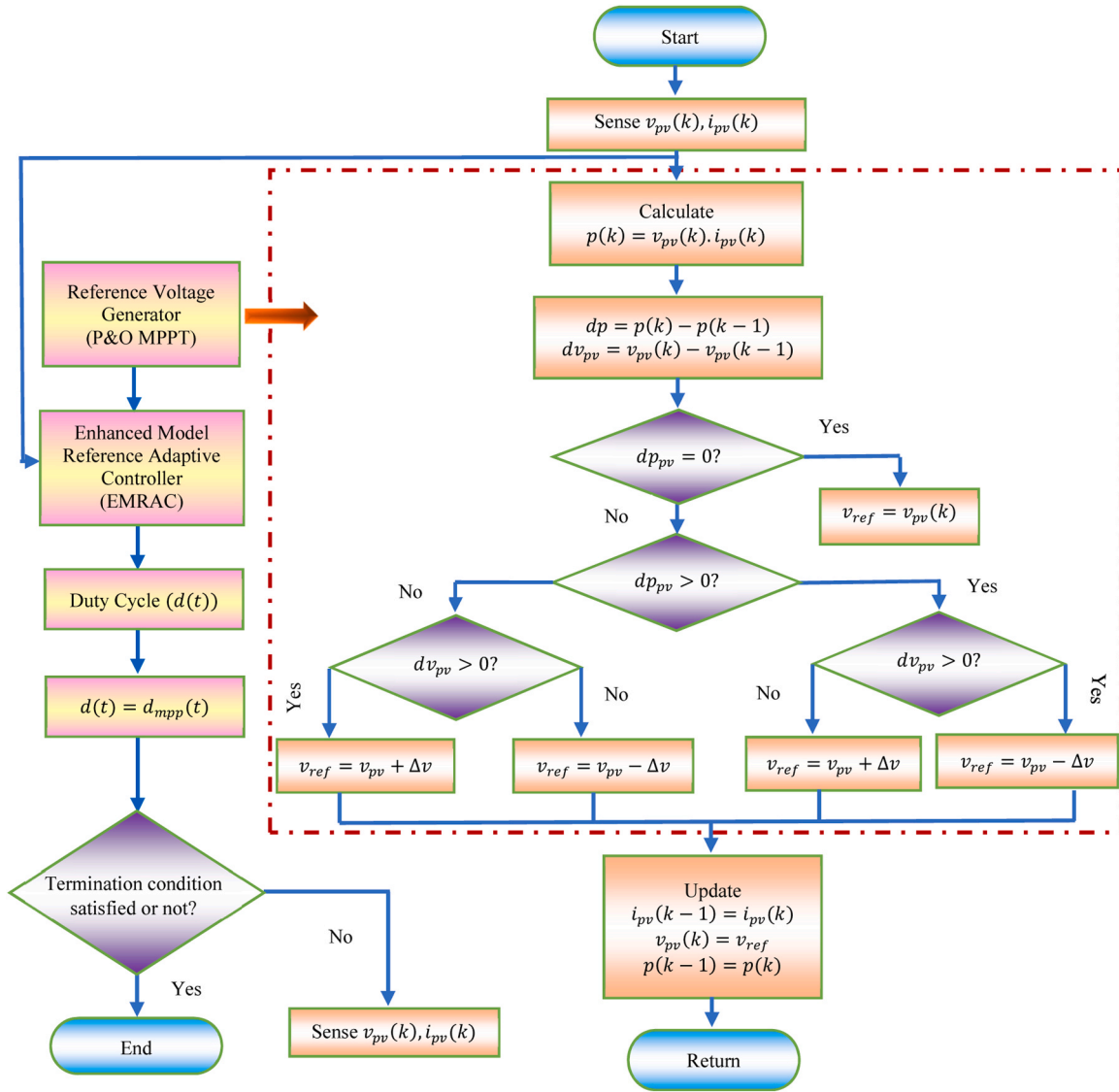


Fig. 8. Flowchart of proposed approach.

systems are exposed to fluctuating environmental factors, including changes in sunshine intensity and temperature. The EMRAC adjusts to these changes by continuously readjusting the control parameters to guarantee optimal performance. It modifies the duty cycle based on variations in the power point and external circumstances. Through real-time adaptation to system state changes and precise adjustment of the converter's duty cycle, EMRAC guarantees efficient and effective operation of the solar PV system. This improvement maximizes power extraction and enhances overall system performance.

5.1. Reference voltage generation stage

In this step, a voltage reference-based P&O technique has been designed for implementation. The P&O algorithm is based on the concept that the rate of change of PV power with respect to voltage is equal to zero at MPP, as described by Eq. (11). A unique reference voltage (v_{ref}) is calculated for each MPP voltage in this phase as discussed in Eq. (12). The flowchart illustrating the determination of v_{ref} for EMRAC-MPPT approach is displayed in Fig. 8.

$$\frac{dp_{pv}}{dv_{pv}} \begin{cases} < 0, \text{ at right side of MPP} \\ = 0, \text{ at MPP} \\ > 0, \text{ at the left side of MPP} \end{cases} \quad (11)$$

$$v_{ref} = \begin{cases} v_{pv} - \Delta v, & \frac{dp_{pv}}{dv_{pv}} < 0 \\ v_{pv}, & \frac{dp_{pv}}{dv_{pv}} = 0 \\ v_{pv} + \Delta v, & \frac{dp_{pv}}{dv_{pv}} > 0 \end{cases} \quad (12)$$

5.2. Proposed EMRAC design

In the previous step, P&O algorithm is employed to calculate v_{ref} , which aims to achieve the MPP under steady-state. Furthermore, it is preferable that the system achieves MPP quickly when there are rapid fluctuations in solar insolation. The strongly dynamic character of the correlation involving voltage and duty cycle is clearly seen by Eq. (8). If adaptive control is not applied, the array voltage may not exhibit critically damped behaviour due to fluctuations in the operating point caused by variations in irradiation. The primary objective of EMRAC strategy is to ensure that array voltage is maintained at a critically damped state. The conventional MRAC exhibits inadequate tracking performance when applied to second-order systems. Here, the extension of the EMRAC from the first to the second order as well as control rule for

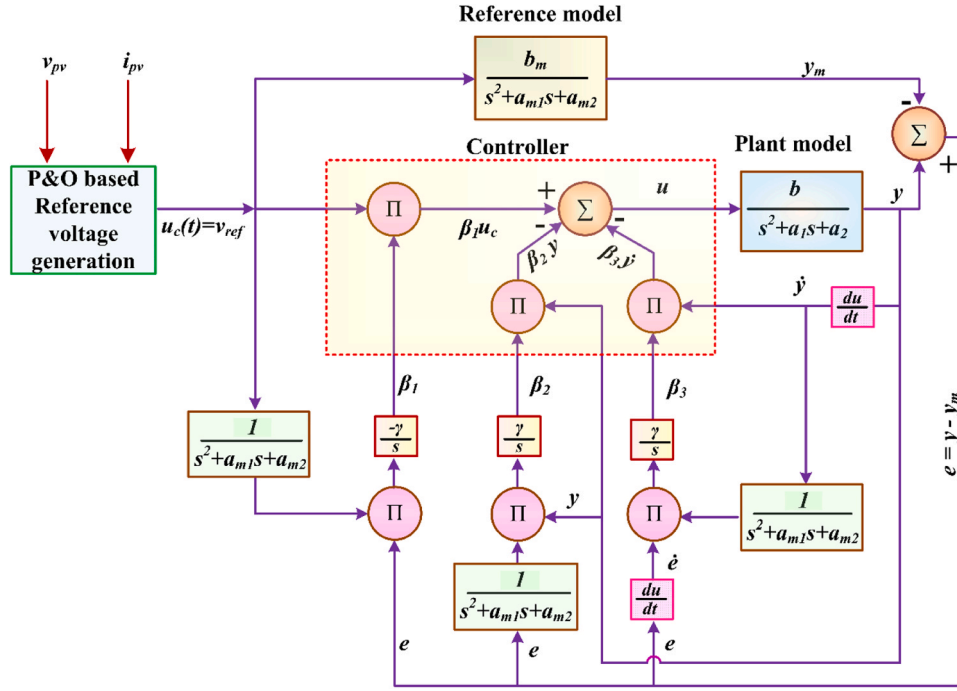


Fig. 9. Structure of the controller in the EMRAC.

second order process are developed. Fig. 8 depicts the flowchart of the suggested controller. The inner architecture of EMRAC is depicted in Fig. 9. The v_{ref} defined in Section 5.1 acts as input ($u_c(t)$) for the system.

The transfer function stated in Eq. (8) is replicated by the plant model shown in Fig. 9. However, for the sake of simplicity, the sign of the plant model is reversed, resulting in only positive coefficients. Consider a second-order system model is described in the time and frequency domains by:

$$\frac{d^2y(t)}{dt^2} = -a_1 \frac{dy(t)}{dt} - a_2 y(t) + bu(t) \quad (13)$$

$$\frac{y(s)}{u(s)} = \frac{b}{s^2 + a_1s + a_2} \quad (14)$$

where y is the output that was measured and u is the control variable. The parameters of the plant model, as denoted as a_1 , a_2 and b are determined by an Eq. (8).

The time and frequency domains are used to display the desired response by:

$$\frac{d^2y_m(t)}{dt^2} = -a_{m1} \frac{dy_m(t)}{dt} - a_{m2} y_m(t) + b_m u_c(t) \quad (15)$$

$$\frac{y_m(s)}{u_c(s)} = \frac{b_m}{s^2 + a_{m1}s + a_{m2}} \quad (16)$$

Where the desired reference model parameters are denoted as a_{m1} , a_{m2} and b_m .

Define the controller as

$$u = \beta_1 u_c - \beta_2 y - \beta_3 \dot{y} = \beta^T \theta \quad (17)$$

where $\theta = [u_c, y, \dot{y}]^T$, and the controller parameter estimation vector is represented as $\beta = [\beta_1, \beta_2, \beta_3]^T$.

By replacing Eq. (17) with Eq. (13), we get:

$$\frac{d^2y(t)}{dt^2} = -(a_1 + b\beta_3) \frac{dy(t)}{dt} - (a_2 + b\beta_2)y(t) + b\beta_1 u_c(t) \quad (18)$$

By comparing the coefficients in the Eq. (15) with the Eq. (18), we

obtain the following:

$$b\beta_1 = b_m \quad (19)$$

$$a_{m2} = a_2 + b\beta_2 \quad (20)$$

$$a_{m1} = a_1 + b\beta_3 \quad (21)$$

The control parameters β_1 , β_2 and β_3 are converged as follows:

$$\beta_1 \approx \frac{b_m}{b}; \beta_2 \approx \frac{a_{m2} - a_2}{b}; \beta_3 \approx \frac{a_{m1} - a_1}{b} \quad (22)$$

The MIT rule was demonstrated using a closed-loop system with a controller that had three adjustment parameters. Define e as the discrepancy between the model's predicted output y_m and the closed-loop system's actual output y . Minimizing the loss function

$$J(\beta) = \frac{1}{2}e^2 \quad (23)$$

To reduce J to a small value, it is advisable to adjust the parameters in the direction opposite to the gradient of J , which is

$$\frac{d\beta}{dt} = -\gamma \frac{\delta J}{\delta \beta} = -\gamma e \frac{\delta e}{\delta \beta} \quad (24)$$

The adjustment parameter's impact on the error may be understood by examining the partial derivative $\frac{\partial e}{\partial \beta}$, also known as the sensitivity derivative of the system.

Solving Eq. (18) using the Laplace transform yields

$$s^2 y(s) = -(a_1 + b\beta_3)s y(s) - (a_2 + b\beta_2)y(s) + b\beta_1 u_c(s) \quad (25)$$

$$\frac{y(s)}{u_c(s)} = \frac{b\beta_1}{s^2 + (a_1 + b\beta_3)s + (a_2 + b\beta_2)} \quad (26)$$

By substituting the values of y and y_m into error ($e = y - y_m$), we may express it as follows:

$$e = \left(\frac{b\beta_1}{s^2 + (a_1 + b\beta_3)s + (a_2 + b\beta_2)} - \frac{b_m}{s^2 + a_{m1}s + a_{m2}} \right) u_c(s) \quad (27)$$

The sensitivity derivatives $\frac{\partial e}{\partial \beta_1}$, $\frac{\partial e}{\partial \beta_2}$ and $\frac{\partial e}{\partial \beta_3}$ are obtained by using Eq. 27

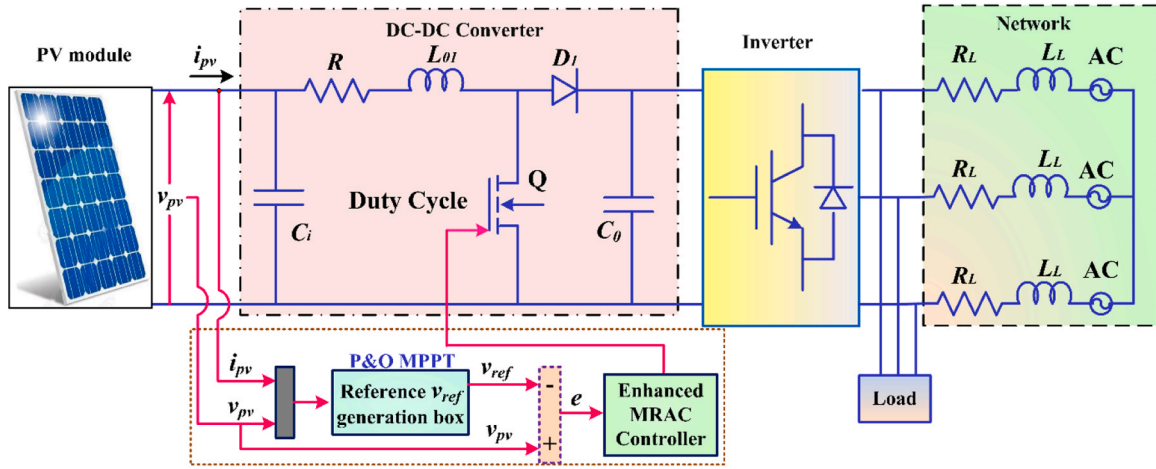


Fig. 10. Three phase GIPVS under study.

Table 1
Grid-integrated PV system parameters.

Parameter	Value	Parameter	Value	
SunPower SPR–305E PV module Parameters		$\alpha_2 = 1/C_i L_{01}$	$1.67 \times 10^7 (\text{rad/sec})^2$	
Rated current	5.58 A	Adaptation gain (γ)	0.08	
Short-circuit current	5.96 A	Grid-integrated PV system parameters		
Rated voltage	54.7 V	System rated power, p_{pv}	100.7 kW	
Open-circuit voltage	64.2 V	Grid voltage	380 V	
Rated power	305.226 W	Grid frequency	50 Hz	
Series resistance	0.37152 Ω	Filter inductance per phase	1.4 mH	
Parallel resistance	269.5934 Ω	Resistance of inductor	0.7 Ω	
Number of parallel modules	66	Filter capacitance per phase	36.87 μF	
Number of series module	5	DC link capacitance	330 μF	
Cells per module	96	Switching frequency	5 kHz	
Proposed Controller Parameters		DC bus voltage	1000 V	
b_m	$5.75 \times 10^8 \text{ V}(\text{rad/sec})^2$	Sampling time	20 μs	
$b = V_0/C_i L_{01}$	$6.45 \times 10^8 \text{ V}(\text{rad/sec})^2$	Grid side converter controller gains		
a_{m1}	$8.17 \times 10^3 (\text{rad/sec})$	Controller	k_p	k_i
$a_1 = 1/C_i R_i$	400 (rad/sec)		DC-link voltage	0.15
a_{m2}	$1.67 \times 10^7 (\text{rad/sec})^2$	D-axis current	0.005	1
		Q-axis current	0.01	1

and Eq. 26.

$$\frac{\delta e}{\delta \beta_1} = \frac{b u_c}{s^2 + a_1 s + b \beta_3 s + a_2 + b \beta_2} \quad (28)$$

$$\frac{\delta e}{\delta \beta_2} = \frac{-b y}{s^2 + a_1 s + b \beta_3 s + a_2 + b \beta_2} \quad (29)$$

$$\frac{\delta e}{\delta \beta_3} = \frac{-b y s}{s^2 + a_1 s + b \beta_3 s + a_2 + b \beta_2} \quad (30)$$

Considering $s^2 + a_1 s + b \beta_3 s + a_2 + b \beta_2 = s^2 + a_{m1} s + a_{m2}$. The sensitivity derivatives are substituted into Eq. (24), in accordance with the MIT rule. The control parameters β_1 , β_2 and β_3 are adjusted using Eqs. (31), (32), and (33) after the rearranging process.

$$\frac{d\beta_1(t)}{dt} = -\gamma \left(\frac{1}{s^2 + a_{m1}s + a_{m2}} u_c(t) \right) e(t) \quad (31)$$

$$\frac{d\beta_2(t)}{dt} = \gamma \left(\frac{1}{s^2 + a_{m1}s + a_{m2}} y(t) \right) e(t) \quad (32)$$

$$\frac{d\beta_3(t)}{dt} = \gamma \left(\frac{1}{s^2 + a_{m1}s + a_{m2}} \dot{y}(t) \right) \dot{e}(t) \quad (33)$$

6. Simulation results and discussion

The simulation of a 100.7 kW three-phase GIPVS is conducted at several scenarios. The P&O, ANN, and INC strategies based controller are being compared with the EMRAC-MPPT approach. Fig. 10 depicts the simulated configuration of a PVS using MATLAB software. To connect the PV module to a three-phase electrical grid, a DC-DC converter and an inverter are used. The simulation specifications utilized for developing the recommended system are shown in Table 1. In order to demonstrate efficacy of the suggested approach, a probabilistic evaluation is conducted across three levels of uncertain scenarios, namely ropp, step irradiance profile, and rapid changing irradiation and temperature profile. The probabilistic assessment is intended to evaluate the performance of the system in the presence of different uncertainties. The objective is to comprehend the probability of various outcomes, taking into account the inherent unpredictability and diversity in real-world circumstances. Various unpredictable factors, such as irradiance, temperature, geographic location, and seasonal variations, contribute to the uncertainty of solar power generation in real-world situations. Probabilistic evaluation enables the prediction of a spectrum of probable results instead of a single definitive outcome, so offering a more thorough understanding of prospective outcomes. Scenarios are selected based on their significance to real-world situations that the system is expected to face. Scenarios encompass both ordinary and exceptional scenarios to guarantee robustness. Every scenario has been carefully designed to accurately simulate various circumstances that the system may encounter. Scenarios are studied to identify their influence on system performance. This entails evaluating the impact of each scenario on various outcomes, such as PV power, efficiency, power loss, fluctuations near MPP and response time metrics. The objective is to comprehend not just the immediate consequences but also the unforeseen disruptions caused by the system. The evaluation of the controller's resilience may be achieved by taking into account probabilistic and uncertain situations and their practical significance. This not only enhances the reliability of the results but also offers practical and applicable insights that are based on real-world situations. The tracking efficiency (η) of MPPT system is

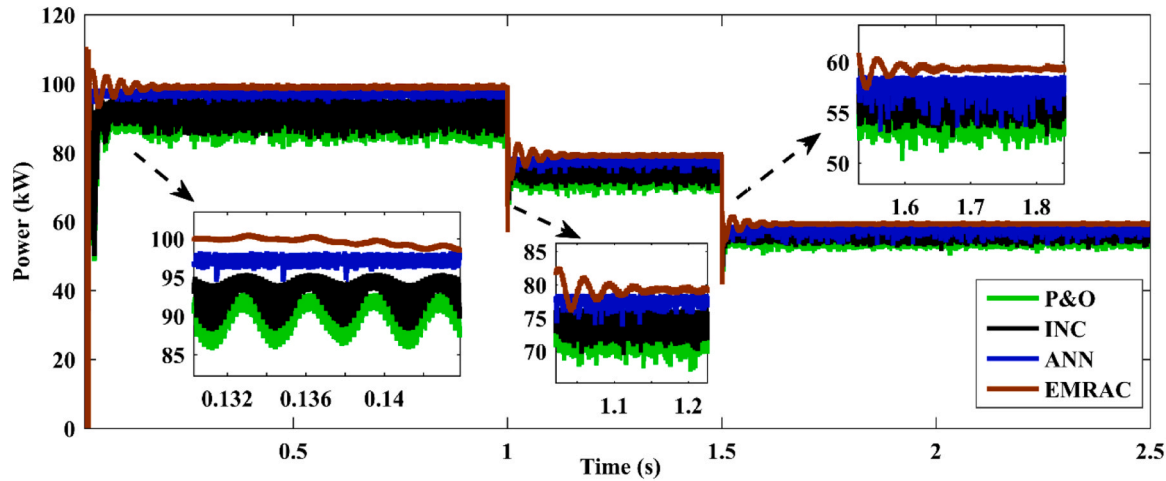


Fig. 11. PV power generated under grid-tied mode using four distinct MPPT approaches.

Table 2
Detail comparative results.

Algorithms	State 1 (1000 W/m ²)	State 2 (800 W/m ²)	State 3 (600 W/m ²)
PV power (kW)			
P&O	90.90	72.45	54.50
INC	92.73	74.58	55.89
ANN	97.05	77.56	57.75
EMRAC	99.03	79.17	59.36
Efficiency (%)			
P&O	90.27	89.92	90.20
INC	92.08	92.58	92.50
ANN	96.37	96.28	95.58
EMRAC	98.34	98.27	98.24
Power Loss (KW)			
P&O	9.73	10.07	9.79
INC	7.91	7.42	7.50
ANN	3.62	3.72	4.42
EMRAC	1.66	1.72	1.75
Response Time (s)			
P&O	0.35	0.34	0.33
INC	0.30	0.29	0.28
ANN	0.19	0.18	0.18
EMRAC	0.10	0.13	0.12
Fluctuation around MPP (kW)			
P&O	11.34	10.76	10.83
INC	7.46	7.57	7.74
ANN	3.55	3.30	3.09
EMRAC	0.80	0.82	0.4

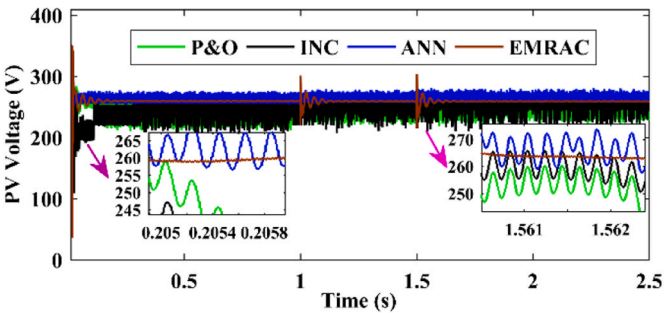
determined by calculating it as follows (Manna et al., 2023):

$$\eta = \frac{\int_{t_1}^{t_2} p_{avg} dt}{\int_{t_1}^{t_2} p_{max} dt} \tag{34}$$

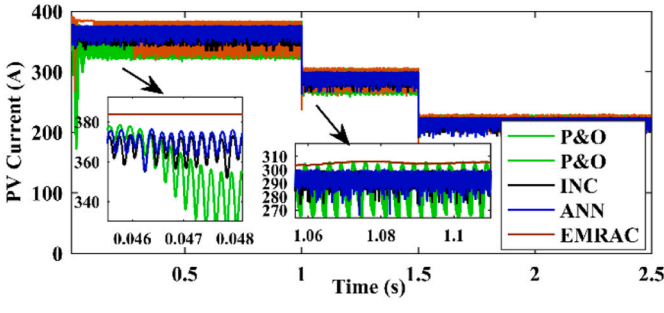
The method starts tracking at time t_1 and concludes at time t_2 . The average power generated throughout the time interval from t_1 to t_2 is represented by p_{avg} , while theoretically generated maximum power is represented by p_{max} . The errors of the four distinct approaches are calculated using the following equations (Ge et al., 2020):

Table 3
Statistical metrics.

Algorithms	State 1 (1000 W/m ²)	State 2 (800 W/m ²)	State 3 (600 W/m ²)
RMSE			
P&O	10.87	8.213	5.954
INC	8.277	6.105	4.6
ANN	3.695	3.11	2.702
EMRAC	1.686	1.401	1.061
MAE			
P&O	10.61	9.115	5.917
INC	7.974	5.983	4.529
ANN	3.656	3.063	2.645
EMRAC	1.673	1.39	1.057
MAPE			
P&O	10.54	10.07	9.793
INC	7.919	7.426	7.496
ANN	3.631	3.802	3.378
EMRAC	1.661	1.725	1.75



(a)



(b)

Fig. 12. (a) PV voltage (b) PV current under grid-tied mode using four different MPPT algorithms.

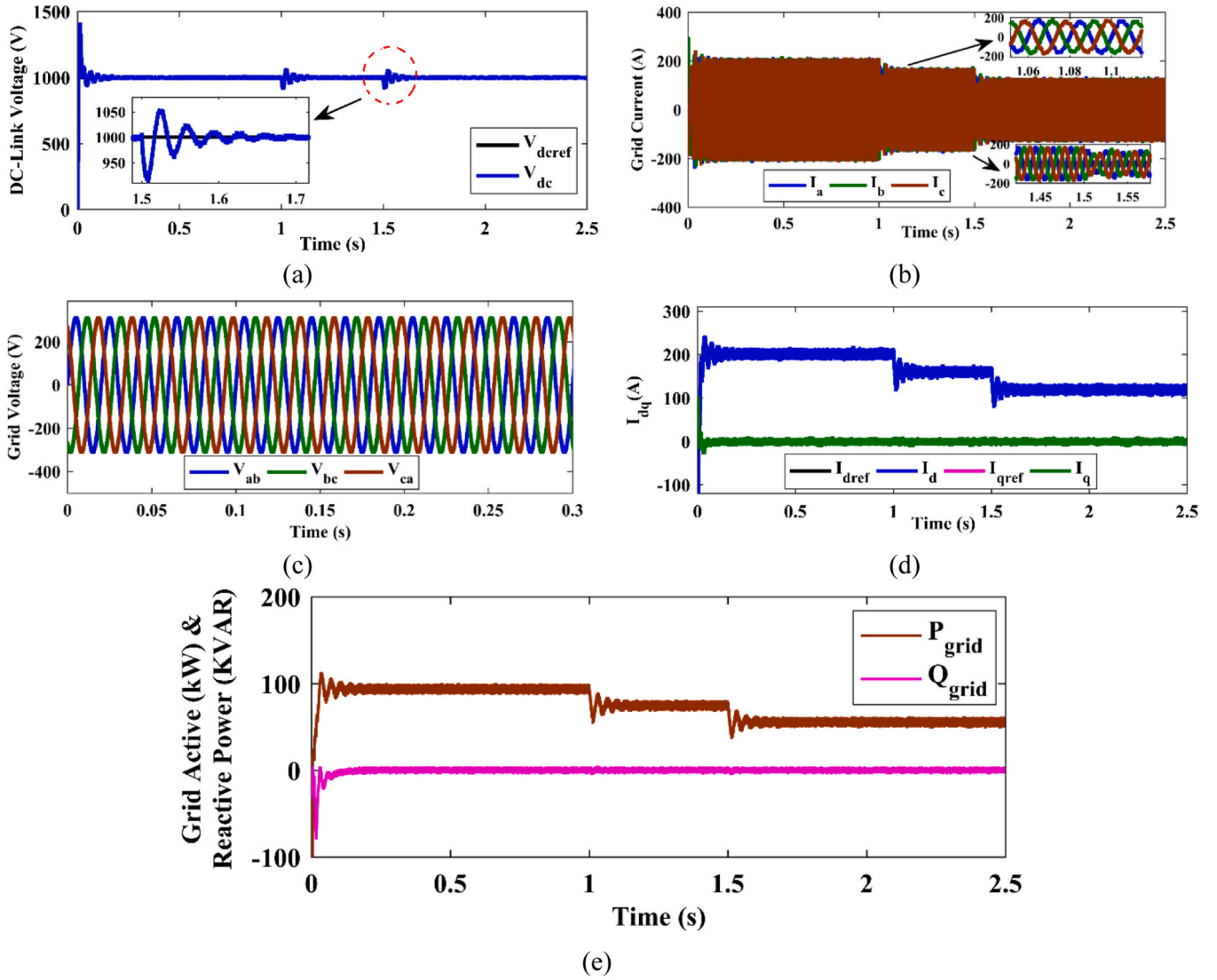


Fig. 13. Grid-side system outcomes (a) DC-link voltage (b) Grid current (c) Grid voltage (d) d-q axis currents (e) Injection of both reactive and active power into the grid.

$$\text{Root mean square error(RMSE)} = \sqrt{\frac{\sum (\text{Actual Value} - \text{Estimated Value})^2}{n}} \quad (35)$$

$$\text{Mean absolute error(MAE)} = \frac{\sum |\text{Estimated Value} - \text{Actual Value}|}{n} \quad (36)$$

$$\text{Mean absolute percentage error(MAPE)} = \frac{1}{n} \sum \left(\frac{|\text{Actual} - \text{Forecasting}|}{|\text{Actual}|} \right) \times 100\% \quad (37)$$

6.1. Level-I uncertainty: variable irradiances and uniform temperature

For this scenario, the different irradiance and uniform temperature levels are considered. At $t = 1$ s, the irradiance undergoes a decrease from 1000 to 800 W/m², and subsequently declines further to 600 W/m² at $t = 1.5$ s. Fig. 11 displays the PV power generated by four distinct MPPT algorithms, namely P&O, ANN, INC, and EMRAC, in the context of grid-tied operation. Table 2 clearly demonstrates that the suggested MPPT strategy surpasses the state-of-the-art MPPT strategies in terms of average power, response time, efficiency, fluctuations around MPP, and power loss.

Power output is the amount of electrical power produced by the PVS. The main objective of MPPT approaches is to maximize this power output. Response time refers to the period required for an MPPT strategy to modify the PV operating point and achieve the MPP subsequent alterations in environmental circumstances. Fast response time is crucial for sustaining maximum power generation in the face of rapidly changing solar radiation levels. Higher response times might result in less effective power extraction and decreased overall system efficiency. Power loss is the discrepancy between the theoretical maximum output power and the actual power output obtained by the MPPT strategy. To get the most out of the PV system, it is important to keep power loss to a minimum. In order to maximize energy output and economic advantages, it is crucial to have a system that operates closer to its MPP, which is achieved by reducing power loss. Efficiency in MPPT pertains to the algorithm's ability to accurately and consistently monitor and sustain the highest possible PV power output, in relation to its theoretical maximum power. Higher MPPT efficiency results in optimal usage of solar energy, resulting in increased total energy generation and enhanced system performance. Fluctuations in the vicinity of MPP pertain to the deviations in power generation around the MPP caused by the flaws of MPPT approach. Ensuring a consistent and reliable power production requires the minimization of fluctuations. Excessive

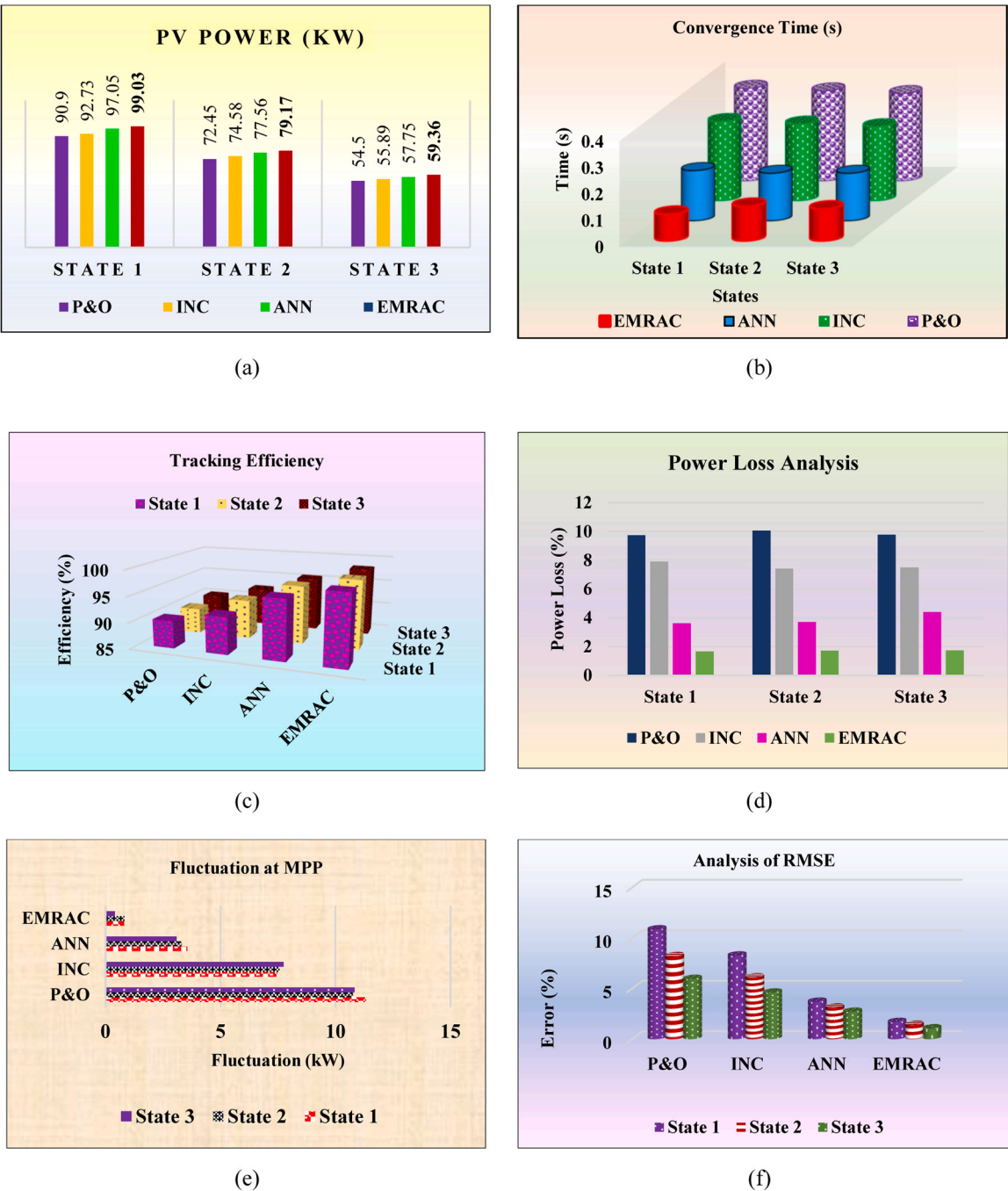


Fig. 14. Comparative evaluation (a) PV Power (b) Response time (c) tracking efficiency (d) power loss (e) fluctuation at MPP (f) RMSE error.

Table 4
Comparison of MPPT controllers at different irradiance and uniform temperature levels.

MPPT Controller	PV Power (kW)		
	1000 W/ m ²	800 W/ m ²	600 W/ m ²
GA optimized FLC (Dehghani et al., 2021)	95.11	75.60	56.14
PSO optimized FLC (Dehghani et al., 2021)	96.15	76.32	56.78
PSO-GA-optimized FLC (Dehghani et al., 2021)	98.85	78.69	58.64
EMRAC	99.03	79.17	59.36

fluctuations might cause inefficiency and decrease the PV system overall performance.

The EMRAC approach yielded average PV power values of 99.03 kW, 79.17 kW, and 59.36 kW for the three intervals, respectively. The proposed approach exhibits an average efficiency of 98.28 %. Nevertheless, other techniques have an efficiency range of 90–96 % while operating at a low speed to achieve the MPP. Furthermore, the EMRAC has an average response time of 0.11 s, which is significantly faster compared to other techniques that range from 0.2 to 0.35 s but these approaches still have consistent fluctuations at MPP. This outcome indicates that the adopted MPPT approach for capturing MPP has the fastest speed. Based on the information provided in Table 2, Fig. 11 and its zoom views, it can be observed that enhanced MPPT technique exhibits the lowest oscillation rate at the MPP. This suggests that it incurs the least amount of

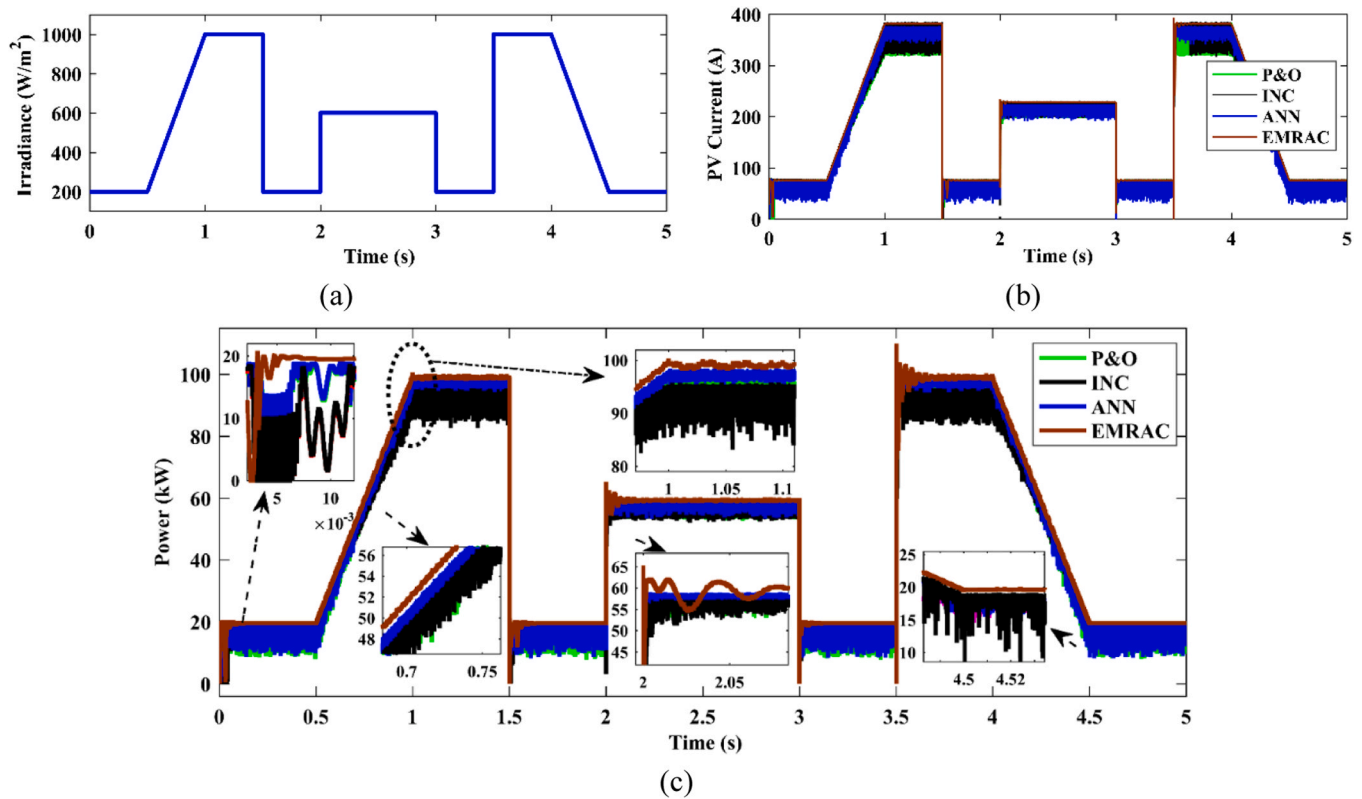


Fig. 15. PV side outcomes; (a) Profile of ropp irradiance (b) PV current (c) PV power.

Table 5
Details comparative results.

Algorithm	1000 W/m^2	200 W/m^2	600 W/m^2
PV power (kW)			
P&O	90.90	17.90	54.50
INC	92.73	18.32	55.89
ANN	97.05	18.97	57.75
EMRAC	99.03	19.79	59.36
Efficiency (%)			
P&O	90.27	89.96	90.20
INC	92.08	91.36	92.50
ANN	96.37	94.19	95.58
EMRAC	98.34	98.26	98.24
Response Time (s)			
P&O	0.38	0.38	0.30
INC	0.37	0.37	0.25
ANN	0.19	0.18	0.18
EMRAC	0.12	0.098	0.15

power loss. The findings indicate that the implemented strategies can be ranked in the following order: EMRAC > ANN > INC > P&O.

Fig. 12 illustrated the PV voltage and current using four different MPPT approaches at varying irradiance levels and constant temperature conditions. This study will evaluate the effectiveness of the designed control scheme using a number of well-established statistical metrics such as MAE, MAPE, and RMSE. This is because variations in output power can significantly impact the overall efficiency. Table 3 provides a thorough comparison of the statistical metrics. It is evident that the EMRAC approach has the lowest values for MAPE, RMSE, and MAE, whereas P&O has the highest error.

The effectiveness of the grid side system using the suggested EMRAC algorithm may be evaluated by analyzing the outcomes shown in Fig. 13. Fig. 13(a) shows that DC-link voltage is efficiently controlled at its nominal value of 1000 V with low oscillation and satisfactory dynamic stability when there is a step change in PV output power. This

indicates the resilience and dependability of the developed controller. Fig. 13(b) displays the phase current of the grid, whereas Fig. 13(c) shows the phase voltage. Furthermore, the grid current components along the d-axis and q-axis accurately adhere to their respective reference values, as seen in Fig. 13(d). Fig. 13(e) demonstrates that the grid does not receive any reactive power injection, while the active power varies in accordance with output of PV array.

Fig. 14a-f illustrates a comparative graphical representation of PV power, response time, efficiency, power loss, fluctuations at MPP and RMSE error analysis for four MPPT strategies. Table 4 presents a summary of the power comparison of PV systems using various controllers that have been recently deployed. It can be seen that the proposed controller produces more power compared to others with different irradiances. It is evident that the suggested controller generates higher power in comparison to other controllers under varying levels of irradiation.

6.2. Level-II uncertainty: Ropp irradiance profile (Ali and Mohamed, 2022)

The solar irradiance pattern shown in Fig. 15(a) is used to evaluate how well the proposed tracking algorithm handles both gradual and abrupt alterations to irradiance profiles. Fig. 15 (b) and (c) shows a comparison of the ANN, P&O, INC, and EMRAC strategies with respect to PV current and PV power respectively. According to PV power shown in Fig. 15(c), it is evident that the suggested EMRAC algorithm exhibits a small settling time and low power steady-state oscillations compared to other techniques. The detailed analysis of all four approaches in terms of average PV power, response time, and efficiency are presented in Table 5. The P&O, and INC algorithms exhibit the poorest tracking performance, with efficiency levels ranging from 90 % to 92 % due to significant power oscillations, while the ANN algorithms display enhanced efficiency. The EMRAC method demonstrates improved efficiency in tracking both transient and steady-state conditions. This

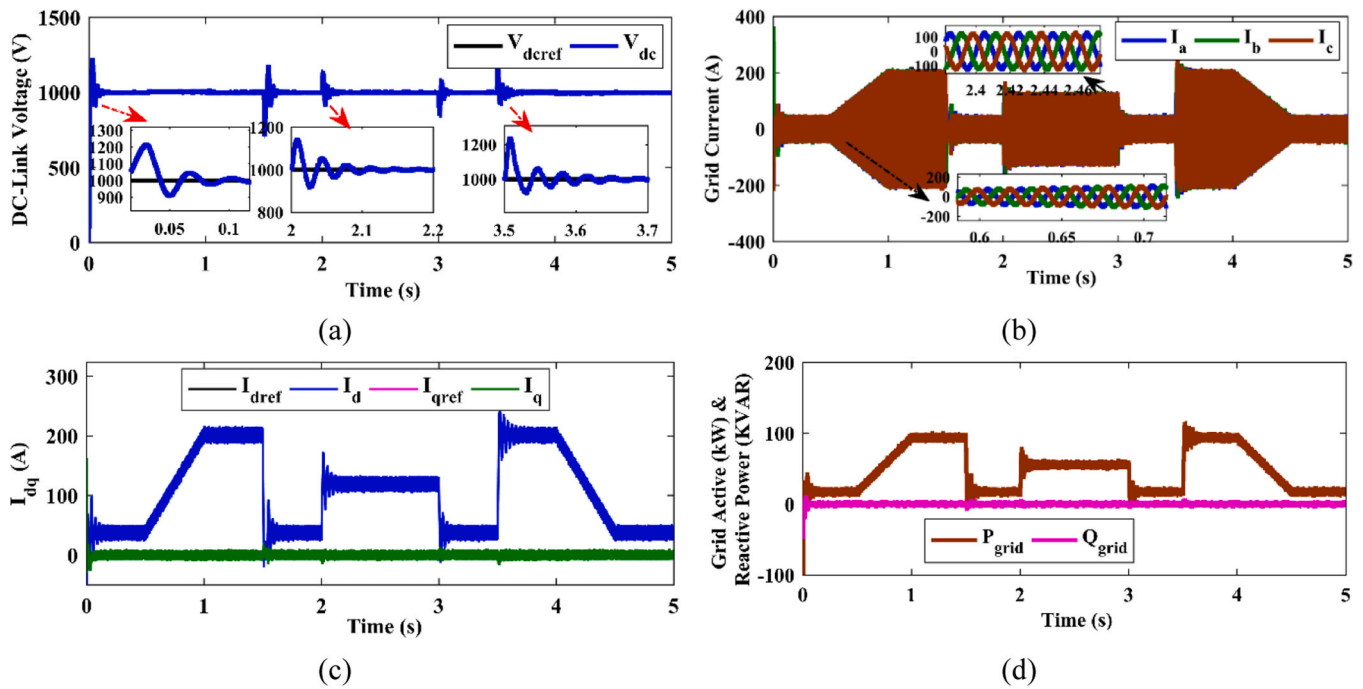


Fig. 16. Grid-side system outcomes (a) DC-link voltage (b) Grid current (c) d-q axis currents (d) Injection of both reactive and active power into the grid.

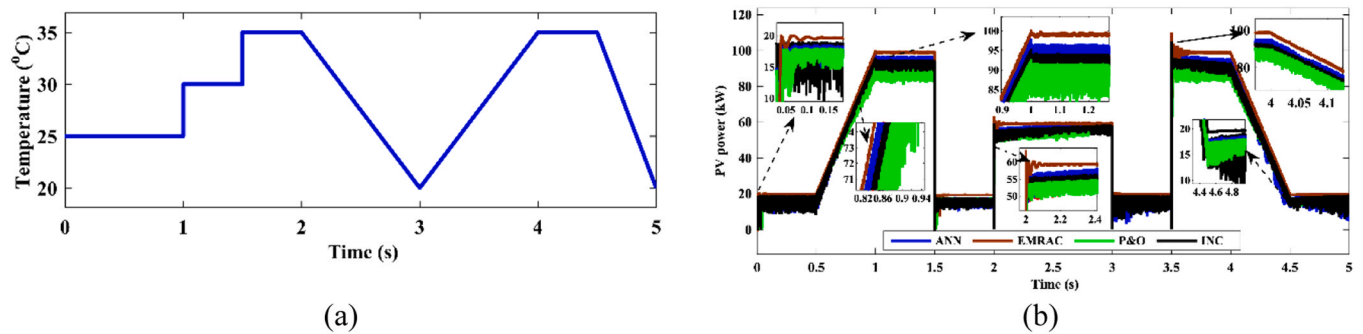


Fig. 17. (a) Temperature profile (b) PV power comparison with four MPPT algorithms.

Table 6

Comparison of EMRAC technique under step, ropp, and simultaneously changing irradiance & temperature profile.

Proposed EMRAC Technique	Step irradiance profile	Ropp irradiance profile	Simultaneously changing irradiance and temperature profile
Avg. Efficiency (%)	98.28	98.28	98.27
Avg. Power loss (kW)	1.71	1.74	1.70
Avg. Response time (s)	0.11	0.12	0.06
Avg. Fluctuation around MPP (kW)	1.01	1.02	1.01

results in a faster MPPT speed and reduces oscillations during steady-state operation.

Fig. 16 shows the results of evaluating the grid side system performance using the suggested EMRAC method. Fig. 16(a) shows that the developed controller is robust and reliable in operation; the DC-link voltage is successfully controlled at its nominal value (1000 V) with a modest oscillation level and adequate dynamic stability under step

variation of PV output power. Fig. 16(b) displays the grid current and Fig. 16(c) further shows that the current components on d and q-axes of the grid track their respective reference values. Fig. 16(d) shows that the active power varies in response to the PV array's output, but no reactive power is being injected into the grid.

6.3. Level-III uncertainty: simultaneously changing irradiance and temperature profile

A ropp irradiance profile and temperature fluctuation profile, as seen in Figs. 15(a) and 17(a) respectively, is taken into consideration in order to evaluate the performance of the suggested method even more. Fig. 17 (b) illustrates a comparison of the maximum photovoltaic PV power achieved utilizing several MPPT systems, including INC, ANN, P&O, and EMRAC, when both temperature and radiation are varied. Upon examining the enlarged version of Fig. 17(b), it can be inferred that the EMRAC approach requires 0.06 s to capture the MPP, whereas other techniques take longer to track the MPP. The ripple is very pronounced in the INC, and P&O approaches, reduced in the ANN approach, and almost non-existent in the EMRAC methodology. Compared to the other method, it can be stated that the recommended MPPT controller maximizes PV power. Thus, the suggested controller outperforms other cutting-edge methods in situations with abrupt radiation and

Table 7
Comparison of EMRAC technique with state-of-the-art techniques.

Parameters	P&O (Bollipo et al., 2020)	FLC (Bollipo et al., 2020)	ANN (Bollipo et al., 2020)	PSO (Bollipo et al., 2020)	ANFIS (Bollipo et al., 2020)	EMRAC
Control Strategy	Sampling Method	Fuzzy Interface system	Back Propagation	Particle tracking	Sampling mode	Adaptive strategy
Tracking accuracy	Low	Medium	High	Medium	High	High
Fluctuation around MPP	High	Medium	Medium	Medium	Low	Low
Tracking Speed	Slow	Medium	Medium	Fast	Fast	Fast
Complexity	Simple	Simple	Medium	Medium	Medium to complex	Medium
Grid Integration	No	Yes	Yes	Yes	Yes	Yes
Cost	Affordable	Affordable	Expensive	Affordable	Expensive	Affordable
Efficiency	Low	Medium	Medium	High	High	High

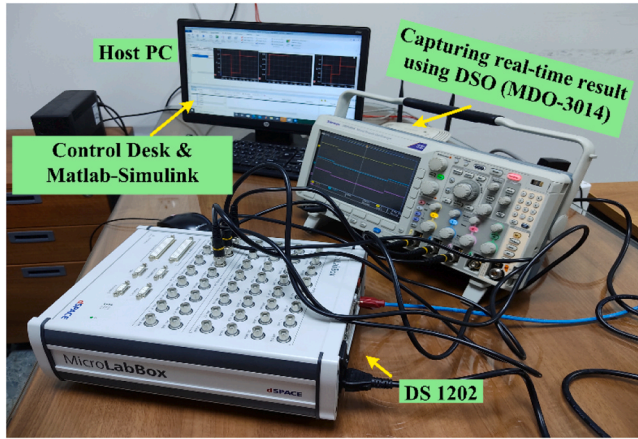


Fig. 18. Experimental setup.

temperature fluctuations.

Table 6 provides a comparison of EMRAC technique under step, ropp, and simultaneously changing irradiance & temperature profile in terms of avg. efficiency, response time, power loss and fluctuations near MPP. The effectiveness of the EMRAC is evaluated by comparing it with state-of-the-art strategies and outcomes are presented in Table 7. The control strategy, tracking speed, tracking accuracy, complexity, cost, efficiency, and grid integration are the important factors to consider.

7. Experimental validation

Conducting a real-time assessment utilizing the dSPACE MicroLab-BOX 1202 controller with a sampling time of 50 μ s allows the proposed EMRAC controller to showcase the robustness of the implemented control algorithm, which is based on the real-time validation. The setup of the test system is shown in Fig. 18. The system is comprised of a 2 GHz dual-core CPU that operates in real-time, a user-programmable FPGA, a Real-Time Interface (RTI) for Simulink to integrate model-based input/output, and the Control Desk experiment software. Control Desk allows users to access the real-time application during runtime using graphical instruments. The MATLAB/ Simulink (R2018b) software is used to model the PV system, which is equipped with a boost converter and an EMRAC MPPT controller. Subsequently, the model is transferred from MATLAB to dSPACE. The following step is compiling the model into C code. Afterwards, the test system is transferred to the control desk, a program that operates through a real-time interface. By utilizing an oscilloscope, the control desk allows the user to observe and track the signals. A MicroLabBox R&D controller board is utilized with the dSPACE in this research. The outcomes such as PV power, voltage, current, grid current, and grid voltage are captured in real-time using an oscilloscope (Tektronix MDO3014, bandwidth-100 MHz, channels 4).

Fig. 19(a) illustrates the practical performance of the suggested controller, showing the outcomes of PV power, voltage, and current when there was a sudden shift in radiation intensity from 1000 to 500 W/m², while maintaining a constant temperature. Fig. 19(b) illustrates the performance of ANN techniques in tracking power, PV voltage, and current in response to changes in solar irradiation.

Figs. 20a and 20(b) display the waveform of PV power, grid current, and grid voltage when radiation level decreases from 700 W/m² to

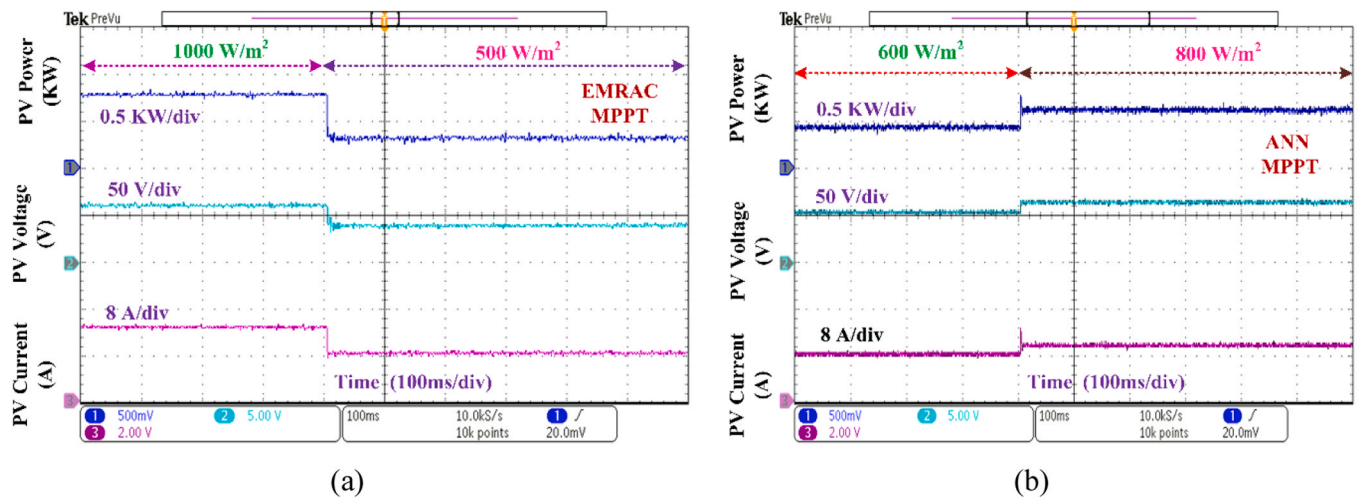


Fig. 19. Experimental results, (a) PV Power, voltage and current under step variation of solar irradiance 1000–500 W/m² for EMRAC MPPT (b) step variation of solar irradiance 600–800 W/m² for ANN MPPT.

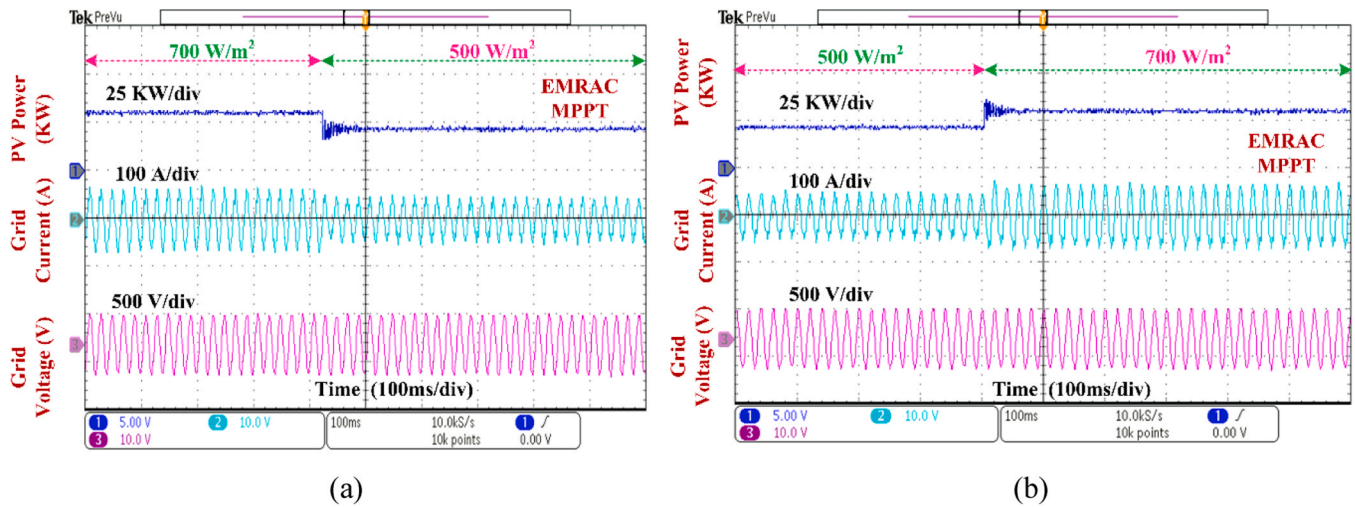


Fig. 20. Experimental results (a) PV Power, grid voltage and grid current under step variation of solar irradiance 700–500 W/m² (b) step variation of solar irradiance 500–700 W/m² for EMRAC MPPT.

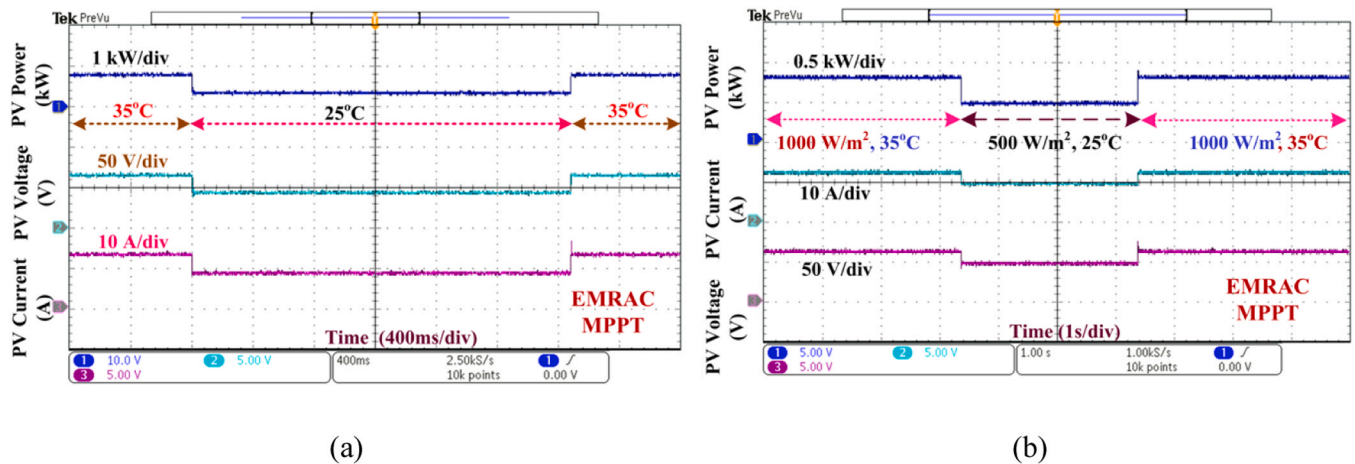


Fig. 21. Experimental results (a) PV Power, voltage and current under step variation of temperature 35°C to 25°C (b) step variation of both solar irradiance and temperature 1000 W/m² & 35°C to 500 W/m² & 25°C for EMRAC MPPT.

500 W/m² and then rises from 500 W/m² to 700 W/m², respectively. The waveforms clearly illustrate the exceptional performance of the EMRAC controller, as the grid current perfectly aligns with the sinusoidal grid voltage. The findings from the PV current, power, and voltage acquired using the dSPACE platform confirm the effectiveness of the EMRAC MPPT controller design.

Furthermore, the efficacy of the proposed approach is evaluated in the presence of varying temperature and simultaneous changes in solar radiation and temperature profiles. This evaluation is conducted using dSPACE, as depicted in Figs. 21(a) and 21(b), respectively. In Fig. 21(a), the temperature starts at 35°C, then abruptly drops to 25°C, and eventually returns to 35°C. Fig. 21(b) illustrates the experimental results when both temperature and irradiance are varied. In this scenario, the irradiance and temperature start at 1000 W/m² and 35°C, respectively. It then abruptly decrease to 500 W/m² and 25°C, before returning back to 1000 W/m² and 35°C. The figure illustrates that the proposed control method effectively tracks the MPP with minimum oscillations across various radiation and temperature levels.

8. Conclusions

This research presented a novel enhanced model reference adaptive control (EMRAC) MPPT approach for grid-integrated solar PV systems

that relies on MIT theorem. The EMRAC MPPT was designed to achieve the objectives: (i) a simple design that is easy to implement, (ii) Higher accuracy and rapid convergence with minimal oscillations near MPP, (iii) adaptability to highly variable atmospheric conditions, and (iv) robustness against unforeseen disturbances. The evaluation framework is devised and executed by employing simulation and experimental validation to test the proposed control scheme in real-world scenarios. In order to demonstrate the efficacy of the EMRAC strategy, a probabilistic evaluation is conducted across three levels of uncertain scenarios: step, ropp irradiance profiles, and rapidly changing irradiation and temperature profiles. The suggested controller has an average response time of 0.11 s to achieve MPP, and an average efficiency of 98.28 %, which is significantly superior than P&O, ANN, and INC techniques. Furthermore, it enhances the PV power generation, minimizes power dissipation, and steady-state fluctuations. Additionally, the suggested MPPT is supported by experimental evidence, which demonstrates its effectiveness at different solar radiation and temperature levels. The experiments were conducted utilizing the dSPACE1202 platform.

In addition to the immediate outcomes, this research has wider implications for the solar PV field. The enhanced tracking speed, accuracy, efficiency and reduced power loss of PV systems, as demonstrated, may potentially result in a broader adoption of solar PV technology. This not only promotes the worldwide movement towards solar based renewable

energy but also tackles important obstacles like as rapidly fluctuations in environmental conditions and interaction with the power grid.

As a potential avenue for future investigation, additional research might concentrate on developing techniques to address mismatched scenarios, such as damage to panel glass, non-uniformity of PV panel temperatures, and the effects of shadows or dust on certain applications. Furthermore, studies could investigate the incorporation of the suggested sophisticated MPPT method with future innovations such as hybrid renewable energy configurations and energy storage systems. The potential limitation of the proposed approach is incompatible for the partially shaded solar PV system. It can be improved in the future work.

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Author contribution

Saibal Manna: performed the experiments, analyzed and interpreted the data, wrote the paper. **Deepak Kumar Singh:** analyzed tools or data and interpreted the data, materials. **Mohammed H. Alsharif:** conceived and designed the experiments. **Mun-Kyeom Kim:** conceived and designed the experiments, contributed reagents

CRediT authorship contribution statement

Mohammed H. Alsharif: Writing – review & editing, Supervision, Project administration. **Mun-Kyeom Kim:** Writing – review & editing, Funding acquisition, Conceptualization. **Saibal Manna:** Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Deepak Kumar Singh:** Supervision, Software, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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