Indian Journal of Pure & Applied Physics
Vol. 63, August 2025, pp. 719-740
DOI: 10.56042/ijpap.v63i8.19481

Adaptive Hybrid ANN and Incremental Conductance Approach for Maximum Power Point Tracking in Solar PV Systems

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Received: 16 May 2025; accepted: 24 June 2025

Current research in solar photovoltaic (PV) energy is primarily directed toward improving the efficiency and output performance of PV arrays. The main objective is to reduce energy losses caused by changing weather patterns and irregular load variations. Traditional single Maximum Power Point Tracking (MPPT) methods frequently fail to strike an effective compromise between fast tracking response and high precision. To overcome this challenge, a novel hybrid approach is proposed that combines an Artificial Neural Network (ANN) with the Incremental Conductance (INC) method for effective MPPT. This paper introduces and demonstrates the implementation of the ANN-INC hybrid technique within photovoltaic systems for enhancing MPPT performance. The proposed hybrid approach utilizes the accuracy of the INC algorithm along with the adaptive learning abilities of the ANN to enhance tracking efficiency under diverse environmental conditions. This method is thoroughly assessed and compared with commonly used techniques such as Perturb and Observe (P&O), standalone INC, ANN, and Fuzzy Logic controllers. Simulation results demonstrate the effectiveness of the hybrid method, showing quicker convergence to the maximum power point, fewer oscillations, and enhanced performance under fluctuating irradiance levels. The ANN-INC technique achieves a high efficiency of approximately 99% and outperforms other approaches by reaching the maximum power point more rapidly with minimal energy losses and reduced fluctuations. Moreover, the hybrid method enhances power extraction efficiency, ensuring reliable and consistent operation of solar PV systems. This comparative analysis emphasizes the practical advantages of combining ANN and INC in addressing the limitations associated with traditional MPPT techniques. Finally, validation through real-time simulation using the OPAL-RT platform confirms the applicability and effectiveness of the proposed approach in real-world conditions.

Keywords: Solar photovoltaic, MPPT, Artificial neural network, Incremental conductance, Power optimization

1 Introduction

The energy sector significantly impacts our climate and environment, contributing to majority of harmful greenhouse gas emissions to environment. To address these issues, it is imperative to enhance the utilization of renewable energy. Renewable energy sources are essential for achieving sustainable, low-emission energy solutions. These technologies have proven capable of significantly meeting electricity demands while minimizing environmental impact. Common renewable sources include solar, fuel cells, wind and biomass. Scientists are increasingly focusing on the utilization of renewable resources due to environmental concerns, escalating temperatures, and the diminishing supply of fossil fuel reserves[1-3]. The move toward cleaner energy production is also driven by the limited availability of fossil fuels traditionally used in conventional power generation systems. Given the harmful environmental effects associated with coal and thermal power plants, renewable energy (RE) technologies are increasingly regarded as more sustainable and environmentally friendly alternatives for transitioning the power sector. Additionally, combining multiple energy sources in a hybrid system to serve the same electrical load enhances the overall reliability of power supply[4-7]. Solar energy stands out as an attractive option because of its ease of installation, silent operation, lack of emissions, clean energy output, worldwide availability, and minimal environmental impact. Photovoltaic (PV) systems, in particular, are becoming increasingly popular as a renewable energy source due to their wide availability, eco-friendly nature, and minimal need for upkeep. Photovoltaic (PV) technology has emerged as a leading energy source due to its long-term cost-effectiveness, scalability with increasing energy demand, and advancements in material utilization. Despite its advantages, PV systems encounter obstacles in efficient power extraction and energy storage, especially during peak sunlight hours when demand is high. Maximizing the output from these renewable sources depends heavily on enhancing key

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performance factors such as energy conversion efficiency and storage capacity. The global solar power market has been expanding at an average annual rate of 30-40% for over a decade[8]. There have been significant efforts for power-related research and development, as well as technological advancements and lower PV module costs as a result of this extraordinary rise, which is mostly due to solar systems linked to the energy distribution network[9]. In order to maximize energy collection, effective MPPT approaches must be developed in light of the quick adoption of unconventional resources, particularly PV schemes. Because solar PV systems are naturally impacted by changes in temperature and irradiance, adaptive MPPT techniques are essential to preserving peak performance. The effectiveness of PV schemes is largely dependent on efficient MPPT techniques, which are essential for maximizing energy production in the face of fluctuating weather. This work classifies MPPT techniques according to their distinct features and performance measures, synthesizing recent developments and comparative studies of MPPT techniques. An extensive analysis of MPPT techniques in[10-11] shows that they may be divided into eight different groups, each of which has unique tracking properties appropriate for different applications. This examination of the selection criteria is a key novelty as it provides a quick study to identify research gaps and useful information for future advances. The inclusion of comparative tabular data enhances the analysis of these methods' benefits in diverse circumstances. Under both normal and variable irradiation conditions, the PV systems with MPPT controllers in[12] can achieve energy conversion efficiencies of above 99%. By assessing power, these simulations provide useful insights into how DC-DC converters function in the real world. Due to their ease of use and low implementation costs, the algorithms used in methods are P&O and INC are still widely employed .While INC offers greater accuracy but adds more complexity, P&O, despite its simplicity, has tracking problems in a number of rapidly changing scenarios[13-16]. INC is the suggested choice for precise energy harvesting due to its increased tracking speed and enhanced efficiency, as demonstrated by a simple comparison of these two algorithms. Various real-world situations can readily use conventional MPPT methods such as hill climbing (HC), perturb and observe (P&O), improved P&O, adaptive reference voltage (ARV), ripple correlation control (RCC), and the lookup table method. Their lower algorithm complexity makes these techniques simple to apply. These techniques are most efficient for uniform irradiation conditions because the PV will produce only one GMPP under these circumstances. These algorithms, however, have rapid oscillations around the MPP that cause power loss. Moreover, ignoring the influence of rapid changing of environmental conditions partial shading conditions leads to a failure in tracking the real MPP[17-19]. In MPPT investigations, the application of ANN-based techniques has grown in popularity. Significant gains in tracing speed and flexibility have been demonstrated when ANN-based controllers are compared to traditional methods[20-22]. These systems demonstrate improved accuracy and flexibility with advanced ANN training methods. A comparison of these algorithms shows that LM offers a stronger link between input and output with less error during training and validation, but SCG achieves higher generalization[23]. The ability of fuzzy logic-based MPPT approaches to adjust to the nonlinear features of variety of PV based systems in environmental circumstances has been the subject of much research. Variations in power, voltage, current, and conductance are among the novel input variables for fuzzy logic MPPT algorithms that have been proposed in several research[24]. Due to its finite input range and clearly defined maxi- mum power point condition in steady states, Algorithm[25] exhibits significant potential for multi-purpose control. When compared to traditional approaches, fuzzy logic controller s implemented in MATLAB/Simulink have demonstrated improved performance in tracking the MPP more accurately and quickly, providing increased efficiency in solar energy systems[26]. To guarantee reliable performance under a variety of circumstances, fuzzy logic controllers must be carefully designed and implemented with rules and input ranges carefully adjusted. AI techniques like ANN, FL, and GA have also showed potential as MPPT and performance pre- diction solutions in solar PV systems. These strategies address partial shading issues that arise when a large number of vertex in the PV curve make it challenging for conventional techniques to identify the global MPP. In P-V system modelling and accurate solar radiation prediction, hybrid AI models that integrate ANN, FL, and GA have proven to function reliably. Despite their advantages, the computational complexity, higher implementation costs, and need for large training datasets of AI-based techniques may limit their practical application in cost- sensitive scenarios[27-30]. Addressing these limitations while optimizing performance must remain the focus of research on solar energy systems. In[31], a simulated annealing methodology and the P&O algorithm were combined to create an MPPT method. Even though P&O is known for being straightforward, it struggles when there is partial shade. The introduction of SA overcomes this limitation by improving convergence accuracy and enabling the algorithm to handle dynamic shading situations. This innovation highlights how important it is to advance conventional methods in order to increase energy efficiency and adapt to shifting climatic conditions. Furthermore,[32] introduced a MPPT hybrid model that mingle the INC algorithm with an integrated back stepping controller (IBSC). In this hybrid model improves the stability and performance of the PV system by utilizing the strong, nonlinear control potential of IBSC and the capabilities of INC for MPP tracking. When compared to traditional algorithms, experi-mental validation shows better efficiency, quicker tracking capabilities, and cost-effectiveness. Conventional algorithms like INC and P&O are normally working due to their ease, but they often suffer from drawbacks such as slow tracking speed and reduced accuracy under varying irradiance. To address these challenges, advanced MPPT techniques incorporating intelligent control strategies have emerged. This paper introduces a Hybrid ANN-Incremental Conductance algorithm designed to combine the strengths of both methods. ANN's capability to predict optimal operating points based on training data and INC's precise gradient based optimization are utilized to achieve superior tracking efficiency. A comprehensive literature review reveals that no researchers have evaluated the effectiveness of MPPT controller in real world scenarios characterized by cloudy, realistic, foggy, and highly variable environment conditions along with load variation. Consequently, this compels the authors to develop an MPPT that can operate efficiently under such circumstances. Therefore, this paper proposes a novel Hybrid ANN- Incremental Conductance algorithm for Maximum Power Point Tracking (MPPT) in solar PV systems. Furthermore, the suggested control approach is characterized by its simplicity in design, ease of implementation, high precision, and rapid tracking capabilities. The proposed method utilizes a sequence of dual-level hybrid MPPT algorithms. The maximum power point tracking process is made better by the ability of artificial neural networks to predict what will happen and the careful optimization of the incremental conductance approach. Initially, In first level the ANN predicts the ideal duty cycle based on input factors like temperature, irradiance, and system variables. This offers a rapid estimation of the MPP. After this in second level, the INC algorithm tweaks the duty cycle in small steps to make it more in line with the PV system's operating point and the real maximum power point. Using a small step size in the INC algorithm makes it possible to find the best operating point with the fewest errors and make sure the system collects the most potential energy. This integrated method facilitates expedited convergence to the Maximum PowerPoint, reduces power losses caused byoscillations around the ideal point, and markedly enhances energy harvesting efficiency. This hybrid method works really well in changing and difficult conditions, like when there is some shade or the amount of light changing quickly. This is because ANN quickly predicts an initial operating point and INC refines things in a planned way.

The key contributions of the proposed research are summarized as follows:

- A novel hybrid ANN-INC MPPT controller has been proposed and deployed for the solar photovoltaic system.
- The performance of the proposed hybrid ANN-INC MPPT algorithm is analyzed and compared with P&O, INC, Fuzzy, and ANN techniques under a range of test scenarios, including realistic and cloudy weather, rapidly changing environmental conditions, and robustness evaluations.
- The effect of two cloud events is evaluated under both realistic and overcast conditions. The proposed ANN-INC MPPT achieves a tracking time of 6.5 ms and an efficiency of approximately 99.2%, with very low voltage and current ripple.
- Four different combinations of temperature and irradiance are tested under highly dynamic atmospheric conditions to assess the performance of the proposed MPPT. The ANN-INC algorithm records tracking times of 6 ms, 3 ms, and 7 ms in three cases, consistently achieving efficiency levels above 99% in each scenario.
- A robustness assessment was performed by introducing random variations in solar irradiance and

Table1 — PV module specifications

Parameters	Value
Series Resistance (R_s)	0.23732 Ω
Shunt Resistance (R_{sh})	240.6015 Ω
Short circuit current(I_{sc})	8.66A
Open circuit voltage (V_{oc})	37.3 V
Rated Current (I_M)	8.15 A
Rated Voltage (V_m)	30.7 V
Rated power (P_m)	250.21 W
Cells per module	60
No. of series module	1
No. of parallel module	1

temperature, along with a load profile based on probabilistic distribution. The system's performance was analyzed across five operating conditions, considering factors such as tracking time, efficiency, voltage and current ripple, output power, energy losses, and error values. The proposed MPPT method achieved an average response time of 5.6 milliseconds and sustained an efficiency close to 99% under all scenarios. When compared with four existing MPPT techniques, the hybrid controller showed better stability, reduced error in locating the maximum power point, and lower power losses.

- Finally, the proposed MPPT technique was tested in a real-time laboratory environment using the OPAL-RT (OP2410) simulator. Its performance was thoroughly verified under varying environmental conditions, including changes in temperature and solar irradiance.

The paper comprises six sections. Section 2 addresses the modeling of photovoltaic systems with boost converters. Section 3 presents the proposed model design for an MPPT controller. Section 4 includes the detail explanation of the simulation results and discussion. Section 5 addresses the empirical validation of the proposed methodology using OPAL-RT simulator, followed by Section 6 presents the conclusions of the work.

2 Modeling of the Solar Photovoltaic Energy Conversion System

2.1 PV Array Modeling

The essential part of the PV scheme is the PV array. It comprises of PV cells. The basic circuit structure of a photo voltaic cell contains the resistors, diodes & the source. A PV cell is mostly used by a single diode model. The specification of PV cell is given in Table 1 with their symbol and value. The equivalent circuit is represented in the Fig. 1. Using Kirchhoff's current law, the output current I_{pvo} is expressed as

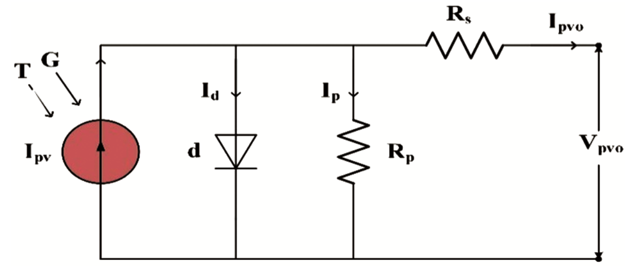

Fig. 1 — Single diode model of PV

$$I_{pvo} = I_p - I_d - I_p \quad \dots (1)$$

$$I_{pvo} = I_p - I_r \left[\exp\left(\frac{q(V+IR_S)}{AkT}\right) - 1\right] - \frac{V+IR_S}{R_p} \quad \dots (2)$$

where R_p & R_s are the parallel & series resistance, I_p is the input source, I_r is the saturation current reversal, V is the voltage outcome, A represent the diode factor, q denotes the charging electron (1.6×10^{-19} C), K denotes Boltzmann constant (1.38×10^{-23} J/K),the Current Ip is affected by temperature & irradiance

$$I_p = \left[I_{sc} + k_i(T_c - T_{ref})\right]\frac{G}{G_{ref}} \quad \dots (3)$$

where Tc is the normal temperature & G is the irradiance, Isc is the short circuit current, T_{ref} & G_{ref} are the reference temperature & irradiance.

The atmospheric conditions plays a crucial role in influencing the behavior of PV systems. The P-V curves and I-V curves of the simulated PV module under temperature and radiation changes are displayed in Fig. 2. In Fig. 2 (a), the PV module's characteristics were examined by modifying the solar radiation by 1000 W/m², 800 W/m², 600 W/m², 400 W/m², and 200 W/m², while in Fig. 2 (b), the temperature was varied by 25°C, 30°C, 35°C, 40°C, and 45°C.

3 Proposed Scheme

The block diagram in Fig. 3 describes a solar PV scheme equipped with an MPPT mechanism using a Hybrid ANN-Incremental Conductance (ANN-INC) algorithm. Solar energy is captured by the PV array, which generates a V_{pv} and current I_{pv} based on G and T conditions. The ANN-INC MPPT controller uses these parameters to calculate the ideal duty cycle needed for high power extraction. The boost regulator is then driven by a PWM generator after receiving the

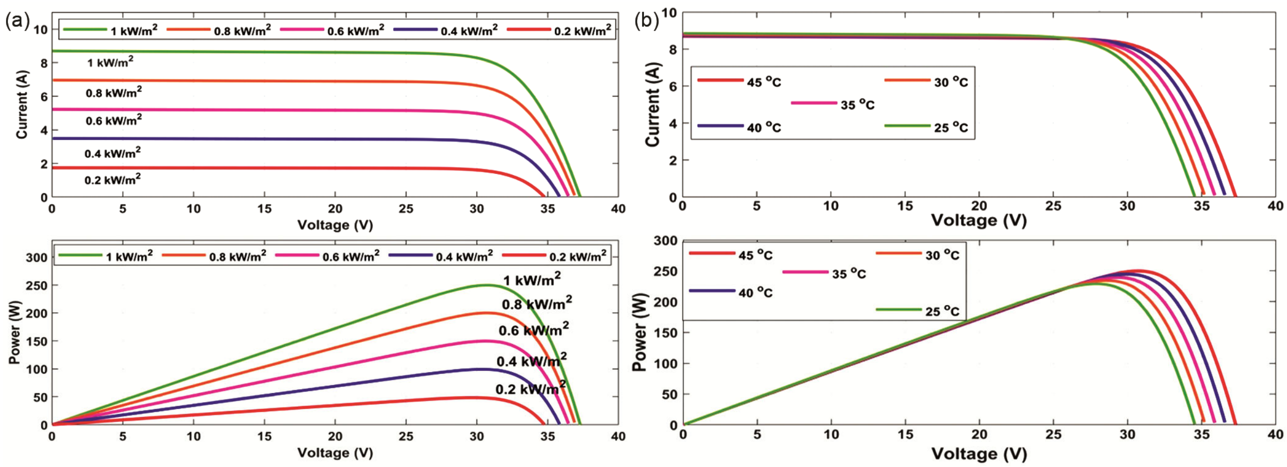

Fig. 2 — P-V and I-V curve: (a) Under varying solar irradiance (W/m^2), and (b) under varying temperature (°C)

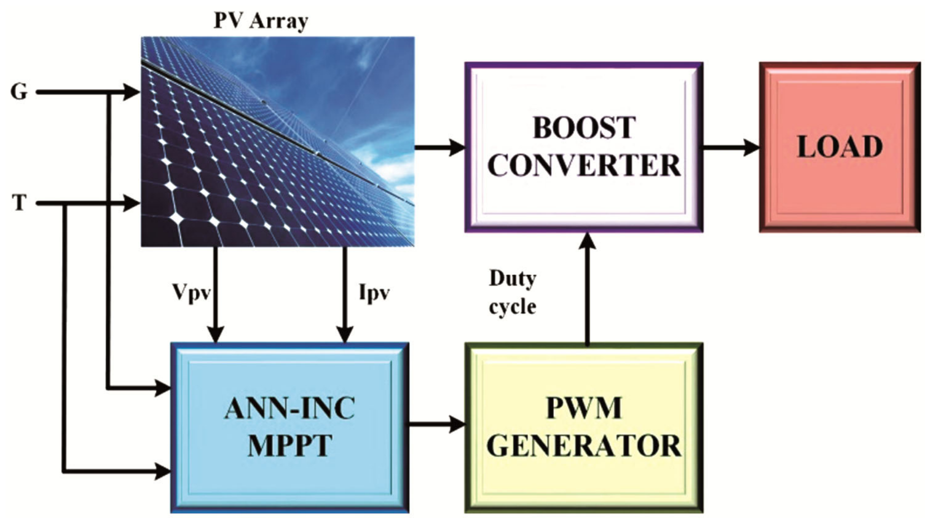

Fig. 3 — Block diagram of the proposed scheme

duty cycle signal. The output voltage is modified by the boost converter to provide the connected load with the most power possible. This closed-loop technology optimizes the performance of the solar PV scheme by constantly adapting to changes in the environment, ensuring efficient energy conversion.

3.1 ANN MPPT

A system that mimics how the human brain learns is called an artificial neural network, or neural network. By utilizing neurons that mimic how the human brain works, an artificial neural network seeks to replicate human intellect. AI technology incorporates artificial neurons into software to enable robots to become self-sufficient. Neural networks are often built on many parallel processors arranged in thirds. Similar to a human's optical nerves processing visual signals, the initial stage receives raw information inputs. The information outputs from the previous step are then sent to each subsequent stage. In most situations, hidden layers are incorporated in ANNs, which are systems constituted of at least 2 layers of neurons: an input and an output layer. x_1 & x_2 represent the PV input, which is the ANN's input, and y_k represents the output V_{MPP} (optimal voltage) in this contribution. The layers are represented in the Fig. 4.The flow diagram of ANN is presented in the Fig. 5.

3.2 INC MPPT

INC is created on observing the P-V curve of photovoltaic cells. Since the output voltage, current and power of the photovoltaic cell satisfy Eq. 4, the relationship concerning dI/dV, -I/V and dP/dV satisfies Eq 5. This approach supervises the duty cycle of the switching device through the relationship between dI/dV and - I/V, to control the rise and fall of

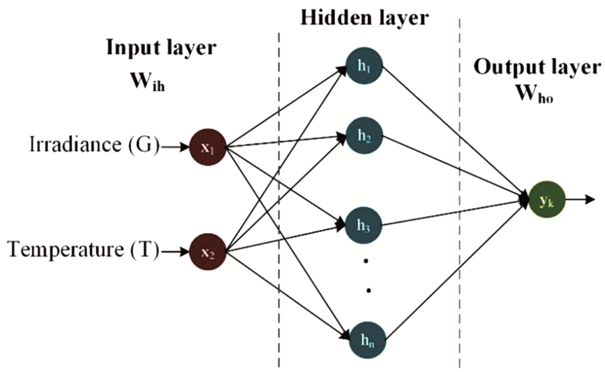

Fig. 4 — Neural network layers

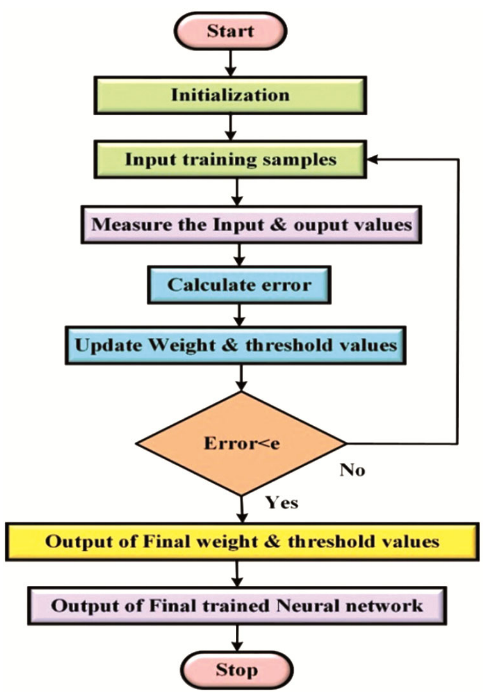

Fig. 5 — Flowchart of ANN

the voltage outcome and make the outcome of the PV cell reach maximum power point. However, duty cycle setting greatly effects performance of the strategy, large duty cycle improves dynamic response speed, but it also makes the steady-state accuracy lower; a small duty cycle can improve steady-state performance, but it also makes the system too slow.

$$\frac{dP}{dV} = I + V\frac{dI}{dV} \quad \ldots (4)$$

$$\frac{dI}{dV} + \frac{I}{V} = \frac{dP/dV}{V} \quad \ldots (5)$$

3.3 Hybrid ANN-INC MPPT

The ANN-INC approach presented in this paper effectively integrates the strengths of ANN and INC algorithms used to increase the efficiency of MPPT in PV Models. In this hybrid approach, the trained ANN predicts an initial duty cycle based on input limits such as solar irradiance, temperature, and the PV array's voltage and current characteristics. This predicted duty cycle is strategically chosen to be the duty cycle closes at the MPP, reducing the search range and computation time for the subsequent INC process. The hybrid ANN-INC algorithm links the predictive capability of ANN with the precise optimization of the INC method to enhance the MPPT process. Initially, the ANN predicts the optimal duty cycle referred with parameters of input such as temperature, irradiance, and system conditions. This provides a quick approximation of the MPP. Following this, the INC algorithm refines the duty cycle by making small, incremental adjustments to further align the PV system’s operating point with the true MPP. The use of a small step size in the INC algorithm allows for high precision in fine-tuning the operating point, reducing deviations and ensuring that the system extracts the maximum possible energy. This combined approach enables faster convergence to the MPP, minimizes power losses due to oscillations around the optimal point, and significantly improves energy harvesting efficiency. The synergy between ANN's ability to quickly predict an initial operating point and INC's methodical refinement makes this hybrid technique particularly effective under dynamic and challenging conditions, such as partial shading or rapidly fluctuating irradiance levels. Here the flowchart shows the ANN-INC algorithm, in Fig. 6, illustrates the systematic interaction between these two techniques. It highlights how the ANN provides a starting point for efficient operation, while the INC algorithm adapts to real-time changes, ensuring an adaptive and robust performance. This combination optimizes the solar PV system’s performance, maximizing energy output and ensuring stable operation across diverse environmental scenarios.

4 Results

The effectiveness of the proposed technique is evaluated through simulation tools to detect potential problems promptly and enhance real-time performance. The performance of the proposed ANN-INC MPPT technique is tested across various conditions to confirm its reliability such as.

• Constant radiation and temperature both

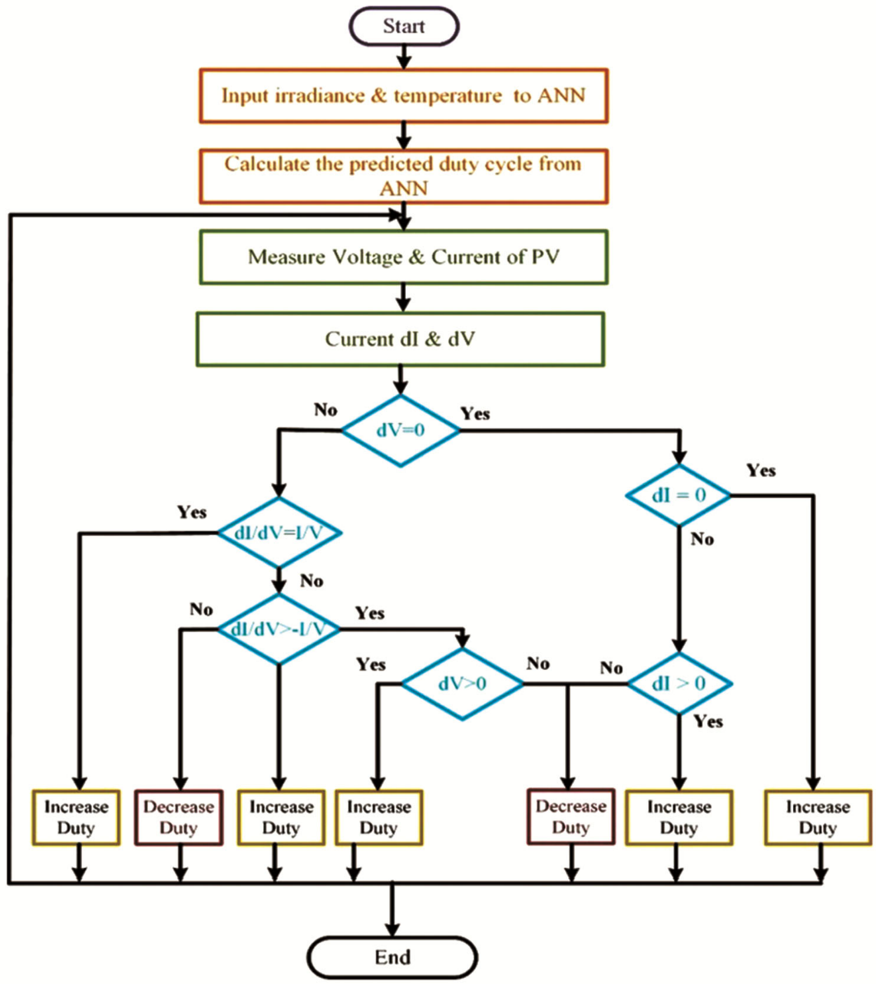

Fig. 6 — Flow diagram of ANN-INC MPPT

- Random radiation and fixed temperature
- Constant radiation and varying temperature
- Varying both temperature and radiation
- Cloudy and Realistic Weather

The comparative performance of proposed ANN-INC method is evaluated and compared against P&O, INC, Fuzzy and ANN methods across different scenarios. The tracking efficiency ($\eta_{tracking}$) of the MPPT approach is calculated using Eq 6. Tracking initiates at the time t_1 and terminates at time t_2, with the average output power during this interval represented as P_{avg}. Additionally, load-related parameters are assessed in each scenario.

$$\eta_{tracking} = \frac{\int_{t1}^{t2} P_{avg} dt}{\int_{t1}^{t2} P_M dt} \qquad \ldots (6)$$

4.1 Case I: Constant Radiation (1000W/M^2) and Temperature (25 °C) Both

The PV parameters & load parameters using proposed ANN-INC MPPT techniques under fixed insolation (1000W/m^2) and constant temperature (25°C) is shown in Fig. 7 and Fig. 8, respectively. The PV power comparison of ANN-INC, P&O, INC, Fuzzy and ANN MPPT techniques under fixed insolation (1000W/m$^{2)}$ and fixed temperature (25°C) is illustrated in Fig. 9. The zoom views clearly demonstrate that the suggested technique has the least oscillation (around MPP) compare to all other techniques. Figure 10 shows the tracking speed of different MPPT algorithms under this conditions. The proposed ANN-INC algorithm can take only 6.5ms to track the MPP while P&O, INC, Fuzzy and ANN can take 72ms, 20ms, 78ms and 73ms, respectively. Figure 11 shows the efficiency curve for different techniques in this condition. . Efficiency is measured by calculating the ratio of actual output power to theoretical power. At 1000 W/m² and 25°C, ANN-INC achieves the highest efficiency (99.8%) compare to P&O (99.5%) and INC (99.6%), while ANN and

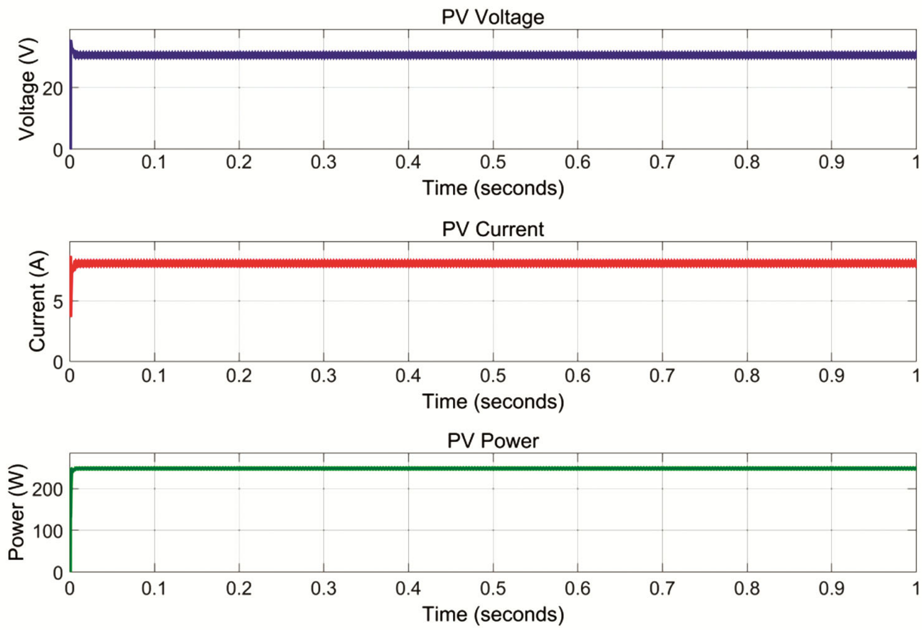

Fig. 7 — PV parameters at uniform irradiance using ANN-INC

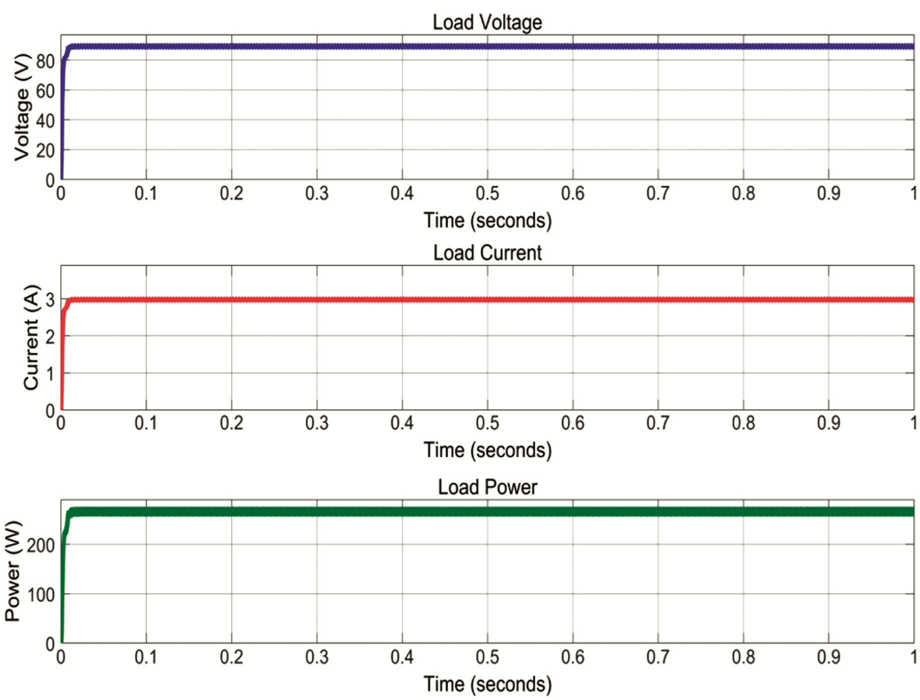

Fig. 8 — Load parameters at uniform irradiance using ANN-INC

Fuzzy methods achieve 98.0% and 98.7%.The figure clearly shows that proposed techniques was most efficient under this condition having highest efficiency as compare to others techniques.

4.2 Case II Random Radiation and Fixed Temperature (25 °C)

The PV parameters & load parameters using proposed ANN-INC MPPT techniques under random radiation and fixed temperature (25 °C) is illustrated in Fig. 12 and Fig. 13 respectively.In this case the value of solar insolation which is varying with time as 1000W/m^2, 800W/m^2, 600W/m^2, 400 W/m^2 & 200 W/m^{2}from 0 to 0.2sec, 0.2 to 0.4sec, 0.4 to 0.6sec, 0.8 to 1.0sec respectively. The PV power comparison of ANN-INC, P&O, INC, Fuzzy and

ANN MPPT techniques under constant temperature (25 °C) and the random solar insolation is illustrated in Fig. 14. It can be seen that the photovoltaic power generated by P&O, INC, Fuzzy, and ANN fails to match the maximum power point (MPP), thus leading to a loss of the actual maximum power due to significantly changing environmental conditions. However, the proposed ANN-INC algorithm continues to monitor the MPP while changing the states with minimal ripples. The proposed controller can take only 6ms while the P&O takes 25ms, INC takes 19ms, Fuzzy take 23ms & ANN take 35ms while tracking the maximum power point. Figure 15 shows the tracking speed under the condition random insolation and fixed value of temperature(25 °C). Table 2 represents the variations of power output across various MPPT methods like P&O, INC, ANN, Fuzzy and a hybrid ANN-INC approach under varying solar irradiance levels. Theoretical power is used as a benchmark for comparison. At 1000 W/m² irradiance, ANN-INC achieves the highest power output (249.6 W), closely matching the theoretical maximum (250.20 W), while P&O and INC show slightly lower performance at 248.9 W and 249.3 W, respectively. At 800 W/m², the ANN-Fuzzy method again outperforms others with 199.8 W, exceeding the results from P&O (199.3 W) and INC (198.6 W). Under lower irradiance conditions (600 W/m²), ANN-INC delivers consistent performance (148.9 W), close to P&O (148.1 W) and Fuzzy Logic (148.8 W). For 400 W/m² and 200 W/m², ANN-INC maintains superior power output (97.4 W and 47.23 W, respectively), demonstrating its robustness under reduced irradiance compared to methods like Fuzzy and ANN. This highlights the hybrid method's ability to approximate theoretical power more effectively across all irradiance levels. Figure 16 evaluates the efficiency of the same MPPT methods across different solar irradiance levels. Efficiency is calculated as the ratio of actual power output to theoretical power. At 1000 W/m², ANN-INC achieves the highest efficiency (99.8%), outperforming P&O (99.5%) and

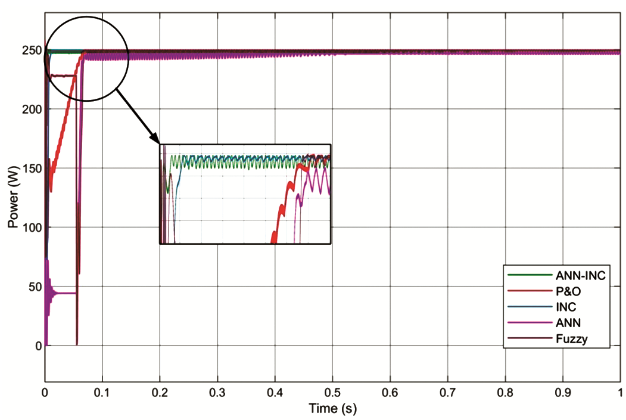

Fig. 9 — P&O, INC, ANN, Fuzzy & ANN-INC comparison with uniform irradiance

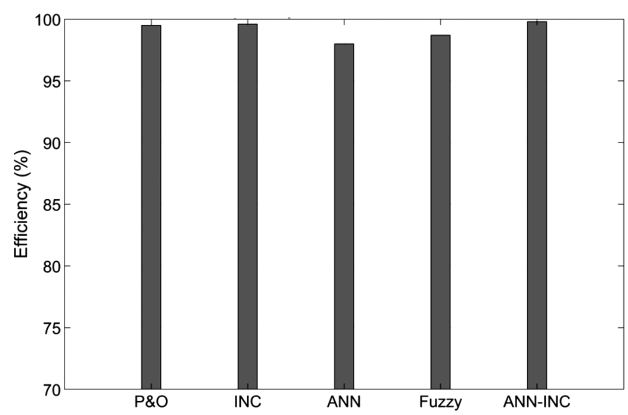

Fig. 11 — Efficiency comparison for P&O, INC, ANN, Fuzzy & ANN-INC with uniform irradiance and temperature

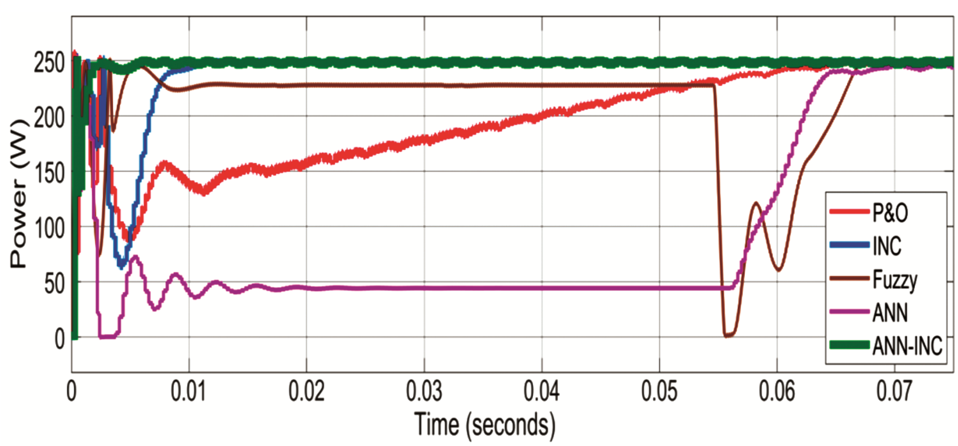

Fig. 10 — Tracking speed comparison for P&O, INC, ANN, Fuzzy & ANN-INC with uniform irradiance & temperature

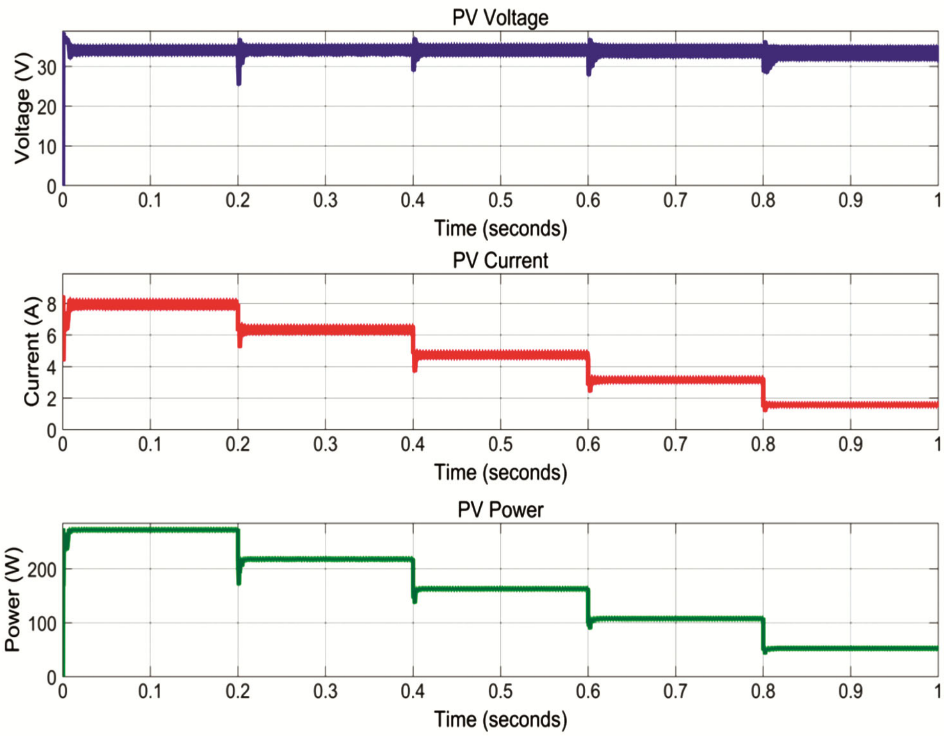

Fig. 12 — PV parameters at varying irradiance using ANN-INC

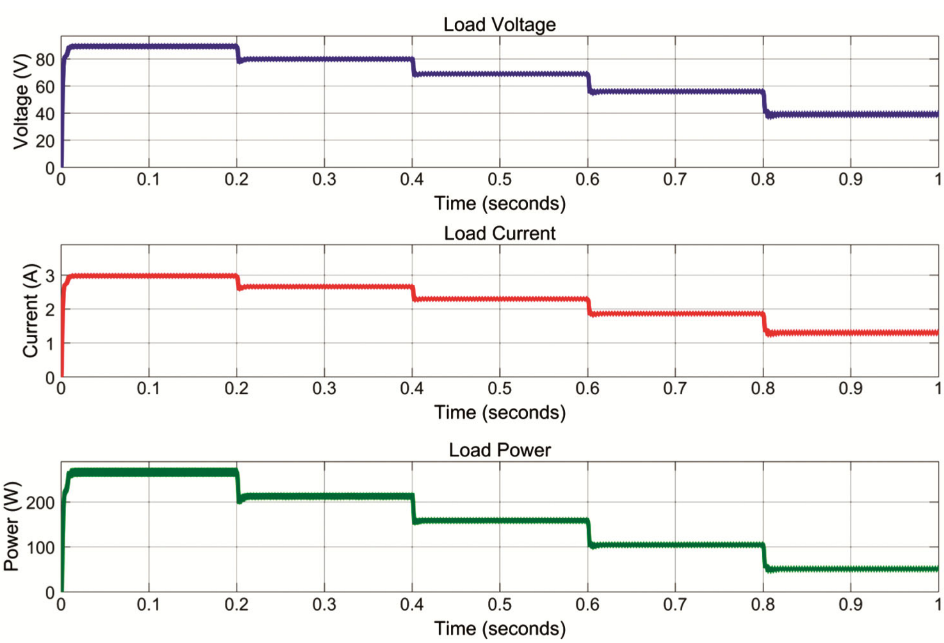

Fig. 13 — Load parameters at varying irradiance using ANN-INC

INC (99.6%), while ANN and Fuzzy methods lag slightly at 98.0% and 98.7%. This trend persists across irradiance levels, with ANN-Fuzzy demonstrating exceptional efficiency (99.9%) at 800 W/m² and consistent performance at 600 W/m² (99.5%). Under low irradiance (400 W/m² and 200 W/m²), ANN-INC sustains its superiority with efficiencies of 98.4% and 97.6%, outperforming Fuzzy Logic (95.8% and 86.4%) and maintaining parity with P&O and INC. This consistent high

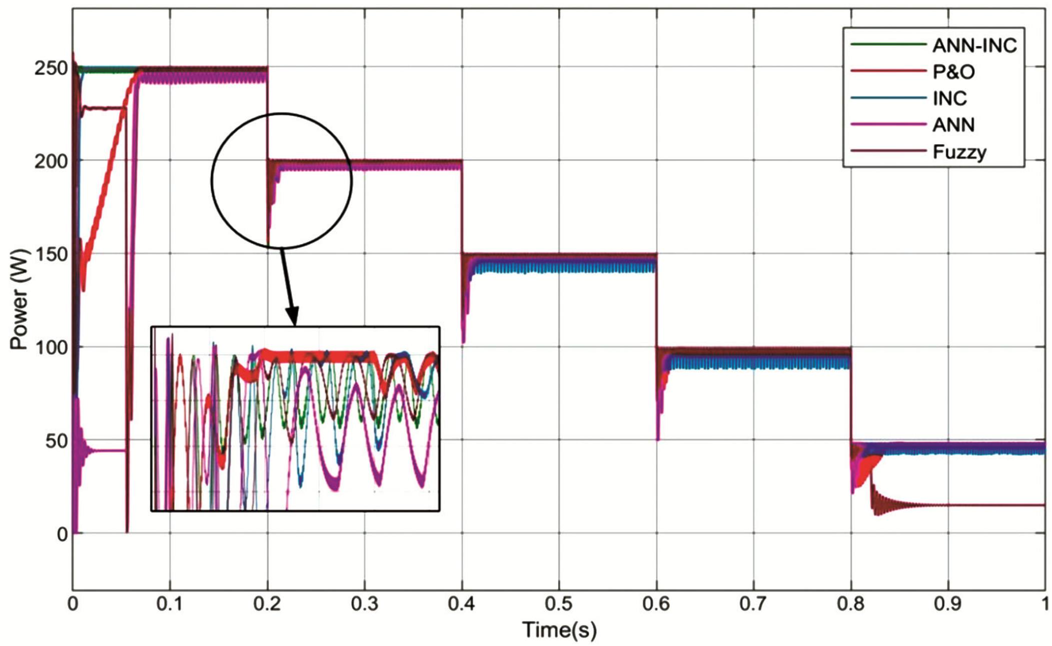

Fig. 14 — P&O, INC, ANN, Fuzzy & ANN-INC comparison with varying irradiance

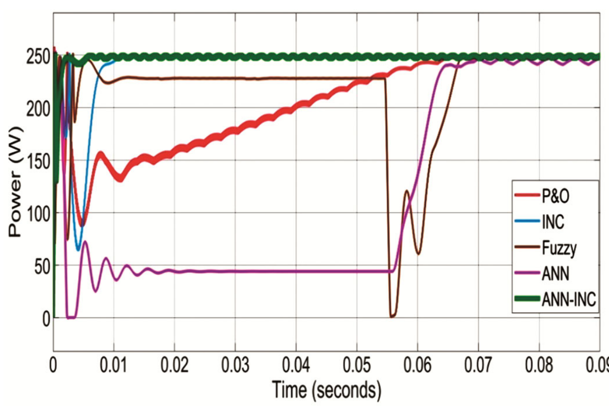

Fig. 15 — Tracking speed comparison for P&O, INC, ANN, Fuzzy & ANN-INC with random irradiance and constant temperature

efficiency across varying conditions highlights ANN-INC capability to optimize energy extraction effectively compared to other methods

4.3 Case III Constant Radiation (1000W/M^2) and Random Value Of Temperature

The PV parameters &load parameters using proposed ANN-INC MPPT techniques under fixed insolation (1000W/m^2) and random temperature is shown in Fig. 17 and Fig. 18, respectively. In this case the value of solar insolation is fixed (1000W/m^2) but temperature is varying with time as 25 °C, 30 °C, 35 °C, 40 °C & 45 °C from 0 to 0.2sec, 0.2 to 0.4sec, 0.4 to 0.6sec, 0.8 to 1.0sec, respectively. The PV power comparison of ANN-INC, P&O, INC, Fuzzy and ANN MPPT techniques under fixed insolation (1000W/m^2) and random value of temperature is illustrated in Fig. 19. The magnified views clearly indicate that the proposed method exhibits less oscillation during state transitions, suggesting reduced power loss compare to all other methods. Figure 20 illustrates the tracking speed of the different MPPT techniques under constant radiation value (1000 W/m²) and varying temperature condition. The suggested approach requires just 3ms to monitor the MPP, whereas P&O, INC, Fuzzy, and ANN necessitate approx. 14ms, 26ms, 36ms, and 28ms, respectively. Figure 21 evaluates the efficiency of the same MPPT methods across same solar irradiance levels and different temperature values. Efficiency is calculated as the ratio of actual power output to theoretical power. At 1000 W/m² and 25 °C, ANN-INC achieves the highest efficiency (99.8%), outperforming P&O (99.5%) and INC (99.6%), while ANN and Fuzzy methods have slightly at 98.0% and 98.7%. This trend persists across different temperature levels, with ANN-INC can achieve high efficiency of 97.9% at 30 °C and 95.7% at 35 °C. At high temperature (40 °C and 45 °C), ANN-INC sustains its superiority with efficiencies of 94.1% and 92.8%, respectively as compared with Fuzzy Logic (90.6% and 87.9%) ,ANN(89.3% and 86.6%), P&O (93% and 90.8%), INC (93.5% and 91.4%). This

Table 2 — Comparative analysis of Power obtained using P&O, INC, ANN, Fuzzy & ANN-INC

Irradiance (W/m^2)	Theoretical power	P&O	INC	Power(W) ANN	Fuzzy	Proposed (ANN-INC)
1000	250.20	248.9	249.3	245.1	247	249.6
800	200	199.3	198.6	198.1	198.5	199.8
600	149.71	148.1	142.3	146.8	148.8	148.9
400	99.025	97.1	95.3	97.4	94.9	97.4
200	48.39	46.25	47.1	47.2	41.8	47.23

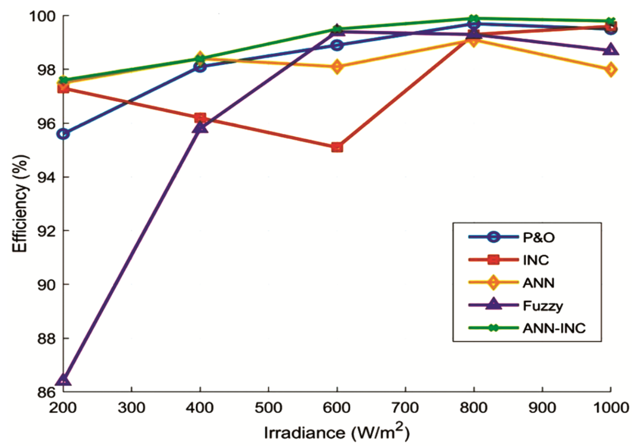

Fig. 16 — Efficiency comparison for P&O, INC, ANN, Fuzzy & ANN-INC with random irradiance and constant temperature

consistent high efficiency across varying conditions shows that ANN-INC capability to optimize energy extraction effectively compared to other methods in this condition of fixed insolation and different temperature variations.

4.4 Case IV: Changing Both Temperature and Radiation

The PV parameters & load parameters using proposed ANN-INC MPPT techniques under random insolation and varying temperature is shown in Fig. 22 and Fig. 23, respectively. In this case the value of solar insolation varying as 1000W/m^2, 800 W/m^2, 600W/m^2, 400W/m^2& 200 W/m^2 and the temperature which also varies as 25 °C, 30 °C,35 °C,40 °C & 45 °C in time duration 0 to 0.2sec, 0.2 to 0.4sec, 0.4 to 0.6sec, 0.8 to 1.0sec respectively. The PV power comparison of ANN-INC, P&O, INC, Fuzzy and ANN MPPT techniques under varying insolation and varying also temperature is illustrated in Fig. 24. The shown magnified views of images clearly indicates that the proposed ANN-INC controller exhibits the least oscillation at the MPP and during state transitions, resulting in a much lower value of power loss compare to other controllers. Moreover, the proposed technique efficiently detects the MPP having reaction time of 7ms while P&O, INC, Fuzzy and ANN can take significant time of 61ms, 13ms, 63ms and 68ms respectively. Figure 25 illustrates the tracking performance of various MPPT techniques under simultaneous changes in both solar irradiance and temperature. Based on multiple case studies conducted under different environmental conditions, it is evident that the proposed ANN-INC method surpasses the P&O, INC, Fuzzy and ANN techniques. It not only achieves rapid and accurate tracking of the true MPP but also exhibits significantly lower ripple during operation compared to other methods.Figure 26 shows the efficiency curve of the different MPPT methods across different solar irradiance levels and different temperature values. Efficiency is calculated as the ratio of actual power output to theoretical power. At 1000 W/m² and 25 °C, ANN-INC achieves the highest efficiency (99.8%), outperforming P&O (99.5%) and INC (99.6%), while ANN and Fuzzy methods have slightly at 98.0% and 98.7%. This pattern persists across different condition of solar irradiance and temperature levels, with ANN-INC can achieve high efficiency of 97.9% at 800 W/m² and 30 °C and also highest efficiency of 95.9% among others at 600 W/m² and 35 °C. At other different conditions of low solar irradiance (400 W/m² and 200 W/m²) and high temperature (40 °C and 45 °C), ANN-INC sustains its superiority with efficiencies of 93.4% and 90.8%, respectively as compared with Fuzzy Logic (91.3% and 87.6%) , ANN(90.1% and 83.8%), P&O (93.2% and 86.8%), INC (91.4% and 83.6%). The consistently superior efficiency observed across varying both solar irradiance and temperature shows that the ANN-INC methods exhibits a robust capability to optimize energy extraction more effectively compared to other methods.

4.5 Case V Realistic and Cloudy Weather

The daily weather profile affects realistic weather with cloud effects. For realistic weather, PV power output of Suggested ANN-INC controller along with P&O, INC, Fuzzy and ANN is shown in Fig. 27. It is

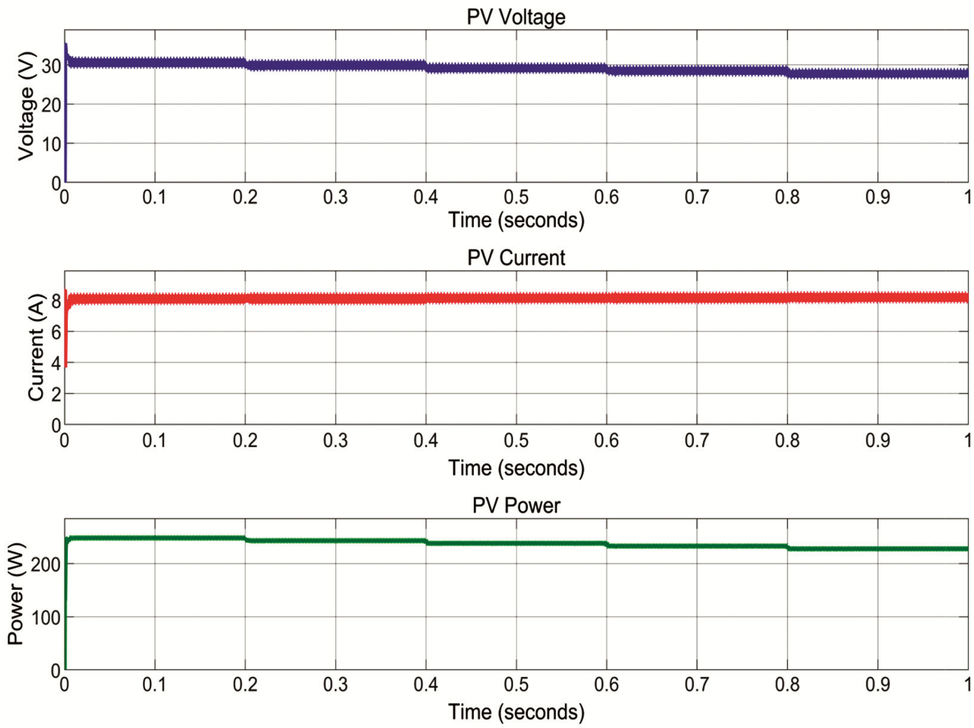

Fig. 17 — PV parameters at uniform irradiance varying Temperature using ANN-INC

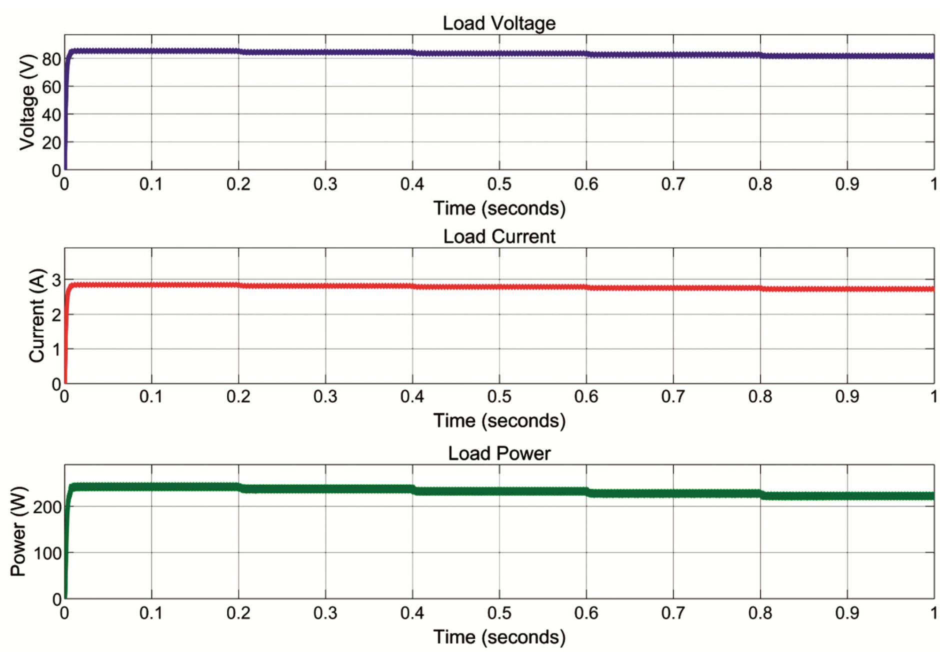

Fig. 18 — Load parameters at uniform irradiance varying Temperature using ANN-INC

observed that the suggested method accurately follows the MPP with negligible ripple, whereas PO, INC Fuzzy and ANN are comparatively less successful in following MPP as they have considerable ripple content. The response of PV power using the proposed ANN-INC controller along with PO, INC, Fuzzy and ANN is shown in Fig. 28 for cloudy weather. A couple of cloud effects are taken into account. We also incorporate the clear and enhanced view of both cloud effects in the output results. The suggested MPPT algorithm demonstrates near 99% success rate in tracking the maximum power point. Although its efficiency drops during overcast weather conditions, it recovers and reaches near 99% once the weather clears. PV Voltage and Current under cloudy weather are shown in Figs. 29 and 30, respectively. Just like in real weather and during the clouds, a relative study of the proposed ANN-INC with PO, INC, Fuzzy and ANN MPPT is conducted. The detailed study shows in an obvious manner the advantages of the suggested MPPT algorithm in voltage ripple, current ripple, tracking time, and overall efficiency as compared to conventional methods.The tracking time for the P&O, INC, Fuzzy and ANN MPPT is 63ms, 45ms, 50ms and 44ms, respectively, whereas the ANN-INC approach achieves maximum power point (MPP) tracking in just 6.5ms. In terms of voltage & current ripple, the P&O, INC, Fuzzy and ANN methods exhibit ripple values of 8V and 4.7A, 7 V and 3.2A, 6 V and 5.5A and 4V and 3.1A, respectively. In contrast, the proposed ANN-INC method exhibits minimal ripple. Furthermore, the tracking efficiencies for the P&O, INC, Fuzzy and ANN algorithms are 94.25%, 93.7%, 93.45% and 95%, respectively, while the ANN-INC method achieves a significantly higher efficiency of 99.2%.

4.6 Robustness Test: Random Value of both Solar Irradiance and Temperature with the Probabilistic Load Distribution

For evaluating the robustness of the proposed ANN-INC method, a test was conducted under conditions of randomly varying solar irradiance and also temperature, combined with the probabilistic load changes. The significance of the probabilistic load distribution signal in robustness tests, especially in the context of MPPT (Maximum Power Point Tracking) is crucial for evaluating how well a PV system and its controller respond to unpredictable, real-world operating conditions. The load variations

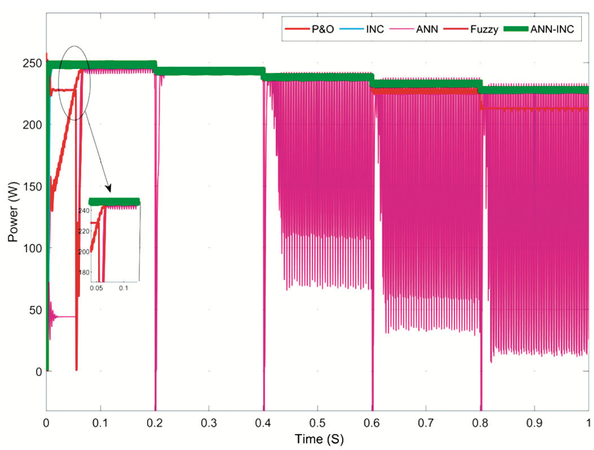

Fig. 19 — P&O, INC, ANN, Fuzzy & ANN-INC comparison with fixed irradiance & varying Temperature

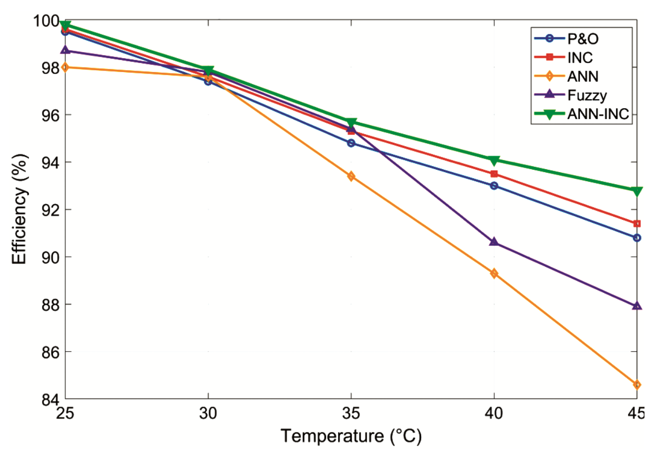

Fig. 21 — Efficiency comparison for P&O, INC, ANN, Fuzzy & ANN-INC with fixed irradiance and varying temperature

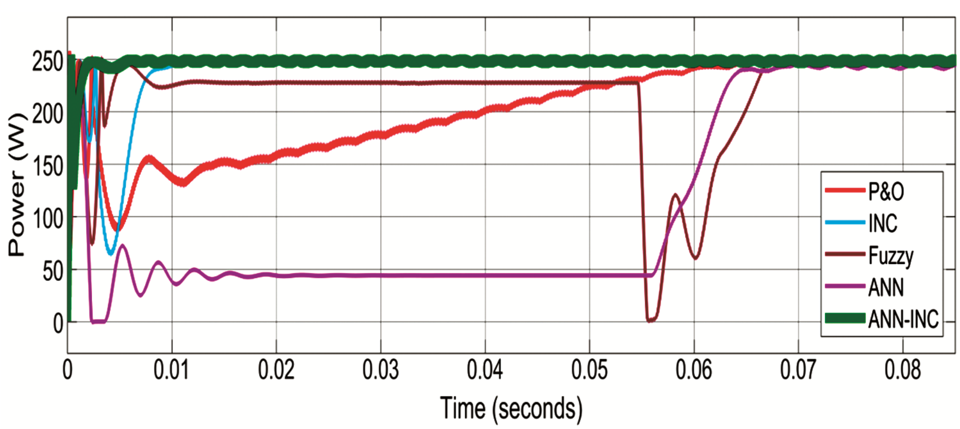

Fig. 20 — Tracking speed comparison for P&O, INC, ANN, Fuzzy & ANN-INC with fixed irradiance and varying temperature

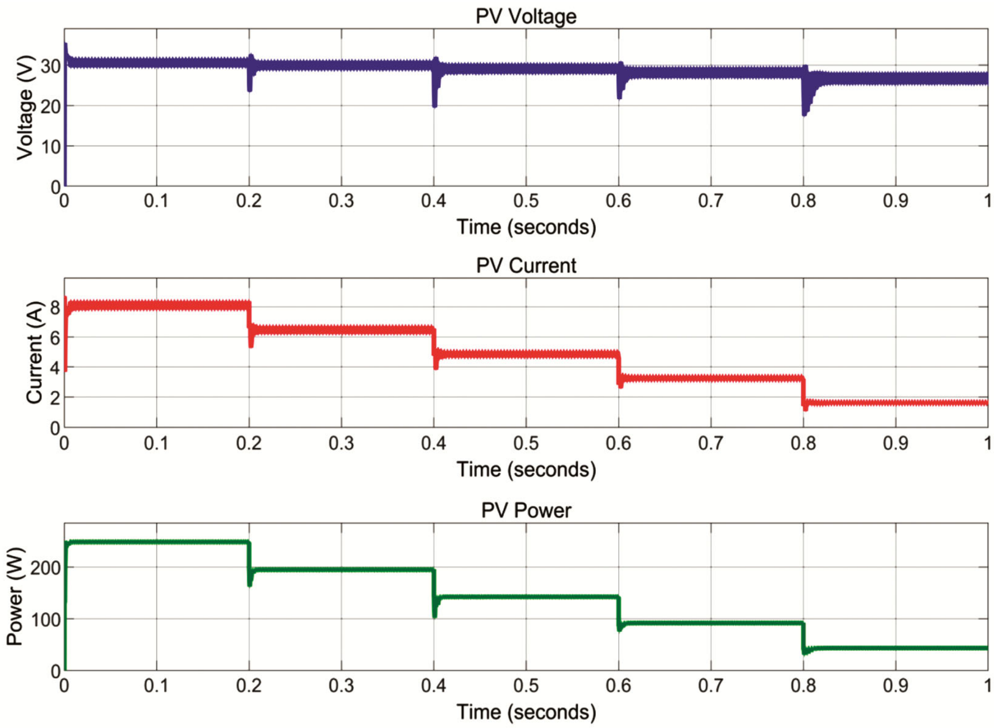

Fig. 22 — PV parameters at random irradiance and varying Temperature using ANN-INC

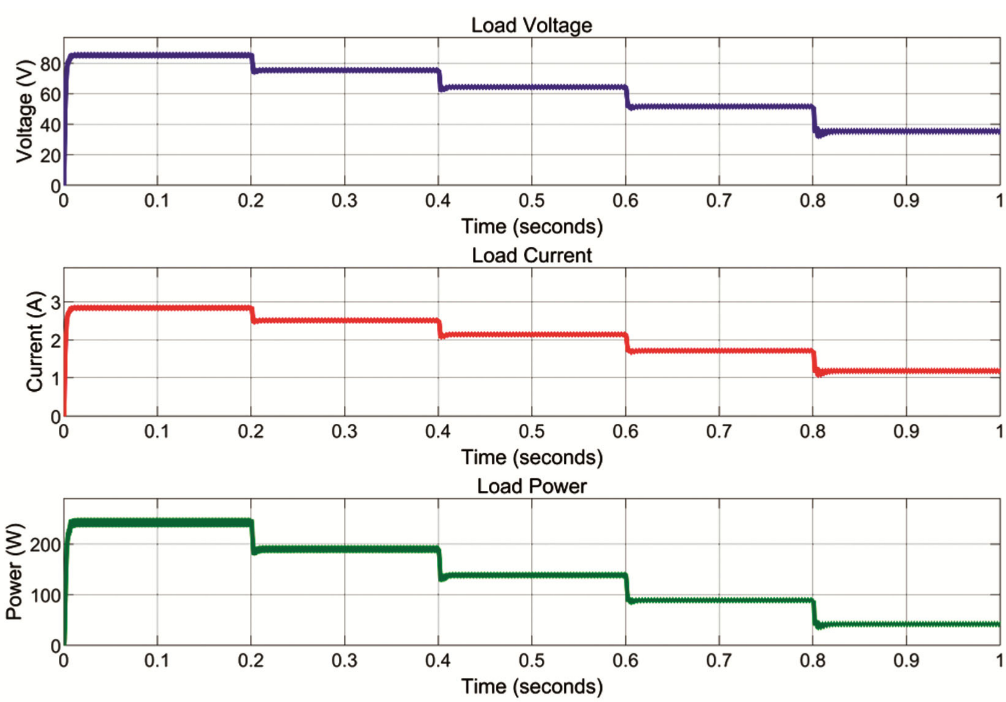

Fig. 23 — Load parameters at random irradiance and varying Temperature using ANN-INC

were introduced in three stages to simulatereal-world disturbances: an initial minor change in load as 5 Ω, after that a mode rate load value change of 10 Ω, after that finally a sudden significant change in load value as 15 Ω. Additionally, the probabilistic distribution of load resistance is 20, 25, 30, 40 and 25 ohms, with periodic changes occurring after every 0.2 seconds. Figure 31 shows the signal of the distribution of the

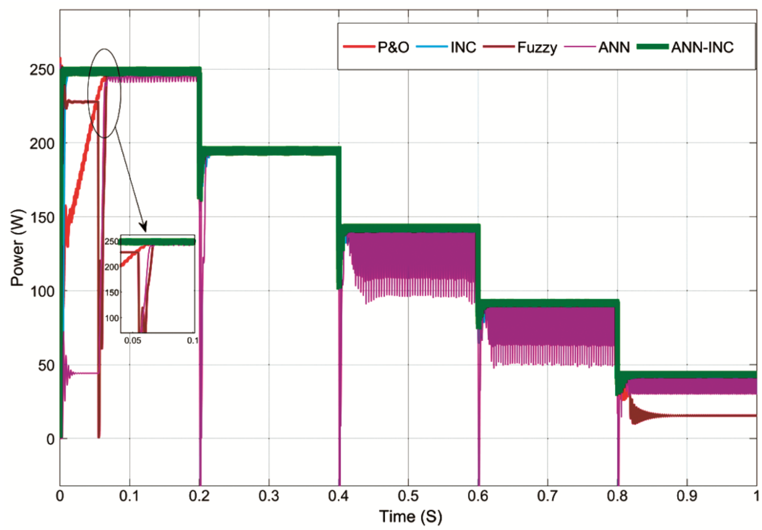

Fig. 24 — P&O, INC, ANN, Fuzzy & ANN-INC comparison with varying both irradiance & Temperature

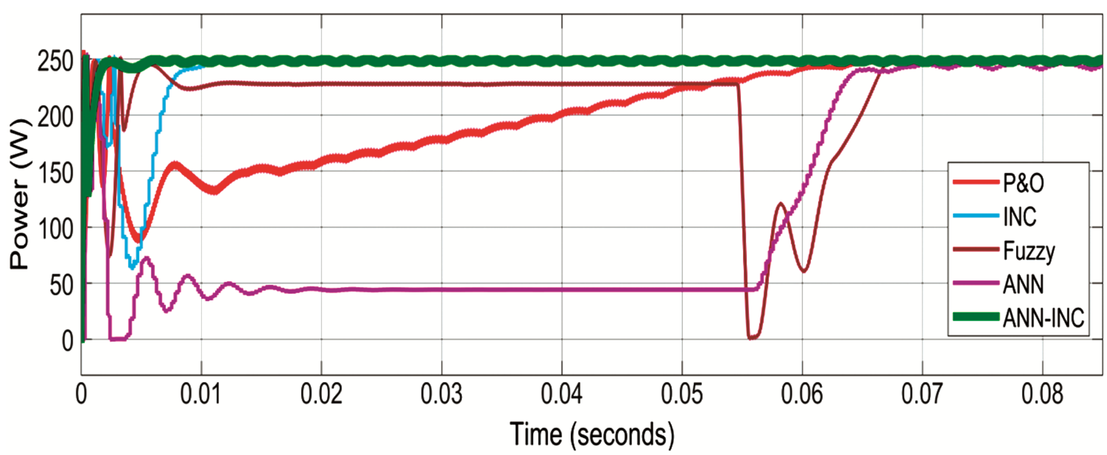

Fig. 25 — Tracking speed comparison for P&O, INC, ANN, Fuzzy & ANN-INC with random irradiance and random temperature

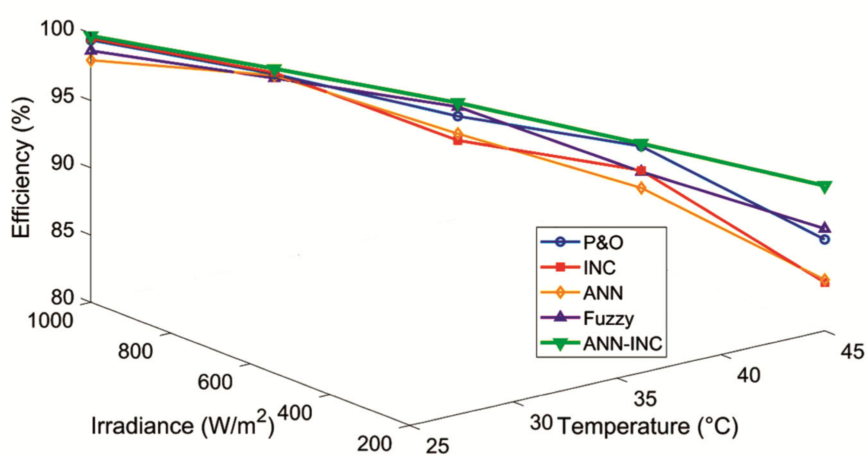

Fig. 26 — Efficiency Comparison for P&O, INC, ANN, Fuzzy & ANN-INC with random both irradiance and temperature

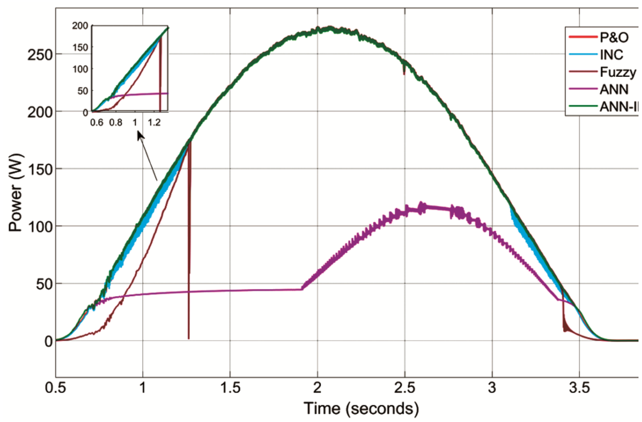

Fig. 27 — PV power curve for realistic weather condition

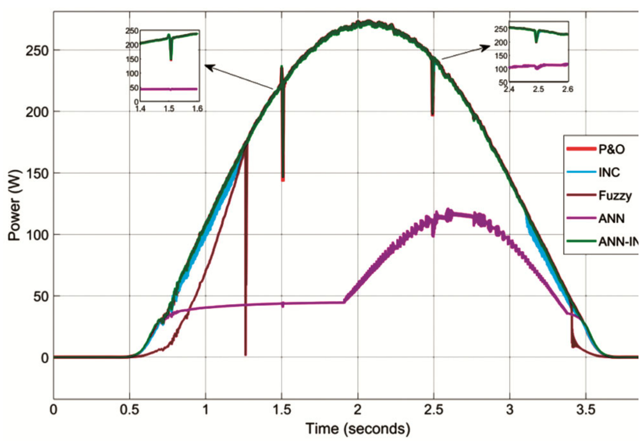

Fig. 28 — PV power curve for cloudy weather condition

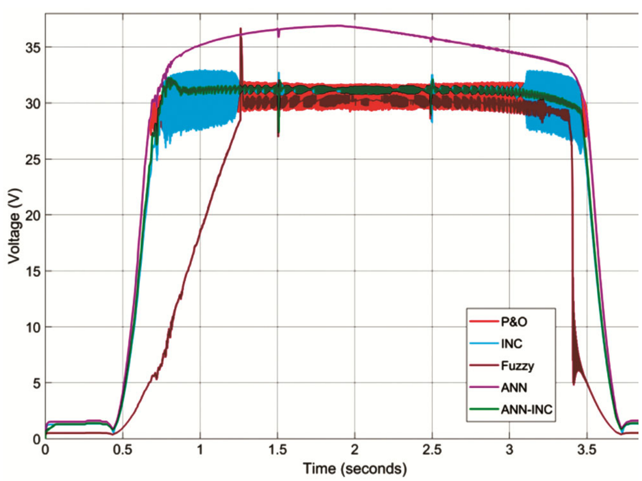

Fig. 29 — PV voltage for cloudy weather condition

probabilistic load. Figure 32 (a-d) shows the curve of PV power, the tracking speed, PV current and the PV voltage obtained from different MPPT techniques during test of reliability. The loss of power in each state of condition is determined based on Eq. 7, with t

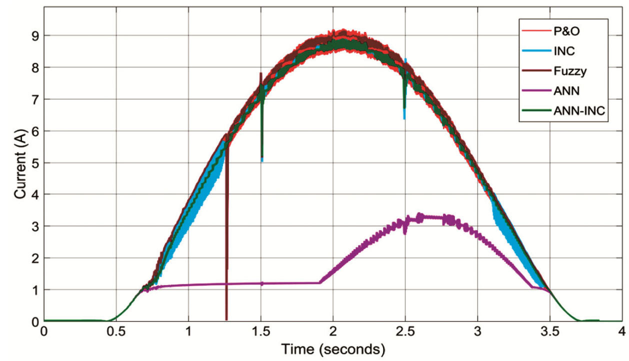

Fig. 30 — PV current for cloudy weather condition

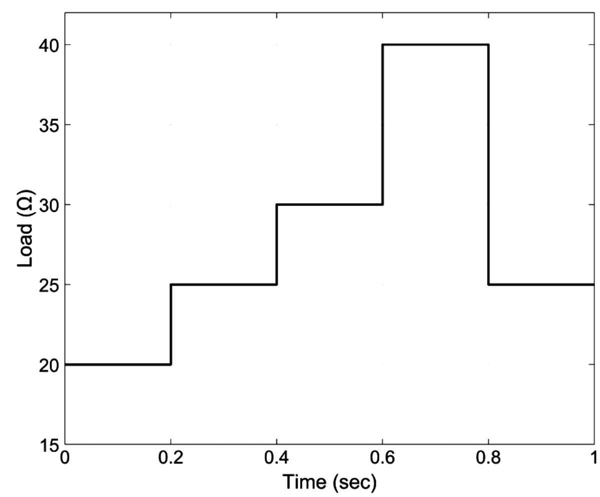

Fig. 31 — Probabilistic load distribution signal

being the time necessary to reach the Maximum Power Point (MPP).To estimate the error rate on recognizing the MPP of several MPPT methods, the errors, that is the root mean square error (RMSE), the mean relative error (MRE), and the mean absolute percentage error (MAPE), will be calculated using Eq. 8-10. Where, n denotes number ofthedatapoints[33].

$$\text{Powerloss} = \frac{\sum P_M(t) - \sum P(t)}{\sum P_M(t)} \times 100\% \quad \ldots (7)$$

$$\text{RMSE} = \sqrt{\frac{\sum(\text{actual} - \text{estimated})^2}{n}} \quad \ldots (8)$$

$$\text{MRE} = \frac{|\,\text{Actual value} - \text{Estimated value}\,|}{\text{Actual value}} \quad \ldots (9)$$

$$\text{MAPE} = \frac{1}{n}\sum \frac{|\,\text{Actual value} - \text{Forcasting}|}{|\,\text{Actual}\,|} \times 100\% \quad \ldots (10)$$

Table 3 clearly shows that the proposed ANN-INC algorithm based controller exhibits minimal current and voltage fluctuations, delivering higher actual and the output power, achieving faster tracking time, and

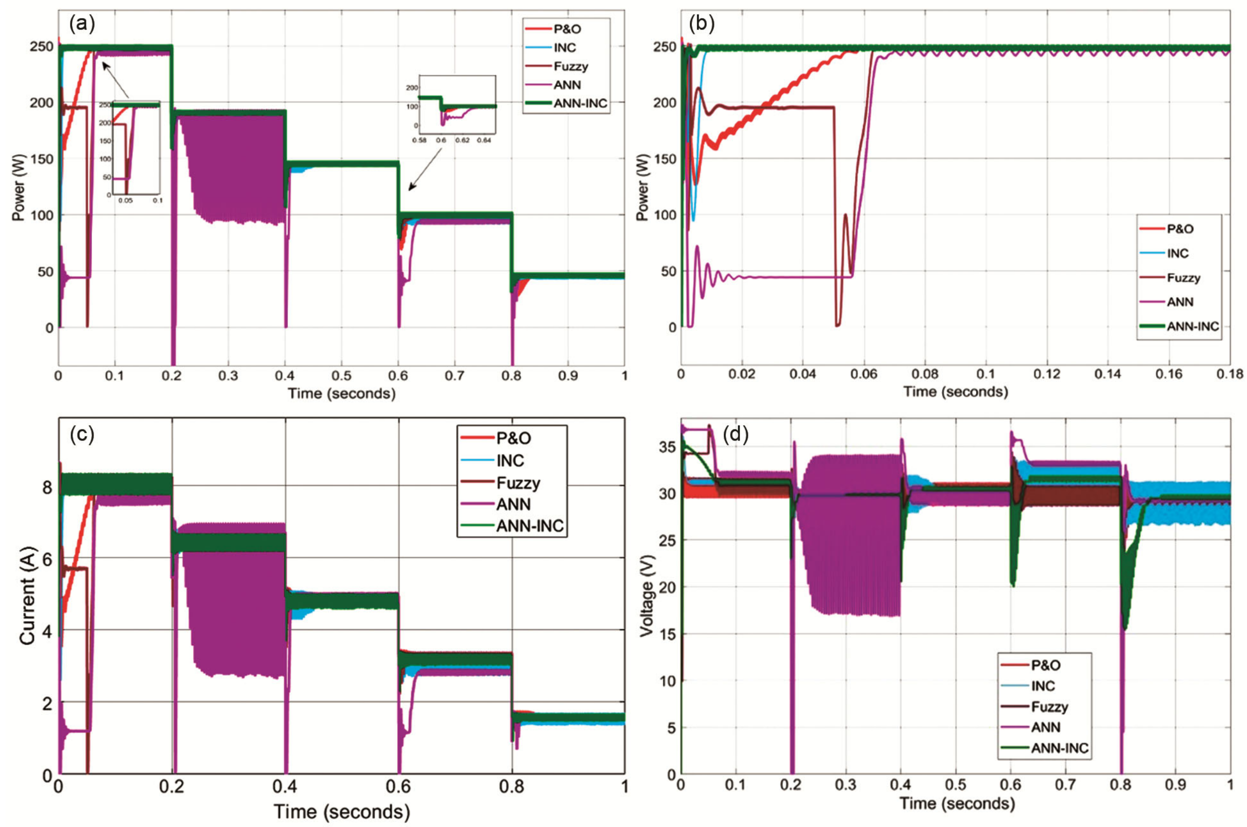

Fig. 32 — Under the condition of both random radiation and temperature with probabilistic distribution of load: (a) PV power; (b) Tracking speed; (c) PV current; (d) PV voltage

demonstrating improved overall and tracking efficiency compare to other techniques. It also shows reduced power loss and consistent accuracy in identifying the maximum power point (MPP) across all five operating duration. Table 3 also provides comparisons of voltage &current ripple, the power loss, overall efficiency, tracking duration, accuracy in tracking and associated error values (MRE, RMSE and MAPE).

5 Experimental Evaluation and Validation of the Proposed ANN-INC Controller

The effectiveness of the proposed MPPT technique was experimentally assessed using the OPAL-RT (OP4510) simulator, as depicted in Fig. 33.The performance of the proposed MPPT method was experimentally evaluated using the OPAL-RT simulator (OP4510), as illustrated in Fig. 33. This simulator, which operates in real-time and has four cores, features the RT-LAB system as one of its key components. The experimental setup consists of two main parts namely, the host computer and the real-time (RT) simulator. The RT-LAB environment compiles the Simulink model and provides a user interface on host computer, which is also used to implement modifications. The RT simulator manages the real-time execution of the model by interfacing with the host computer via a Telnet connection, using dedicated system software. The Simulink model was executed on the OPAL-RT (OP4510) platform, with experimental validation carried out under test conditions that included time-varying solar irradiance and temperature. To assess the controller's performance, solar irradiance was randomly varied from 1000 W/m² to the 800 W/m², then to the 600 W/m², 400 W/m², and finally 200 W/m². Simultaneously, temperature was adjusted from 25 °C to 30 °C, 35 °C, 40 °C, and 45 °C. The outcomes of the ANN-INC MPPT controller under the scenarios of varying both temperature and irradiance are shown in Fig. 34. The proposed controller rapidly responded to abrupt environmental changes, maintaining minimal oscillation near the MPP and exhibiting very low ripple. These results confirm that the ANN-INC controller experiences virtually no power loss even under dynamic atmospheric conditions.

Table 3 — Comparison under robustness test in different states

MPPT technique	State 1 0-0.2sec	State 2 0.2-0.4sec	State 3 0.4-0.6sec	state 4 0.6-0.8sec	State 5 0.8-1sec
Average power output (W)					
P&O	248.9	195.7	142.4	92.1	43.6
INC	248.4	195	143.4	91.8	42.4
Fuzzy	247	195.3	142.7	73.5	19.1
ANN	245.1	195	106	87.3	31.0
ANN-INC	249.6	195.9	144.2	93.5	44.2
Power loss (%)					
P&O	0.52	2.15	4.88	6.98	9.83
INC	0.72	2.50	4.21	7.27	12.33
Fuzzy	1.28	2.37	4.68	25.77	60.54
ANN	2.04	2.50	29.19	11.79	35.99
ANN-INC	0.24	2.05	3.68	5.57	8.65
PV voltage ripple (V)					
P&O	3.644	3.446	3.528	4.041	3.286
INC	3.554	3.440	3.531	3.539	3.127
Fuzzy	3.729	3.553	3.612	3.655	1.518
ANN	3.730	4.556	3.579	3.613	3.207
ANN-INC	1.350	1.020	1.014	1.118	0.978
PV current ripple (A)					
P&O	8.24	6.66	4.98	3.31	1.78
INC	8.26	6.67	4.97	3.29	1.75
Fuzzy	8.66	6.98	5.24	3.47	1.90
ANN	8.68	8.77	5.23	3.30	1.76
ANN-INC	5.03	3.06	1.84	1.11	0.29
Tracking time (ms)					
P&O	60	62	55	49	54
INC	40	44	46	39	42
Fuzzy	44	48	41	39	43
ANN	45	54	32	37	32
ANN-INC	6.5	5.5	4	5.7	7
Root mean square error (RMSE)					
P&O	8.613	6.343	7.291	6.220	5.261
INC	8.472	6.241	6.780	6.462	6.746
Fuzzy	8.432	5.235	7.013	14.541	17.353
ANN	8.672	5.870	29.16	10.068	15.363
ANN-INC	1.074	2.07	0.872	0.987	0.639
Mean relative error (MRE)					
P&O	0.0052	0.0215	0.0488	0.0698	0.0983
INC	0.0072	0.0251	0.0421	0.0727	0.1233
Fuzzy	0.0128	0.0237	0.0468	0.2577	0.6055
ANN	0.0204	0.0250	0.2919	0.1179	0.3599
ANN-INC	0.0024	0.0205	0.0421	0.0755	0.0865
Mean absolute percentage error *(MAPE)*					
P&O	0.518	2.171	4.932	6.941	9.873
INC	0.709	2.721	4.379	7.431	12.412
Fuzzy	1.291	2.465	4.731	23.131	52.420

(*Contd.*)

Table 3 — Comparison under robustness test in different states (*Contd.*)

MPPT technique	State 1	State 2	State 3	state 4	State 5
	0-0.2sec	0.2-0.4sec	0.4-0.6sec	0.6-0.8sec	0.8-1sec
ANN-INC	0.238	2.010	0.087	2.109	1.052
Tracking efficiency (%)					
P&O	99.48	97.85	95.11	93.01	90.10
INC	99.28	97.5	95.71	92.7	87.62
Fuzzy	98.72	97.65	95.31	74.22	39.47
ANN	97.96	97.5	70.80	88.16	64.06
ANN-INC	99.76	97.95	96.31	94.42	91.34

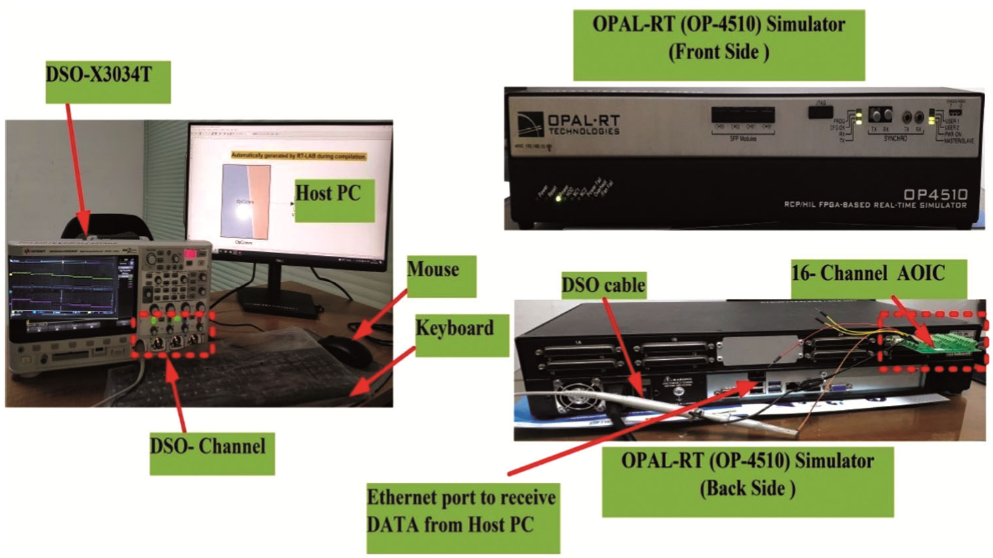

Fig. 33 — Experimental design for validation of the proposed ANN-INC technique

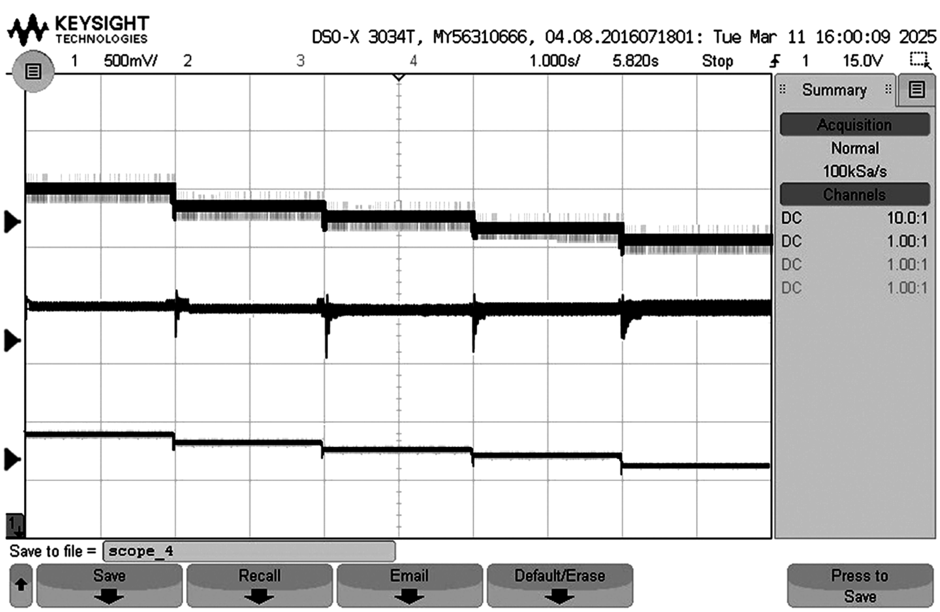

Fig. 34 — Experimental output result of ANN-INC MPPT under varying both temperature and irradiance

6 Conclusions

The application of Hybrid ANN-INC algorithm for MPPT in PV scheme represents a significant advancement in the field, offering the potential to greatly enhance tracking efficiency and energy extraction under varying environmental conditions. By combining the precision of the Incremental Conductance algorithm with the adaptive learning capability of ANN, the hybrid method achieves faster convergence to the maximum power point, reduces oscillations, and improves performance under different atmospheric conditions. This innovative approach effectively ad-dresses the limitations of conventional MPPT methods, emphasizing the practical advantages of incorporating intelligent control strategies in solar energy systems. The proposed MPPT technique achieves close to 99% efficiency in tracking the maximum power point, even under cloudy and real-world weather conditions, with minimal current and voltage ripple compared to four other methods. While there is a slight decline in performance during heavily overcast periods, the efficiency quickly rebounds to near-optimal levels as conditions improve. Additionally, simulation outcomes and comparative studies highlight the effectiveness of the hybrid method, showing its capability to closely match theoretical power output and sustain high efficiency across diverse irradiance levels. At 1000 W/m² and 25 °C, ANN-INC achieves the highest efficiency (99.8%), outperforming P&O (99.5%) and INC (99.6%), while ANN and Fuzzy methods have slightly at 98.0% and 98.7%. This pattern persists across different condition of solar irradiance and temperature levels, with ANN-INC can achieve high efficiency of 97.9% at 800 W/m² and 30 °C and also highest efficiency of 95.9% among others at 600 W/m² and 35 °C. At other different conditions of low solar irradiance (400 W/m² and 200 W/m²) and high temperature (40 °C and 45 °C), ANN-INC sustains its superiority with efficiencies of 93.4% and 90.8% respectively as compared with Fuzzy Logic (91.3% and 87.6%) , ANN(90.1% and 83.8%), P&O (93.2% and 86.8%), INC (91.4% and 83.6%). The tracking time to achieve MPP in all cases for proposed ANN-INC MPPT algorithm is very less compare to other four methods and it varies between 4ms to 8ms respectively. The robustness evaluation demonstrates that the ANN-INC MPPT controller can effectively handle unexpected disturbances. The controller's performance was further verified in real-time using the OP4510 simulator in a laboratory setup. The experimental findings closely matched the simulation results, confirming both the accuracy and practical feasibility of the proposed method. The integration of ANN and INC in the proposed Hybrid ANN-INC MPPT system offers a systematic and adaptive approach to optimizing solar PV performance. This not only showcases the potential to revolutionize MPPT techniques but also highlights its significant contribution to the efficient utilization of solar energy resources. The Hybrid ANN-INC MPPT system sets a new standard for tracking efficiency and energy extraction in PV systems, paving the way for enhanced performance and reliability in solar energy generation.

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