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MPPT controllers for 100 KW photovoltaic station

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Abstract:

Extracting peak power from solar panels requires reliable tracking systems. Therefore, a photovoltaic system was built using MATLAB/Simulink software and tested under various control strategies. The main objective was to compare the performance of a fuzzy logic controller (FLC) with that of a standard perturbation and observation (P&O) algorithm. The test conditions were simplified by applying a gradual increase in solar irradiance and conducting tests at several fixed temperature points. The FLC easily outperformed the P&O method at the peak power point with an efficiency of 99.3%. At the end of the work, a genetic algorithm (GA) was used to automatically fine-tune the FLC. The optimization gains were constrained primarily by the computational limitations of the simulation hardware; executing the GA to achieve higher optimization margins would require significantly more processing time and higher-performance workstations to prevent system saturation.

Keywords: Photovoltaic systems, maximum power point tracking MPPT, fuzzy logic control FLC, perturbation and observation algorithm P&O, genetic algorithm GA.

Résumé :

L'extraction de la puissance maximale des panneaux solaires exige des systèmes de suivi fiables. Un système photovoltaïque a donc été conçu à l'aide du logiciel MATLAB/Simulink et testé selon différentes stratégies de contrôle. L'objectif principal était de comparer les performances d'un contrôleur à logique floue (FLC) à celles d'un algorithme standard de perturbation et d'observation (P&O). Les conditions de test ont été simplifiées par une augmentation progressive de l'irradiance solaire et des tests effectués à plusieurs températures fixes. Le FLC a largement surpassé la méthode P&O au point de puissance maximale, avec une efficacité de 99,3 %. En fin d'étude, un algorithme génétique (AG) a été utilisé pour optimiser automatiquement le FLC. Les gains d'optimisation ont été limités principalement par les capacités de calcul de l'ordinateur utilisé ; l'exécution de l'AG pour obtenir des marges d'optimisation plus élevées nécessiterait beaucoup plus de temps de traitement et des stations de travail plus puissantes pour éviter la saturation du système.

Mots-clés : Systèmes photovoltaïques, MPPT, contrôle à logique floue, perturbation et observation, algorithme génétique.

المخلص:

يتطلب استخلاص ذروة الطاقة من الألواح الشمسية أنظمة تتبع موثوقة. لذلك، تم بناء نظام كهروضوئي باستخدام برنامج MATLAB/Simulink، وتم اختباره في ظل استراتيجيات تحكم مختلفة. كان الهدف الرئيسي هو مقارنة أداء وحدة التحكم المنطقية الضبابية (FLC) بخوارزمية الاضطراب والملاحظة (P&O) القياسية. تم تبسيط ظروف الاختبار، حيث تم تطبيق زيادة تدريجية في الإشعاع الشمسي وإجراء اختبارات عند عدة نقاط حرارية ثابتة. تفوقت وحدة التحكم المنطقية الضبابية (FLC) بسهولة على طريقة الاضطراب والملاحظة (P&O) عند نقطة الطاقة القصوى بكفاءة عالية بلغت 99.3%. في نهاية العمل، تم استخدام خوارزمية جينية (GA) لضبط وحدة التحكم الضبابية تلقائياً. كانت مكاسب التحسين محدودة في المقام الأول بسبب قيود قدرة المعالجة لجهاز الكمبيوتر المستخدم؛ حيث كان تنفيذ الخوارزمية الجينية لتحقيق هوامش تحسين أعلى يتطلب وقتاً أطول بكثير ومحطات عمل بمواصفات أقوى لتفادي بطء أو تشبع النظام.

الكلمات المفتاحية: الأنظمة الكهروضوئية، تتبع نقطة الاستطاعة القصوى (MPPT)، التحكم بالمنطق الضبابي (FLC)، الاضطراب والمراقبة (P&O)، الخوارزمية الجينية (GA)، التغير التدريجي للإشعاع.

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List of abbreviations and symbols

AC/DC	Alternating/ direct current
ANN	Artificial neural networks
CSP	Concentrated solar power
CV	Constant voltage
DSP	Digital signal processors
FLC	Fuzzy logic controller
G	Incident solar irradiance (W/m^2)
GA	Genetic algorithms
GMPP	Global maximum power point
Gref	The reference irradiance at standard test conditions (1000 W/m^2)
HC	Hill climbing
I0	Diode saturation current (A)
Imp	Current at the maximum power point
InC	Incremental conductance
Iph	Photocurrent (A)
Ipv	PV output current (A)
ISC	Short-circuit current (A)
Isc,ref	Short-circuit current at reference conditions
K	Boltzmann's constant (J/K)
Ki	The temperature coefficient of short-circuit current (positive for silicon modules)
Kv	Temperature coefficient of open-circuit voltage (negative for silicon modules)
MPP	Maximum power point
MPPT	Maximum power point tracking
NOCT	Under nominal operating cell temperature
OCV	Open circuit voltage
P&O	Perturb and Observe
Pmax	Maximum power
PSO	Particle Swarm Optimization

PV	Photovoltaic
PWM	Pulse-width modulation
R_s	Series resistance (Ω)
R_{sh}	Shunt resistance (Ω)
SCC	Short circuit current
SDM	Single diode model
STC	Standard test conditions
T_{pv}	Cell temperature (Kelvin)
T_{ref}	Reference temperature 25°C at standard test conditions
V_{mp}	Voltage at the maximum power point
V_{MP}	Optimal voltage
VOC	Open-circuit voltage (V)
V_{pv}	PV output voltage (V)
V_t	Thermal voltage (V)
q	The electron charge (C)
n	Diode ideality factor

General Introduction

General Introduction

To get the optimal function of clean energy, the world needs to use photovoltaic systems to replace fossil fuels. But the big problem is the weather change, and the electrical characteristics of photovoltaic cells exhibit a highly non-linear behavior, so the output power changes fast with irradiance and temperature. To force optimal function in all conditions, the designed apparatus is made up of a DC-DC converter controlled by an MPPT command (maximum power point tracking).

This work aims to study a high-capacity 100 KW solar power plant. This plant consists of a photovoltaic array made up of 47 parallel strings, each string containing 10 PV panels connected in series. In practice, the maximum power point is only achieved under standard test conditions (STC) with a solar irradiance of 1000 W/m^2 and an ambient temperature of 25°C . However, due to varying weather conditions throughout the day, an MPPT controller connected to a DC-DC step-up converter was used to maximize the power output of the solar panels and deliver it to the load.

In the industrial site, engineers use the Perturbation and Observation (P&O) algorithm because it is easy to program. In large-scale systems of 100 kW, if the turbulence step is small, the dynamic tracking speed is very slow when solar radiation changes, and if it is large, it results in large steady-state oscillations around the peak. This vibration leads to a loss of system equipment efficiency and wasted energy.

To overcome these critical limitations, intelligent methods have been used to track the maximum power point, including fuzzy logic control and a combination of fuzzy logic control and genetic algorithms. These intelligent methods do not require precise mathematical equations.

This work treats three chapters:

Chapter 1 includes the mathematical modeling of a photovoltaic panel using a single-diode model. Photovoltaic panel characteristic curves were obtained under standard conditions using MATLAB/Simulink software. The influence of various environmental conditions, such as solar irradiance and ambient temperature, on these curves is also highlighted.

Chapter 2 reviews traditional methods for Maximum Power Point Tracking (MPPT) of photovoltaic systems, using the Perturbation and Observation (P&O) algorithm of a 100 KW solar power plant as an example.

Chapter 3 explores intelligent methods for MPPT for photovoltaic systems. Fuzzy logic-based MPPT, as well as a combination of fuzzy logic and a genetic algorithm, was used to track the MPPT of a 100 KW solar power plant.

This work ends with a general conclusion that summarizes the results obtained.

Chapter I: Modeling and analysis of the photovoltaic system

I.1 Introduction:

The world needs to eliminate carbon emissions; therefore, the focus is on renewable energy. Solar energy is one of the most important of these, as it is considered an ideal source of clean and environmentally friendly energy. It can be directly converted into electricity using solar cells.

This chapter highlights the fundamentals of solar energy technology and the main components of a photovoltaic (PV) system, starting with the PV array, then the power conditioning unit, and finally the peak power point tracking (PPT) controller. Due to its simplicity, a single-diode model was used to plot the characteristic curves of the PV array.

I.2 Renewable energy:

Renewable energy is energy that comes from natural sources such as sunlight and wind. Renewable energy sources are plentiful and all around us. In contrast, fossil fuels (such as coal, oil, and gas) are non-renewable resources that take hundreds of millions of years to produce. Using fossil fuels to produce energy yields harmful greenhouse gas emissions, such as carbon dioxide.

Countries are striving to reduce their reliance on traditional fossil fuel power plants to minimize their environmental impact. They are also working to utilize environmentally friendly energy sources, such as solar, wind, hydroelectric, and geothermal power [1]. However, these renewable energy systems (such as solar panels or wind turbines) cannot be installed anywhere. Each location has its own specific climatic conditions [2]. The efficiency of renewable energy systems varies depending on the climatic conditions of the region where they are located. Therefore, a thorough site study is necessary before selecting the most suitable system [3].

I.3 Types of renewable energy:

Since renewable energy is derived from the natural world, there are five main categories of renewable energy sources, namely solar, hydroelectric, wind, and geothermal (see Table I.1). The choice of system to be used for generating energy depends on the surrounding environmental factors; therefore, an environmental analysis of the location is necessary [4].

Table I.1. Types of renewable energy.

Energy Type	Definition
• Solar Energy	Solar energy is clean radiation from the sun. This radiation is converted into electricity or heat using special technologies. Photovoltaic cells are used to generate electricity directly. While concentrated solar power and solar thermal power technologies use sunlight to produce heat that can be used to generate electricity or for heating purposes. Immense amounts of solar radiation reach the Earth, covering global energy demand and even exceeding it. This energy is clean and environmentally friendly, making it an important resource for sustainable development [4]
• Wind Energy	Wind turbines are used to transform the kinetic energy of moving air into electrical power. Wind speed, air properties, and turbine design are the main factors that determine how much energy can be extracted from wind. Energy storage systems can be connected with modern onshore and offshore wind power systems to enhance grid stability and reliability. These systems are commonly employed for sustainable electricity generation [5].
• Hydropower	Through the use of turbines, hydropower transforms the energy of flowing or stored water into mechanical energy, which is subsequently converted into electrical energy by generators. In addition to supporting water management operations, it consists of technologies like run-of-river, reservoir-based, and pumped storage that offer dependable and adaptable renewable energy [6].
• Geothermal Energy	The heat stored underground can be accessed through wells that utilize hot rocks, water, or steam reservoirs. This thermal energy is used to generate electricity via heat engines or for direct heating applications [7].

I.4. Architecture of a photovoltaic power generation system:

The architecture of a photovoltaic power generation system consists of several stages designed to harvest solar energy and convert it into high-quality electrical power (see figure I.1). To ensure efficiency and reliability, the photovoltaic system integrates several hardware components and control units, including the PV array, power conditioning unit (DC-DC converter), maximum power point tracking (MPPT) controller, energy storage system, and the load.

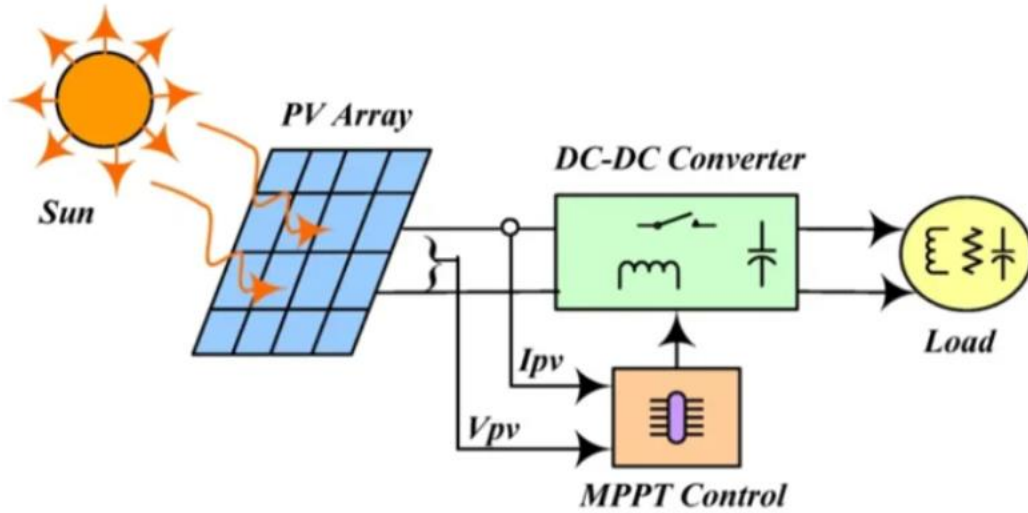


Figure I.1. Architecture of a photovoltaic power generation system [8].

I.4.1 PV array:

The PV array is the primary energy source of the photovoltaic system. It consists of multiple solar cells that convert photons from solar radiation directly into DC electricity through the photovoltaic effect. Since the output of a single cell is limited, cells are connected in series and parallel to form panels and arrays that meet the required voltage and power levels for specific applications. The performance of the array is highly dependent on environmental factors such as solar irradiance, ambient temperature, and panel orientation [8-9].

I.4.2 Power conditioning unit (DC-DC converter):

The voltage at the output of the PV panels jumps up and down all the time during the day. For this reason, a DC-DC converter has been used. It connects the PV array directly to the load or storage system. This essential component converts this fluctuating voltage to a stable DC current. In

addition, high-efficiency converters must be selected for this purpose. This selection is crucial because it prevents power loss during the conversion process [8].

I.4.3 Maximum power point tracking (MPPT) controller:

The characteristic power-voltage curve of any PV array is non-linear and has a specific operating point corresponding to the maximum power output, depending on weather conditions [8]. For this reason, a Maximum Power Point Tracking (MPPT) controller is used in photovoltaic systems. This controller acts as an intelligent component of the system and is typically integrated into a microcontroller. The MPPT controller runs specialized algorithms to track this optimal point. As the weather changes, the maximum power point transferred from the array to the load is changed. Therefore, the MPPT controller tracks this point continuously. This allows the maximum power to be extracted from the photovoltaic array even with fluctuations in solar irradiance or temperature [9].

I.4.4 Energy storage system:

Solar energy fluctuates constantly depending on weather conditions. For example, cloud cover over a photovoltaic array can reduce its output by up to 70% in a single second. Therefore, an energy storage system must be integrated into the PV system. Battery storage units are typically incorporated into this system to ensure continuous operation. These units store excess energy when the PV array reaches its peak output and then release this energy when solar irradiance decreases or disappears completely at night. Ultimately, this simple system achieves a balance between supply and demand [9, 10].

I.4.5 The load:

In a photovoltaic solar power system, a load is used to consume electrical energy. Depending on the system design, a direct current (DC) load can be operated directly, or an inverter can be used to supply an alternating current to the AC load. Currently, modern systems utilize a central controller to manage the entire system. This approach optimizes energy consumption and protects the battery system. Moreover, this intelligent control extends the lifespan of the storage system [9].

I.5 Electrical modeling of the photovoltaic module:

To predict exactly the performance of the PV array under different atmospheric conditions, its equivalent circuit must be used to plot its current-voltage curve and determine its key efficiency parameters. There are three commonly used equivalent circuit models for photovoltaic array: the single-diode model, the two-diode model, and the three-diode model.

The single-diode model is widely used due to its simplicity and accuracy. In this work, the single-diode model shown in Figure I.2 was used to obtain the electrical parameters of the photovoltaic cell array.

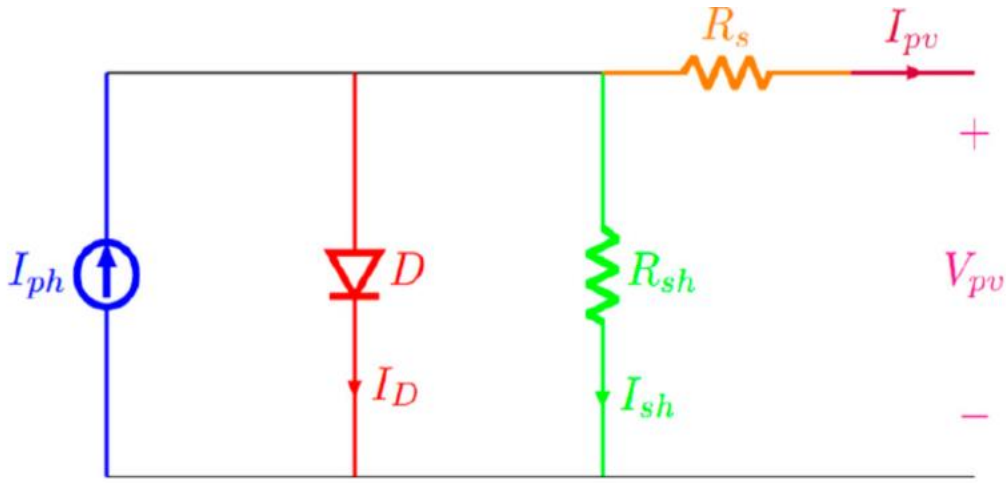


Figure I.2. The equivalent circuit of a PV cell based on the single-diode model [11].

A photocurrent source I_{ph} coupled in parallel to a diode D and a switching resistor R_{sh} makes up the analogous circuit. A conduction resistor R_s is connected in series with these three parts. The photocurrent I_{ph} is dependent on the cell temperature and is directly proportional to the incident of solar irradiation. The diode has an idealization coefficient n , a saturation current I_0 , and P-N junction characteristics. Leakage currents over the P-N junction are represented by the switching resistor R_{sh} , while internal losses resulting from contact resistance and semiconductor material resistance are represented by the conduction resistor R_s [11].

Applying the Kirchhoff's current law to the equivalent circuit yields the output current of the PV array as given by the following equation:

$$I = I_{ph} - I_D - I_{sh} \quad (I.1)$$

The diode current I_D and the shunt current I_{sh} can be calculated using the equations (I.2) and (I.3), respectively [11].

$$I_D = I_0 \left[\exp \left(\frac{V_{pv} + I_{pv} R_s}{n \times V_t} \right) - 1 \right] \quad (I.2)$$

$$I_{sh} = \frac{V_{pv} + I_{pv} R_s}{R_{sh}} \quad (I.3)$$

Replacing the equations (1.2) and (1.3) into equation (1.1) results in the complete current-voltage characteristic equation for the single-diode model of the PV array, as given by the following equation.

$$I_{pv} = I_{ph} - I_0 \left(e^{\frac{V_{pv} + R_s I_{pv}}{n \times V_t}} - 1 \right) - \frac{V_{pv} + I_{pv} R_s}{R_{sh}} \quad (I.4)$$

The thermal voltage V_t can be obtained using the following equation [11]:

$$V_t = \frac{k \times T_{pv}}{q} \quad (I.5)$$

I.5.1 Electrical parameters of the PV model:

The single-diode model has five unknown parameters, namely, I_{ph} , I_0 , n , R_s , and R_{sh} . These parameters cannot be found in the manufacturer's data of the PV panel, and they must be extracted to accurately model its behavior [11]. These unknown parameters can be obtained using the data provided in the PV panel's datasheet, such as the short-circuit point ($V = 0$, $I = I_{sc}$), the open-circuit point ($V = V_{oc}$, $I = 0$), and the maximum power point ($V = V_m$, $I = I_m$). Additionally, the slope conditions at these points provide the necessary limit conditions [11].

The ideality factor n can be expressed in terms of the resistances R_s and R_{sh} using the following equation derived from the maximum power point condition [11]:

$$n = \frac{V_m + R_s \times (I_m - I_{sc})}{V_t \times \ln k_1} \quad (I.6)$$

Where k_1 can be obtained using the following equation:

$$k_1 = \frac{R_{sh} - R_s}{R_s} \times \frac{I_m \times (R_{sh} + R_s) - V_m}{V_m - I_m \times R_s} \quad (I.7)$$

The reverse saturation current I_0 is derived from the short-circuit condition [11] as given by the following equation:

$$I_0 = \frac{R_s n V_t}{R_{sh} (R_{sh} - R_s)} \exp \left(-\frac{I_{sc} R_s}{n V_t} \right) \quad (I.8)$$

The photocurrent I_{ph} can be calculated using the following equation [11]:

$$I_{ph} = I_{sc} + [I_0 \left(\exp^{\frac{I_{sc}R_s}{nV_t}} - 1 \right)] + \frac{I_{sc}R_s}{R_{sh}} \quad (I.9)$$

This equation shows that the five unknown parameters are related. R_s and R_{sh} can be used to analytically express the photocurrent I_{ph} , as well as the diode parameters I_0 and n . since only R_s and R_{sh} need to be optimized to achieve an accurate match between the model and experimental data, this relationship reduces the complexity of the parameter determination problem from five dimensions to two dimensions [11].

I.6 Analysis of photovoltaic (PV) characteristics:

A photovoltaic array's non-linear output, which is strongly influenced by environmental factors, characterizes its electrical behavior. Analyzing the characteristic curves under standard test conditions (STC), which are specified by a sun irradiation of 1000 W/m^2 , an ambient temperature of 25°C , and an air mass of 1.5 AM, is crucial to establishing a theoretical baseline for the system's performance.

The data sheet for the 1Soltech 1STH-215-P polycrystalline photovoltaic panel used in the PV system for this work is presented in the following table.

Table I.2. Technical specifications of the 1Soltech 1STH-215-P module at STC [12].

Parameter	Symbol	Value	Unit
Maximum power point MPP	P_{max}	213.15	W
Voltage at MPP	V_{mp}	29.0	V
Current at MPP	I_{mp}	7.35	A
Open circuit voltage	V_{oc}	36.3	V
Short circuit current	I_{sc}	7.84	A
Number of PV cells	N_s	60	-

The Simulink of the MATLAB 2015A version was used to model and simulate the system under study in order to assess its dynamic behavior under various operating conditions. The Simulink model for the used PV system under STC conditions is shown in the following figure.

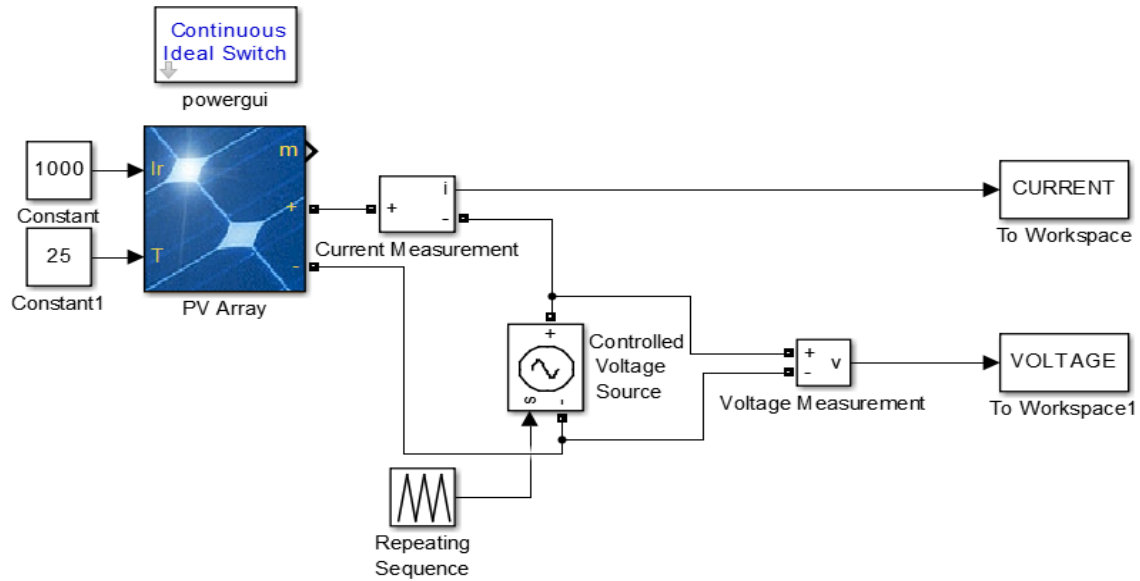


Figure I.3. Simulink model of the used PV system with 1Soltech 1STH-215-P PV panel.

I.6.1. Current–voltage (I–V) characteristics

Figure I.4 shows the current-voltage (I-V) curve of the PV panel used in the simulated system. Based on this figure, the output current of the used PV panel remains close to its short-circuit current (I_{sc}) at low voltages. However, its current begins to drop sharply as its output voltage rises to the "knee" region, eventually reaching zero at the PV panel's open-circuit voltage (V_{oc}).

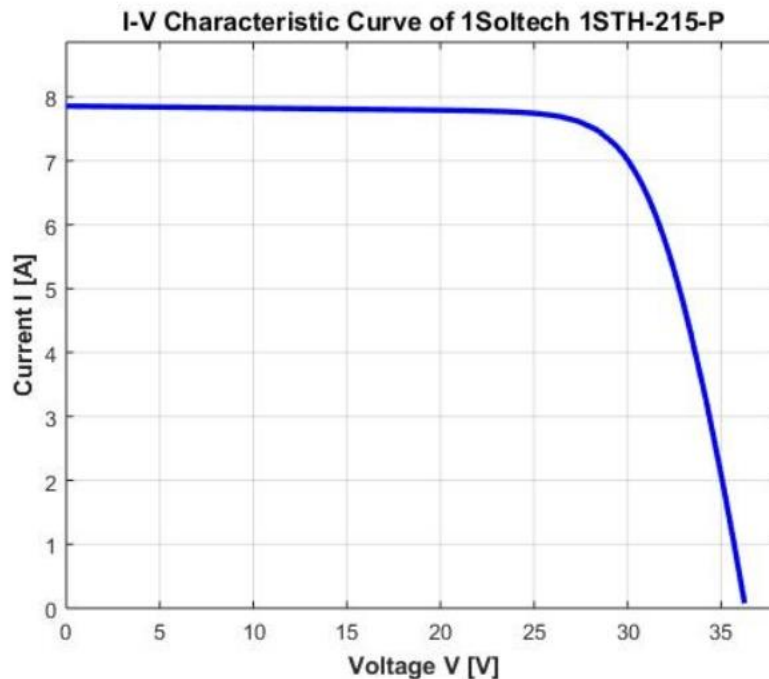


Figure I.4. Current-voltage curve of the 1Soltech 1STH-215-P module at STC conditions.

I.6.2. Power–voltage (P–V) characteristics

The power–voltage (P–V) curve is derived from the product of the PV panel's current and its voltage (that means $P = I \times V$). As shown in Figure I.5, the P-V curve shows a distinct peak where the generated power of the used PV panel is at its maximum point. This point occurs at the optimal voltage (V_{mp}), and any deviation from this value results in a loss of efficiency.

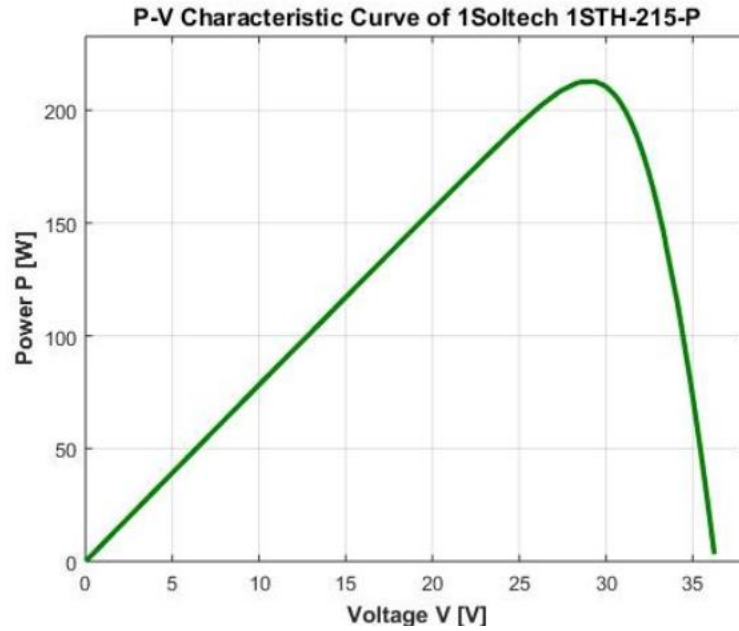


Figure I.5 P-V curve of the 1Soltech 1STH-215-P PV panel at STC conditions.

I.6.3. Electrical characteristics and MPP position

Figure I.6 shows the I-V and P-V characteristic curves of the used PV panel at STC conditions. This figure allows for the identification of the operating limits and the maximum power point. The vertical alignment of the Maximum Power Points (MPPs) across both the I-V and P-V characteristics confirms the optimal operating voltage (V_{mpp}) where the system extracts the maximum available energy, providing the necessary reference for the MPPT control logic.

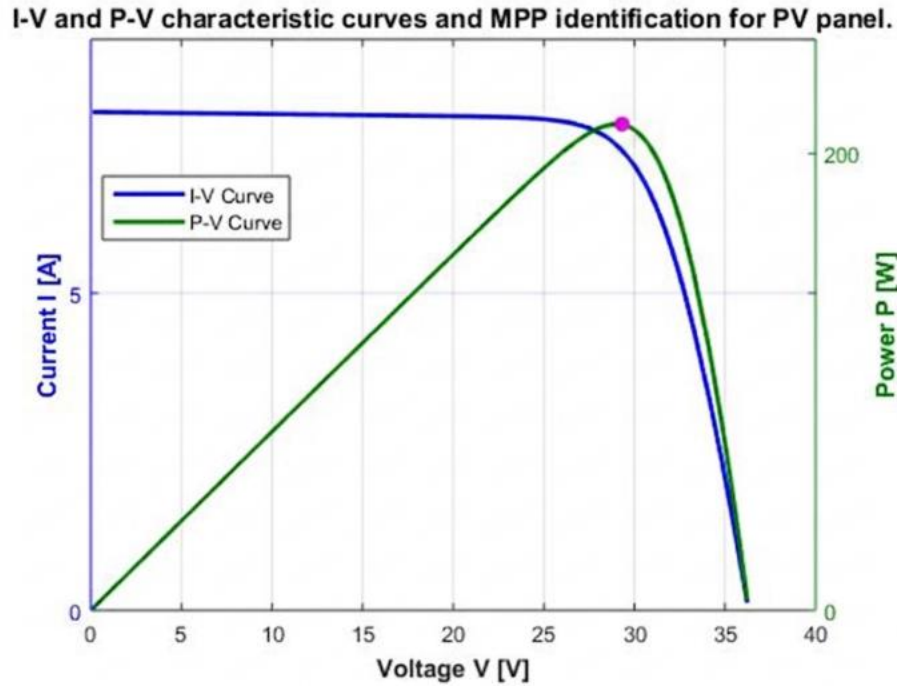


Figure I.6. I-V and P-V characteristic curves and MPP position for the used PV panel at STC conditions.

I.7 Influence of the environmental conditions on the PV panel's performance

The performance of photovoltaic panels depends on the weather conditions, such as the solar radiation and the ambient temperature. These environmental conditions directly alter the PV panel's electricity production, changing current and voltage, and affecting the overall efficiency of the PV system. Therefore, these changes have to be understood to build accurate models and design an optimal system.

In the next subsection, the effects of solar radiation and ambient temperature on the P-V and the I-V curves will be examined in detail.

I.7.1 Effect of the solar irradiance on the PV panel's performance

The photocurrent (I_{ph}) varies directly with the amount of sunlight falling on the PV panel. This occurs because the incident photons collide with the solar cell and generate electron-hole pairs. Therefore, when sunlight is intense, a greater current and a higher output power will be obtained [11].

The relationship between the photocurrent and the solar radiation is expressed by the following equation [11]:

$$I_{ph} = [I_{sc(ref)} + k_i(T - T_{ref})] \left(\frac{G}{G_{ref}} \right) \quad (I.10)$$

Figure I.7 shows the I-V and P-V characteristic curves for different levels of solar irradiance (1000, 800, and 600 W/m²). Based on these curves, a decrease in the solar radiation level leads to a proportional decrease in the output current of the PV panel, which significantly reduces the maximum power generated by the PV panel.

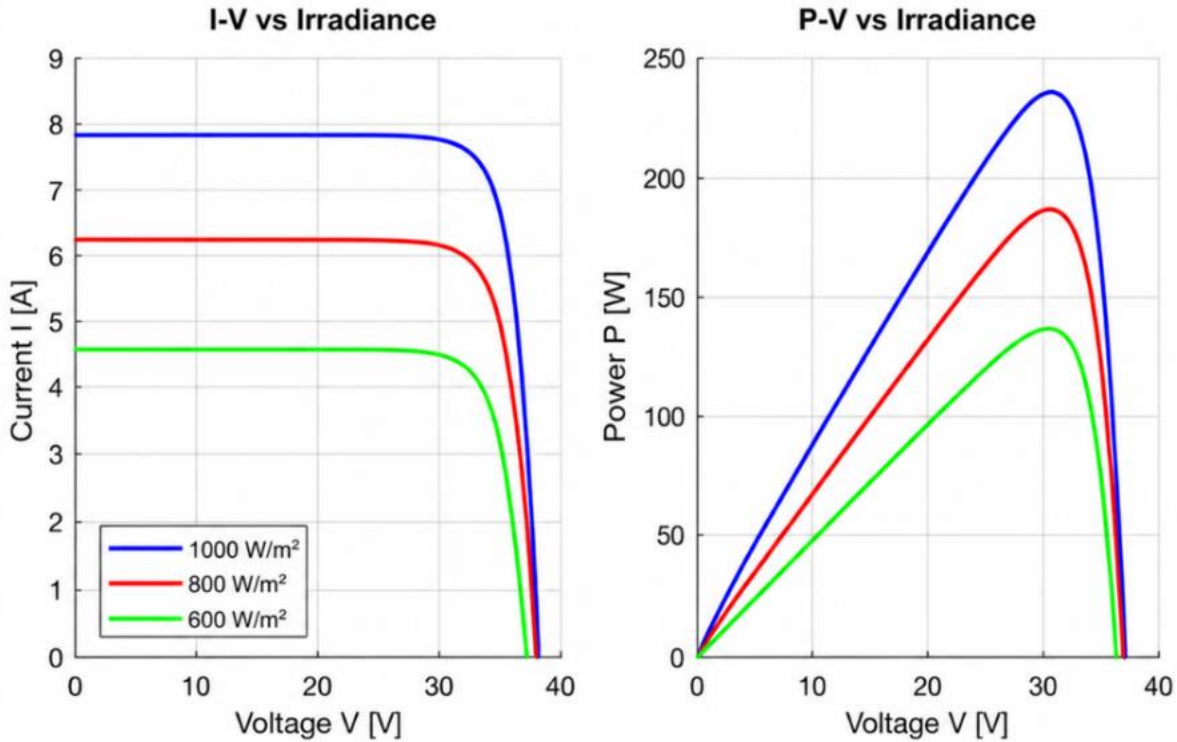


Figure I.7. I-V and P-V curves for the PV panel for different levels of solar irradiance.

As the solar irradiance increases, the short-circuit current of the PV panel I_{sc} increases linearly, while its open-circuit voltage V_{oc} increases logarithmically. Consequently, the PV panel's maximum power output P_{max} increases with higher solar irradiance levels [11].

I.7.2 Effect of the ambient temperature on the PV panel's performance

Ambient temperature significantly affects the electrical characteristics of the PV panels. Unlike solar radiation, temperature negatively impacts their performance [11].

The dependence of the PV panel's short circuit current and open circuit voltage on the ambient temperature can be given by the following equations [11].

$$I_{sc}(T) = I_{sc}(ref) \left[1 + \frac{k_i}{100} \times (T - T_{ref}) \right] \quad (I.11)$$

$$V_{oc}(T) = I_{scV_{oc}}(ref) \times \left[1 + \frac{k_v}{100} \times (T - T_{ref}) \right] \quad (I.12)$$

As the ambient temperature rises, the open-circuit voltage of the photovoltaic panel decreases due to increased charge carrier recombination and thermal excitation. Additionally, the short-circuit current increases slightly. Furthermore, the peak power point decreases, which is the dominant effect [11].

The effect of the ambient temperature on the PV panel's performance was evaluated at various ambient temperatures (25°C, 45°C, and 60°C). Figure I.8 shows that increasing the ambient temperature causes a notable drop in the PV panel's open-circuit voltage, leading to a degradation in the overall conversion efficiency.

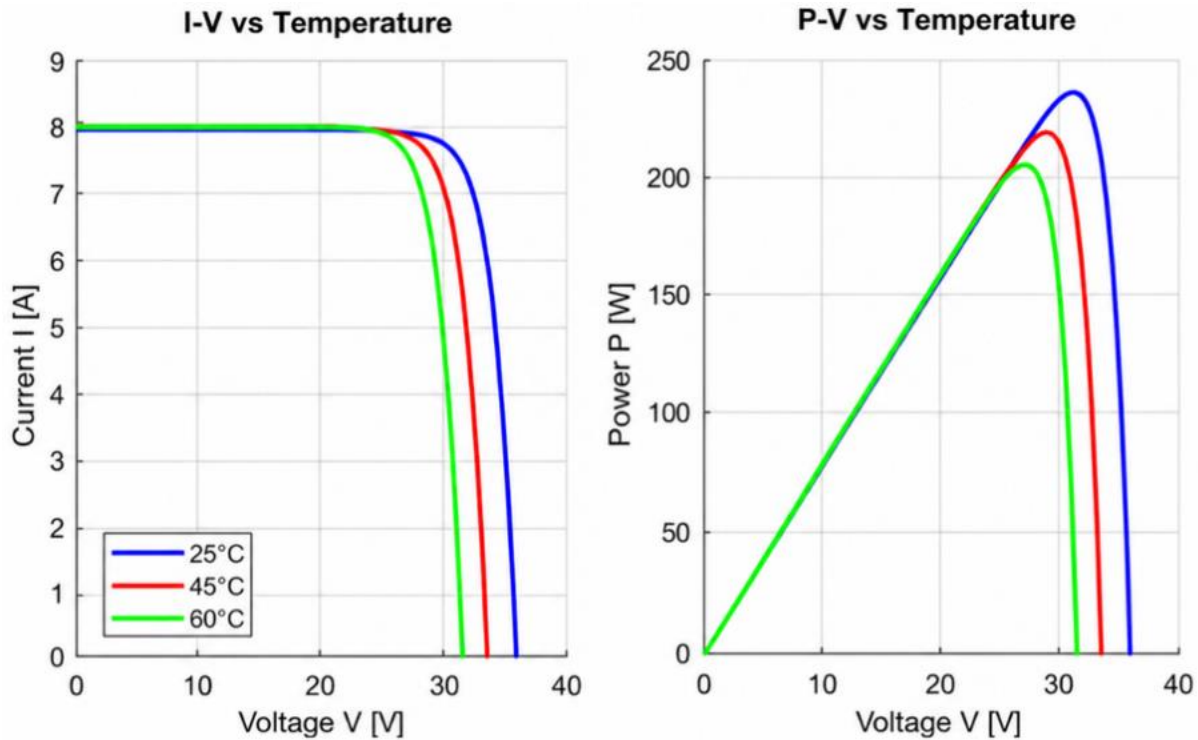


Figure I.8. I-V and P-V characteristic curves of the impact of temperature.

I.7.3 The combined effect of the solar radiation and the ambient temperature on the PV panel's performance

The interaction between irradiance and temperature determines the overall performance of a PV system under real-world operating conditions. The PV panel's maximum output power is given by the following equation:

$$P_{max} = V_{mp} \times I_{mp} \quad (I.13)$$

Under standard test conditions (STC), the PV panel achieves its rated maximum power point, which is given in its datasheet. Under nominal operating cell temperature conditions (that means $G = 800 \text{ W/m}^2$, $T = 20^\circ\text{C}$), the PV panel's output power point is lower than that given at STC due to reduced irradiance [11]. The series resistance R_s is generally stable under varying environmental conditions, while the shunt resistance R_{sh} shows greater sensitivity, particularly to temperature variations, which affects leakage currents in the PV panel [11].

I.7.4 Technical and electrical characteristics of the designed PV array (100 KW)

After analyzing the characteristics of a single PV panel, this section focuses on the used PV array for this study. It is composed of 470 PV panels known as '1Soltech 1STH-213-P.'. It is configured in a hybrid structure, where each 10 PV panels are connected in series to form a string, and then the 47 strings are connected in parallel to form the used PV array.

This specific configuration is designed to achieve a total nominal power of approximately 100 KW, which serves as the tracked power for testing and developing the control algorithms presented in the subsequent chapters.

This configuration was specifically designed to achieve a total nominal power of approximately 100 KW, which serves as a power tracked for testing and developing the control algorithms presented in later chapters.

Figure I.9 shows the current-voltage (I-V) and power-voltage (P-V) curves of a 100 KW photovoltaic array under standard test conditions (STC). Table I.3 summaries the obtained values of the used 100 KW PV array at STC. Based on these obtained results, the overall operating characteristics of the power station can be summarized as follows:

- **Maximum Power (P_{max}):** The curves show that the array reaches a maximum power of approximately 100180 W, confirming the accuracy of the chosen configuration.

- **Open Circuit Voltage (V_{oc}):** The total array voltage is 363 V. This value is the result of the series addition of the PV panel, providing a suitable input voltage for the DC-DC Boost Converter.
- **Short-Circuit Current (I_{sc}):** The total current reaches 368.5 A due to the 47 parallel strings, representing the primary input current of the system.

The characteristic curves shown above represent the ideal theoretical performance of the PV array. However, since the maximum power point indicated by the magenta circle in the plot fluctuates continuously with environmental changes, this model will serve as the primary reference for the deep study in the following chapter.

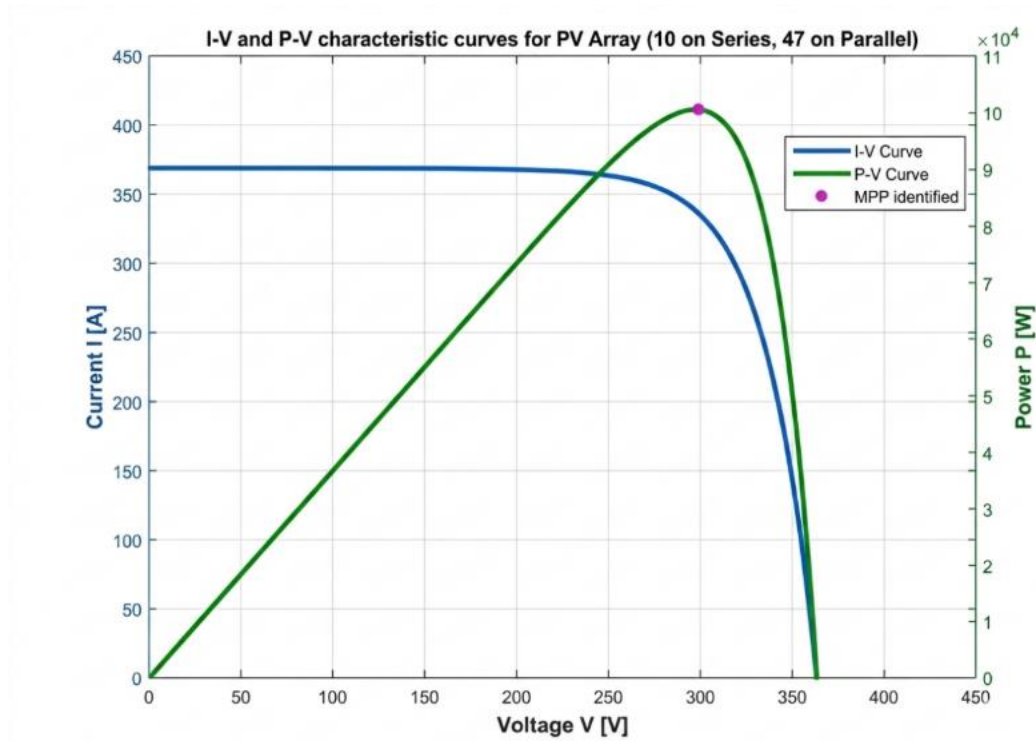


Figure I.9: I-V and P-V characteristic curves of the 100 KW PV Array at STC.

Table I.3.: Summary of the 100 KW PV Array Specifications

Parameter	Array Level Value
Maximum Power (P_{max})	100.18 KW
Voltage at P_{max} (V_{mp})	290 V
Current at P_{max} (I_{mp})	345.4 A
Open-Circuit Voltage (V_{oc})	363 V
Short-Circuit Current (I_{sc})	368.5 A

I.8 Conclusion

This chapter presents the theoretical framework and complete modeling of a 100 KW photovoltaic array. A single-diode model of the PV panel is used to determine its electrical behavior. In addition, its current-voltage and power-voltage curves were plotted and analyzed under standard test conditions. Furthermore, the impact of environmental variations on the PV panel's characteristic curves is highlighted. Moreover, the peak power point of the PV panel is examined due to its variability with weather conditions. In the next chapters, peak power point tracking algorithms will be employed to monitor these power peaks.

Chapter **II**:

Traditional methods for maximum power point tracking of photovoltaic system

II.1 Introduction

To ensure optimal power extraction from photovoltaic systems, Maximum Power Point Tracking (MPPT) works as a bridge. It connects the solar panels to the electrical load, usually through a DC-DC converter driven by a specific digital algorithm. Today, many new advanced or mixed control strategies can be found in research; however, traditional MPPT methods remain the primary choice for industrial and commercial projects. They are widely preferred because they offer an excellent balance: they are simple, do not require heavy calculations, and can be easily programmed into standard microcontrollers.

This chapter examines and analyzes classical MPPT methods. A brief overview of common standard algorithms, including the Incremental Conductance (InC) and Constant Voltage (CV) methods, is provided. In particular, the Perturb and Observe (P&O) method is analyzed in detail due to its widespread use and efficiency under stable atmospheric conditions. Finally, simulation models are built using MATLAB, where the controller is tested and evaluated under various atmospheric conditions.

II.2. Traditional MPPT algorithms for PV systems

Maximum Power Point Tracking (MPPT) is an essential control into photovoltaic systems to ensure the extraction of the maximum available power from the PV array. This is achieved by continuously tracking the Maximum Power Point (MPP) and adjusting the duty cycle of the DC-DC converter to match the load requirements under varying atmospheric conditions, such as solar irradiance and temperature [1].

To maintain optimal efficiency, various traditional algorithms have been developed, each differing in complexity, tracking speed, and hardware requirements. The following sections provide a detailed overview of the most prominent traditional MPPT algorithms.

II.2.1 The perturb and observe (P&O) algorithm for MPPT in PV system

To ensure every possible watt is extracted from solar panels, implementing a Maximum Power Point Tracking (MPPT) system is crucial in everyday engineering. The practical function of this method is to monitor the maximum power point (MPP) during operation. Then, by manually or automatically adjusting the DC-DC converter's duty cycle, the power output can be precisely tuned

to the load. This tracking remains effective even under sudden changes in atmospheric conditions, such as solar irradiance and ambient temperature [1]. Over the past few years, engineers have developed several traditional algorithms to maintain the efficiency of photovoltaic systems. These traditional methods differ significantly from other advanced approaches due to their complex design, fast tracking of peak power, or need for specific hardware chips to run software.

II.2.2 The incremental conductance (InC) algorithm for MPPT in PV system

The InC algorithm relies on a fundamental mathematical principle: at the peak power point, the power derivative of the photovoltaic array relative to its voltage drops to zero, i.e., $dP/dV = 0$. To determine this point, the controller continuously compares two different values: the current conductivity, given as I/V , and the differential conductivity, given as dI/dV . This allows the photovoltaic system to accurately determine whether it is operating at peak power or whether it is still to its left or right. Unlike the traditional P&O method, the InC approach can theoretically stabilize changes once the peak power point is reached. This stabilization step is crucial because it reduces unwanted vibrations and provides more stable performance when weather conditions change rapidly [1]. While older methods always focus on tracking slopes and power shifts, other engineering strategies attempt to simplify the entire process by directly modifying the control signal.

II.2.3 The hill climbing (HC) algorithm for MPPT in PV system

The hill climb algorithm is essentially similar to the P&O algorithm but differs in the parameter it modifies. Instead of modifying the photovoltaic panel voltage, this algorithm directly modifies the DC-DC converter's duty cycle. This direct control approach simplifies implementation in digital controllers and follows the same logic of increasing or decreasing the duty cycle based on power feedback to reach the peak of the power-voltage curve [1].

In contrast to these iterative search methods, some traditional strategies rely on fixed electrical characteristics of the PV cells for faster but less precise tracking.

II.2.4 The constant voltage (CV) and open-circuit voltage algorithms for MPPT in PV system

These methods rely on a simple operating principle: the peak voltage (V_{mpp}) is typically a fixed percentage, often between 70% and 80%, of the open-circuit voltage (V_{oc}). This constant voltage

setup is basic and requires very few sensors, keeping the overall cost very low. However, it suffers from a loss of tracking accuracy when ambient temperature changes significantly. It also forces the system to measure the photovoltaic panel's open-circuit voltage (V_{oc}) intermittently, causing slight power dips during these testing periods [1].

Short-circuit current (SCC) is similar to open-circuit voltage (OCV); these methods use a linear relationship between the maximum power point current (MPP) and the short-circuit current (i.e., $I_{mpp} = k \times I_{sc}$, where $k \approx 0.78\text{--}0.92$). It is a simple method but also requires timed short-circuit measurements [14].

Table II.1. Comparison of traditional MPPT Techniques [1].

MPPT Method	Cost	Complexity	Response Time	Efficiency
P&O	Low	Low	Slow	Moderate
InC	Moderate	Moderate	Varies	Moderate
CV	Low	Low	Slow	Low
HC	Low	Low	Medium	Moderate

For this work, the P&O method has been used to handle the MPPT task in the used solar installation. Engineers prefer this approach because it has a highly basic architecture, costs very little, and runs easily on real PV hardware. In practice, the code forces a tiny shift on the operating voltage, then checks the new power level. A positive step in power tells our system to maintain the exact same tracking path. Conversely, any drop in power forces the algorithm to switch its direction right away [1].

The PV array's output power can be calculated using the following equation:

$$P(k) = V(k) \times I(k) \quad (\text{II.1})$$

The change in the power of a photovoltaic array is determined by comparing its current power with its previous power, as given by the following equation :

$$\Delta P = P(k) - P(k - 1) \quad (\text{II.2})$$

The operating voltage of the photovoltaic array is updated according to the ΔP signal using the following equation:

$$V(k) = V(k - 1) \pm \Delta V \quad (II.3)$$

where ΔV indicates the size of our voltage perturbation. This formula is crucial because it sets the actual step we apply to the PV operating voltage. When a voltage shift boosts our power output, the controller maintains that exact tracking path. Therefore, when the power decreases, the system immediately changes the direction of the adjustment. This loop is left to operate continuously until the system reaches the peak of the power-voltage curve, where the slope decreases to almost zero [1].

Even though this P&O method creates minor vibrations around the MPP during steady weather, engineers still choose it over other techniques. Its main strengths are a highly straightforward design, decent efficiency, and minimal setup costs [1], [15].

II.3. Design and system implementation

This section describes the technical architecture of the 100 KW PV system and the implementation logic of the tracking controller within the MATLAB/Simulink environment.

The photovoltaic system was modeled to simulate a high-capacity 100 KW power plant. The array is composed of 1Soltech 1STH-215-P solar panels; its datasheet is given in Table II.2. To achieve the required power rating, the configuration consists of 10 PV panels connected in series per string and 47 strings connected in parallel, see Figure II.1.

This array is integrated with a DC-DC step-up transformer and a resistive load. Figure II.2 shows the overall simulation diagram illustrating the interrelationship between the photovoltaic array, the transformer, and the MPPT controller.

The control mechanism of the Maximum Power Point Tracking (MPPT) system relies entirely on the classic optimization and observation method. Instead of writing direct code, the actual control steps are presented using a clear flowchart, as shown in Figure II. 3. This flowchart accurately illustrates how the system makes decisions for updating the operating cycle. The algorithm operates in an infinite loop, checking power levels and changing voltage to reach the maximum power point.

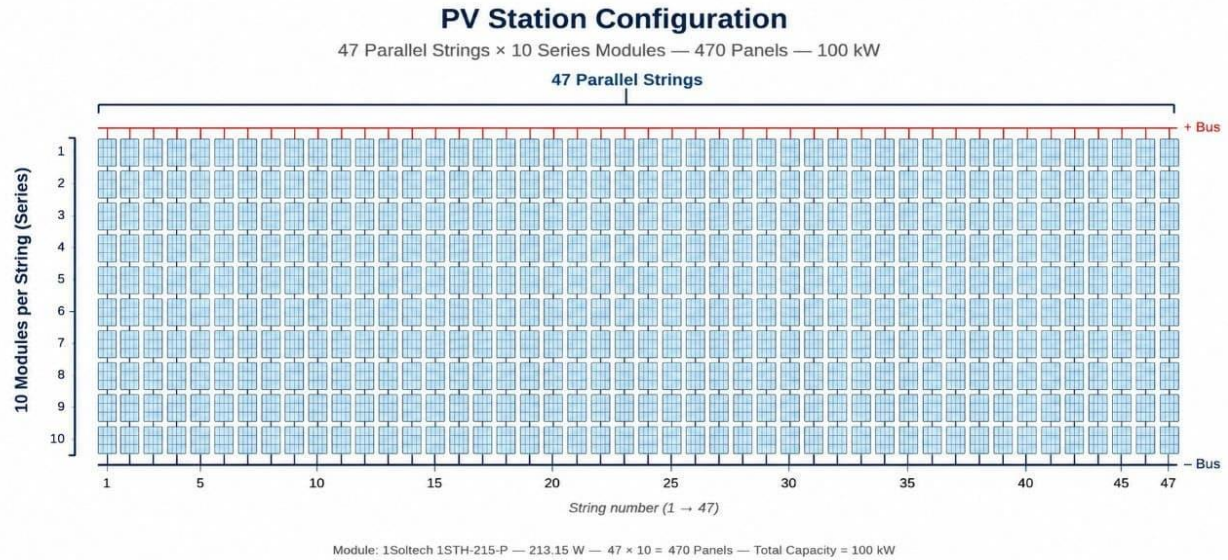


Figure II.1: PV Station Configuration

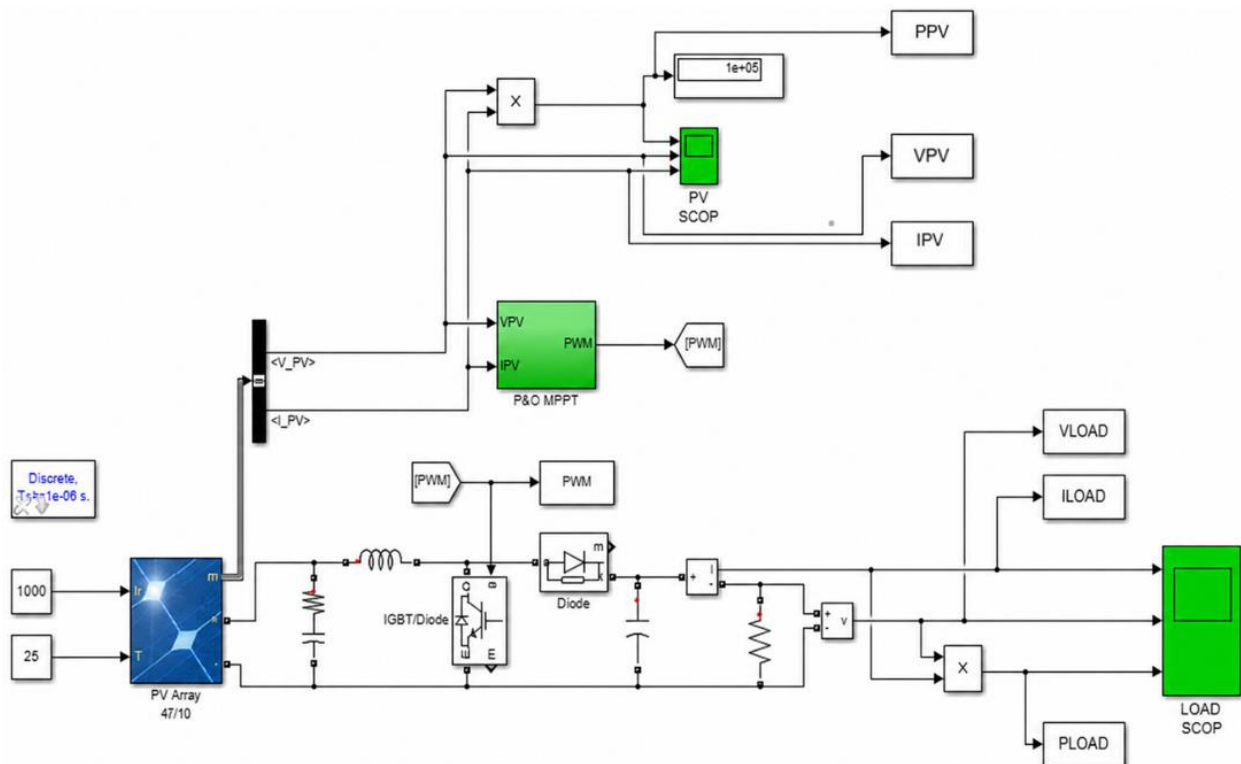


Figure II.2: MATLAB/Simulink model of the 100 KW PV system with P&O method

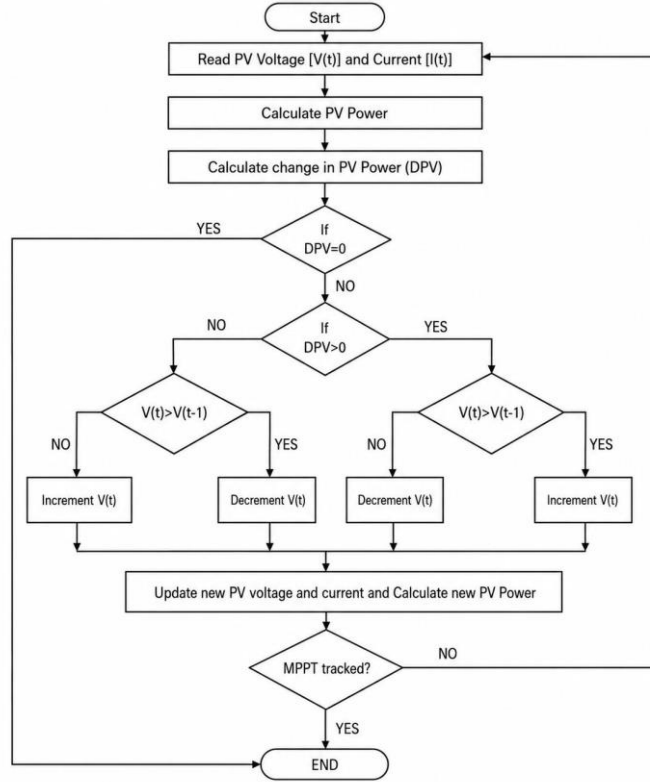


Figure II.3: Flowchart of the implemented Perturb and Observe (P&O) algorithm [1]

II.4. Simulation results and performance evaluation

This section presents the simulation results for a 100 KW photovoltaic array system. The analysis evaluates the performance of the P&O algorithm's tracking under various scenarios. The results are organized as follows:

1. **Control signals:** Analysis of the Duty Cycle and PWM.
2. **Electrical parameters:** Evaluation of Voltage and Current for both the PV array and the load.
3. **Power analysis:** Verification of the 100 KW power extraction and delivery.

II.4.1 Performance analysis under standard test conditions (STC)

The system is initially tested under standard test conditions (i.e., solar irradiance $G = 1000 \text{ W/m}^2$ and ambient temperature $T = 25^\circ\text{C}$). Figure II.3 shows the PWM control signal and the regulated duty cycle resulting from the P&O algorithm. Figure II.4 shows the voltage and current characteristics matrix for both the photovoltaic array and the load under P&O control. Figure II.5

shows the output power of the photovoltaic array (KW) and the load power consumption (KW) regulated by the P&O algorithm.

The simulation results are divided into three main graphs. Figure II.4 illustrates the high-frequency switching process and provides a detailed, magnified view of the steady-state operating cycle. Immediately afterward, the extent to which the array output matches the actual load requirements can be observed through the curves in Figure II.5. To complete the overview, Figure II.6 shows the array generating 100 KW of power along with the final power delivered directly to the load stage.

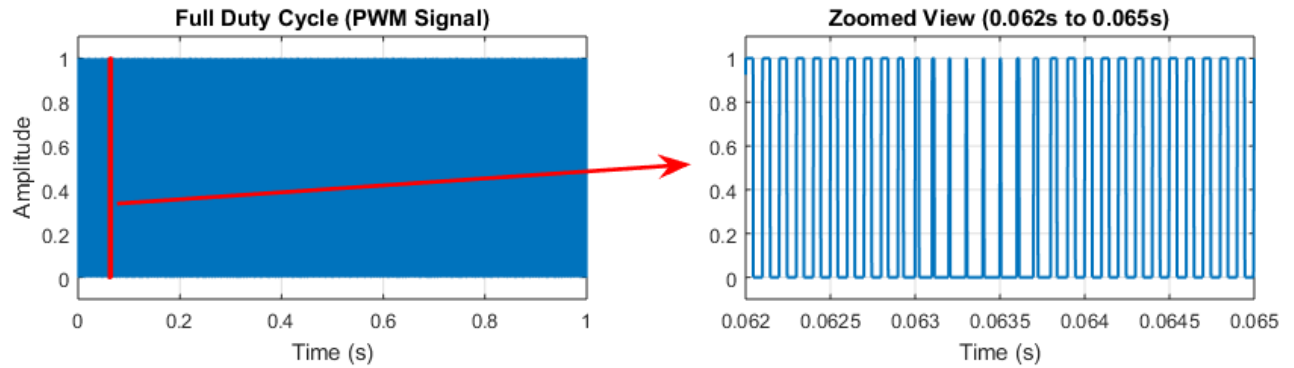


Figure II.4: PWM control signal and regulated duty cycle generated by the **P&O algorithm** under STC.

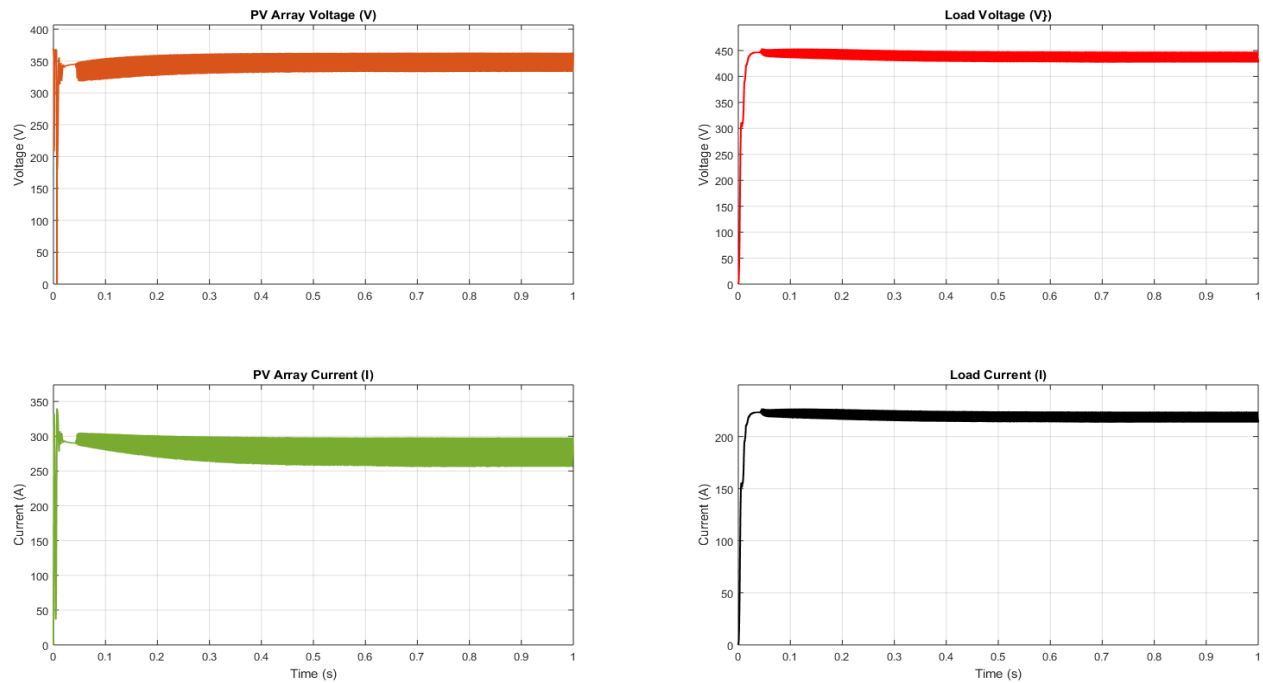


Figure II.5: Voltage and Current characteristics for both PV Array and Load under **P&O control** at STC.

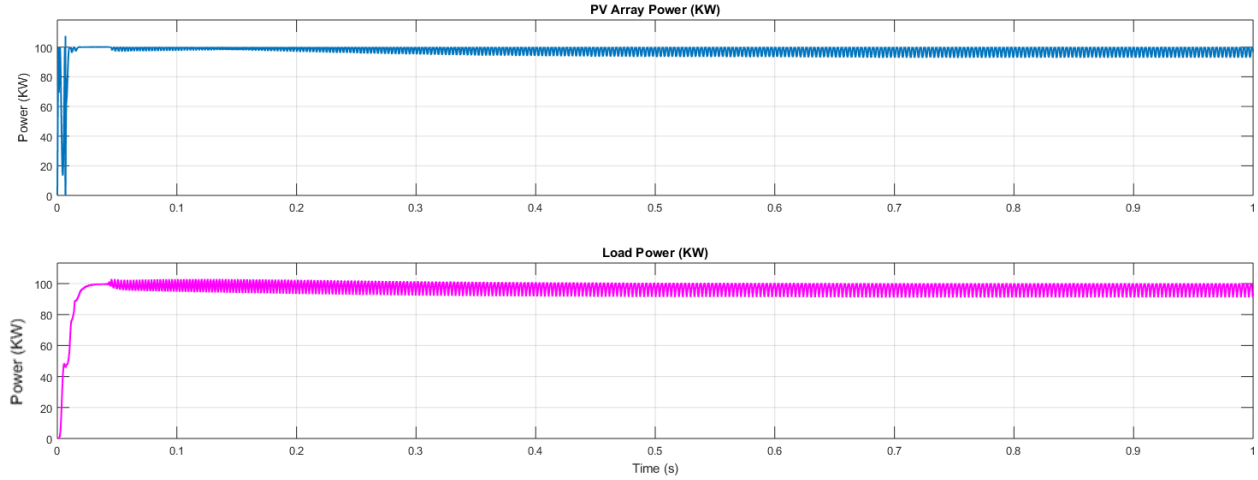


Figure II.6: PV Array output power (KW) and load power consumption (KW) regulated by the **P&O algorithm** at STC.

The driving signal displayed in **Figure II.4** reveals the rigid nature of this classic tracking approach. Once our algorithm reaches the peak power zone, the duty cycle locks into a nonstop square-wave vibration. This unsteady control choice directly destabilizes our electrical parameters, forcing continuous oscillations into the voltage and current waveforms shown in **Figure II.5**. Even though the system manages to reach the nominal 100 KW area in **Figure II.6**, this constant hunting by the duty cycle spreads into our power matrix, causing chronic efficiency drops at the load stage.

II.4.2 The effect of ambient temperature on a photovoltaic system

This subsection details the system's adaptation to thermal changes. Where, the system is tested for ambient temperature of 40 °C. Figure II.7 illustrates the duty cycle adjustment. Figure II.8 shows the resulting electrical parameters, and Figure II.9 displays the power levels, illustrating the impact of this temperature on the operating point as tracked by the P&O algorithm.

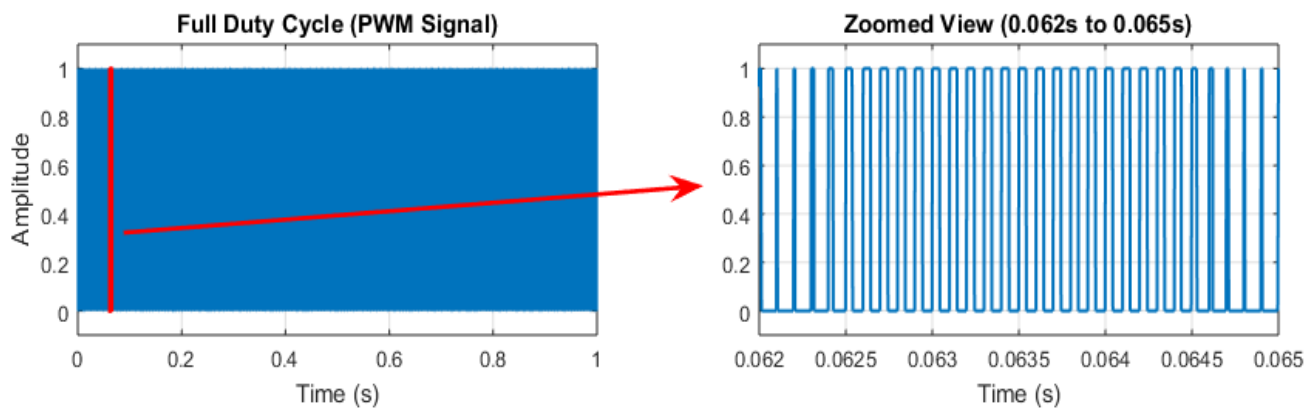


Figure II.7: PWM signal and Duty Cycle behavior for the **P&O algorithm** at $T = 40^{\circ}\text{C}$

Chapter II: Traditional maximum power point tracking for photovoltaic system

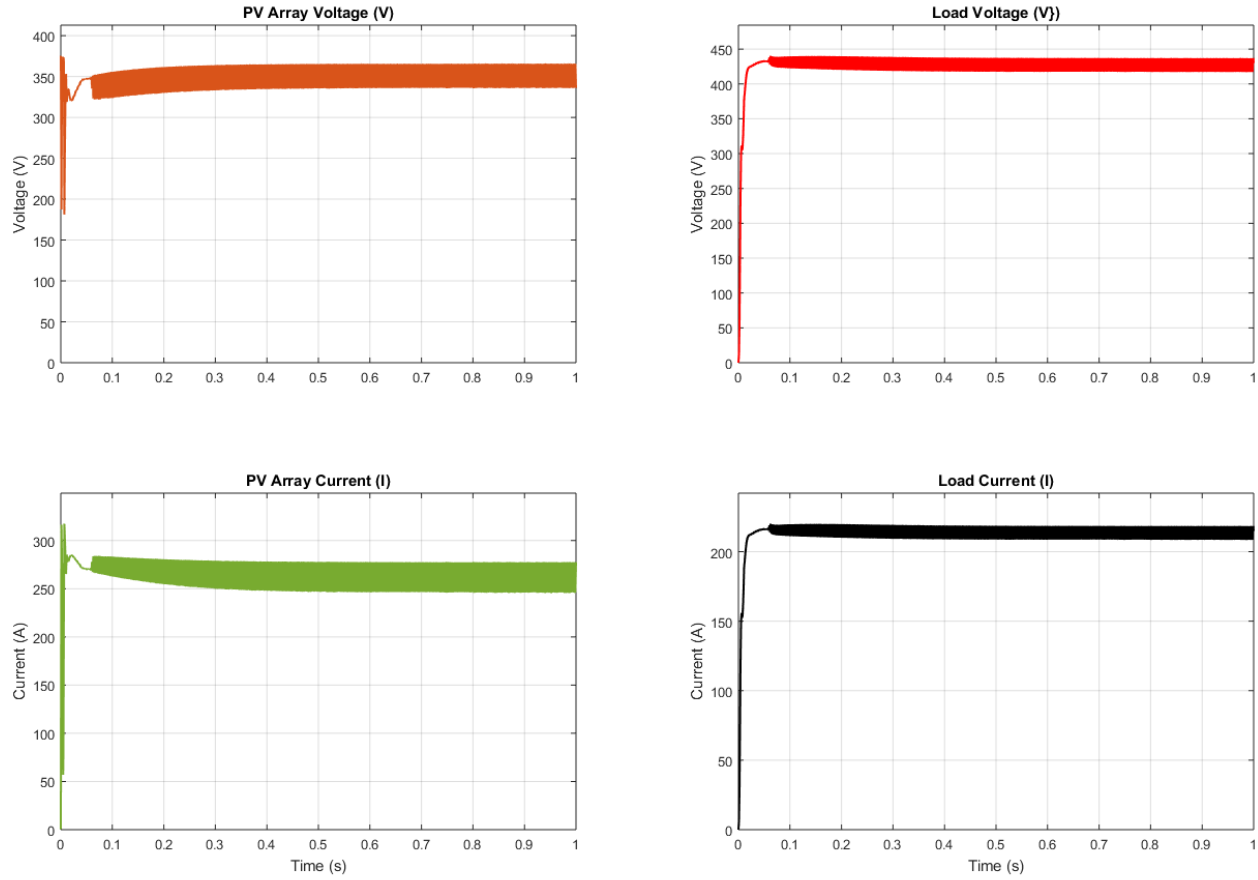


Figure II.8: Voltage and Current characteristics (V-I Matrix) for the PV Array and Load under **P&O control** at $T = 40^{\circ}\text{C}$.

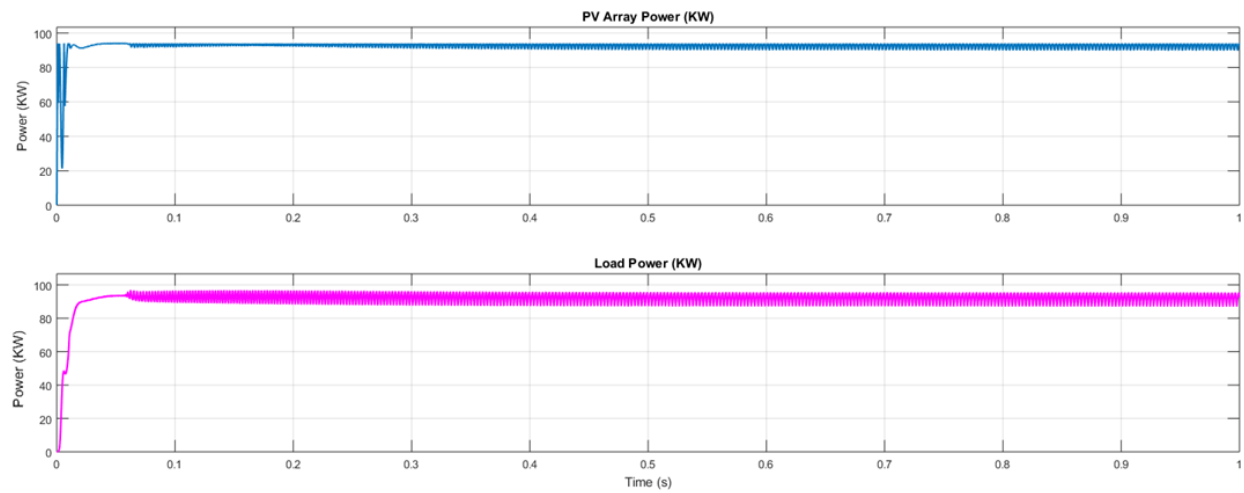


Figure II.9: Power profiles of the PV Array and the Load stage using the **P&O algorithm** at $T = 40^{\circ}\text{C}$.

Looking at the PWM control signal in Figure II.7, a clear shift in the baseline is observed compared to the baseline under standard conditions. This shift is due to the operating point being predetermined by the high temperature of photovoltaic cells. Operating under these high thermal conditions degrades the overall electrical output. Because of the physical properties of silicon, both the array voltage and current are initially lower in Figure II.8, keeping the peak power tracked in Figure II.9 within a lower range of 92–93 KW. Since the turbulence step size is constant, the PWM loop continues to oscillate significantly around this low peak without settling into a steady state. The following figures present the system behavior at 50°C. Figures II.10 and II.11 show the control and electrical adjustments, while Figure II.12 presents the power generation. Despite the high thermal stress, the P&O algorithm maintains the maximum possible output.

At a constant high temperature of 50°C, the control signal in **Figure II.10** shows that the controller operates the duty cycle within much narrower electrical bounds to maintain its tracking. Under this severe thermal condition, a lower open-circuit voltage is already established within the voltage-current matrix of **Figure II.11**, limiting the maximum available power to approximately 87 KW in **Figure II.12**. Since the classic logic lacks the ability to scale down its step size near this peak, the PWM signal continuously hunts back and forth, resulting in thicker and rougher steady-state power ripples at the load stage.

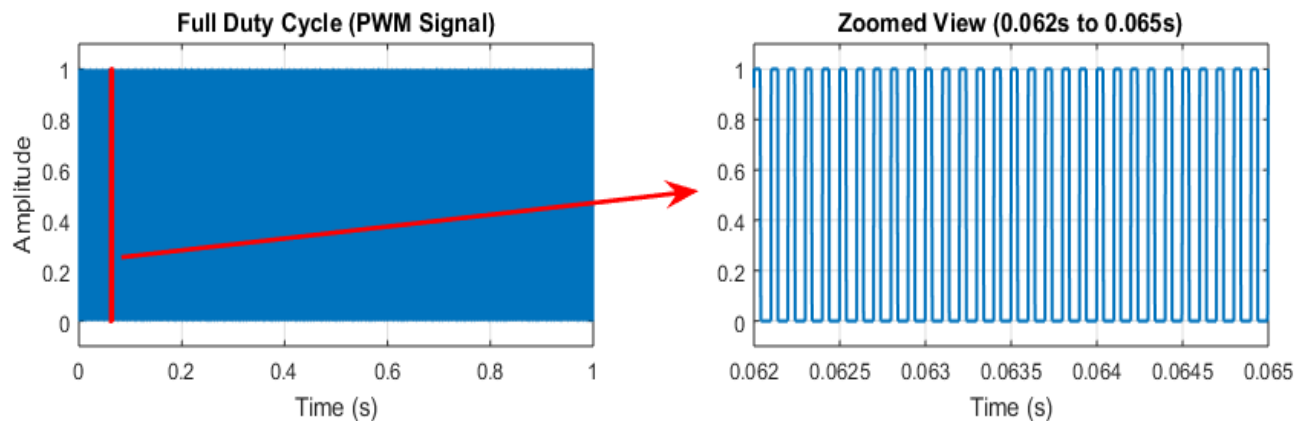


Figure II.10: PWM signal and Duty Cycle behavior for the **P&O algorithm** at $T = 50\text{ }^{\circ}\text{C}$.

Chapter II: Traditional maximum power point tracking for photovoltaic system

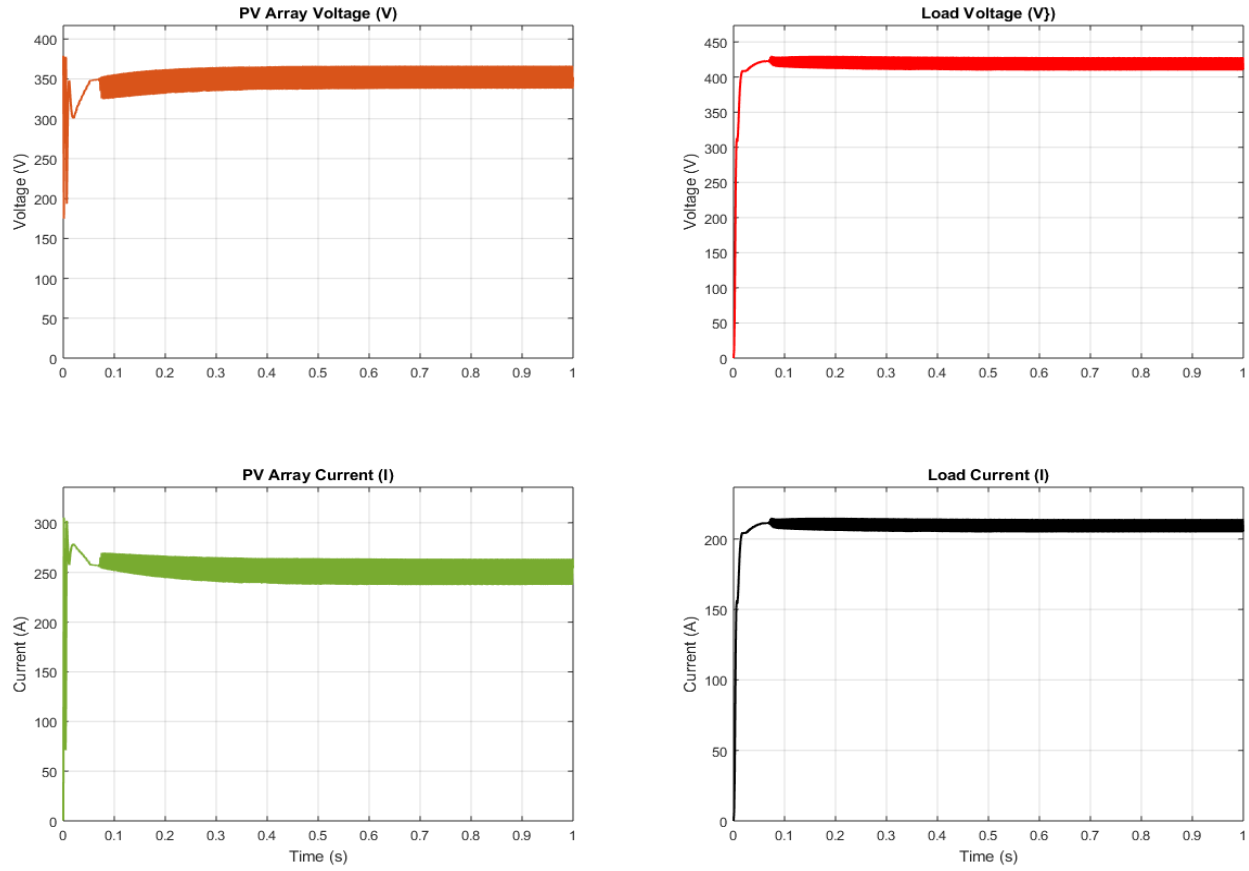


Figure II.11: Voltage and Current characteristics (V-I Matrix) for the PV Array and Load under **P&O control** at $T = 50\text{ }^{\circ}\text{C}$.

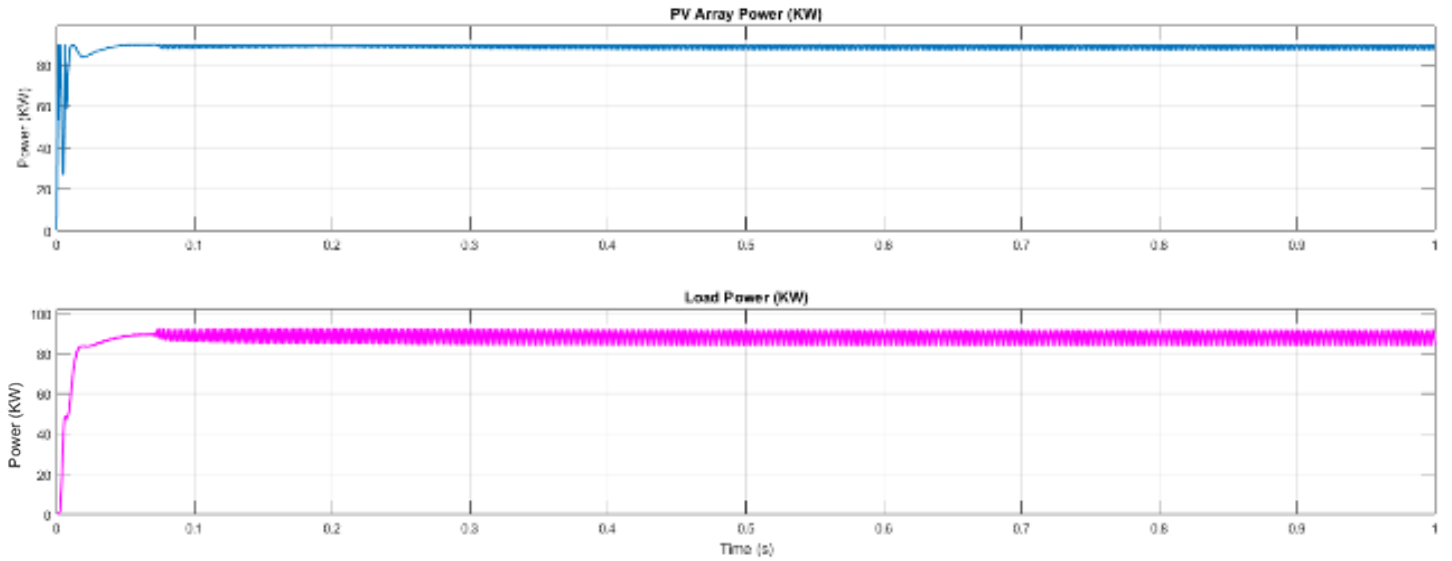


Figure II.12: Power profiles of the PV Array and the Load stage using the **P&O algorithm** at $T = 50\text{ }^{\circ}\text{C}$.

II.4.3 The effect of solar irradiance (Ramp Profile) on a photovoltaic system

This subsection details the system's adaptation to solar irradiance ramp. Figure II.14 demonstrates the continuous duty cycle updates. Figures II.15 and II.16 capture the linear transition of all electrical and power variables, showing the high tracking speed and stability of the P&O algorithm throughout the irradiance ramp that is presented in Figure II.13.

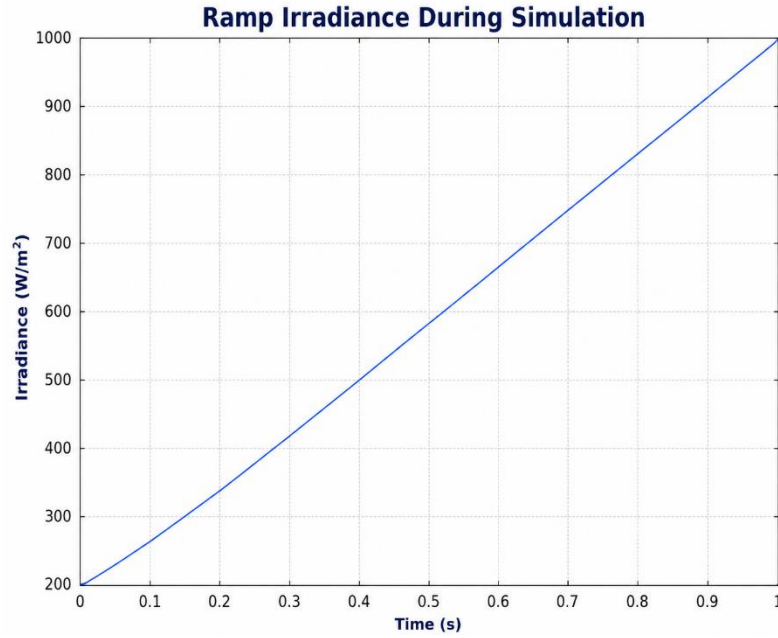


Figure II.13: Ramp irradiance during all the ramp simulations.

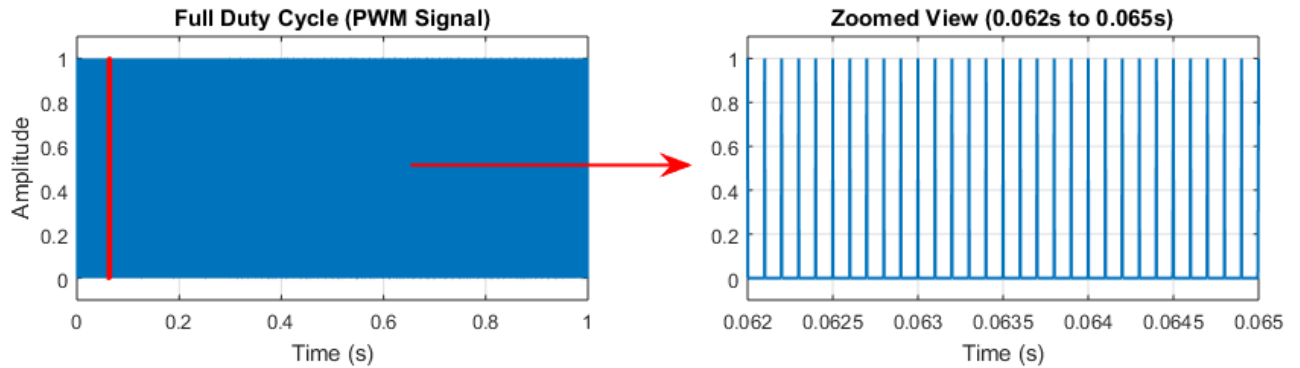


Figure II.14: Dynamic Duty Cycle adjustment by the **P&O algorithm** during an irradiance ramp.

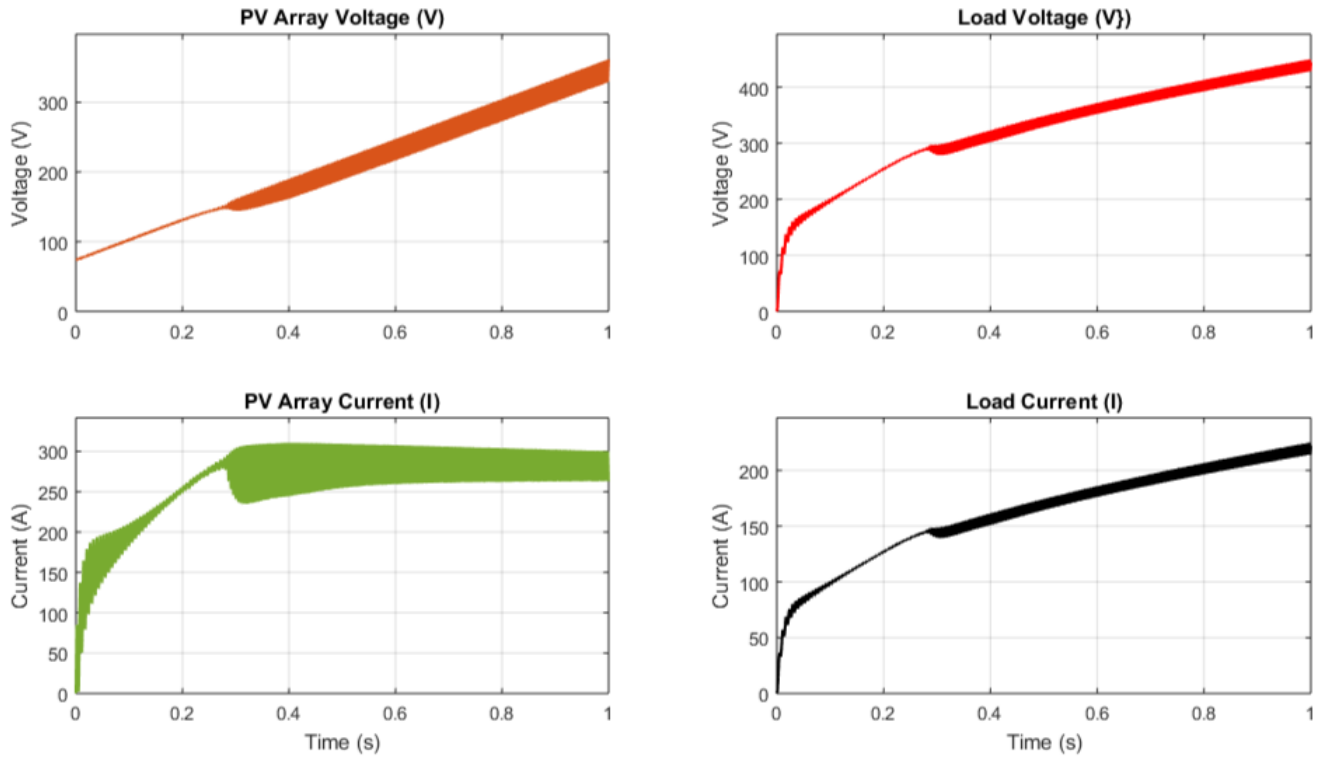


Figure II.15: Evolution of Voltage and Current for both PV Array and Load under **P&O** control during the ramp.

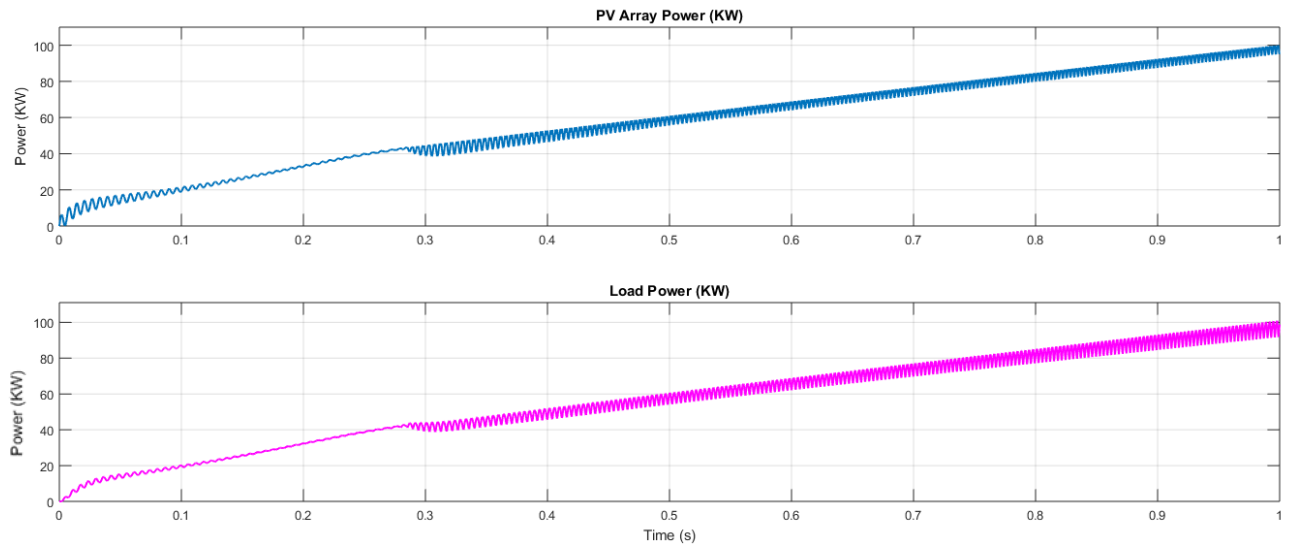


Figure II.16: Dynamic power profiles (PV Array vs. Load) during the irradiance ramp using the **P&O** algorithm.

The control signal and PWM duty cycle adjustment in **Figure II. 14** perfectly illustrates the classic limitation of fixed-step logic during dynamic transitions, where the duty cycle climbs in a rigid,

staircase-like formation to follow the changing environment. This restriction creates a severe tracking lag (latency) between the true moving peak and the actual operating point, which is clearly visible in the evolution of voltage and current in **Figure II.15** and the dynamic power profiles in **Figure II. 16**. The fixed steps are either too small to rapidly catch up with the moving irradiance or too large to settle cleanly, leading to a combination of transient instability and excessive power deviations from the optimal trajectory before eventually returning to a noisy steady state.

II.5. Synthesis of P&O Limitations for MPPT in PV system

Looking closely at the various simulation tests run under different operating temperatures and shifting solar profiles, we can put together a clear evaluation of how the traditional P&O logic handles things. Even though this classic approach shows it can get reasonably close to the Maximum Power Point (MPP) during steady weather, its operation creates some serious drawbacks when applied to a high-power 100 KW setup:

1. **Steady-State Duty Cycle Fluctuation:** Looking at all the previously studied cases for ambient temperatures of "25 °C, 40 °C, and 50 °C", The **duty cycle** cannot maintain a stable value after reaching the peak power region. This happens because the step size is fixed, forcing the **MPPT loop** to jump back and forth around the maximum power point. This unstable switching action directly affects the PV voltage and current profiles, creating continuous ripples that reduce the system efficiency.
2. **Shifting Weather Response Deficit:** Rapid changes in weather expose a major bottleneck in how this fixed-step approach performs. Whenever the solar irradiance follows a linear ramp profile, we notice a massive lag because the duty cycle can only climb in a rigid, staircase pattern while trying to catch the moving peak. Operating far from the ideal path during these fast transitions heavily damages the overall efficiency, leaving the setup to struggle before it eventually drops back into a noisy steady state.

II.6 Conclusion

This chapter reviews conventional Maximum Power Point Tracking (MPPT) techniques used in photovoltaic (PV) systems. The Perturbation and Observation (P&O) method was used for a 100 KW PV system consisting of a 10-series PV array each with 47 parallel PV panels.

Simulation models were built using MATLAB software, and the controller was tested and compared under various atmospheric conditions. Furthermore, the limitations of the Perturbation and Observation method were highlighted. Continuous instability in atmospheric conditions leads

to efficiency degradation and compromises component integrity, directly emphasizing the need for advanced intelligent control strategies with variable steps, which will be detailed in the next chapter.

Chapter III: Artificial intelligent maximum power point tracking techniques for photovoltaic system

III.1 Introduction

Photovoltaic systems are nonlinear by nature, and their maximum power point changes continuously according to atmospheric conditions. For this reason, intelligent MPPT techniques are used to improve tracking accuracy, reduce oscillations around the maximum power point, and enhance the dynamic response of the system. Among these techniques, fuzzy logic is widely used because it does not require an exact mathematical model of the PV system and can handle nonlinear behavior effectively. Furthermore, a hybrid approach combining fuzzy logic with a Genetic Algorithm (GA) can be investigated to further refine the controller parameters.

In this chapter, artificial intelligence-based MPPT techniques for PV systems are introduced. Then, the Fuzzy Logic MPPT method adopted in this work is presented and explained, along with the integration of the Genetic Algorithm. After that, the simulation model is developed in order to evaluate the behavior and performance of the proposed MPPT controller. Finally, the obtained results are discussed and summarized.

III.2. Overview of intelligent MPPT techniques

Intelligent algorithms are characterized by their ability to "learn" or "reason" through complex scenarios. These techniques are categorized based on their computational logic and bio-inspired origins.

- **Artificial neural networks (ANN):** These mimic the human brain's neural structure, consisting of input, hidden, and output layers. They are highly effective at mapping non-linear irradiance and temperature data to the optimal duty cycle but require extensive training datasets. [1]
- **Bio-Inspired algorithms:** This group includes metaheuristic methods such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). They are particularly efficient in detecting the Global Maximum Power Point (GMPP) when the PV array is subject to partial shading. [1]
- **Fuzzy logic control (FLC):** FLC is a heuristic approach that translates human linguistic knowledge into control rules. It is highly robust and allows for a variable-step size, which effectively eliminates the oscillations inherent in traditional methods. [1]

To better understand the strengths and weaknesses of these methods, a comparative analysis is presented in the following table.

Table III.1: Comparaison of intelligent MPPT techniques [1]

MPPT Method	Cost	Complexity	Response Time	Accuracy	Efficiency
FLC	Moderate	High	Medium	High	High
ANN	Expensive	High	Medium	High	High
GA	Moderate	High	Fast	Medium	High
PSO	Moderate	Medium	Fast	Medium	High

III.3. Theoretical foundation of fuzzy logic control

The selection of Fuzzy Logic for this 100 KW project is justified by its ability to handle system uncertainties and its superior performance in both steady and dynamic states. Unlike traditional algorithms, FLC operates by processing linguistic variables. As defined by **Katche et al. [1]**, the tracking logic is based on two primary inputs: the Error (E) and the Change of Error (dE).

Following the mathematical framework presented in [1], the inputs are calculated as follows:

1. **Error (E):** the slope of the power-voltage curve can be presented using the following equation:

$$E(k) = \frac{P_{pv}(k) - P_{pv}(k-1)}{V_{pv}(k) - V_{pv}(k-1)} \quad (III.1)$$

2. **Change of Error (dE):** the variation in the slope between two sampling intervals cab be represented using the following equation:

$$dE(k) = E(k) - E(k - 1) \quad (III.2)$$

Ppv and Vpv represent the instantaneous power and voltage of the PV array, respectively, at the k-th sampling time.

III.3.1 The three stages of implementing the FLC

The transition from numerical inputs to an intelligent control signal occurs in three sequential stages:

1. **Fuzzification:** Crisp input signals (E and dE) are converted into fuzzy linguistic sets (e.g., Small, Zero, Large) using Membership Functions (MFs).
2. **Inference Engine:** This stage applies "IF-THEN" rules from the Rule Base to the fuzzified inputs to determine the fuzzy output.
3. **Defuzzification:** The fuzzy output is converted back into a crisp numerical value, representing the change in the duty cycle.

III.3.2 Design and configuration of the proposed FLC for PV system

For the 100 KW simulation, an inference system was implemented in MATLAB/Simulink. This specific design is optimized for high-power stability and real-time processing

III.3.2.1. Membership functions and scaling for FLC

The FLC uses a combination of triangular and trapezoidal membership functions to ensure sensitivity near the peak, see figure III.1.

- **Input 1 (E):** Scaled within the range **[-500, 500]** with 5 linguistic variables (NB, NS, ZE, PS, PB).
- **Input 2 (dE):** Scaled within the range **[-100, 100]** with 3 variables (N, ZE, P).
- **Output (ΔD):** Defined between **[-0.1, 0.1]** to provide fine control over the DC-DC converter.

Figure III.1 illustrates the membership functions (MFs) configuration for the inputs and output variables of the FLC system.

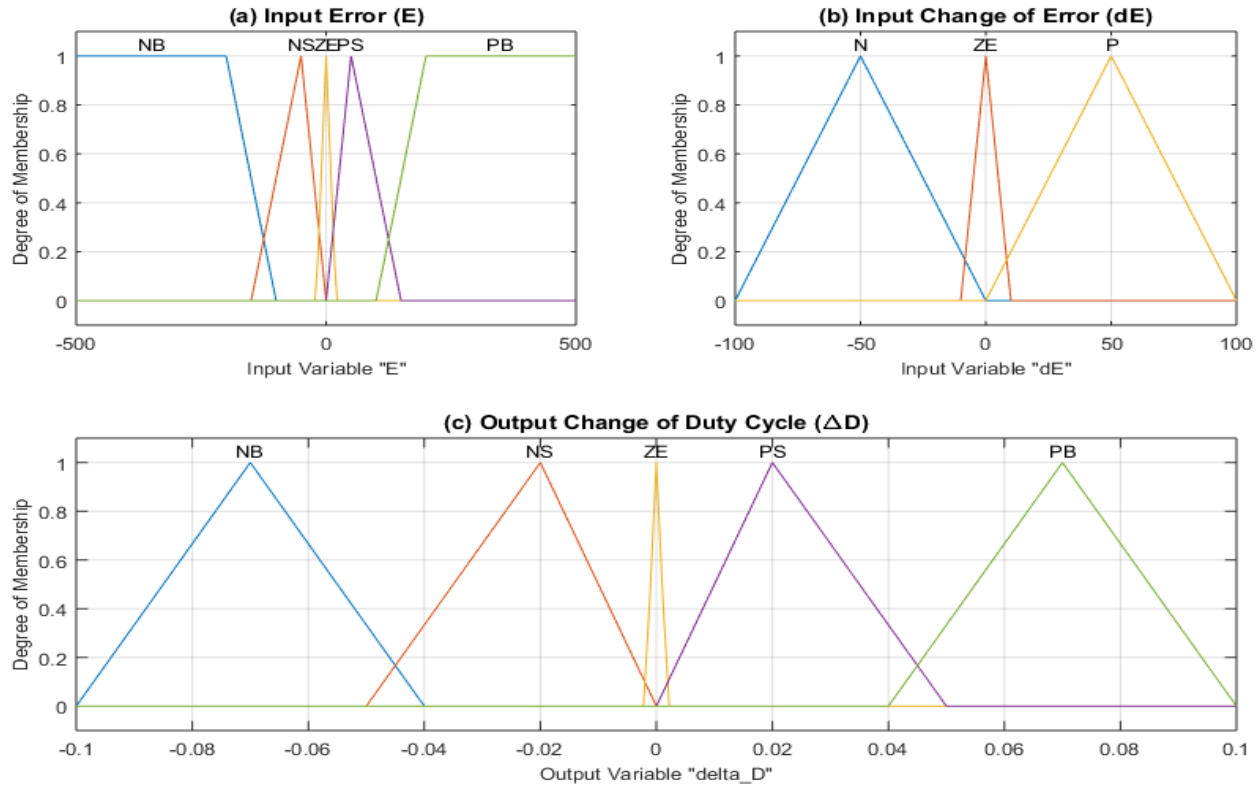


Figure III.1: Membership functions of the Fuzzy Logic Controller: **(a)** Input error (E), **(b)** Input change of error (dE), **(c)** Output change of duty cycle (ΔD).

The first input, Error (E), is fuzzified into five linguistic sets (NB, NS, ZE, PS, PB) using a combination of trapezoidal and triangular shapes to enhance sensitivity near the equilibrium. The second input, Change of Error (dE), is divided into three symmetrical triangular MFs (N, ZE, P) to preserve computational simplicity. Finally, the output variable (ΔD) employs five triangular sets. The central ZE membership function of the output is designed with a narrow base. This specific structural design minimizes steady-state oscillations by executing minor and precise duty cycle adjustments when the system operates close to the global maximum power point.

III.3.2.2. Fundamental rules and surface logic in a fuzzy logic controller

The fuzzy logic controller is governed by five fundamental rules that represent the core of the decision-making process in a maximum power point tracking system, see the table III.2:

- 1. If (E is NB) and (dE is N) then (ΔD is NB)
- 2. If (E is ZE) and (dE is ZE) then (ΔD is ZE)
- 3. If (E is PB) and (dE is P) then (ΔD is PB)
- 4. If (E is NS) and (dE is ZE) then (ΔD is NS)

- 5. If (E is PS) and (dE is ZE) then (ΔD is PS)

Table III.2: The 5-Rule matrix for the proposed FLC.

Rule No.	IF Error (E)	AND Change of Error (dE)	THEN Output (ΔD)	Operational Objective / Description
1	Negative Big (NB)	Negative (N)	Negative Big (NB)	The operating point is far to the right of the MPP. Rapidly decrease the duty cycle to pull the system back toward the peak.
2	Zero (ZE)	Zero (ZE)	Zero (ZE)	The system has successfully reached the Maximum Power Point (MPP). Freeze the duty cycle to eliminate oscillations.
3	Positive Big (PB)	Positive (P)	Positive Big (PB)	The operating point is far to the left of the MPP. Rapidly increase the duty cycle to accelerate toward the peak.
4	Negative Small (NS)	Zero (ZE)	Negative Small (NS)	The system is slightly to the right of the MPP. Apply a fine, minor negative adjustment for precise tuning.
5	Positive Small (PS)	Zero (ZE)	Positive Small (PS)	The system is slightly to the left of the MPP. Apply a fine, minor positive adjustment for precise tuning.

III.3.2.3. Justification for the 5-Rule approach

Although this system can generate up to 15 rules, a simplified base of only 5 rules was selected for this work. This choice was made to:

- Reduce execution time: Fewer rules ensure faster real-time processing.
- Lower computational load: It minimizes the processing burden on the microcontroller.

- Ensure stability: These 5 rules are fully sufficient to track the MPP efficiently.

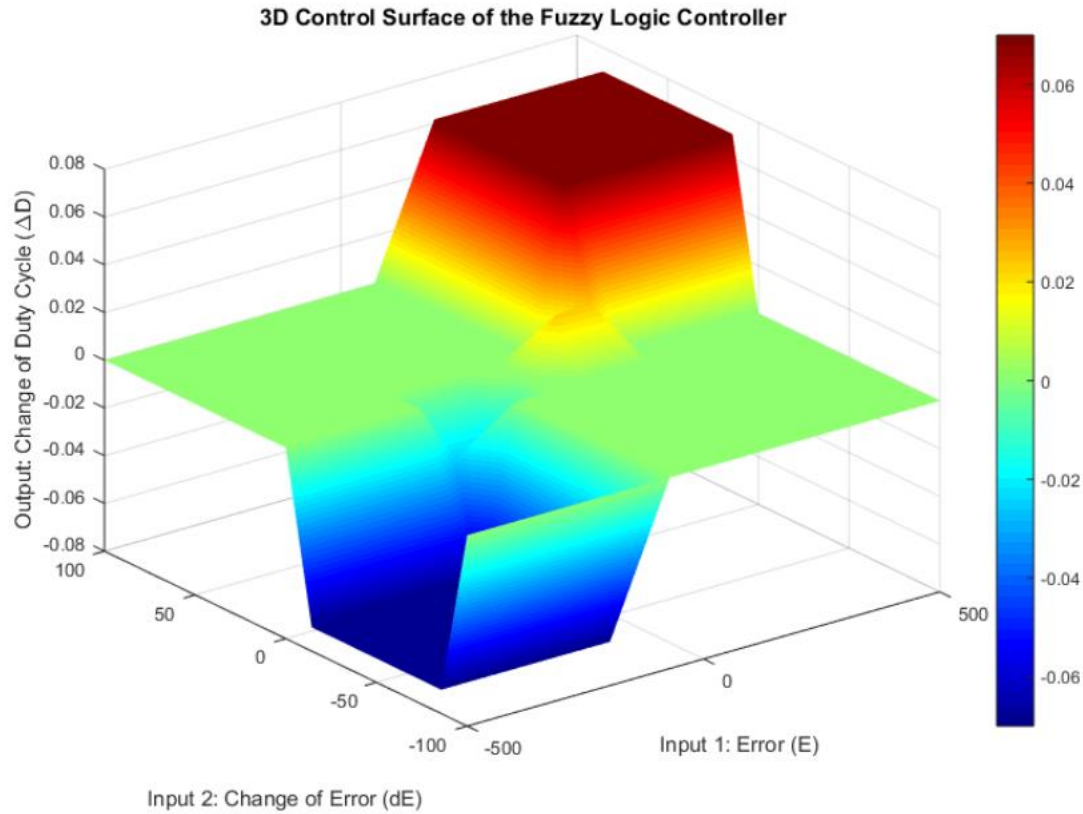


Figure III.2: Rule Surface of the Mamdani FLC

Figure III.2 illustrates the 3D control surface of the proposed Fuzzy Logic MPPT controller. Based on this figure, the smooth yet non-linear surface proves that the 5-rule base effectively covers the system's operational trajectories without causing control discontinuities. The prominent green flat plateau around the center ($E=0$, $dE=0$) guarantees that the output duty cycle variations (ΔD vanishes to zero when the Maximum Power Point (MPP) is tracked, thereby eliminating steady-state hunting and oscillations. Conversely, the steep red and blue regions depict the aggressive control actions taken under severe tracking errors to accelerate transient response.

III.4 Simulation results and performance evaluation of FLC

This section presents the simulation results of the proposed Mamdani-type Fuzzy Logic Controller (FLC) implemented on the 100 KW PV station, see the figure III.3. To ensure a fair and comprehensive comparative analysis, the intelligent controller is subjected to the exact same

environmental test profiles (constant and variable parameters) used for the traditional P&O algorithm in chapter II.

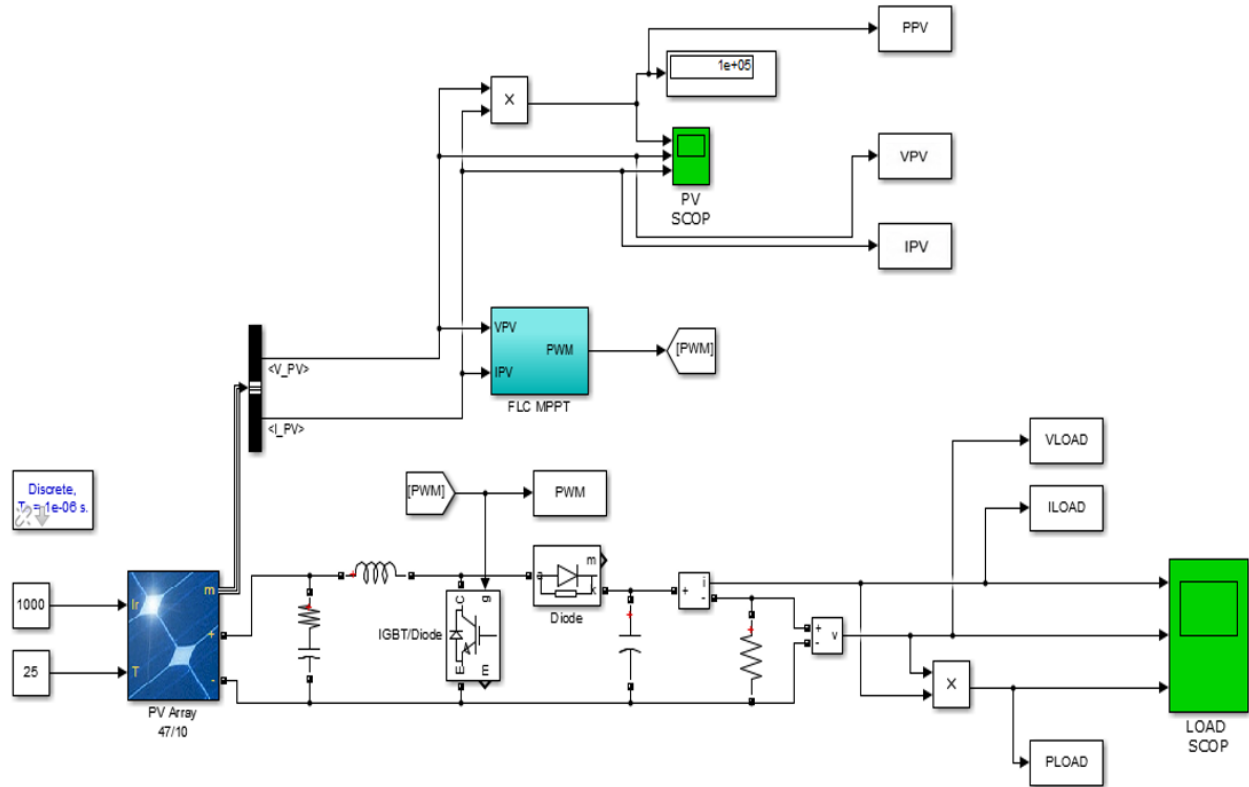


Figure III.3: MATLAB/Simulink model of the 100 KW PV station for FLC method.

III.4.1. Performance under standard test conditions (STC)

This scenario evaluates the primary tracking capability and accuracy of the FLC at a constant ambient temperature of 25°C and a fixed solar irradiance of 1000 W/m².

Figures III.4, III.5, and III.6 illustrate the core simulation profiles obtained under standard test conditions using the proposed fuzzy logic controller. Specifically, Figure III.4 presents the real-time modulation of the duty cycle control signal, Figure III.5 displays the electrical voltage and current trends for both the PV source and the load stage, while Figure III.6 depicts the corresponding tracked power waveforms.

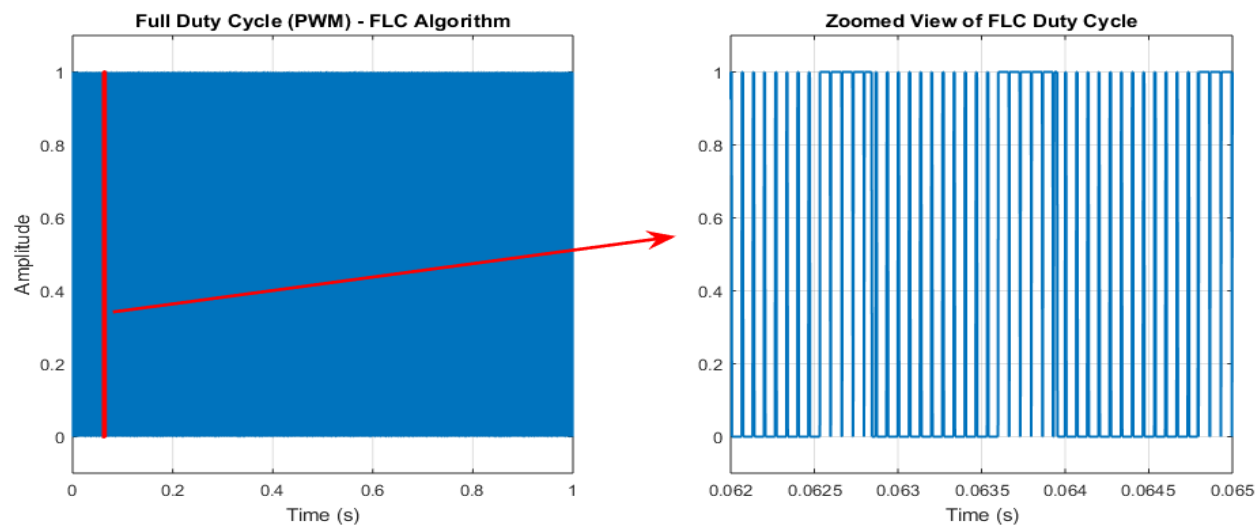


Figure III.4: PWM Control Signal and Dynamic Duty Cycle behavior for the FLC at STC.

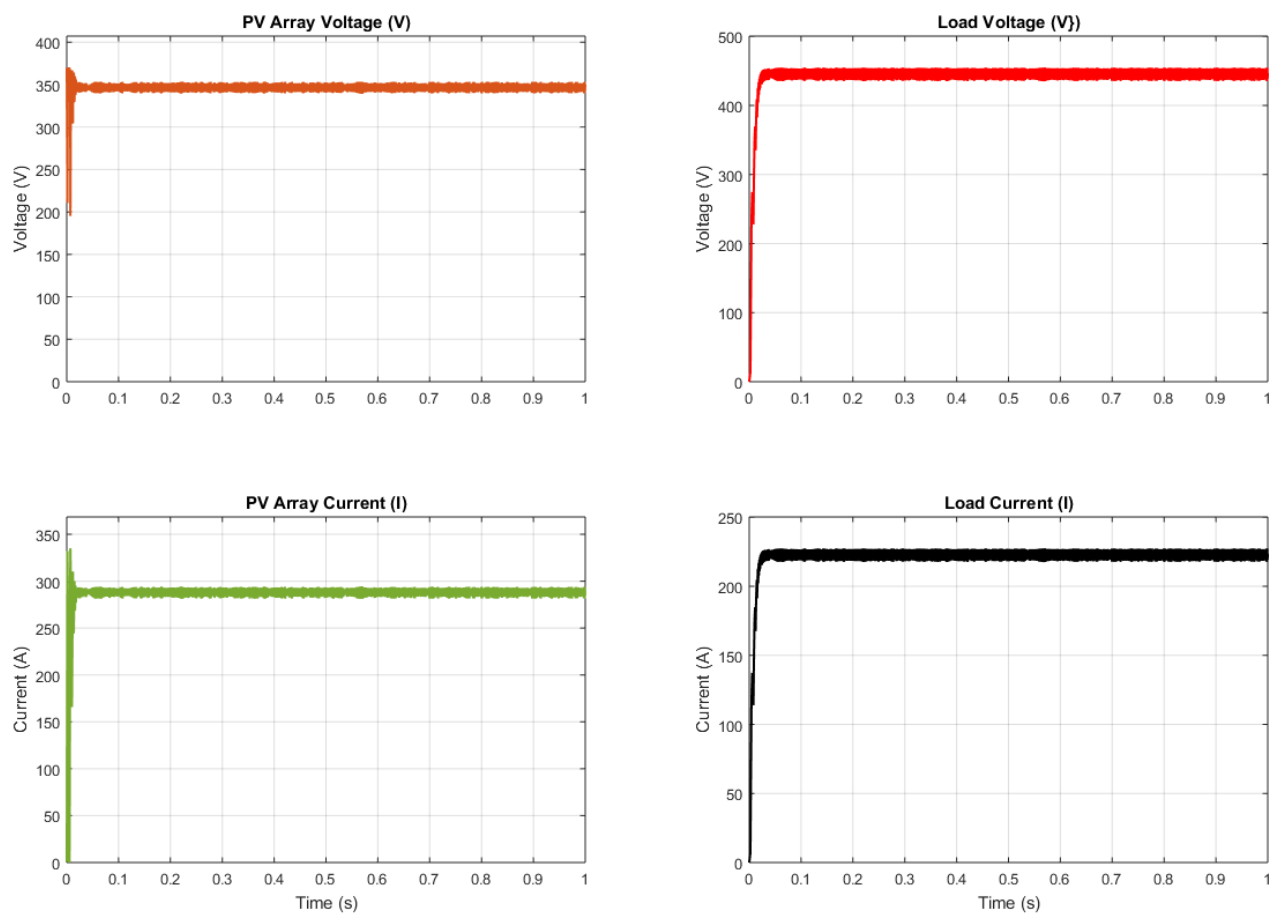


Figure III.5: Voltage and Current characteristics (V-I Matrix) for the PV Array and Load under FLC control at STC.

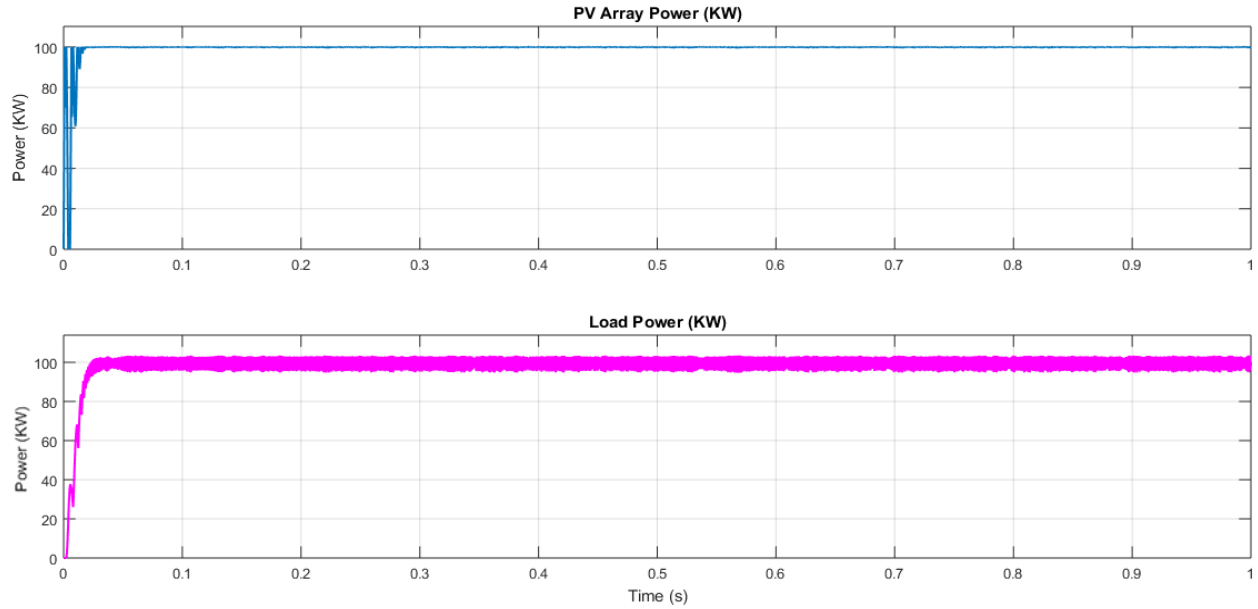


Figure III.6: Power profiles of the PV Array and the Load stage using the FLC at STC.

Based on the previous figures, the baseline evaluation under Standard Test Conditions (STC: 25°C, 1000 W/m²) serves as the primary benchmark for assessing the tracking speed and oscillation elimination capabilities of the FLC:

- **Ultra-Fast settling time:** As demonstrated in the power profile (**Figure III.6**), the FLC drives the PV system from an unforced state to its maximum operating capacity of approximately 100 KW within an exceptional settling time of less than 0.02s. This immediate convergence is attributed to the execution of the extreme rules (If E is PB then ΔD is PB and If E is NB then ΔD is NB), which apply large step modifications to the converter's duty cycle during the initial startup phase.
- **Elimination of Steady-State oscillations:** Traditional MPPT algorithms, such as Perturb and Observe (P&O), inherently suffer from continuous power hunting around the peak, resulting in permanent power losses. In stark contrast, **Figure III.6** reveals an almost perfectly linear and smooth power curve once steady-state is reached.
- **Control signal smoothness:** This high electrical stability is fully supported by the high-frequency switching behavior shown in **Figure III.4**. The zoomed view showcases that the duty cycle achieves a highly regulated, micro-step modulation pattern around its nominal value. This confirms that the narrow design of the central membership function ZE for the

output variable (ΔD) successfully minimizes the tracking step size as the error approaches zero, effectively locking the system at the absolute Maximum Power Point (MPP).

- **Impedance matching:** Consequently, **Figure III.5** establishes that the FLC maintains the optimal PV array voltage $V_{mp} \approx 350V$ and current $I_{mp} \approx 285 A$, while the DC-DC Boost converter reliably steps up the load voltage to a ripple-free 450 V level.

III.4.2. Performance under medium thermal elevation ($T = 40^\circ C$)

This scenario screens the behavioral adjustment and electrical performance of the FLC when the PV system operates under a moderate temperature increase of $40^\circ C$ while maintaining a stable irradiance of $1000 W/m^2$.

The operational curves recorded under medium thermal elevation are compiled in Figures III.7, III.8, and III.9. Figure III.7 tracks the baseline adjustment of the PWM duty cycle signal, Figure III.8 details the responsive voltage and current metrics for the array and load circuits, and Figure III.9 presents the output and array power profiles under this specific thermal condition.

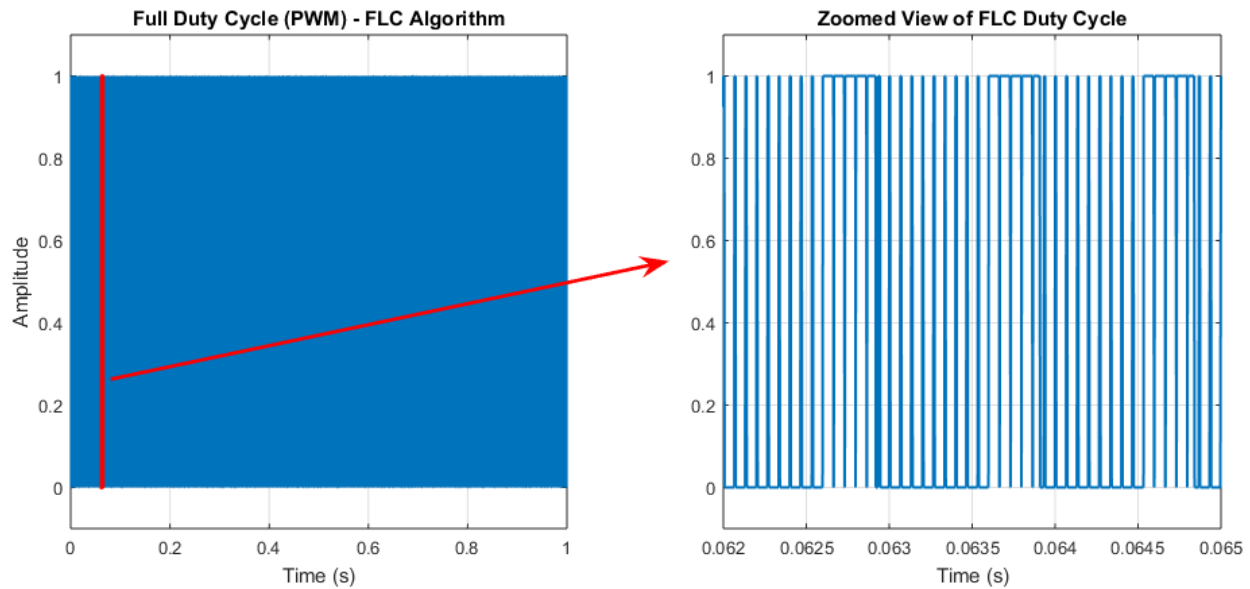


Figure III.7: PWM control signal and dynamic duty cycle behavior for the FLC at $T = 40^\circ C$.

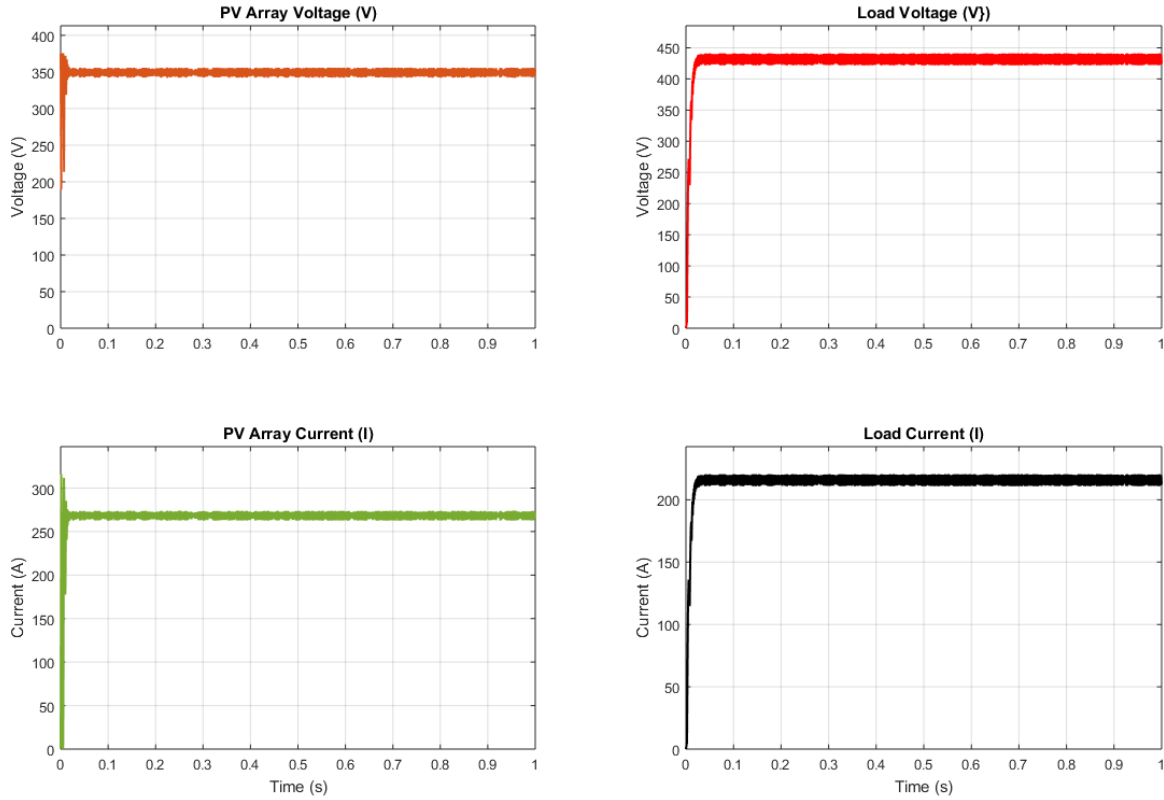


Figure III.8: Voltage and current characteristics (V-I Matrix) for the PV array and load under FLC control at $T = 40^{\circ}\text{C}$.

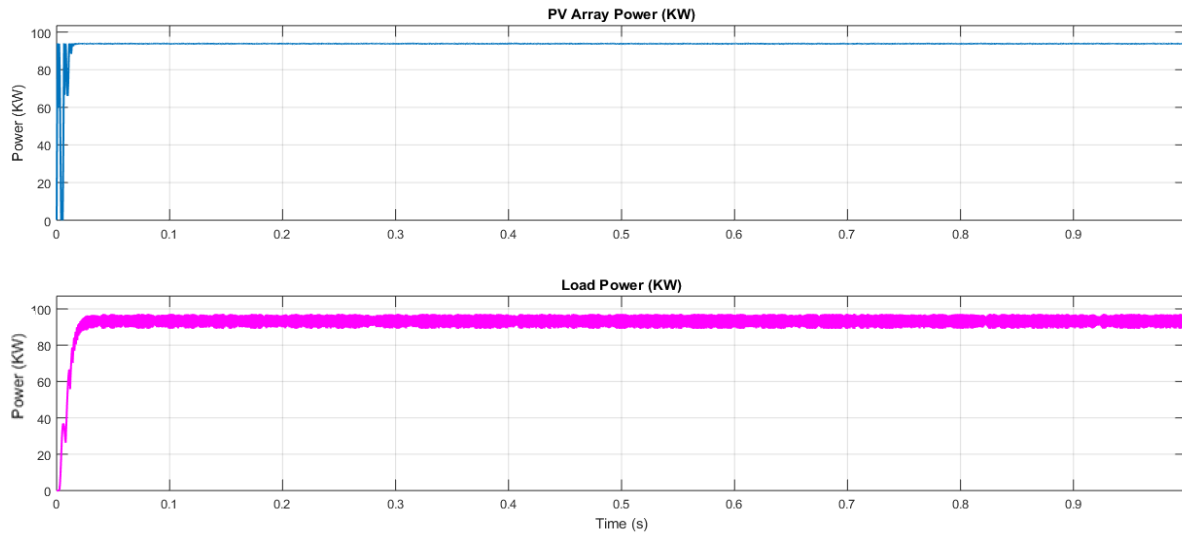


Figure III.9: Power profiles of the PV array and the load stage using the FLC at $T = 40^{\circ}\text{C}$.

III.4.3. Performance under ambient temperature of ($T = 50^{\circ}\text{C}$)

This case analyzes the robustness and steady-state adaptability of the FLC when the PV array operating temperature rises to a critical level of 50°C while maintaining an irradiance of 1000 W/m^2 . The system behavior under severe thermal stress is represented through Figures III.10, III.11, and III.12. Figure III.10 outlines the duty cycle control adaptation executed by the FLC, Figure III.11 shows the resulting electrical voltage and current variations across the system stages, and Figure III.12 tracks the total power generation profiles.

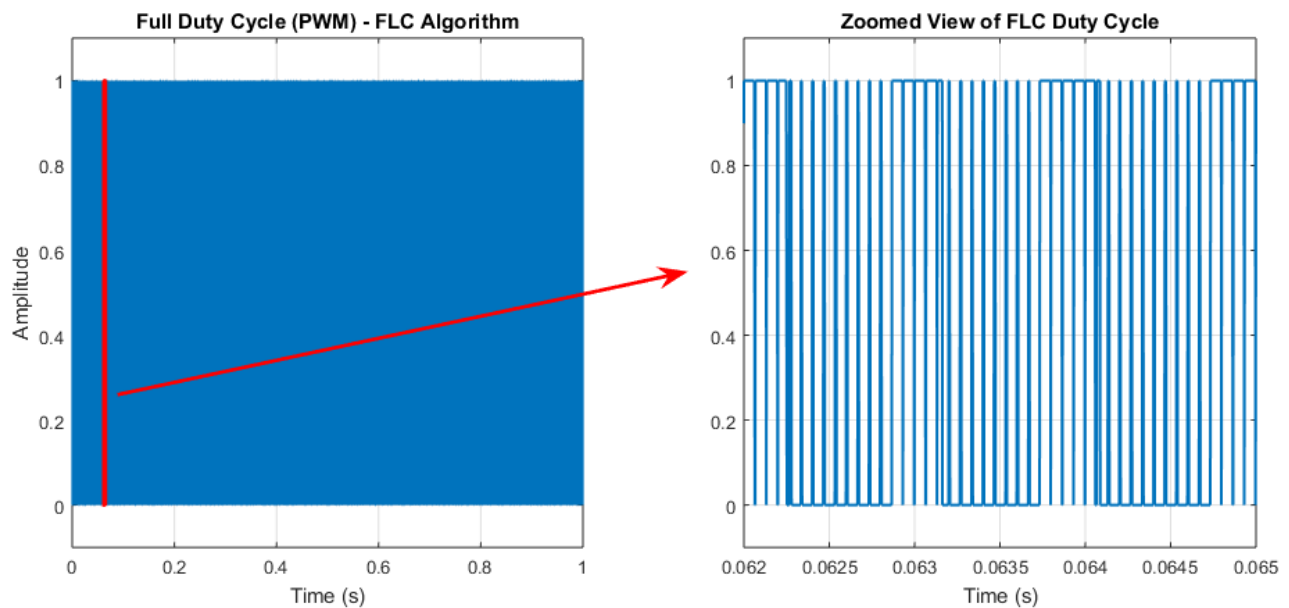


Figure III.10: PWM Control Signal and duty cycle behavior for the FLC at $T = 50^{\circ}\text{C}$.

Chapter III: Artificial intelligent maximum power point tracking techniques for photovoltaic system

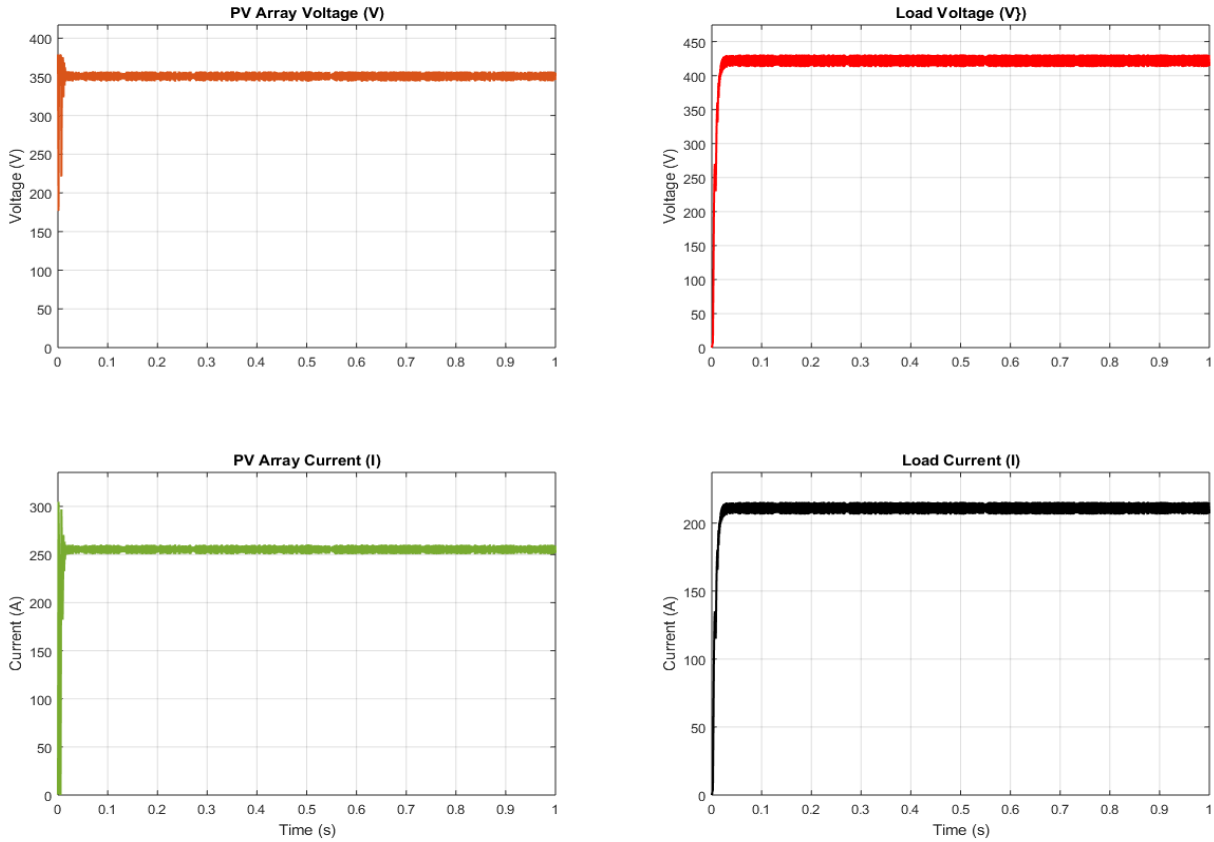


Figure III.11: Voltage and current characteristics (V-I Matrix) for the PV array and load under FLC control at $T = 50^{\circ}\text{C}$.

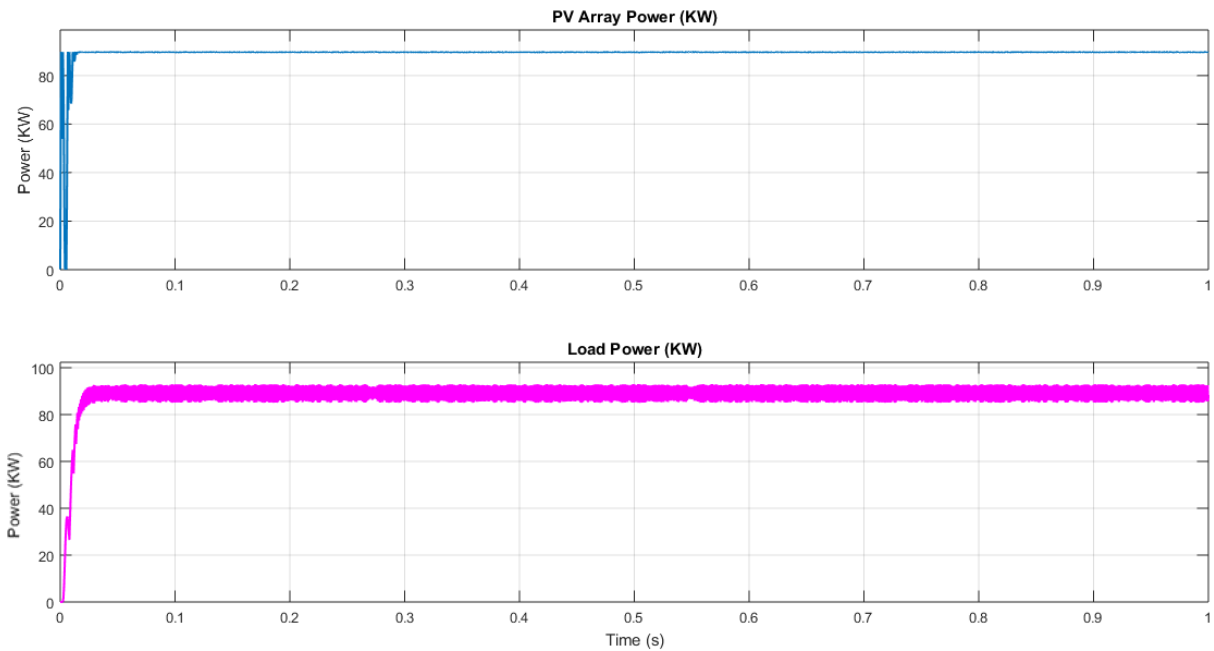


Figure III.12: Power profiles of the PV array and the load stage using the FLC at $T = 50^{\circ}\text{C}$.

Operating under thermal stress (40°C and 50°C) introduces severe non-linear degradation to the PV array's electrical characteristics, primarily driving down the open-circuit voltage. The simulation verifies the adaptive nature of the FLC in re-optimizing the tracking path under these challenging environmental conditions.

Table III.3: FLC parametric response under elevated operating temperatures.

Parameter Evaluated	Medium Thermal Elevation (40°C)	High Thermal Stress (50°C)
Tracked PV Power Output	≈93.5kW (Figure III.9)	≈88.5kW (Figure III.12)
Optimal PV Voltage (V _{mp})	Settles at ≈ 345V (Figure III.8)	Drops further to ≈ 340V (Figure III.11)
Optimal PV Current (I _{mp})	Fixed at ≈ 270A (Figure III.8)	Sits at ≈ 260A (Figure III.11)
Boosted Load Voltage	Stabilized at ≈ 430V (Figure III.8)	Maintained at ≈ 425V (Figure III.11)

- **Intelligent duty cycle realignment:** When the temperature climbs to 40°C and 50°C, the FLC detects the immediate drift of the operating point caused by the shrinking voltage profile. As illustrated in **Figure III.7** and **Figure III.10**, the controller recalculates the slope error in real-time and systematically realigns the baseline duty cycle command.
- **Absence of Divergence/Hunting:** Despite the significant reduction in peak power capacity due to semiconductor physics (losing roughly 6.5 KW at 40°C and 11.5 KW at 50°C relative to STC), the power curves in **Figure III.9** and **Figure III.12** exhibit no signs of tracking divergence, oscillations, or computational hunting. The system smoothly stabilizes at the new degraded thermal peaks, confirming the exceptional robustness and reliable parameter independence of the intelligent control structure.

III.4.4. Performance under variable solar irradiance (Ramp Profile)

This dynamic scenario tests the tracking agility and response speed of the intelligent 5-rule fuzzy logic controller during rapid and continuous fluctuations in solar intensity.

The dynamic tracking results recorded during continuous linear irradiance transitions are compiled in Figures III.13, III.14, and III.15. Figure III.13 illustrates the real-time tuning and modulation of the duty cycle parameter, Figure III.14 shows the simultaneous evolutionary paths of the electrical

voltage and current parameters, and Figure III.15 presents the continuous dynamic power trajectories delivered to the load.

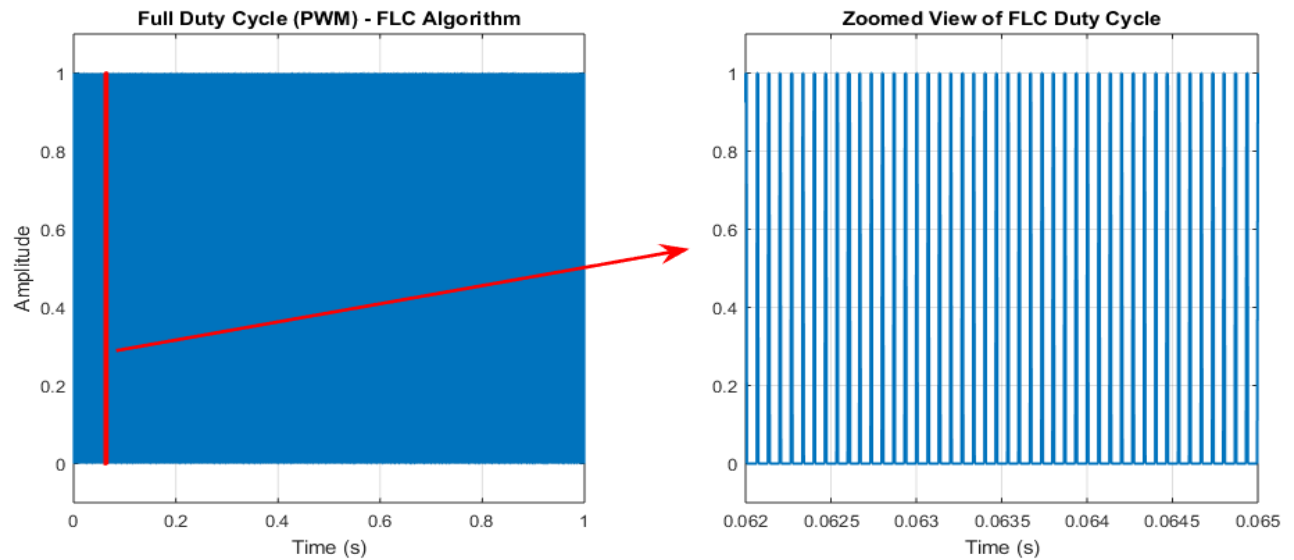


Figure III.13: Dynamic duty cycle adjustment by the FLC during an irradiance ramp.

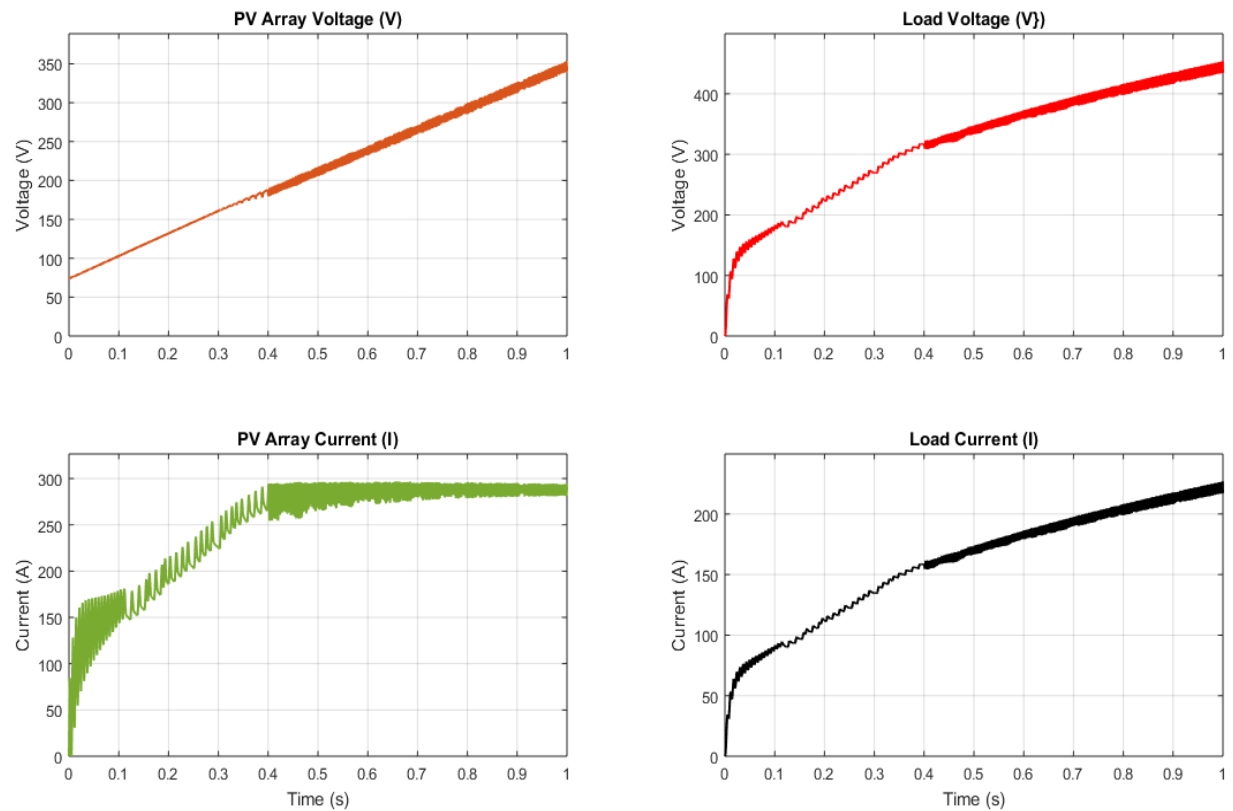


Figure III.14: Evolution of voltage and current for both PV Array and Load under FLC control during the ramp.

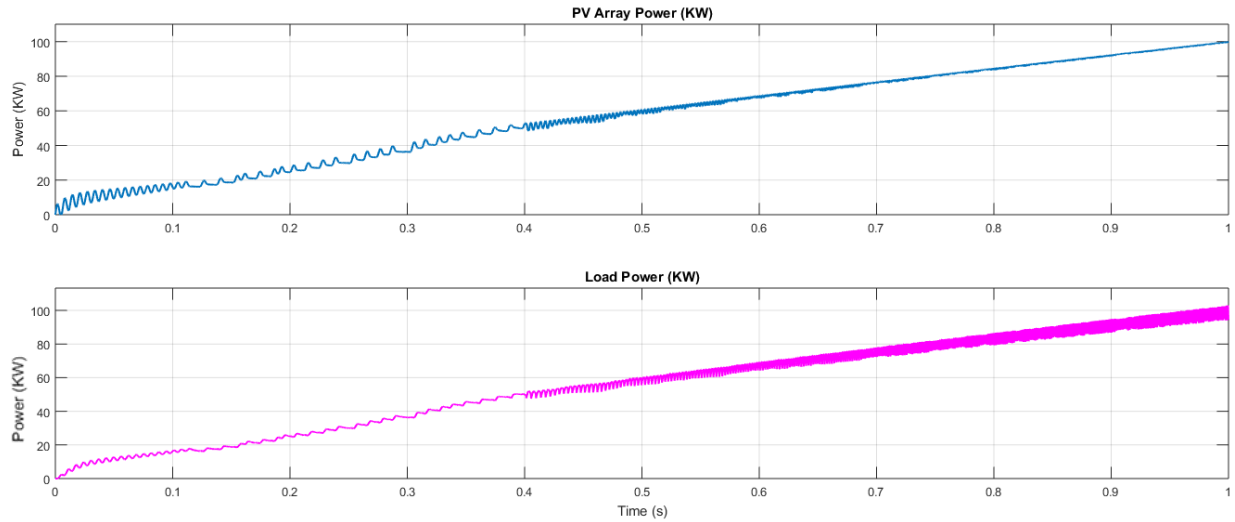


Figure III.15: Dynamic power profiles (PV array vs. Load) during the irradiance ramp using the FLC.

The dynamic ramp profile represents the most demanding testing environment, simulating rapid, continuous weather fluctuations where the global MPP is constantly moving in a linear trajectory.

- **Adaptive Step-Sizing mechanism:** The dynamic tracking behavior is clearly reflected in the evolution of the PWM control signal (**Figure III.13**). The zoomed view proves that the FLC does not maintain a static step size. Instead, it automatically scales its control actions based on the ramp slope.
- **Analysis of the transition phase $t = 0$ s to $t = 0.4$ s:** In **Figure III.14**, during the initial 0.4s interval, the PV array current displays visible, controlled macro-oscillations. This is a highly desirable control feature: since the irradiance is changing rapidly from a low baseline, the input error (E) and change of error dE) continuously trigger active fuzzy rules that demand immediate step corrections to catch up with the moving target. This active tracking minimizes the "tracking lag" that commonly plagues classical fixed-step methods.
- **Smooth convergence and peak extraction:** Once the system smoothly crosses the 0.4 s threshold, the algorithm establishes precise alignment with the environmental profile. As shown in **Figure III.15**, both the PV array power and the load stage power scale upward in a highly linear, synchronized manner, reaching the full target capacity of 100KW precisely at $t = 1$ s with flawless continuity.

III.5. Comparative performance evaluation: Traditional P&O vs. proposed FLC

To highlight the engineering merits of the developed intelligent controller, a direct comparative evaluation is established between the traditional Perturb and Observe (P&O) algorithm and the proposed 5-rule Fuzzy Logic Controller (FLC), see the table III.4.

Table III.4: Quantitative and qualitative comparison between P&O and FLC results.

Performance Criterion	Traditional P&O Algorithm	Proposed 5-Rule FLC Structure
Transient Response (Settling Time)	Slow convergence (≈ 0.1 s to 0.15 s)	Ultra-fast convergence (< 0.02 s)
Steady-State Behavior	Permanent hunting and power oscillations	High-stability flat profile (Zero-oscillations)
Control Step-Size (ΔD)	Fixed/Static (Trade-off conflict)	Dynamic and Adaptive (Variable step)
Tracking Efficiency (η_{MPPT})	Moderate ($\approx 95\%$ - 96.5%) due to ripple losses	Superior ($\approx 99.3\%$ - 99.9%)
Robustness under Climatic Variations	Weak (Prone to tracking divergence)	Highly Agile (Instantaneous adaptation)

III.6. Effectiveness and agility under climatic fluctuations

The core superiority of the proposed FLC over the traditional P&O algorithm manifests prominently during rapid transitions in climatic conditions (solar irradiance and ambient temperature):

- The P&O Miscalculation Flaw: Under a fast irradiance ramp, the traditional P&O often becomes "confused" and misinterprets the atmospheric increase in power because of its own manual duty cycle perturbation. This technical limitation forces the P&O to continuously perturb the system in the wrong direction, causing a severe tracking lag and pushing the operating point away from the true global MPP.
- The FLC Adaptive Advantage: Conversely, because the FLC continuously processes two simultaneous inputs the Error (E) and the Change of Error (dE) it possesses the intelligence to instantly differentiate between an internal perturbation result and an external

environmental shift. As confirmed by the dynamic ramp profiles, the FLC automatically expands its control step-size (ΔD) during sharp irradiance slopes to catch the moving peak with zero tracking lag, and narrows it down instantly when the climate stabilizes.

Consequently, the FLC successfully extracts excellent power outcomes from the 100 KW solar station compared to fixed-step P&O networks under unstable weather profiles. However, these results are not perfectly stable, as the system still exhibits noticeable oscillations around the MPP peak.

III.7. Optimization of the Fuzzy Logic MPPT Controller Using Genetic Algorithms

Despite the operator's expertise and knowledge in defining inference rules and membership functions for classical Fuzzy Logic Controllers (FLC), some suboptimal adjustments or errors may still appear. To eliminate human trial-and-error and further enhance the stability of the 100 KW PV system, an automated optimization framework was implemented using Genetic Algorithms (GA).

III.7.1. Theoretical background of genetic algorithms

Genetic algorithms are stochastic global search and optimization techniques based on the principles of evolutionary biology and natural selection. The core mechanism, as illustrated in the Figure III.16, involves maintaining a population of candidate solutions (chromosomes) that evolve over sequential generations. The algorithm screens this population by executing specific probabilistic operators to explore and exploit the search space [16]. Its different stages are summarized as follows:

1. **Evaluation:** Each chromosome represents a set of physical controller parameters. Its performance is quantified using a specialized objective function.
2. **Selection:** Individuals with higher performance scores are selected with a greater probability to pass their genetic material to the next generation, adhering to the "survival of the fittest" rule.
3. **Crossover:** Pairs of parent chromosomes exchange segments of their structure to produce new offspring, combining successful traits to explore novel regions in the parameter domain.

4. **Mutation:** Random, low-probability alterations are injected into the offspring's parameters. This operator ensures genetic diversity and prevents the optimization loop from becoming trapped in **local optima** (premature convergence).
5. **New Generation Formation:** Replace the old population with newly generated offspring.
6. **Termination Check:** Stop the algorithm if termination criteria are satisfied.
7. **Output Solution:** Return the best chromosome obtained during evolution.

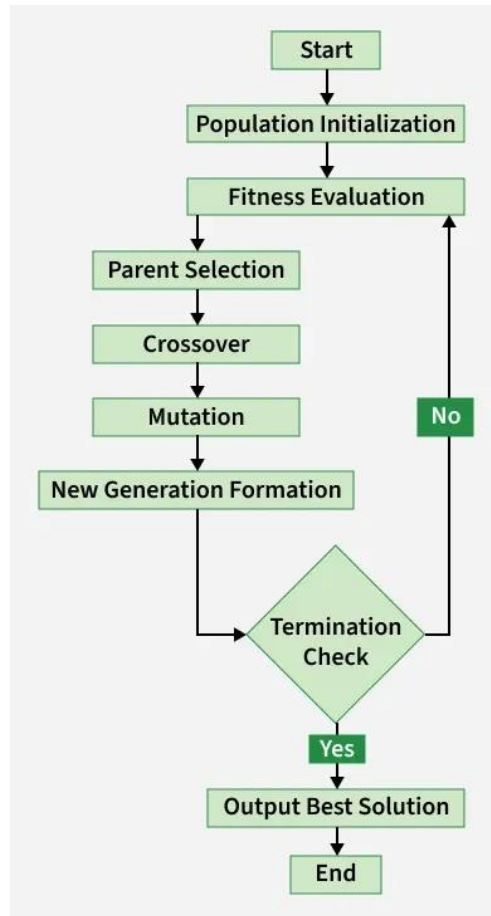


Figure III.16: Genetic algorithm steps.

III.7.2. Methodology and simulation setup

In this study, the GA was specifically deployed to optimize the real-valued support parameters $x = [a, b, c]$ of the output membership function representing the Zero change (ZE) in the duty cycle (ΔD). By precisely squeezing or shifting this specific function, the controller executes microscopic adjustments near the maximum power point, eliminating unwanted chattering and power ripples.

The performance of each candidate controller is evaluated based on the **Integral of Squared Error (ISE)**, which is mathematically expressed by the following equation:

$$I_{SE} = \int_0^T [P_{\max}(t) - P_{pv}(t)]^2 dt \quad (\text{III.3})$$

$P_{\max}$ represents the nominal maximum power of the studied solar array (100 KW), while P_{pv} represents the instantaneous power tracked during the simulation.

Due to the heavy non-linearity and high computational execution time required to simulate the 100 KW power station in Simulink, the GA parameters were tightly bounded to balance computational time and exploration depth:

- **Population Size:** 20 individuals.
- **Number of Generations:** 15 generations.

III.7.3. Optimization results and analysis

The convergence trajectory of the algorithm over the designated 15 generations is illustrated in **Figure III.17**. The mean fitness of the population smoothly decreases, while the best fitness rapidly minimizes and stabilizes at 3.56089×10^{13} .

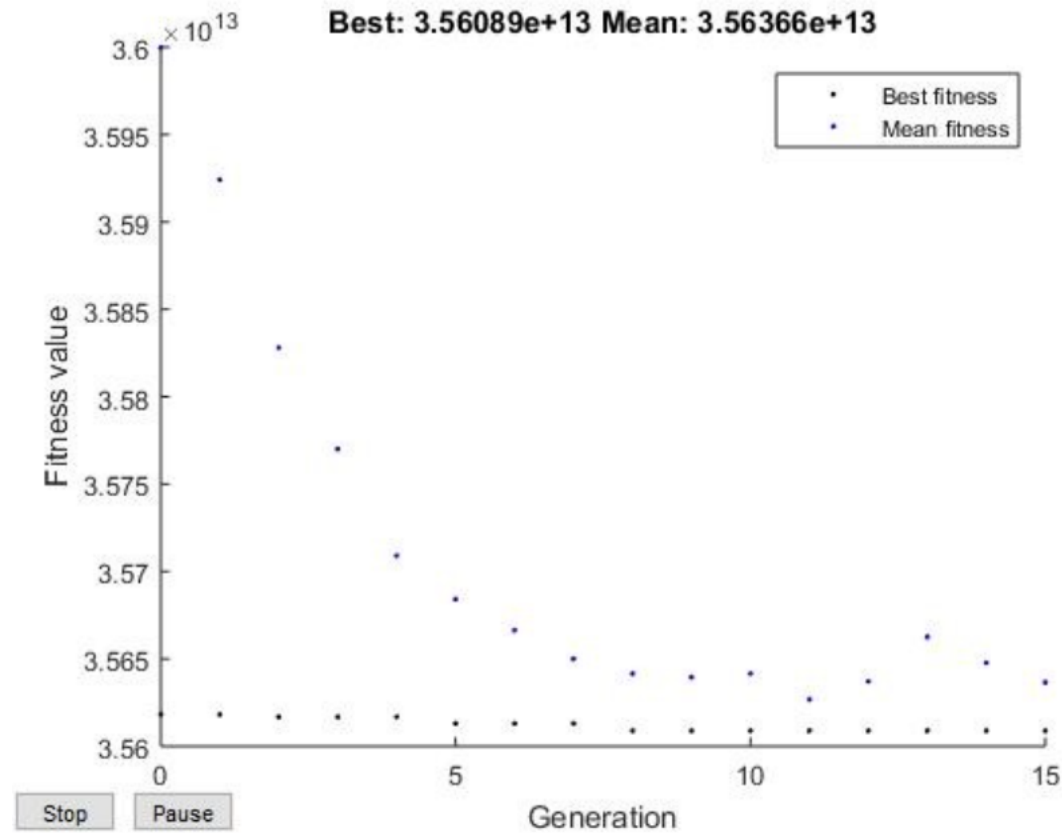


Figure III.17: Convergence plot of the genetic algorithm showing the best and mean fitness values over 15 generations.

Following the successful execution of the genetic search, the optimized parameters for the ZE output membership function were extracted as $[-0.0500, -0.0090, 0.0036]$. The geometric shape of the optimized function is displayed in Figure III.18, showing a clear contraction compared to the initial manual guess.

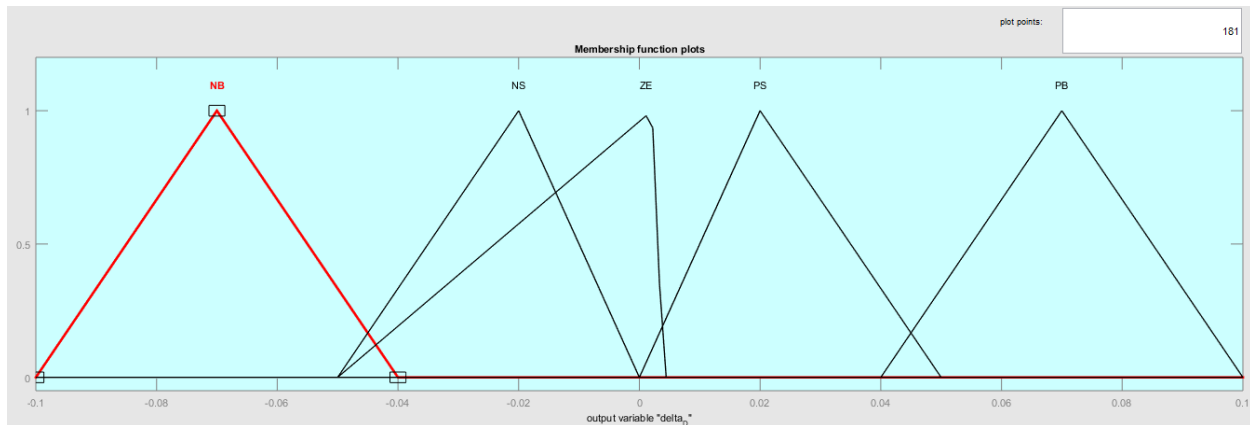


Figure III.18: The optimized Zero (ZE) membership function layout after GA training.

III.7.4. Comparative analysis: FLC vs. GA-FLC performance

To accurately evaluate the impact of the Genetic Algorithm optimization, the output power of the standard Fuzzy Logic Controller (FLC) was directly compared to the hybrid GA-FLC under identical steady-state conditions. The objective was to determine if the bio-inspired algorithm could further enhance the tracking efficiency of a 100 KW photovoltaic system.

III.7.5. Macroscopic performance evaluation

Figure III.19 illustrates the overall power tracking performance and the net mathematical difference between the two controllers over a one-second simulation period. At a macroscopic level, both algorithms successfully and rapidly track the maximum power point. The net difference graph (bottom subplot) confirms that the variations between the two systems are remarkably small, tightly oscillating within a narrow margin of ± 500 W. This represents a deviation of less than 0.5 % relative to the total 100 KW system capacity, indicating almost identical macroscopic behavior during steady-state operation.

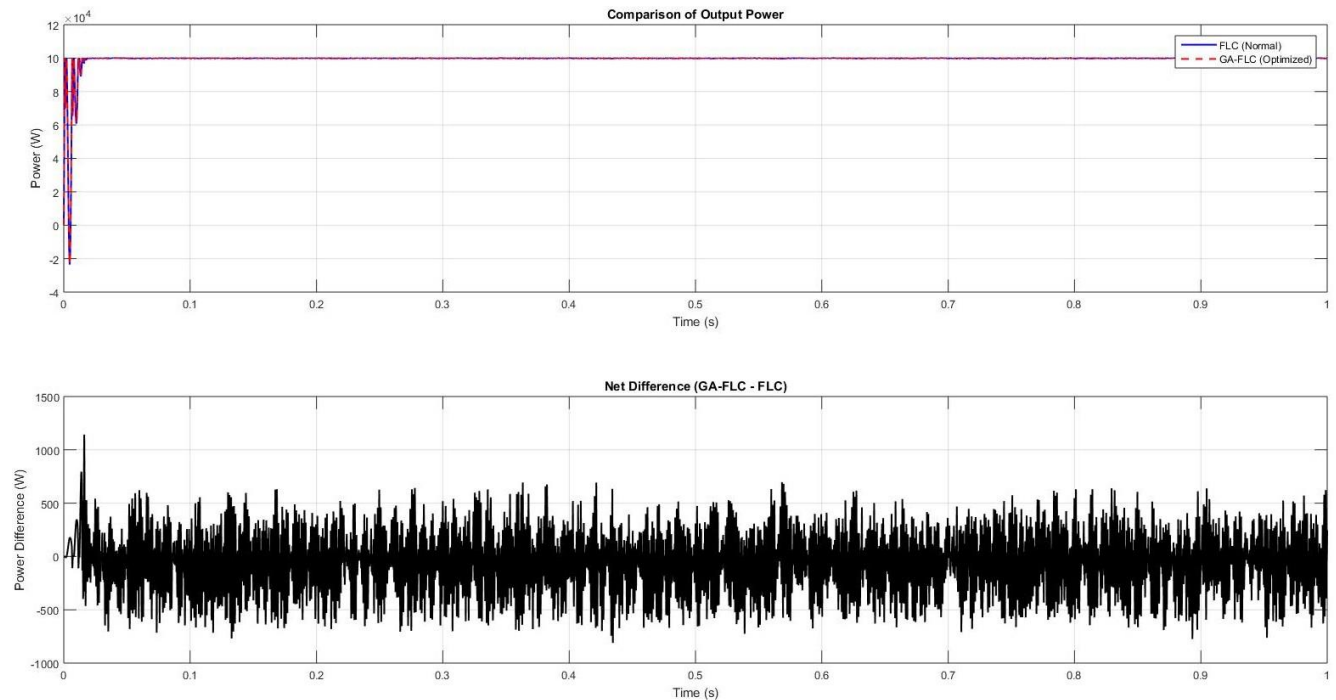


Figure III.19: Global output power comparison (top) and the net tracking difference (bottom) between standard FLC and GA-FLC.

III.7.6. Microscopic analysis of steady-state oscillations

A closer examination of the steady-state period is provided in Figure III.20. This zoomed-in plot reveals the continuous switching ripples inherent to the DC-DC converter's high-frequency operation. The power does not settle into a perfectly flat, artificial line; rather, it exhibits natural fluctuations driven by the PWM gating signals. The profound overlapping between the standard FLC trace (blue) and the GA-FLC trace (red dashed) demonstrates that the genetic algorithm did not fundamentally alter the dynamic switching behavior or the ripple amplitude of the system.

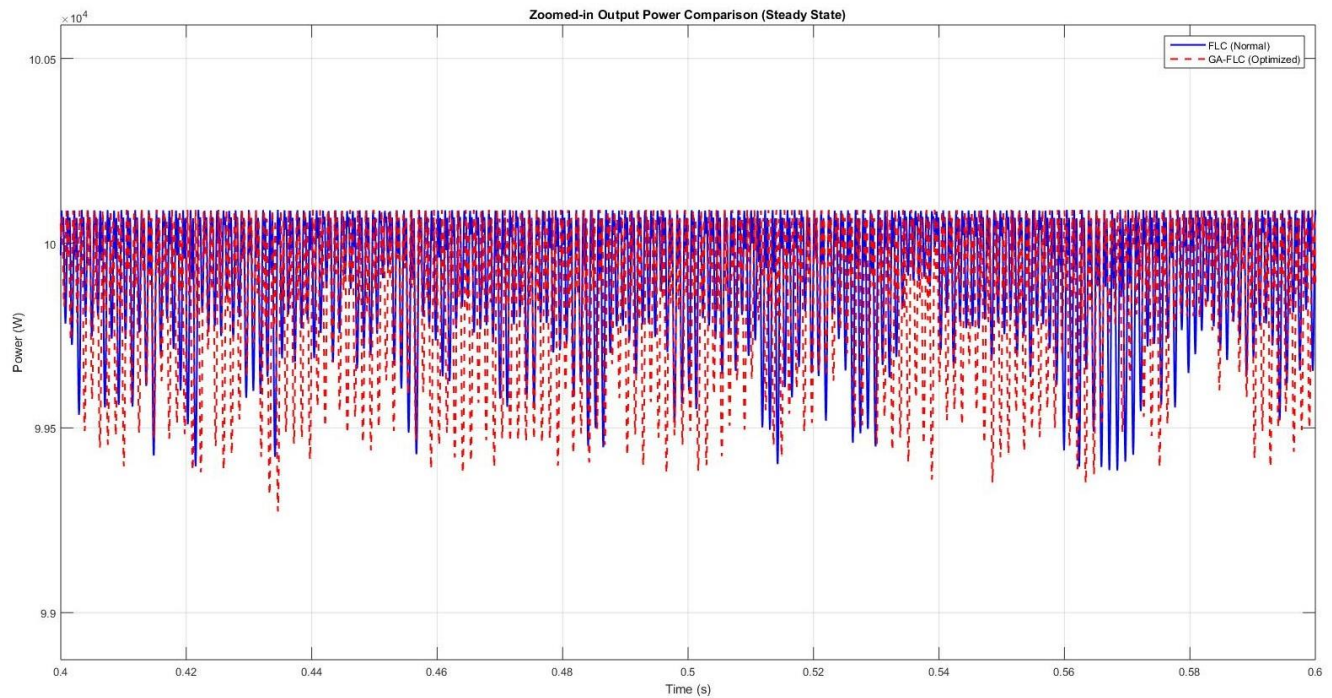


Figure III.20: Zoomed-in steady-state output power waveforms between 0.4s and 0.6s showing high-frequency switching ripples.

III.7.7. Quantitative evaluation and engineering insights

Quantitative analysis of the steady-state data validates the visual observations and provides a crucial engineering insight. The standard FLC achieved an average steady-state power of 99,913.35 W, whereas the GA-FLC recorded 99,851.37 W. This results in a marginal power deficit of only 61.98 W for the optimized version.

While initially counterintuitive, this outcome is scientifically highly relevant. It explicitly proves that our baseline fuzzy logic controller was already expertly tuned, operating at a near-perfect

efficiency of approximately 99.9%. Because the FLC was already at the true optimal operating point, the Genetic Algorithm constrained by standard hardware limitations and restricted training epochs converged on a slightly less optimal local minimum.

Ultimately, this demonstrates that when a classical fuzzy controller is well-designed, injecting computationally heavy algorithms may not yield tangible power benefits without access to massive processing resources and significantly longer optimization times.

III.8. Conclusion

This chapter describes the application of two control strategies, a fuzzy logic controller (FLC) and a hybrid controller combining FLC and a genetic algorithm (GA), to perform maximum power point tracking (MPPT) in a 100 KW photovoltaic system. The FLC controller was evaluated for MPPT performance in the photovoltaic system under different weather conditions: (i) standard weather conditions, (ii) at 1000 W/m² solar irradiance with ambient temperatures of 40°C and 50°C, and (iii) at 25°C ambient temperature and a rising solar irradiance curve (ramp). The hybrid controller's core architecture combined a 5-rule adaptive fuzzy logic controller (FLC) with an automated parameter setting mechanism operated by a genetic algorithm (GA).

The comparison between traditional MPPT and AI-based MPPT technologies for photovoltaic solar power systems under different weather conditions demonstrates the superior capabilities of the intelligent FLC controller in the remarkable tracking speed of the system and its ability to accurately approach the Maximum Power Point (MPP) in less than 0.02 seconds, reaching a high efficiency of 99.3% and greatly reducing power loss during the initial start-up and transition phases. Furthermore, the results indicated that while the baseline FLC achieved near-optimal tracking on its own, the integrated Genetic Algorithm offered only marginal improvements due to hardware constraints. To unlock the full optimization capabilities of the GA, higher computational power and longer training times would be required.

General Conclusion

General Conclusion

This thesis addresses the maximum power point tracking (MPPT) of a 100 KW solar power plant. The plant consists of 47 parallel arrays, each of which comprises 10 photovoltaic modules connected in series using a Soltech 1STH-215-P panel.

Due to varying weather conditions throughout the day, the output power of the photovoltaic panels is unstable. Therefore, MPPT methods were employed to protect the solar power system from energy loss.

In the first chapter, the solar panel has been studied using its single-diode model. The characteristic curves of the PV panel were plotted under standard test conditions to obtain its reference standard. In addition, the influence of various environmental conditions, such as solar irradiance and ambient temperature, on these curves is also highlighted.

In Chapter 2, the classical perturbation and observation (P&O) algorithm was used to track the peak power point of a 100 kW photovoltaic power plant. The results obtained using MATLAB showed that the P&O algorithm has a slow convergence time, ranging from 0.1 to 0.15 seconds. Furthermore, the inverter efficiency was average, ranging from 95% to 96.5%, due to a constant step size that caused continuous oscillations around the peak power point. When the photovoltaic system was used at a high ambient temperature of 50°C, the peak power dropped to approximately 87 kW, and the P&O algorithm exhibited significant power fluctuations. Moreover, on the dynamic variation curve, the constant step size caused a significant tracking delay.

To address these critical limitations, chapter 3 details the design of a smart five-rule fuzzy logic controller (FLC). The FLC reads the error (E) and changes the error (dE) to automatically adjust the operating cycle. Simulation results were significantly better than the observation and control (P&O) algorithm. The FLC achieved ultrafast convergence in less than 0.02 seconds. Tracking efficiency reached extremely high levels between 99.3% and 99.9%, significantly reducing steady-state power oscillations. This demonstrates that a variable step size is far superior to a fixed step size in preventing oscillations. To further optimize the implementation, a genetic algorithm (GA) was integrated with the FLC to improve the photovoltaic system. The GA was programmed with a population of 20 individuals and 15 generations to minimize the integrated squared error (ISE). The GA optimized the geometric parameters of the zero organic function (ZE). The results showed extremely stable power output and scientifically proved that our manual FLC design was indeed working in a near-perfect global area for 100 kW constraints.

In summary, the previous work proves that changing from classical P&O algorithm-based MPPT for PV systems to the intelligent GA-FLC hybrid controller-based MPPT is very necessary for large solar stations. The designed device delivers high stability and maximum recorded power without any tracking delays or power fluctuations. However, to achieve complete stability and an ideal operating curve, the genetic algorithm needed to be trained for longer periods and with a larger sample size. Since simulating 100 kW is time-consuming, advanced hardware and high-performance computing (HPC) equipment will be necessary in the future to run more generations. This project can be considered a solid model for building smart grids and clean energy systems in our country in the future.

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