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**Contribution aux algorithmes MPPT par l'intégration de
l'optimisation bio-inspirée dans les systèmes photovoltaïques**

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*In loving memory of my grandmother, whose spirit continues to inspire me;
and to my mother and father, for their endless love and unwavering support.*

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Abstract

This thesis investigates advanced modeling and control strategies to enhance the performance of photovoltaic systems under variable environmental conditions. An adaptive photovoltaic model based on fuzzy logic with genetically optimized rules is proposed to accurately represent the nonlinear behavior of PV generators, achieving improved prediction accuracy and robustness under dynamic irradiance and temperature variations. In parallel, an enhanced indirect MPPT approach combining a (P&O) algorithm with a Grasshopper Optimization Algorithm–tuned Tilted Integral Derivative controller is developed using an experimentally identified small-signal model. The proposed control strategy ensures improved voltage regulation and reduced oscillations around the maximum power point. Simulation and experimental results confirm the effectiveness and robustness of the proposed approaches compared to conventional techniques.

Resumé

Cette thèse s'intéresse à des stratégies avancées de modélisation et de commande visant à améliorer les performances des systèmes photovoltaïques fonctionnant sous des conditions environnementales variables. Un modèle photovoltaïque adaptatif basé sur la logique floue et des règles optimisées par algorithme génétique est proposé afin de représenter avec précision le comportement non linéaire des générateurs photovoltaïques, en offrant une meilleure précision de prédiction et une robustesse accrue face aux variations d'irradiance et de température. En parallèle, une approche MPPT indirecte améliorée, combinant l'algorithme (P&O) et un régulateur TID (Tilted Integral Derivative) optimisé par l'algorithme d'optimisation des sauterelles (GOA), est développée à partir d'un modèle petit signal identifié expérimentalement. La stratégie de commande proposée assure une meilleure régulation de la tension et une réduction des oscillations autour du point de puissance maximale. Les résultats de simulation et expérimentaux confirment l'efficacité et la robustesse des approches proposées par rapport aux méthodes conventionnelles.

المخلص

تتناول هذه الأطروحة استراتيجيات متقدمة للنمذجة والتحكم تهدف إلى تحسين أداء الأنظمة الكهروضوئية في ظل الظروف البيئية المتغيرة. تم اقتراح نموذج كهروضوئي تكيفي قائم على المنطق الضبابي مع قواعد مُحسَّنة باستخدام الخوارزميات الجينية، وذلك لتمثيل السلوك غير الخطي لمولدات الطاقة الكهروضوئية بدقة عالية، مما يحقق تحسناً ملحوظاً في دقة التنبؤ وزيادة في المتانة تحت تغيرات الإشعاع الشمسي ودرجة الحرارة. وبالتوازي مع ذلك، تم تطوير منهج محسَّن للتتبع غير المباشر لنقطة القدرة العظمى (MPP) ، يجمع بين خوارزمية (P&O) ومنظم من نوع التكامل الاشتقاق المائل (TID) مضبوط باستخدام خوارزمية (GOA) وذلك اعتماداً على نموذج خطي حول نقطة القدرة العظمى تم تحديده تجريبياً. تضمن استراتيجية التحكم المقترحة تحسين تنظيم الجهد وتقليل التذبذبات حول نقطة القدرة العظمى وتؤكد نتائج المحاكاة والتجارب العملية فعالية ومتانة المناهج المقترحة مقارنة بالتقنيات التقليدية.

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Nomenclature

E	Energy of a photon (photon energy) (J)
h	Planck's constant
ν	Frequency of the light wave (Hz)
I	Photovoltaic system output current (A)
I_{ph}	Photocurrent generated under irradiance and temperature variations (A)
I_D	Diode current representing diffusion and recombination effects (A)
I_{sh}	Current flowing through the shunt (parallel) resistance (A)
I_0	Reverse saturation current of the diode (A)
V_T	Thermal voltage of the p–n junction (V)
R_s	Series resistance modeling internal ohmic losses (Ω)
R_p	Shunt (parallel) resistance modeling leakage effects (Ω)
k	Boltzmann constant
q	Electron charge
T, T_c	Cell temperature (operating temperature) (K)
T_{STC}	Cell temperature under STC (25 °C)(K)
G	Solar irradiance (W m^{-2})
G_{STC}	Irradiance under STC (1000 W m^{-2})
K_i	Short-circuit current temperature coefficient ($\text{A } ^\circ\text{C}^{-1}$)
I_{sc}	Short-circuit current at 25 °C
n	Ideality factor (diode ideality factor)
f_s	DC–DC converter switching frequency (Hz)
$\Delta I, \Delta V$	Incremental variations of current and voltage for MPPT decision logic
ΔI_L	Inductor current ripple in DC–DC converters (A)

Nomenclature

ΔV_{out}	Output voltage ripple in DC–DC converters (V)
R_o	Physical load resistance (Ω)
R_i	Equivalent input resistance seen from the PV side (Ω)
D, D^*	Duty cycle of DC–DC converter and its optimal value for MPP tracking
r_t	The total number of rules
j	The number of linguistic states per input
i	The number of input variables
x^*	Final crisp (defuzzified) output of fuzzy control
m	The number of the linguistic states used
μ_A	The degrees of membership of the inputs
μ_B	The degrees of membership of the outputs
$\mathbf{x}_{i,j}$	The value of a specific parameter in a candidate solution
N	The population size (number of chromosomes)
D	The number of parameters to identify (dimension of the problem)
ρ	A uniformly distributed random number in the interval $[0, 1]$
x_j^L	The lower bound of the search space for the j^{th} parameter
x_j^U	The upper bound of the search space for the j^{th} parameter
S_i	The Social Interaction component
G_i	The Gravitational Force component
A_i	The Air Advection component
r_1, r_2, r_3	Random numbers between 0 and 1, to introduce randomness and stochasticity
S	The strength of the social forces, determined by the distance
δ	The distance between the grasshoppers
f	The intensity of attraction (a constant parameter)
l	The attractive length scale (a constant parameter)
g	The gravitational constant
$\hat{e}_g$	The unit vector pointing towards the center of the Earth (or down)
u	The constant drift (magnitude of the wind force)
$\hat{e}_w$	The unit vector in the wind's direction

Nomenclature

C	The Controlling Parameter that balances exploration and exploitation
ub_d	The upper bound of the search space in the D^{th} dimension
lb_d	The lower bound of the search space in the D^{th} dimension
$C_{\max}$	The maximum value of the controlling parameter C
$C_{\min}$	The minimum value of the controlling parameter C
I	The current iteration number
Max_iter	The maximum number of iterations (the stopping criterion for the optimization)
N_c	Number of cells
N_s	Number of panels in series
N_p	Number of panels in parallel
I_m^g	Global PV current (A)
V_m^g	Global PV voltage (V)
R_s^g	Fixed global series resistance (Ω)
R_s^1	Internal and contact resistance of a PV cell (Ω)
R_p^g	Fixed global shunt resistance (Ω)
R_p^1	Leakage (shunt) resistance of a PV cell (Ω)
V_T^g	The global thermal voltage of the PV array (V)
V_T^1	The thermal voltage of a single diode (V)
ω	Wind speed ($\text{m}\cdot\text{s}^{-1}$)
K_r	Manufacturer parameter (dimensionless, positive)
I_{ph}^g	Global photo-current of PV generator (A)
I_{ph}^1	Photo-current of one single PV panel (A)
α	Temperature coefficient ($\text{A}\cdot\text{C}^{-1}$ or manufacturer-dependent)
$I_{sh,0}^1$	Nominal short-circuit current for a single diode (A)
I_{0d}^g	Global reverse saturation current (A)
I_{0d}^1	Reverse saturation current of one diode (A)
E_g	Band-gap energy of semiconductor (eV or J)
I_{sr}^1	Single diode current (A)
V_{oc}^1	Open-circuit voltage of one PV panel (V)

Nomenclature

β	Temperature coefficient for monocrystalline PV tech ($V \cdot ^\circ C^{-1}$)
$X^{\aleph}$	The normalized input vector
$G^{\aleph}$	The normalized solar irradiance
$T_c^{\aleph}$	The normalized cell temperature
$V_m^{\aleph_g}$	The normalized global PV voltage
$n^{\aleph}$	The normalized ideality factor
$R_s^{\aleph_g}$	The normalized global series resistance
$R_P^{\aleph_g}$	The normalized global parallel resistance
D_{mpp}	The duty cycle of the boost converter at the MPP
R_{mpp}	The resistance of the PV panel at the (MPP) (Ω)
R_{load}	The resistive load connected to the output of the boost converter (Ω)
f_p	The frequency of the sine wave that disturbs the duty cycle (Hz)
A_p	The amplitude of the sine wave that disturbs the duty cycle
δv_{pv}	The perturbation in PV voltage (v)
δd	The perturbation in the duty cycle
K_t, K_i, K_d, n	Tilt, Integral, and Derivative Gains and additional tuning parameter

Abbreviation

AI	Artificial Intelligence
BOA	Bisector of Area
CDER	Centre de Développement des Énergies Renouvelables
COG	Center of Gravity
DC	Direct Current
EMI	Electromagnetic Interference
FLC	Fuzzy Logic Controller
GA	Genetic Algorithm
GOA	Grasshopper Optimization Algorithm
IncCon	Incremental Conductance
ITAE	Integral Time Absolute Error
LOM	Largest of Maximum
MOM	Mean of Maximum
MPP	Maximum Power Point
MPPT	Maximum Power Point Tracking
MSE	Mean Squared Error
P&O	Perturb and Observe
PID	Proportional–Integral–Derivative
PN	P-N Junction
PSO	Particle Swarm Optimization
PV	Photovoltaic
PWM	Pulse Width Modulation
SI	Swarm Intelligence

Abbreviation

SOM	Smallest of Maximum
STC	Standard Test Conditions
TID	Tilt-Integral-Derivative

General Introduction

The efficient exploitation of photovoltaic (PV) energy systems under real operating conditions remains a major research challenge due to the strong nonlinearity of PV generators and their pronounced sensitivity to environmental variations [1,2]. Solar irradiance, ambient temperature and wind speed continuously affect the electrical characteristics of PV arrays, leading to time-varying power-voltage behavior and frequent displacement of the maximum power point (MPP) [3–5]. Consequently, ensuring accurate system modeling and reliable maximum power point tracking (MPPT) is fundamental to maximizing energy extraction and guaranteeing stable PV system operation [6,7].

Photovoltaic Cell Modeling

A photovoltaic (PV) cell is commonly represented by an equivalent single-diode model characterized by five lumped parameters: the photocurrent I_{ph} , the diode reverse saturation current I_s , the diode ideality factor n , the series resistance R_s , and the shunt resistance R_{sh} [8,9]. Under standard test conditions (STC), these parameters are assumed to be constant and must be accurately identified to ensure reliable model behavior. Several parameter-extraction methods have been reported in the literature. Analytical methods derive closed-form expressions using characteristic points provided in manufacturer datasheets, such as the short-circuit current, open-circuit voltage, and maximum power point; although computationally efficient, these approaches rely on simplifying assumptions and may suffer from reduced accuracy when the nonlinear nature of the model is pronounced [10,11]. Numerical and iterative methods formulate the extraction process as a nonlinear equation-solving problem, typically employing techniques such as Newton–Raphson or least-squares optimization; while more accurate, these methods are sensitive to initial guesses and may experience convergence difficulties [12,13]. Metaheuristic

optimization techniques, including genetic algorithms, particle swarm optimization, and other evolutionary strategies, have also been widely adopted to identify fixed PV parameters by minimizing the error between measured and simulated I–V characteristics; despite their strong global search capability, these methods often involve high computational cost and require careful tuning of algorithm parameters to avoid premature convergence or excessive computation time [14, 15]. Consequently, the choice of parameter-extraction technique represents a trade-off between accuracy, robustness, and computational efficiency in fixed-parameter PV modeling.

Maximum Power Point Control

Beyond accurate PV modeling, maximum power point tracking (MPPT) is essential for optimal energy extraction. The widely used Perturb and Observe (P&O) algorithm is popular for its simplicity and low computational demand, operating by perturbing the operating point and observing power changes to reach the maximum power point (MPP) [16]. Researchers have proposed enhancements such as variable step-size, adaptive, and predictive strategies to reduce oscillations and improve tracking speed [17]. However, these modifications often increase complexity, require careful tuning, and may remain sensitive to rapid irradiance changes [18, 19]. Indirect MPPT architectures, in which the algorithm generates a reference voltage or current and a secondary control loop regulates the DC–DC converter, have also received significant attention [20, 21]. Researchers have implemented various control strategies for the inner loop, including classical PI/PID controllers, sliding mode controllers, and model-predictive controllers [22–25]. While these approaches improve stability and reduce oscillations, their performance is strongly dependent on accurate controller tuning, system modeling fidelity, and the handling of parameter variations [26]. For instance, PI/PID controllers require precise tuning to achieve fast response without overshoot, whereas sliding-mode or predictive controllers demand higher computational effort and may be sensitive to measurement noise. Moreover, model-based indirect MPPT schemes can suffer from degraded performance if the small-signal or equivalent circuit representation does not accurately capture the system dynamics, particularly under varying irradiance or temperature conditions [20, 21, 23].

Research motivation

Problem Statement

Modeling side: Conventional fixed-parameter PV models cannot adequately capture real-time variations in environmental conditions, such as irradiance and temperature. This results in discrepancies between predicted and actual PV behavior, which adversely affects the design and performance of MPPT controllers.

Control side: Traditional MPPT algorithms, including the Perturb and Observe (P&O) method, are prone to oscillatory behavior around the Maximum Power Point (MPP) and exhibit degraded performance under rapidly changing irradiance or load conditions, leading to energy losses and reduced system efficiency.

Hypothesis

Modeling side: coupling fuzzy-based adaptive PV models with the Genetic Algorithm (GA) for real-time parameter identification can significantly improve the accuracy of PV cell modeling under dynamic weather conditions.

Control side: employing an experimentally identified small-signal PV system model in conjunction with a Tilted Integral-Derivative (TID) controller optimized via Grasshopper Optimization Algorithm (GOA) can enhance MPPT performance, reducing oscillations around the MPP and maintaining high energy extraction efficiency under fast-varying environmental and load conditions.

Project Objectives

The main objective of this thesis is to improve the reliability and efficiency of photovoltaic systems by addressing two separate contributions, namely accurate PV modeling and advanced MPPT control design. To achieve this goal, the study focuses on several key tasks:

- Developing an adjustable-parameter PV model using a fuzzy logic mechanism with GA-optimized rules to predict PV current under varying climatic conditions.
- Experimentally validating the PV model.

- Deriving an experimental small-signal model of the complete PV system to capture real-world dynamics, including parasitic and nonlinear effects.
- Implementing a TID voltage controller integrated with the P&O algorithm, optimized via GOA to minimize voltage tracking error and improve MPPT efficiency.
- Evaluating the proposed P&O-TID-GOA strategy experimentally under varying irradiance and load conditions to assess improvements in dynamic response and power ripple reduction.

Thesis Outline

This thesis begins with a general introduction that outlines the research context, motivations, and objectives aimed at improving the performance of photovoltaic energy conversion systems under dynamic operating conditions. The manuscript is structured into four chapters that progressively address the modeling, control, and optimization aspects of photovoltaic systems.

Chapter 1 establishes the fundamental background required for the remainder of the thesis. It provides a general overview of photovoltaic energy systems by introducing the basic principles of photovoltaic energy conversion and the overall architecture of a PV system. The chapter discusses the main components involved in photovoltaic power generation and highlights the key factors influencing system performance under varying operating conditions. In addition, it presents classical Maximum Power Point Tracking (MPPT) techniques, outlining their general operating principles and practical significance. **Chapter 2** focuses on control strategies for maximizing the extracted power from photovoltaic systems. It provides a detailed review of MPPT techniques, highlighting the operating principles and limitations of conventional methods under rapidly changing environmental conditions. The chapter then introduces advanced and bio-inspired optimization-based MPPT approaches, emphasizing their ability to enhance tracking accuracy, dynamic response, and robustness compared to classical techniques. **Chapter 3** develops a dynamic photovoltaic modeling approach capable of accurately representing PV behavior under variable environmental conditions. A fuzzy logic-based mechanism is introduced to supervise the evolution of key PV model parameters, while a genetic algorithm is used to optimally update the fuzzification rules by minimizing the modeling error. The proposed adjustable-parameter PV model is validated using experimental

data, demonstrating a significant reduction in prediction error compared to conventional fixed-parameter models. The results confirm the robustness, adaptability, and suitability of the proposed model for advanced MPPT control design. **Chapter 4** focuses on the design and implementation of an advanced MPPT control strategy for photovoltaic systems based on a GOA-tuned TID controller. A small-signal model of the PV system is experimentally identified and used to accurately tune the controller parameters for improved voltage regulation and dynamic response. The proposed P&O–TID–GOA approach is evaluated under varying irradiance and load conditions, showing reduced oscillations around the maximum power point and faster convergence compared to conventional methods. Experimental results confirm the effectiveness, robustness, and practical feasibility of the proposed control strategy in real operating conditions.

Finally, the general conclusion synthesizes the main outcomes of this research by highlighting the complementary contributions of adaptive photovoltaic modeling and advanced MPPT control strategies.

Chapter 1

Photovoltaic System

Fundamentals

1.1 Introduction

Renewable energy technologies have evolved into reliable and efficient solutions for meeting the growing global demand for electricity. Driven by increasing environmental concerns, climate change, and the progressive depletion of fossil fuel reserves, renewable sources have become essential components of modern energy systems, supporting sustainable development and accelerating the global energy transition [27–30]. Among these sources, solar energy is particularly attractive because of its large global potential, wide geographic availability, and continual improvements in photovoltaic (PV) technology and manufacturing. Solar energy is harnessed primarily by two approaches: solar thermal systems, which convert solar radiation into heat, and photovoltaic systems, which convert sunlight directly into electricity using semiconductor devices. Photovoltaic cells are the elementary units of PV systems; in practice, large numbers of cells are interconnected in series and parallel to form modules and arrays, allowing designers to scale systems to meet diverse power requirements and installation constraints [31, 32]. Despite their advantages, PV systems face important technical challenges that motivate further research. The electrical output of PV generators is highly nonlinear and strongly dependent on environmental conditions (especially irradiance and temperature) which vary continuously over time. High irradiance generally increases power output, while elevated temperatures reduce open-circuit voltage and degrade conversion efficiency.

Partial shading, spectral changes, and aging introduce additional complexity, producing multiple local maxima in the power–voltage characteristic and increasing the risk of power losses and hotspot formation. These factors make reliable extraction of maximum energy difficult in real operating environments and demand robust control and adaptation strategies [33–35]. Because PV systems operate under continuously changing irradiance and temperature, their power–voltage characteristics vary in real time. Maximum Power Point Tracking (MPPT) techniques are therefore required to adjust the operating point of the PV generator so it coincides with the maximum power point (MPP). Classical MPPT algorithms perform well under steady conditions but may become less effective during rapid transients or partial shading, creating the need for more robust and adaptive control strategies [36, 37]. This chapter presents the fundamental principles of photovoltaic systems, these fundamentals provide the necessary background for the subsequent chapters.

1.2 Photovoltaic Effect and PV Cell Structure

1.2.1 Photovoltaic Effect

When light reaches a solar cell, part of the incident energy is converted directly into electricity without any movement or reaction that produces waste or pollution. This remarkable property is at the heart of all photovoltaic installations. The photovoltaic effect was first observed by Antoine Becquerel in 1839, who highlighted the particular behavior of energy; the change in a material’s conductivity under the influence of light [38]. In 1876, a photoelectric phenomenon was observed in selenium, and this material was used to measure light before silicon was developed [39]. Silicon cell technology is now well mastered, and current developments focus on improving efficiency and reducing manufacturing costs [40].

To generate an electric current in a semiconductor, energy must be supplied that allows electrons to be extracted from the valence band and transferred to the conduction band, i.e., energy greater than the bandgap. High temperature or light, whose photons carry energy $E = h\nu$, can produce this effect. When light enters a semiconductor, if its energy exceeds the bandgap, it can make the material transition from an insulating to a conductive state, a phenomenon enhanced as the semiconductor’s temperature rises [41].

When an electron is extracted from the valence band to the conduction band, it leaves a hole behind, which can be filled by a nearby electron, creating a new hole

in turn, continuing through the material. For the charges released by illumination to generate energy, they must flow into an external circuit, which is achieved via a junction intentionally created in the semiconductor. This junction, together with doping, generates an internal electric field that drives negative charges to one side and positive charges to the other, enabling current flow [42].

1.2.2 PV Cell Mathematical Modeling

Numerous comparable circuits have been put out in the literature to evaluate the PV cell's behavior [43–47], among which the single-diode model is a fundamental and widely adopted representation, it achieves the ideal balance of being accurate enough for identification yet simple enough for real-time control. While more complex models (such as the double-diode or five-parameter models) can capture additional physical effects, they significantly increase computational complexity and parameter uncertainty, which can hinder system identification accuracy and real-time MPPT performance. A PV cell's most common configuration consists of a current source, a diode, and a number of resistors coupled in series and parallel as represented in Figure 1.1. The following formulas can be used to determine how

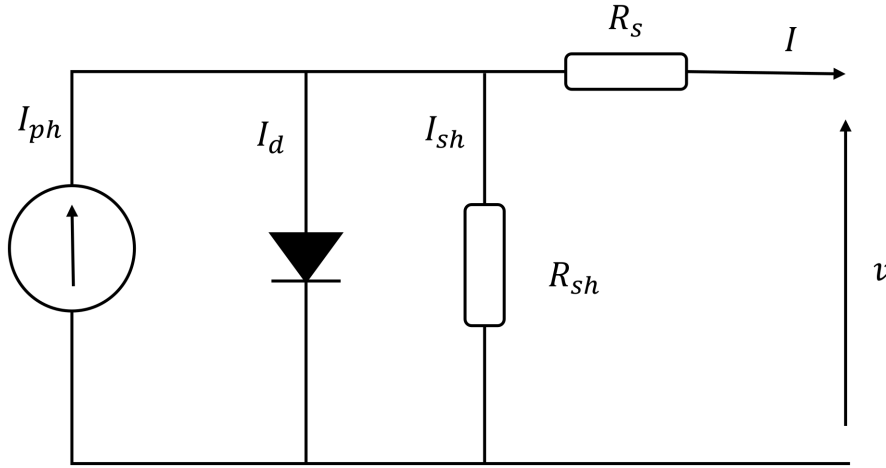


Figure 1.1: The Equivalent Circuit of PV Cell

much current a solar cell generates [48]:

$$I = I_{ph} - I_{od} - I_{sh} \quad (1.1)$$

Where I is the PV array output current, I_{ph} is the photo current, I_{od} is the diode current, and I_{sh} is the parallel resistance current.

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Temperature and irradiance have an impact on what I_{ph} produces. I_{ph} rises with high temperature or irradiation [49]. I_{ph} is computed using the following equation:

$$I_{ph} = \frac{G}{G_{STC}} (I_{sc} + K_i (T - T_{STC})) \quad (1.2)$$

Where: K_i is the cell's short-circuit current temperature coefficient ($A^\circ C^{-1}$), I_{sc} is the cell's short-circuit current at $25^\circ C$, T is the cell's temperature ($^\circ C$), T_{STC} is the cell's temperature under STC ($25^\circ C$), G is the solar irradiance ($W m^{-2}$), and G_{STC} is the irradiance under STC ($1000 W m^{-2}$).

On the other hand, the diode current I_D is mainly temperature dependent, as described in Equation 1.3

$$I_{od} = I_0 \left[e^{\frac{V+IR_s}{nV_T}} - 1 \right] \quad (1.3)$$

With:

$$V_T = \frac{kT}{q} \quad (1.4)$$

Where I_0 is the reverse saturation current, k is the Boltzmann constant ($1.38 \times 10^{-23} J K^{-1}$), T is the temperature of p-n junction (K), and q is the electron charge ($1.6 \times 10^{-19} C$).

Equation 1.5 describes the relationship between the module's output current I and its voltage V :

$$I = I_{ph} - I_0 \left[e^{\frac{V+IR_s}{nV_T}} - 1 \right] - \frac{V + IR_s}{R_p} \quad (1.5)$$

Where R_p is the parallel (shunt) resistance (Ω), R_s is the series resistance (Ω).

1.2.3 PV Cell Technologies

The fundamental unit of a photovoltaic (PV) system is the solar cell, a device that converts incident solar irradiance directly into electrical energy in the form of direct current (DC). Structurally, a conventional solar cell is based on a PN junction fabricated from semiconductor materials, operating under principles comparable to those of a diode. Among the various semiconductor options, silicon remains the most extensively used material in commercial solar cell manufacturing due to its technological maturity, availability, and reliability. The choice of cell material strongly influences both the power conversion efficiency and the overall production cost, leading to diverse performance-to-cost trade-offs across technologies [50–53]. The main photovoltaic cell material classifications are outlined below:

Monocrystalline Silicon

Monocrystalline silicon is currently the most widely adopted and dominant photovoltaic cell technology in commercial solar panels. It is manufactured from a single, high-purity silicon crystal, a structure that enables efficient electron movement and minimizes electrical losses. As a result, it achieves high power conversion efficiency, typically ranging from 17% to 24%, allowing greater energy generation compared to other silicon-based technologies. It also exhibits a low temperature coefficient, meaning that its output power is less affected by temperature increases, which improves thermal stability and reduces efficiency degradation in hot operating conditions. Additionally, monocrystalline cells perform comparatively better under low irradiance levels, such as in cloudy weather or early/late daylight hours, contributing to more consistent energy harvesting. These cells are known for their long service life and high reliability due to the uniform crystal structure and mature manufacturing process. Owing to their high efficiency and durability, monocrystalline cells are particularly suitable for installations with limited surface area, high-performance system requirements, and applications prioritizing long-term energy yield [50, 53].

Polycrystalline Silicon

Polycrystalline silicon cells are a well-established PV technology manufactured by melting and solidifying multiple silicon crystals, forming a material with more grain boundaries than single-crystal silicon. These boundaries slightly limit electron flow, leading to a moderate conversion efficiency of about 15%–18%, lower than monocrystalline cells. In contrast, their fabrication process requires less energy and is simpler, reducing production costs, which makes polycrystalline cells a popular and economical option for large-scale and utility solar installations where space is not a limiting factor [51, 53].

Amorphous Silicon

Amorphous silicon cells are a thin-film PV technology based on silicon deposited in a non-crystalline form, which limits electron mobility and results in very low efficiency, typically around 6%–9%, yielding less power than crystalline silicon cells. Their manufacturing process is simpler and less energy-demanding, making them low-cost, and they can be deposited on flexible substrates, enabling lightweight and bendable solar modules. Consequently, a-Si cells are mainly used in applications where affordability and flexibility are prioritized over high efficiency [52, 53].

1.3 PV Module and Array Configuration

Photovoltaic (PV) modules are composed of several solar cells connected in series and/or parallel to achieve the desired voltage and current levels. The interconnection of multiple modules forms a PV array, which serves as the main source of electrical power in solar energy systems. The configuration of these modules directly influences the overall performance of the system, including its output power, voltage, and current characteristics. Proper arrangement and sizing of the modules are therefore essential to ensure optimal energy generation and efficient operation under varying environmental conditions .

1.3.1 I–V and P–V Characteristics

The current–voltage (I–V) and power–voltage (P–V) characteristics are fundamental for understanding the electrical behavior and performance of photovoltaic (PV) modules. The I–V characteristic defines the relationship between the output current and voltage of a PV device under specific irradiance and temperature conditions. It is highly nonlinear, governed by the diode equation (Equation 1.5) and influenced by intrinsic parameters of the solar cell, particularly the series resistance (R_s) and shunt resistance (R_{sh}). As a result of this nonlinear behavior, a PV module has an optimum operating point , known as the maximum power point (MPP), located near the “knee” or “bend” of the I–V curve. A typical I–V characteristic can be divided into two distinct regions: the current source region, located to the left of the MPP, and the voltage source region, located to the right (Figure 1.2). In the current source region, the internal impedance of the module is high, and the output current remains nearly constant as the terminal voltage varies. In contrast, in the voltage source region, the internal impedance is low, and the terminal voltage remains nearly constant over a wide range of output current. The short-circuit current (I_{sc}) represents the maximum current when the terminals are shorted, while the open-circuit voltage (V_{oc}) corresponds to the maximum voltage available when no current flows.

1.3.2 Irradiance and Temperature Effects

In photovoltaic (PV) systems, the characteristics of the I–V (current–voltage) and P–V (power–voltage) curves are strongly modulated by environmental conditions, particularly solar irradiance and temperature. An increase in irradiance predom-

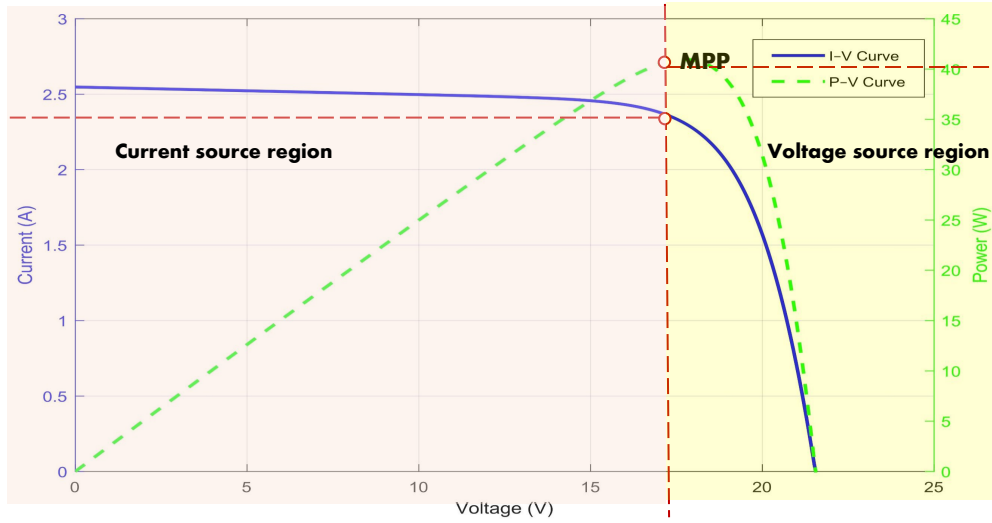


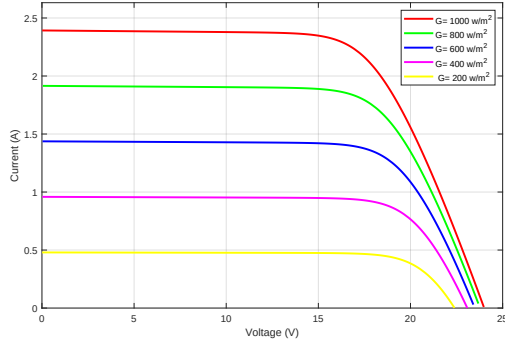
Figure 1.2: I-V and P-V Characteristics of the PV Module

inantly elevates the photocurrent (Figure 1.3a), leading to a higher short-circuit current and an upward shift of the I-V curve; accordingly, the maximum power point (MPP) increases substantially, which results in an upward translation of the P-V curve (Figure 1.3b). In contrast, temperature primarily influences the voltage behavior of the PV module: as the cell temperature rises, the open-circuit voltage decreases owing to the semiconductor’s intrinsic properties, causing the I-V curve to shift toward lower voltages (Figure 1.3c). This reduction in voltage lowers the MPP voltage and thus diminishes the maximum extractable power, manifesting as a downward shift in the P-V curve (Figure 1.3d). Consequently, while higher irradiance enhances power generation by increasing current, elevated temperature degrades performance by reducing voltage and limiting power output.

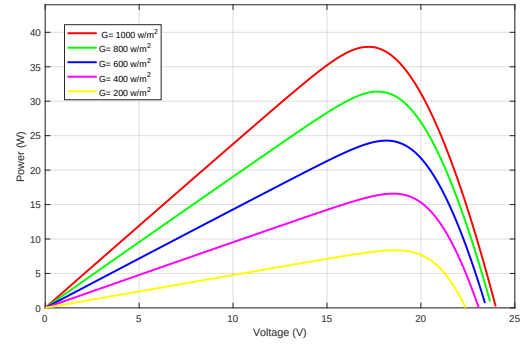
1.3.3 Series and Parallel Configurations of PV Modules

In photovoltaic systems, modules can be connected in series, in parallel, or in a combination of both to meet the desired voltage and current requirements of the array. In a series configuration, the positive terminal of one module is connected to the negative terminal of the next, resulting in the total voltage of the string being the sum of the individual module voltages, while the current remains equal to that of a single module. Mathematically, the total voltage of a series string is expressed as:

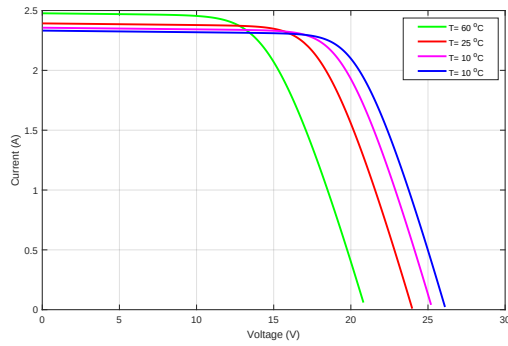
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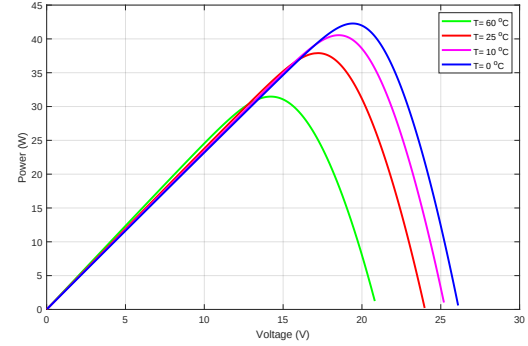
(a) I-V curve under varying irradiance at $T = 25\text{ }^{\circ}\text{C}$



(b) P-V curve under varying irradiance at $T = 25\text{ }^{\circ}\text{C}$



(c) I-V curve under varying temperature at $G = 1000\text{ W/m}^2$



(d) P-V curve under varying temperature at $G = 1000\text{ W/m}^2$

Figure 1.3: Effects of irradiance and temperature on PV module characteristics

$$V_{\text{string}} = \sum_{i=1}^{N_s} V_i \approx N_s \cdot V_{\text{module}} \quad (1.6)$$

where N_s is the number of modules in series and V_{module} is the voltage of a single module, while the current is:

$$I_{\text{string}} = I_{\text{module}} \quad (1.7)$$

This arrangement is advantageous for achieving higher system voltages (Figure 1.4) and reducing current-related losses in the cables, but it is sensitive to shading or faults in individual modules, which can affect the performance of the entire string. In contrast, a parallel configuration connects all the positive terminals together and all the negative terminals together (Figure 1.4), increasing the total current while maintaining the voltage at the level of a single module. The total current of a parallel connection is given by:

$$I_{\text{array}} = \sum_{j=1}^{N_p} I_j \approx N_p \cdot I_{\text{module}} \quad (1.8)$$

where N_p is the number of parallel strings, and the voltage remains:

$$V_{\text{array}} = V_{\text{module}} \quad (1.9)$$

For large PV arrays, a combination of series and parallel connections is commonly employed to achieve both the required voltage and current (Figure 1.4). In such series-parallel configurations, several series strings are connected in parallel. The total voltage of each series string is:

$$V_{\text{string}} = N_s \cdot V_{\text{module}} \quad (1.10)$$

while the total current of the array is:

$$I_{\text{array}} = N_p \cdot I_{\text{module}} \quad (1.11)$$

where N_p represents the number of parallel series strings. This combined arrangement optimizes system performance, allowing for higher power output and improved reliability. Proper design considerations, including module matching and the integration of bypass and blocking diodes, are essential to mitigate losses due to shading, reverse currents, and partial failures, thereby ensuring stable and efficient operation of the photovoltaic system.

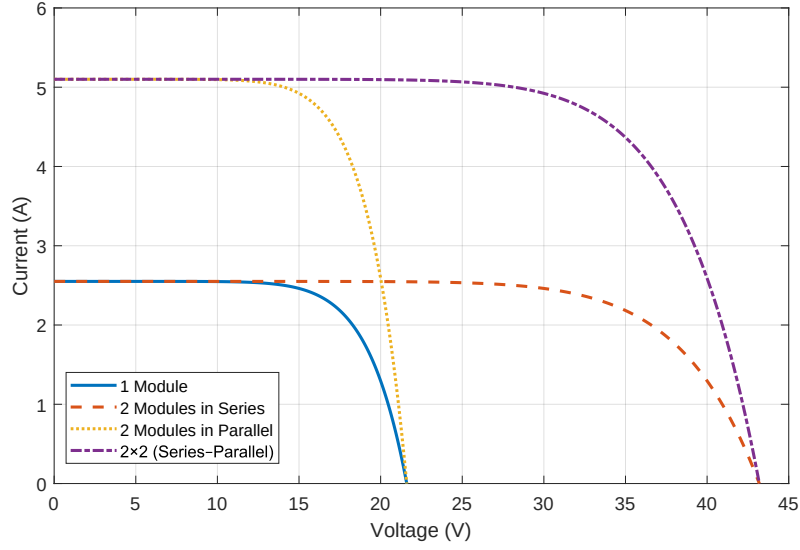


Figure 1.4: I-V curves for different PV panel connections

1.4 DC-DC Converters in Photovoltaic Systems

In photovoltaic (PV) systems, the electrical power generated by solar modules often does not match the voltage and current requirements of the load or the energy storage system. Therefore, power electronic converters are essential to efficiently transfer energy between the PV modules and the load. Among these, DC-DC converters play a crucial role in regulating voltage levels, optimizing power extraction, and ensuring system stability.

DC-DC converters are electronic circuits designed to convert a source of direct current (DC) from one voltage level to another. They can be classified based on their output voltage relative to the input voltage: step-up (boost), step-down (buck), or step-up/step-down (buck-boost) converters. These converters are widely employed in PV applications, particularly in Maximum Power Point Tracking (MPPT) systems, where precise voltage control is critical for extracting maximum energy from solar modules under varying irradiance and temperature conditions.

1.4.1 Buck Converter

The buck converter, also known as a step-down converter, reduces the input voltage to a lower output voltage while ideally maintaining the same power. Its operation relies on a switching element (typically a transistor), a diode, an inductor, and a capacitor (Figure 1.5). The average output voltage V_{out} is determined by the duty

cycle D of the switching signal applied to the transistor:

$$V_{\text{out}} = D \cdot V_{\text{in}} \quad (1.12)$$

where V_{in} is the input voltage. Buck converters are commonly used in PV systems to match the high-voltage output of solar arrays to low-voltage loads or battery banks [54–56].

The inductor L and output capacitor C_{out} can be calculated to ensure continuous conduction and limit voltage/current ripple:

$$L \geq \frac{V_{\text{out}} \cdot (1 - D)}{f_s \cdot \Delta I_L} \quad (1.13)$$

$$C_{\text{out}} \geq \frac{\Delta I_L}{8 \cdot f_s \cdot \Delta V_{\text{out}}} \quad (1.14)$$

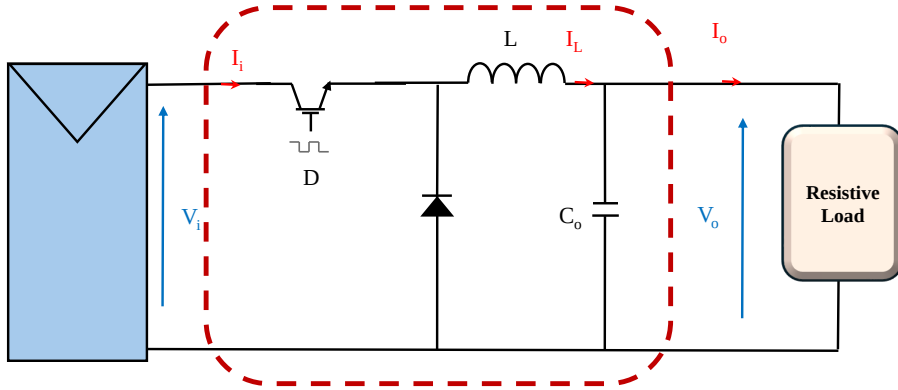


Figure 1.5: Schematic of a Buck Converter

1.4.2 Boost Converter

The boost converter, or step-up converter, increases the input voltage to a higher output voltage (Figure 1.6). It shares a similar structure with the buck converter but operates in a complementary mode. The output voltage V_{out} is related to the duty cycle D as follows:

$$V_{\text{out}} = \frac{V_{\text{in}}}{1 - D} \quad (1.15)$$

Boost converters are particularly suitable in PV systems when the required load voltage exceeds the module voltage, ensuring efficient energy transfer [54–56]. The

design equations for the inductor L and output capacitor C_{out} are:

$$L \geq \frac{V_{\text{in}} \cdot D}{f_s \cdot \Delta I_L} \quad (1.16)$$

$$C_{\text{out}} \geq \frac{I_{\text{out}} \cdot D}{f_s \cdot \Delta V_{\text{out}}} \quad (1.17)$$

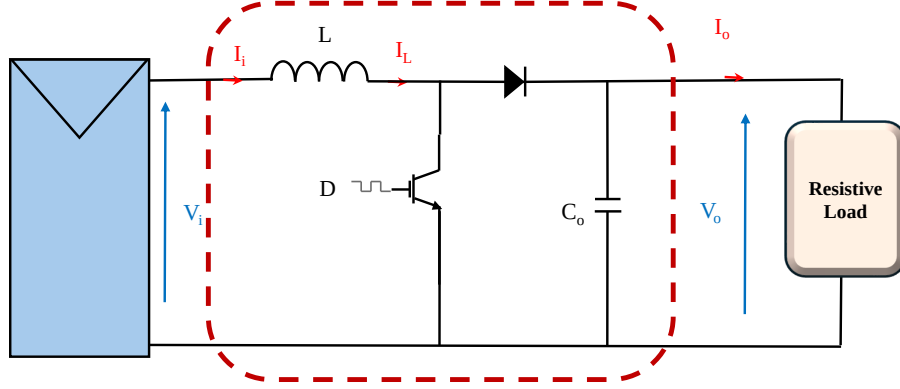


Figure 1.6: Schematic of a Boost Converter

1.4.3 Buck-Boost Converter

The buck-boost converter combines the functionalities of both step-up and step-down converters, allowing the output voltage to be either higher or lower than the input voltage depending on the duty cycle (Figure 1.7). The ideal output voltage is given by:

$$V_{\text{out}} = \frac{D}{1 - D} \cdot V_{\text{in}} \quad (1.18)$$

This topology ensures the load receives a stable voltage, independent of fluctuations in the PV array output [54–56]. The inductor and capacitor values can be calculated as:

$$L \geq \frac{V_{\text{in}} \cdot D}{f_s \cdot \Delta I_L} \quad (1.19)$$

$$C_{\text{out}} \geq \frac{I_{\text{out}} \cdot D}{f_s \cdot \Delta V_{\text{out}}} \quad (1.20)$$

These parameters are essential to ensure stable operation, minimize ripples, and improve the efficiency of PV systems under variable irradiance and temperature conditions.

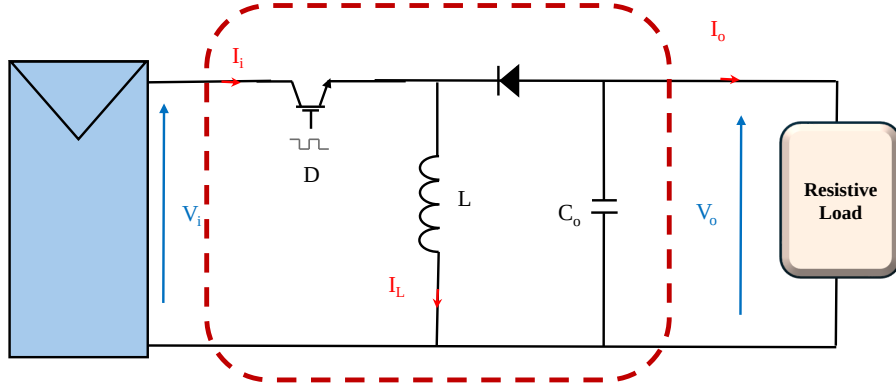


Figure 1.7: Schematic of a Buck Boost Converter

1.5 Maximum Power Point Tracking (MPPT)

Maximum Power Point Tracking (MPPT) is an essential control technique used to extract the highest possible power output from photovoltaic (PV) systems under varying environmental conditions. Numerous MPPT algorithms have been developed and reported in the literature [47, 57, 58], each aiming to enhance tracking accuracy, reduce steady-state oscillations, and ensure rapid response to changes in irradiance and temperature.

1.5.1 Principle of Maximum Power Extraction

The power–voltage (P–V) characteristic of a PV module exhibits a unique global maximum, the Maximum Power Point (MPP), corresponding to a specific voltage and current pair (V_{opt} , I_{opt}). To operate at this point, a DC–DC converter is typically inserted between the PV generator and the load (Figure 1.5, Figure 1.6, and Figure 1.7). The converter acts as an adaptive interface, transforming the fixed load resistance R_o into an equivalent input resistance R_i as seen from the PV side, i.e., the resistance perceived at the PV terminals. By controlling the duty cycle D , the MPPT modifies this equivalent resistance until it matches the optimal value corresponding to the MPP.

For a boost converter, the voltage transfer characteristic is given by Equation 1.15, which leads to the impedance transformation

$$R_i = R_o(1 - D)^2. \quad (1.21)$$

Since the physical load R_o is constant, varying the duty cycle adjusts the input

resistance according to

$$R_i(D) = \frac{V_{PV}}{I_{PV}}. \quad (1.22)$$

The system reaches the MPP when the duty cycle takes the optimal value D^* , defined as the duty cycle that satisfies

$$R_i(D^*) = R_{MPP} = \frac{V_{MPP}}{I_{MPP}}. \quad (1.23)$$

Here, D^* represents the specific duty cycle at which the converter forces the PV generator to operate at its maximum power point. Figure 1.8 illustrates the I–V characteristic of the PV module with load lines of different slopes, showing how the duty cycle of the boost converter modifies the equivalent input resistance and shifts the PV operating point toward the maximum power point.

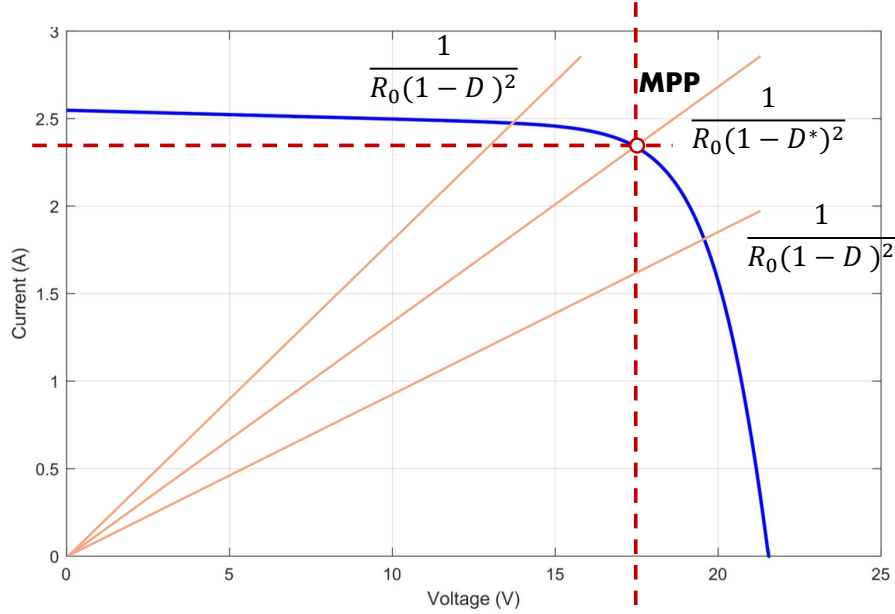


Figure 1.8: I–V characteristic of the PV module with varying equivalent input resistances.

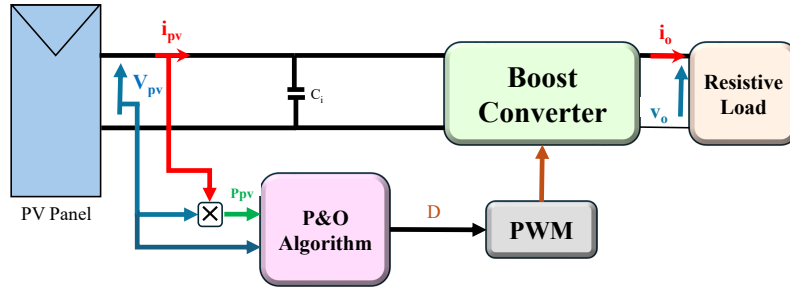
1.5.2 Conventional MPPT Methods

In practice, ensuring that a photovoltaic system operates at its maximum power point requires an automatic search and adjustment process. This can be efficiently achieved by implementing one of the established approaches known as Maximum Power Point Tracking (MPPT) methods, which continuously adapt the operating

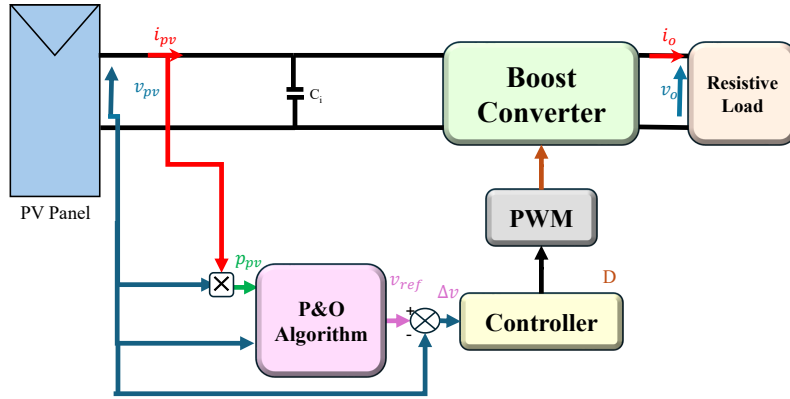
conditions of the PV system to extract the highest possible power under varying environmental factors

Perturb & Observe

Many authors use the P&O algorithm because it is one of the easiest methods to implement and it can be implemented in direct (Figure 1.9a) mode or indirect mode (Figure 1.9b), depending on the chosen control variable [59, 60].



(a) Control architecture of the PV system using direct P&O-MPPT strategy.



(b) Control architecture of the PV system using indirect P&O-MPPT strategy.

Figure 1.9: Comparison of control architectures for direct and indirect P&O-MPPT strategies in photovoltaic systems.

Based on the conventional method diagram shown in Figure 1.10 and Figure 1.11, in the direct mode of the P&O algorithm, the control variable is the duty cycle. The decision-making is performed using direct measurements of the PV system's output

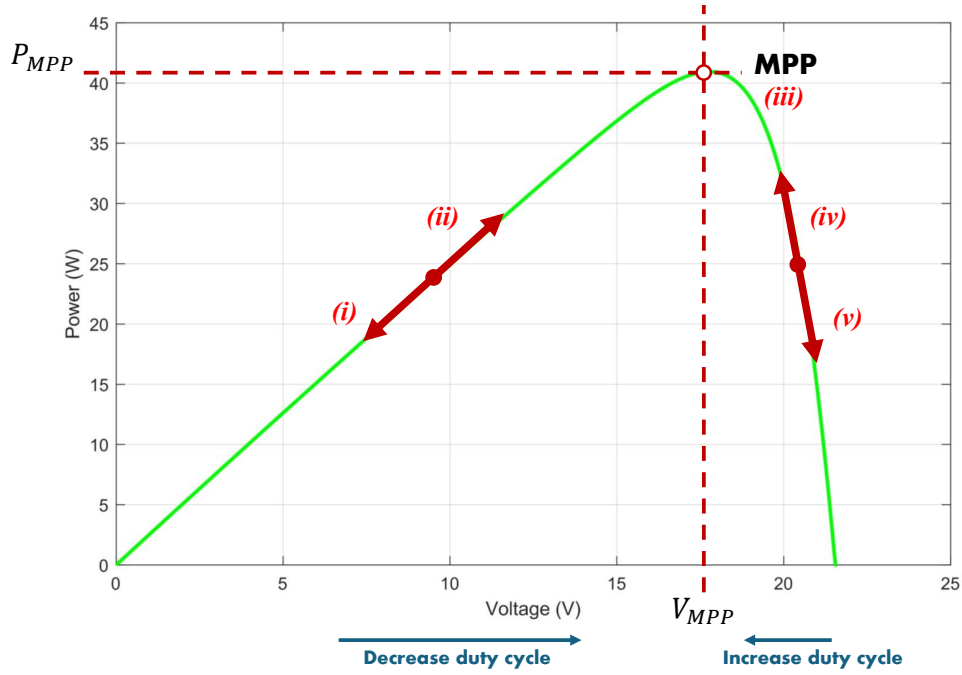


Figure 1.10: Illustration of the Perturb and Observe (P&O) algorithm on the P–V characteristic curve.

power. The algorithm perturbs the duty cycle D , measures the resulting power and voltage, and compares them to previous values. If the power increases and the voltage change is in the same direction, the duty cycle continues to change in the same way. If power and voltage change in opposite directions, the duty cycle reverses its direction. This process gradually drives the operating point toward the Maximum Power Point (MPP), while producing small oscillations around it. The cycle repeats continuously, allowing the system to adapt to varying environmental conditions. In the indirect mode of the P&O algorithm, the control variable is not the duty cycle directly, but a reference voltage that is regulated to track the Maximum Power Point, as illustrated in Figure 1.12. An additional regulation loop is required to adjust the duty cycle so that the PV system's output voltage follows the reference voltage. The decision making logic is similar to that of the direct mode, but the perturbations are applied to the reference voltage rather than directly to the duty cycle. This approach offers several advantages, including reduced oscillations, improved stability, and enhanced flexibility, making it particularly suitable for PV systems operating under rapidly changing environmental conditions. The four possible combinations linking the sign of the voltage correction to the sign of the resulting power gradient are listed in Table 1.1. The table also shows, for each case, the sign of the duty-cycle

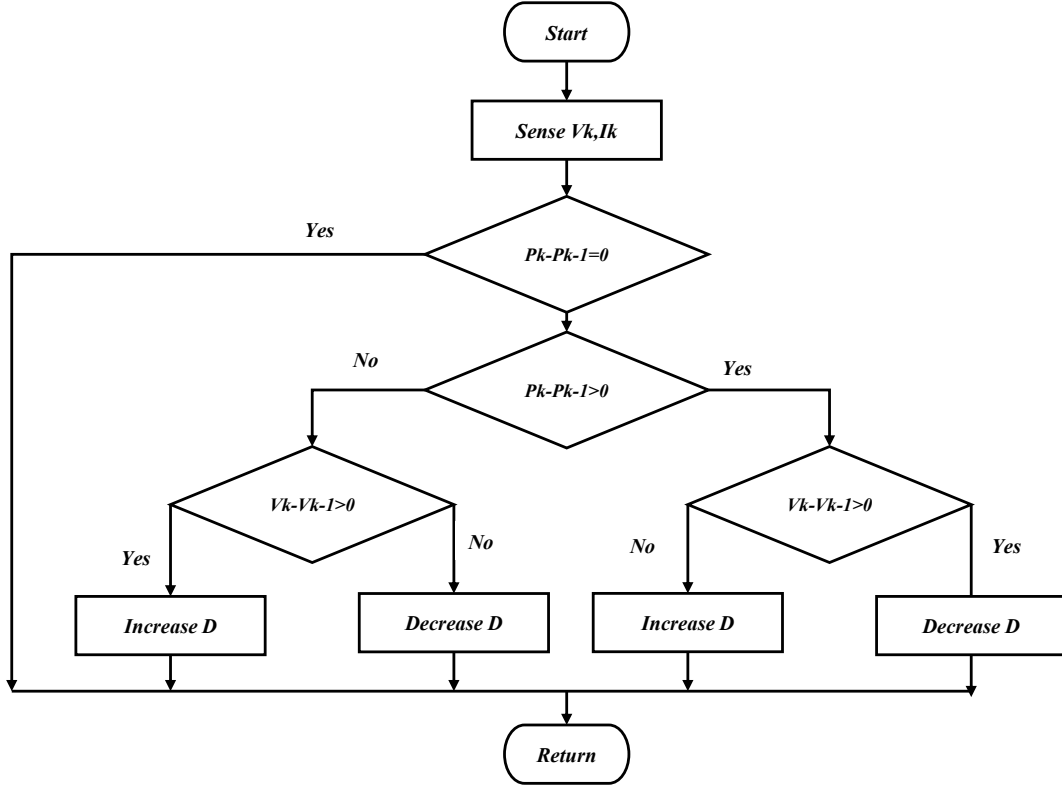


Figure 1.11: Flowchart of The P&O Algorithm in Direct Mode

perturbation that should be applied accordingly. Despite the simplicity and ease of

Table 1.1: Decision rules of the P&O algorithm

Case	Sign of ΔV	Sign of ΔP	Action on D
i	—	—	Decrease D
ii	+	+	Decrease D
iii	0	0	No change in D
iv	—	+	Increase D
v	+	—	Increase D

implementation of the P&O algorithm, it presents several notable limitations. In steady-state operation, the algorithm inherently produces small oscillations around the maximum power point (MPP) due to the periodic perturbation of the duty cycle or voltage, which ultimately reduces the overall efficiency of the photovoltaic system. A second drawback of this method is the risk of transient divergence during

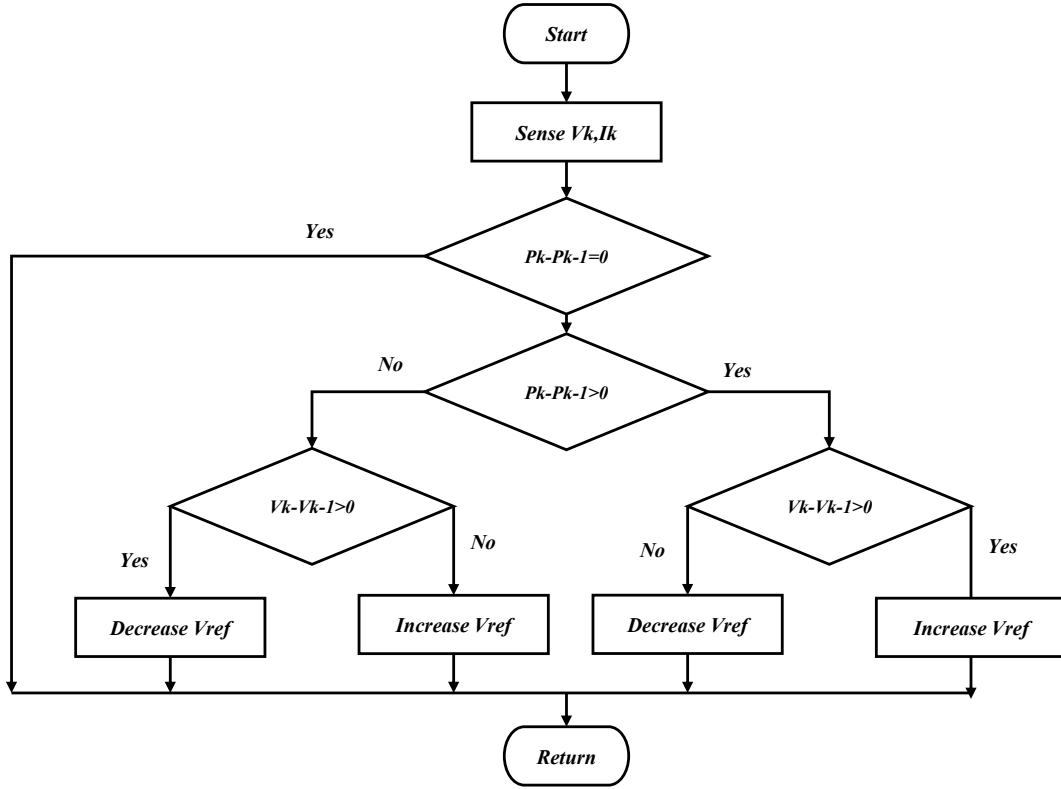


Figure 1.12: Flowchart of The P&O Algorithm in Indirect Mode

rapid irradiance variations. Under such conditions, the operating point may progressively deviate from the actual MPP, leading to suboptimal energy extraction and potentially unstable behavior.

Incremental Conductance

The Incremental Conductance (IncCond) method determines the position of the operating point relative to the maximum power point (MPP) by analyzing the slope of the power–voltage (P–V) curve (Figure 1.13). On the P–V characteristic, the slope $\frac{dP}{dV}$ is positive on the left of the MPP, zero at the MPP, and negative on the right of the MPP. The fundamental condition at the MPP is expressed as $\frac{dP}{dV} = 0$.

The IncCond algorithm computes the incremental power variation ΔP and voltage variation ΔV , and evaluates the ratio $\frac{\Delta P}{\Delta V}$ (Figure 1.14).

By comparing this value with zero, the controller can accurately determine whether it needs to increase or decrease the PV operating voltage to move toward the MPP. The three possible combinations linking the sign of the slope of the power–voltage curve and the corresponding operating point relative to the maximum

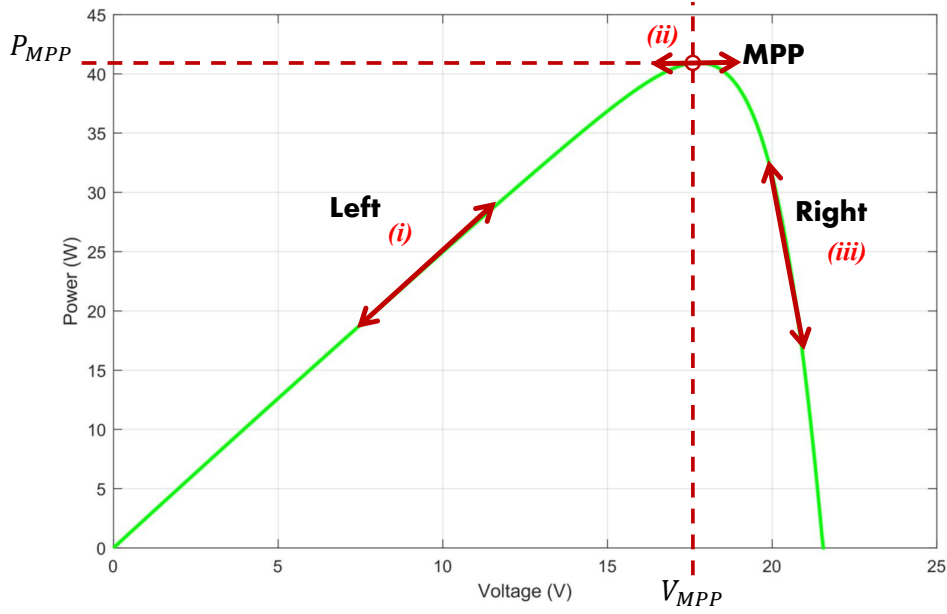


Figure 1.13: Illustration of the Incremental Conductance algorithm on the P–V characteristic curve.

power point (MPP) are listed in Table 1.2. The table also shows, for each case, the sign of the duty-cycle perturbation that should be applied accordingly [50].

Table 1.2: Decision rules of the Incremental Conductance (IncCond) Algorithm Using Duty Cycle

Case	Condition	Action on D
Left (i)	$dI/dV > -I/V_0$	Decrease D
At MPP (ii)	$dI/dV = -I/V$	No change in D
Right (iii)	$dI/dV < -I/V$	Increase D

Although the Incremental Conductance algorithm provides improved accuracy and dynamic response compared to the P&O method, both approaches still share key limitations. In particular, both algorithms exhibit small steady-state oscillations around the MPP, which reduce overall efficiency. Additionally, under rapid irradiance changes, both methods may misinterpret variations in power as perturbations, risking divergence from the actual MPP. For these reasons, P&O and IncCond algorithms are often used in enhanced or hybridized forms in modern MPPT systems to overcome these inherent drawbacks and improve performance under varying en-

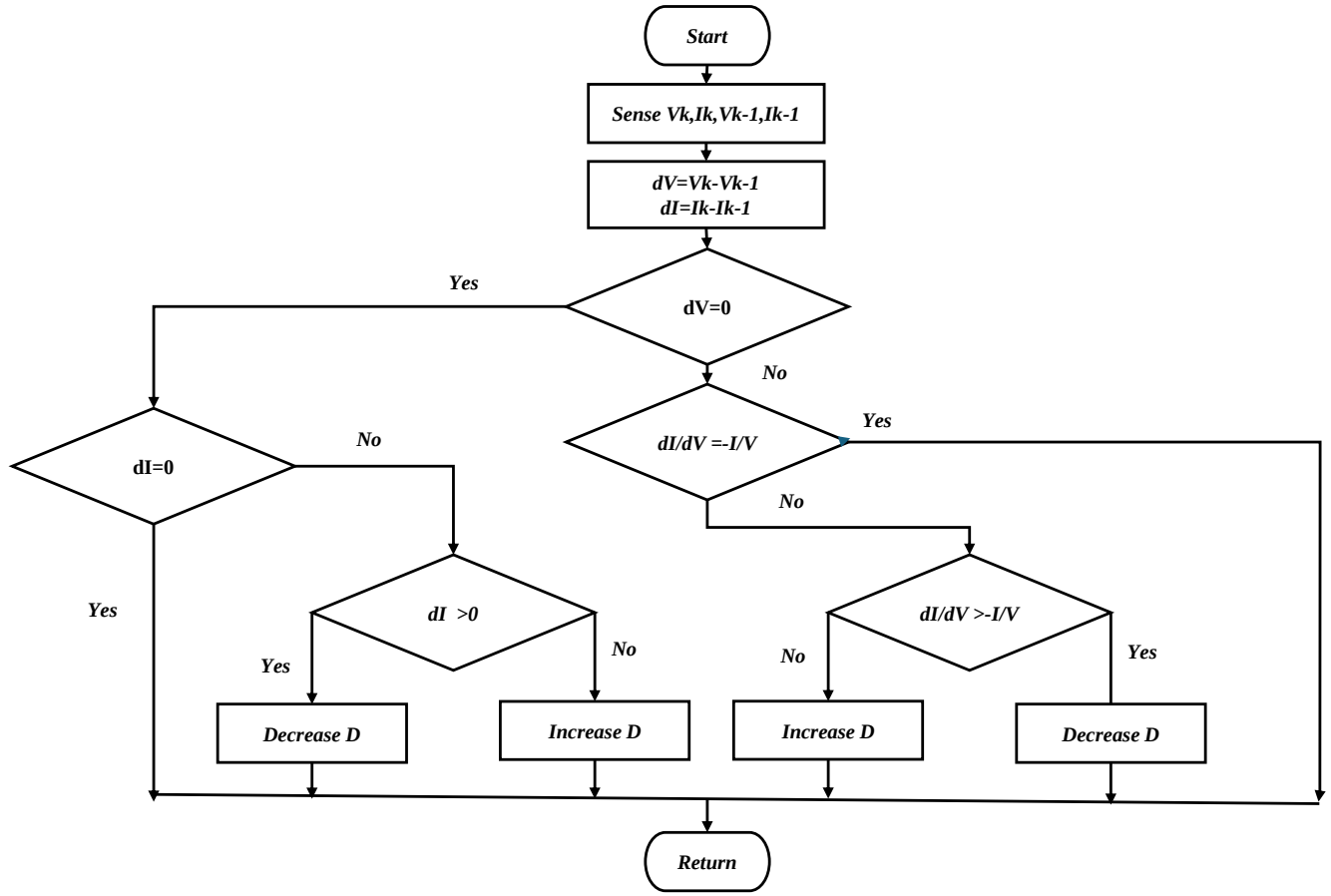


Figure 1.14: Flowchart of The Incremental Conductance Algorithm

vironmental conditions.

1.6 Conclusion

This chapter has introduced the fundamental concepts of photovoltaic systems, beginning with the physical mechanisms of energy conversion and progressing to the system-level electrical behavior. A key finding is that PV generators exhibit strong nonlinear characteristics that are continuously shaped by environmental conditions specifically irradiance and temperature which directly impacts the position and stability of the maximum power point (MPP).

While conventional maximum power point tracking (MPPT) methods offer simplicity and effectiveness under stable conditions, their sensitivity to dynamic environmental variations and inherent tracking oscillations limit their performance in practical applications. These limitations underscore the need for more sophisti-

cated solutions capable of ensuring accurate, stable, and adaptive maximum power extraction under rapidly changing conditions.

In response to these challenges, intelligent approaches based on fuzzy logic and metaheuristic optimization have emerged as promising alternatives. The next chapter is structured around two complementary axes: system modeling and control, where optimization methods are strategically assigned based on their respective strengths:

- **For modeling:** The Genetic Algorithm (GA) is employed to identify unknown parameters and fine-tune fuzzy inference systems, enabling accurate representation of PV cell behavior under varying operating conditions. GA's robust exploration capabilities make it particularly suitable for parameter identification in nonlinear PV models.
- **For control:** The Grasshopper Optimization Algorithm (GOA) is utilized to design and optimize MPPT controllers, ensuring rapid and precise tracking of the maximum power point despite environmental fluctuations and system nonlinearities. GOA's balanced exploration-exploitation characteristics provide enhanced dynamic response and tracking accuracy under varying atmospheric conditions.

Accordingly, the following chapter presents Intelligent Strategies for PV Systems: Modeling, Control, and Optimization, providing a theoretical foundation for fuzzy logic-based approaches and demonstrating how GA and GOA can be effectively applied the former for accurate PV system modeling and the latter for enhanced MPPT control performance.

Chapter 2

The Intelligent Strategies for PV Systems: Modeling, Control, and Optimization

2.1 Introduction

Solar photovoltaic (PV) energy has emerged as a key renewable energy source due to its availability, sustainability, and ability to directly convert solar radiation into electrical power. Nevertheless, the electrical behavior of PV generators is inherently nonlinear and strongly influenced by environmental conditions such as solar irradiance and temperature. These variations continuously shift the operating point of the PV system, making it difficult to naturally operate at the Maximum Power Point (MPP), where the maximum extractable power is obtained [61–64]. As discussed in the previous chapter, conventional Maximum Power Point Tracking (MPPT) techniques such as Perturb and Observe (P&O) and Incremental Conductance (INC) are widely used due to their simplicity and ease of implementation [65]. However, their performance becomes limited under rapidly changing atmospheric conditions, where oscillations around the MPP and slow dynamic response can lead to energy losses and reduced efficiency [66]. These limitations highlight the need for more advanced control strategies capable of improving tracking accuracy, robustness, and adaptability. In this context, the development of efficient MPPT strategies relies not only on improved control algorithms but also on accurate modeling of PV sys-

tems. Since PV characteristics are nonlinear and depend on temperature and irradiance, precise modeling becomes essential for predicting system behavior and ensuring reliable controller design [67–71]. Computational intelligence techniques, such as fuzzy logic-based modeling, have been introduced to better capture these nonlinear dynamics and enhance system representation. Furthermore, optimization methods have become a fundamental tool in PV system design and control [72, 73]. Bio-inspired and population-based algorithms, including Genetic Algorithms (GA) and the Grasshopper Optimization Algorithm (GOA), provide powerful mechanisms for parameter estimation, controller tuning, and performance enhancement. These approaches improve convergence, robustness, and adaptability compared with conventional analytical and heuristic methods, particularly under variable operating conditions [74, 75].

Based on these considerations, this chapter presents a comprehensive framework integrating PV modeling, MPPT control performance, and bio-inspired optimization techniques. It first examines PV system modeling using computational intelligence to address nonlinear behavior and parameter variability. Next, it analyzes the performance and implementation aspects of MPPT controllers, highlighting the limitations of conventional approaches and the need for advanced strategies. Finally, it introduces bio-inspired optimization methods, focusing on Genetic Algorithms and the Grasshopper Optimization Algorithm, as effective tools for improving modeling accuracy and control performance in photovoltaic systems.

2.2 PV System Modeling Using Computational Intelligence

2.2.1 Nonlinear Behavior Of The PV System

The primary difficulty in modeling a Photovoltaic (PV) system is that it does not follow a simple linear path. Unlike a standard resistor where current and voltage change in a straight line, a solar cell is a semiconductor device that behaves like a complex diode. Its output is transcendental, meaning the math required to solve for current and voltage is layered and cannot be simplified into basic algebra. This nonlinear morphology is fundamentally modulated by four critical phenomenological parameters:

Series Resistance (R_s): This parameter accounts for the ohmic losses within the

semiconductor bulk, the metal-semiconductor contact interfaces, and the busbar conduits. A non-negligible R_s induces a parasitic voltage drop that attenuates the slope of the $I - V$ characteristic near the open-circuit region, thereby degrading the Fill Factor (FF).

Shunt Resistance (R_{sh}): Representing the cross-junction leakage current, R_{sh} is a proxy for manufacturing imperfections and crystalline defects. At low irradiance levels, the dominance of R_{sh} increases as the leakage current becomes a significant fraction of the total photo-generated current, precipitously reducing the conversion efficiency.

Ideality Factor (n): This dimensionless parameter quantifies the deviation of the cell from the ideal diffusion theory, reflecting the carrier recombination mechanisms within the depletion region. Variations in n modify the curvature of the knee in the $I - V$ characteristic, introducing complexity in Maximum Power Point (MPP) localization.

Environmental Stochasticity: The PV output is a dynamic function of ambient conditions. The short-circuit current (I_{sc}) maintains a near-linear proportionality with incident solar irradiance, while the open-circuit voltage (V_{oc}) exhibits an inverse sensitivity to junction temperature.

2.2.2 Accurate Modeling for PV Systems

The efficacy of a Maximum Power Point Tracking (MPPT) controller is fundamentally constrained by the accuracy of the underlying PV system model. Because the Maximum Power Point (MPP) is a dynamic target that shifts with varying atmospheric conditions, the controller must rely on a model that can precisely characterize the knee of the $P - V$ curve. Inaccurate modeling leads to technical inefficiencies, such as steady-state oscillations around the MPP and slow convergence speeds during rapid irradiance transients. To address these challenges, various mathematical and computational strategies are employed to manage the system's inherent nonlinearity, as summarized in [Table 2.1](#).

2.2.3 Fuzzy Logic-Based PV Modeling

In recent years, the pursuit of higher tracking efficiency and system adaptability has led to the development of advanced algorithms that extend beyond conven-

Table 2.1: Comparative Analysis of Modeling Methods for Nonlinearity Mitigation

Method Category	Advantages	Limitations
Numerical Iterative Methods (e.g., Newton–Raphson)	High precision for static conditions	May fail to converge under rapid weather changes.
Analytical (Lambert W Function)	Provides an exact, explicit solution for current; mathematically rigorous and eliminates iteration.	Cannot account for multiple peaks in case of shading.
Linearization Small-Signal Modeling	Simplifies control design around a specific operating point	Only accurate near a specific operating point; fails during large atmospheric swings.
Artificial Intelligence Fuzzy Logic (FLC)	Does not require an exact mathematical model; excellent at handling imprecise or noisy sensor data.	Performance depends heavily on the designer’s expertise in defining the rules.
Bio-Inspired Metaheuristics (e.g., GA, GOA)	Capable of searching the entire P – V space efficiently; robust against nonlinear traps.	Can be computationally intensive; requires careful tuning of search parameters to avoid delay.

tional MPPT control techniques. Within the diverse classifications of modern control, Fuzzy Logic Control (FLC) stands out as a premier computational intelligence tool [76]. This approach encompasses a method capable of learning from system behavior and adapting to environmental variations, such as rapid changes in irradiance or temperature, without relying on an explicit or rigid mathematical model. The FLC-based strategies offer a powerful framework for managing the nonlinear and time-varying characteristics of photovoltaic systems [77]. This allows for a more flexible and robust modeling process that effectively bridges the gap between complex atmospheric inputs and optimal electrical output.

Fuzzy Logic Control (FLC)

Fuzzy Logic Control (FLC) was introduced by Lotfi A. Zadeh in 1965 through the concept of fuzzy sets [78]. Unlike classical binary logic, it allows variables to take values between 0 and 1, enabling the representation of uncertainty and imprecision. FLC is inspired by human reasoning and uses linguistic “if-then” rules to model expert decision-making. This approach is particularly effective when the system lacks an accurate mathematical model or exhibits strong nonlinearities. Its ability to handle vague information and adapt to varying conditions makes it a robust and flexible technique for controlling nonlinear systems such as photovoltaic (PV) generators [76,79]. Unlike conventional control methods, fuzzy logic control does not depend on precise mathematical equations but instead uses a set of inference rules based on linguistic variables and logical operators such as AND, OR, and THEN. Its structure generally includes three main stages (Figure 2.1).

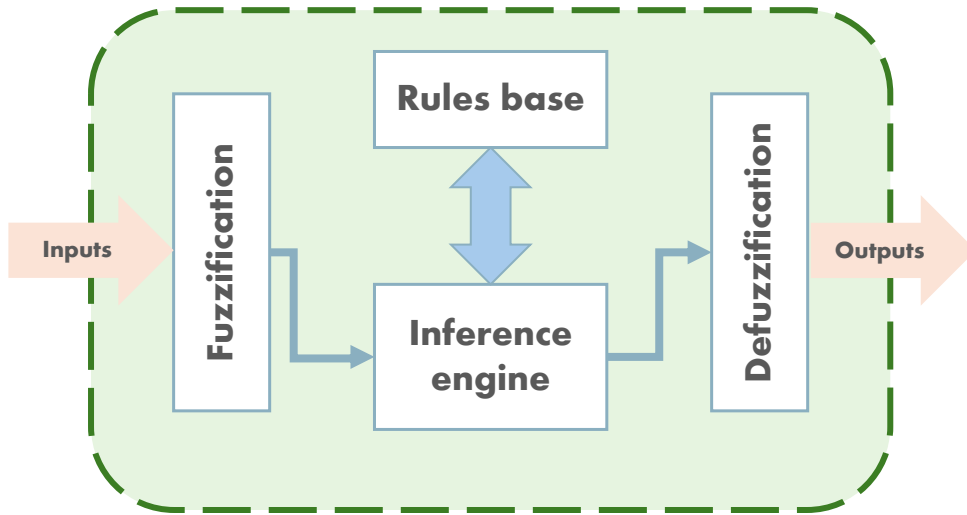


Figure 2.1: Structure of fuzzy logic controller

Fuzzification : In the fuzzification stage, numerical inputs are transformed into linguistic variables that describe the system’s behavior using qualitative terms such as BS (Big Small), S (Small), M (Medium), H (High), and BH (Big High). These linguistic states enable the controller to interpret uncertain information and make gradual decisions based on expert reasoning. Each input variable is represented by a set of membership functions that define the degree of belonging to each linguistic state, forming the basis of the fuzzy inference process [80]. The shape of the membership functions plays a crucial role in defining the fuzzy sets and directly affects the controller’s sensitivity

and smoothness. Commonly used shapes include triangular, trapezoidal, and Gaussian functions (Figure 2.2). Triangular and trapezoidal forms are preferred for their simplicity and ease of computation, while Gaussian functions provide smoother transitions between linguistic states, improving control precision. The choice of membership shape depends on the desired balance between computational efficiency and control accuracy [76].

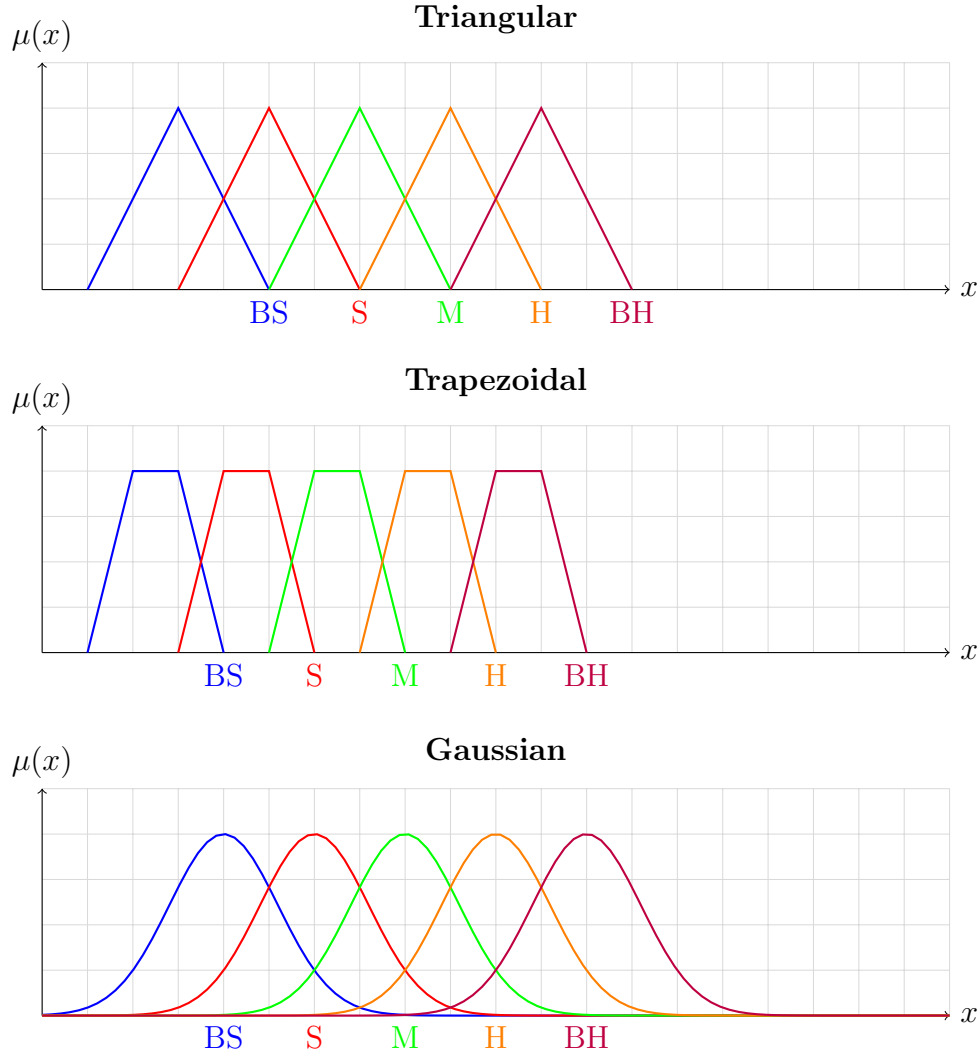


Figure 2.2: Membership functions of the fuzzy system

Inference Engine : The inference engine constitutes the decision making core of the fuzzy controller, where the relationships between the fuzzified input variables and the desired output are established. At this stage, the linguistic inputs obtained during fuzzification are processed through a set of predefined

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fuzzy rules that encode the expert knowledge of the system, typically organized in a multidimensional rule matrix. Each rule adopts a linguistic structure of the form *IF (condition) THEN (action)*, where the antecedent describes the system state and the consequent defines the corresponding control action. The total number of rules depends on the number of inputs and their associated linguistic terms, and is given by:

$$r_t = j^i \quad (2.1)$$

where r denotes the total number of rules, j the number of linguistic states per input, and i the number of input variables [79]. To evaluate these rules, the inference engine applies fuzzy operators to determine the degree of activation of each rule and to aggregate their outputs into a unified control decision. Several inference mechanisms exist, with the Mamdani and Sugeno approaches being the most widely used. The Mamdani method employs fuzzy sets for both antecedents and consequents, producing a fuzzy output that requires a defuzzification stage. In contrast, the Sugeno method uses fuzzy antecedents but replaces consequents with mathematical functions, offering faster computation and smoother control surfaces. Other less commonly used methods, such as the Tsukamoto or Larsen approaches, represent variations in rule evaluation and aggregation strategies. The choice of inference method depends on the required balance between interpretability, computational efficiency, and control performance [81].

Defuzzification : Defuzzification represents the final stage of the fuzzy control process, where the aggregated fuzzy output obtained from the inference engine is converted into a crisp control signal suitable for implementation in real time systems. Since the inference mechanism typically produces a fuzzy set defined over the output universe, defuzzification provides a numerical value that best represents this set according to a chosen criterion. Several defuzzification techniques exist, the most widely used being the Centre of Gravity (COG) method, which computes the center of gravity of the aggregated membership function [80]. In its general form, the COG can be expressed as:

$$x^* = \frac{\sum_{i=1}^r \sum_{j=1}^m \left(\mu_A^{(i,j)} \cdot \mu_B^{(i,j)} \cdot n_i \right)}{\sum_{i=1}^r \sum_{j=1}^m \left(\mu_A^{(i,j)} \cdot \mu_B^{(i,j)} \right)}. \quad (2.2)$$

An alternative approach is the Bisector of Area (BOA) method, which determines the crisp value n such that the area under the aggregated membership

function is divided into two regions of equal magnitude [80]. This is defined by the condition:

$$\int_{n_{\min}}^n \left(\sum_{i=1}^r \sum_{j=1}^m \mu_A^{(i,j)}(x) \right) dx = \frac{1}{2} \int_{n_{\min}}^{n_{\max}} \left(\sum_{i=1}^r \sum_{j=1}^m \mu_A^{(i,j)}(x) \right) dx. \quad (2.3)$$

Other commonly used techniques include the Mean of Maximum (MOM), the Smallest of Maximum (SOM), or the Largest of Maximum (LOM) [78].

Although the choice of defuzzification method depends on the desired balance between computational efficiency and control accuracy, the centroid method remains the most widely adopted in control applications due to its robustness and its ability to capture the global behavior of the output fuzzy set.

2.3 The performance and implementation of the Maximum Power Point Tracking controller

2.3.1 Performance Constraints of Conventional MPPT Methods

Limitations of Conventional MPPT Methods

Despite its widespread adoption due to low implementation cost and limited computational requirements, the classical Perturb and Observe approach remains inherently constrained in terms of tracking reliability under realistic field conditions. Because it relies on a local perturbation-based decision process, it becomes highly sensitive to abrupt power variations caused by fast irradiance changes or partial shading, often resulting in misleading tracking direction and delayed stabilization. As shown in Figure 2.3, if irradiation increases during the application of a perturbation intended to initially reach the maximum power point (MPP), the new operating point is not at an MPP of the new P–V curve (position C). In addition, since the power gradient is calculated and remains positive, the algorithm continues to suggest positive voltage perturbations, which further moves the operating point away from the true maximum power point (position D). Moreover, P&O suffers from slow tracking speed when stability is prioritized, and when higher tracking speed is applied, continuous perturbations can introduce power oscillations, revealing a persistent trade-off between fast response, reduced oscillatory behavior, and

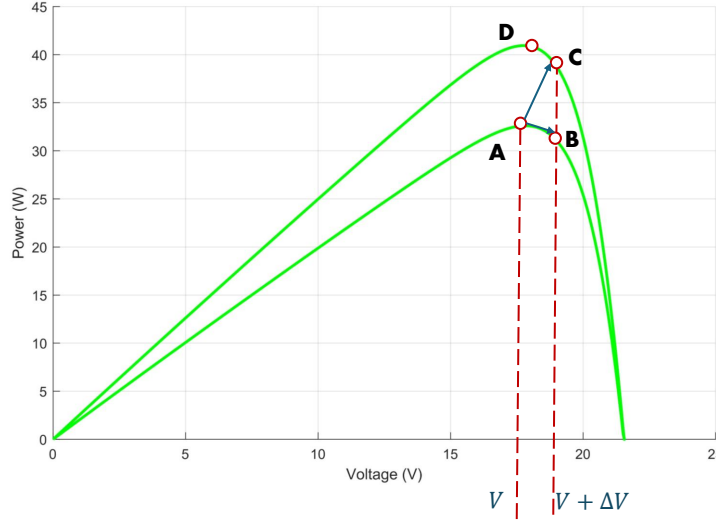


Figure 2.3: The Effect of Rapid Irradiance Variation on MPP Tracking Using P&O Method

stable MPP convergence. To mitigate these drawbacks, advanced MPPT architectures have evolved toward direct and indirect control enhancements reinforced by computational optimization layers. In direct MPPT methods, the duty cycle is increasingly determined using intelligent global search mechanisms. In this context, algorithms may evaluate a broader duty cycle space to identify the best operating region before applying a validated update. In indirect MPPT methods, classical voltage-guided perturb decisions are now frequently combined with feedback control loops strengthened by computational techniques, where controllers are paired with optimizers that tune controller parameters for example.

Challenges of Conventional MPPT Methods

Reliable deployment of Maximum Power Point Tracking (MPPT) in renewable energy converters faces a number of practical challenges that extend beyond algorithm accuracy. Real-time implementation remains one of the most critical barriers, as many MPPT algorithms validated in simulation become difficult to deploy on embedded hardware due to limited processing capability, memory constraints, acquisition latency, and sensor bandwidth limitations. Complexity and implementation cost also increase significantly for advanced global search or hybrid MPPT architectures, requiring high-performance digital controllers, fast sensing circuits, and sometimes external optimization layers, which may limit scalability and industrial

acceptance. Furthermore, parameter tuning poses a persistent engineering burden, particularly for optimization-based MPPT. Additionally, dynamic meteorological conditions, such as rapid irradiance transitions, temperature fluctuations, or unpredictable shading trajectories, demand high-speed sensing, adaptive duty-cycle control, and robust decision logic capable of operating reliably in non-stationary power landscapes. Measurement noise and acquisition uncertainties introduce further constraints in hardware systems, especially when numerical derivatives, power gradients, or feedback loops are used, requiring filtering, noise cancellation, or estimator-based architectures to prevent control divergence even though these mitigation layers add delay and complexity.

2.3.2 Control Strategy Implementation

Direct Mode Control

Direct mode control is based on the principle that the controller acts directly on the converter's control input to maximize power extraction from the photovoltaic system. In this approach, the controller continuously observes the PV output and adjusts the primary control variable typically the duty cycle of the DC-DC converter so that the system operates as close as possible to the maximum power point. This method allows fast adaptation to changes in environmental conditions without intermediate references [82].

Indirect Mode Control

Indirect mode control relies on the principle of reference tracking. Instead of manipulating the converter directly, the MPPT controller calculates an ideal operating point, expressed as a voltage or current reference, corresponding to the maximum power output. A secondary control loop then adjusts the converter to maintain the desired operating point, providing smoother operation and improved stability under varying environmental conditions [82].

The choice between direct and indirect MPPT control strategies is fundamentally determined by the specific priorities and objectives of the study, as different applications may emphasize different performance aspects such as dynamic response, steady-state stability, implementation simplicity, or sensitivity to measurement noise. To assist in making an informed selection, it is useful to systematically compare the two approaches. [Table 2.2](#) provides a comprehensive comparison be-

Table 2.2: Comparison between Direct and Indirect MPPT Control Strategies

Aspect	Direct Mode Control	Indirect Mode Control
Control principle	Acts directly on the converter duty cycle to reach the MPP.	Generates a voltage/current reference corresponding to the MPP and tracks it through an inner control loop.
Control variable	Duty cycle D of the DC–DC converter.	Reference voltage V_{ref} or current I_{ref} .
Dynamic response	Fast response to irradiance and temperature variations.	Slower than direct mode due to reference generation and tracking stages.
Stability	May exhibit oscillations around the MPP in steady state.	Improved stability and smoother operation.
Implementation complexity	Simple structure and easy implementation.	More complex due to additional control loop.
Sensitivity to noise	More sensitive to measurement noise.	Less sensitive due to reference filtering and control loop.
Suitability	Suitable for fast real-time tracking applications.	Suitable when stability and smooth operation are prioritized.

tween these control strategies, summarizing their main characteristics, advantages, and potential limitations, thereby guiding the choice of the most suitable MPPT method for a given photovoltaic system design and study objective.

2.4 Bio-Inspired Optimization Methods

2.4.1 Genetic Algorithm (GA)

The concept of Genetic Algorithms (GAs) originates from the theory of natural selection proposed by Charles Darwin, which emphasizes the principle of “survival of the fittest.” Building on this biological foundation, John Holland and his colleagues at the University of Michigan formalized the concept in the 1970s, introducing GAs as a computational model of natural evolution [83]. A Genetic Algorithm is a stochastic, population-based optimization technique that simulates the process of natural evolution to search for optimal or near-optimal solutions within complex problem spaces. By iteratively improving a population of candidate solutions through operations analogous to selection, crossover, and mutation, GAs explore and exploit the search space effectively [84, 85]. Owing to their robustness, adaptability, and global search capability, GAs have become a powerful tool for solving nonlinear, multidimensional, and multimodal optimization problems, where traditional deterministic methods often struggle to converge to the global optimum [86].

Initialization

The Genetic Algorithm process begins with the creation of an initial population consisting of a set of individuals, each representing a potential solution to the optimization problem. Every individual, commonly referred to as a chromosome, is composed of a number of genes (Figure 2.4), which correspond to the problem’s decision variables or parameters. These genes are concatenated into a structured form to represent a complete solution. The initial population is usually generated randomly within the predefined search space to ensure a wide and diverse distribution of possible solutions. This diversity is essential for promoting an effective exploration of the search space and preventing premature convergence toward local optima [86]. Mathematically, the initialization can be expressed as:

$$x_{i,j} = x_j^L + \rho \times (x_j^U - x_j^L) \quad \forall i \in [1, N]; \quad \forall j \in [1, D] \quad (2.4)$$

where i is the chromosome/index in the population, j is the parameter/index within a chromosome, N is the population size (number of chromosomes), D is the number of parameters to identify (dimension of the problem), ρ is a uniformly distributed random number in the interval $[0, 1]$, and x_j^L and x_j^U are the lower and upper bounds of the search space for the j -th parameter. If we already know some acceptable solutions to the optimization problem, it is possible to inject them directly during

initialization. In this case, the search process will be faster, requiring fewer generations [87]. Once the initial population is generated, three steps allow the algorithm to progress from one generation G to the next $G+1$ until the stopping condition is met (usually a maximum number of generations, G_{max}).

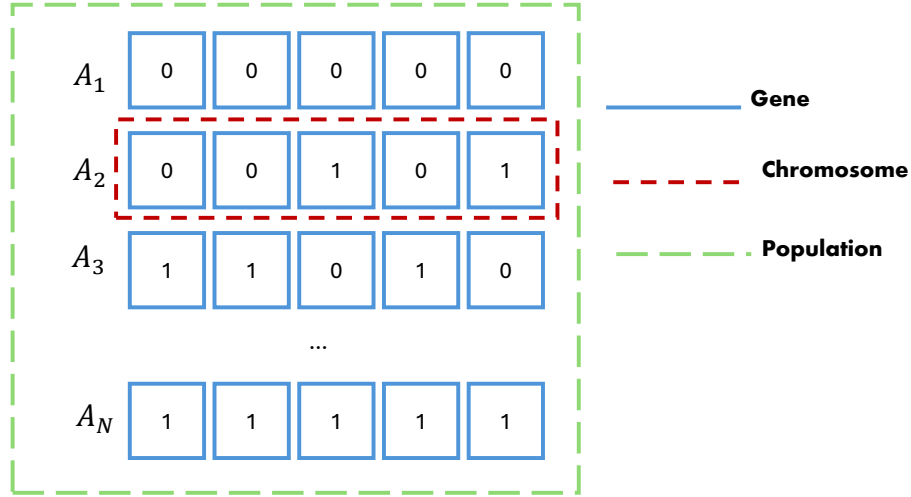


Figure 2.4: Genetic Algorithm Population Structure

Fitness Assignment

Once the initial population is generated, each individual must be evaluated to determine how well it solves the optimization problem. This is accomplished using a fitness function, which quantitatively measures the quality or performance of each chromosome. The fitness function thus defines the selection pressure of the algorithm by distinguishing superior solutions from inferior ones [88]. The fitness value represents the individual's ability to compete within the population commonly referred to as its adaptability or reproductive success [85]. Higher fitness values correspond to better solutions and therefore increase the probability of being selected for reproduction in subsequent generations.

Selection

The selection phase is a crucial step in the GA, as it determines which individuals are chosen to contribute to the next generation. The main objective of this stage is to select the fittest individuals from the current population, allowing them to pass their genetic information to their offspring (children). The selection mechanism is

based on the principle that individuals with higher fitness values have a greater probability of being selected for reproduction [83]. In practice, pairs of parent chromosomes are chosen according to their fitness scores, ensuring that well performing solutions have a higher chance to generate offspring and transmit their advantageous characteristics. This process helps guide the search toward promising regions of the solution space while maintaining a balance between exploration and exploitation. Several selection methods have been proposed in the literature, each with its own characteristics [83,86,87], one of the most common method is the roulette wheel selection, or fitness proportionate selection, where each individual is assigned a portion of a virtual wheel proportional to its fitness value. A random spin then determines the selected individuals. Although straightforward, this method may introduce bias when fitness differences among individuals are significant. To address this limitation, the tournament selection method is often used (Figure 2.5), in which a subset of individuals is randomly drawn from the population and the one with the highest fitness within the group is chosen. This approach is computationally efficient and offers greater control over the selection pressure. Another widely adopted strategy is the rank based selection, where individuals are ordered according to their fitness values, and the probability of selection is based on rank rather than absolute fitness. This ranking mechanism mitigates the dominance of exceptionally fit individuals and helps preserve diversity within the population.

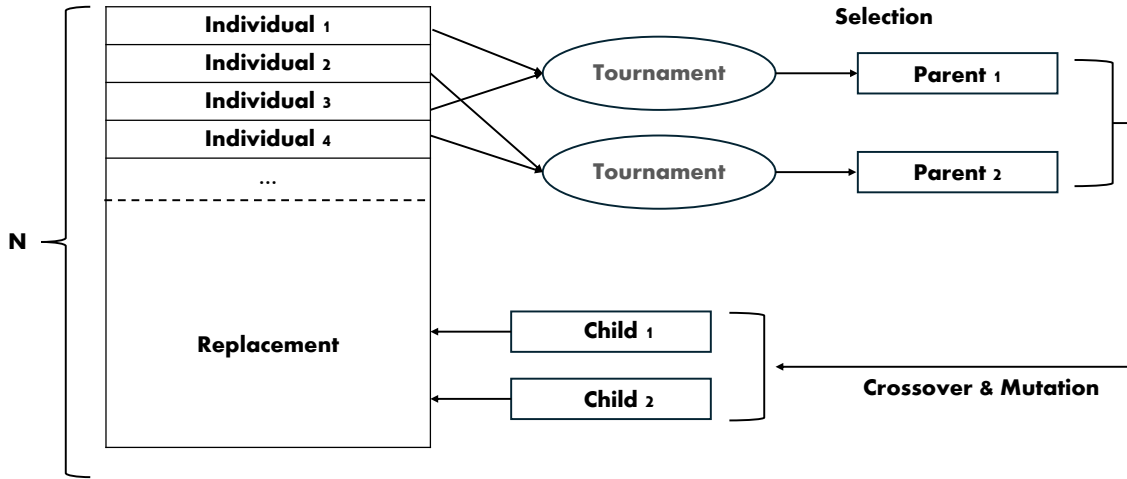


Figure 2.5: Tournament selection

Crossover

The crossover, also known as recombination, represents the most significant phase in a genetic algorithm. It is the primary mechanism responsible for introducing variability and improving the overall quality of solutions within the population. This operator allows the exchange of genetic information between two selected parent chromosomes to generate new offspring [87]. If the parents contain valuable genetic material, their combination can produce offspring with superior characteristics, potentially leading to better solutions in subsequent generations. The crossover process begins once two parents have been selected. A crossover point is randomly chosen along the chromosome string, and the genes of the two parents are exchanged around this point. Various crossover schemes can be employed such as one-point (Figure 2.6), two point, or multi point crossover where segments of genetic material are exchanged between parent individuals at predefined positions, thereby generating new offspring that combine inherited characteristics from both parents [86]. This exchange continues until the crossover point is reached, forming two new offspring that inherit characteristics from both parents. The new offspring then replace the less fit individuals in the population, ensuring evolutionary progress toward optimal solutions.

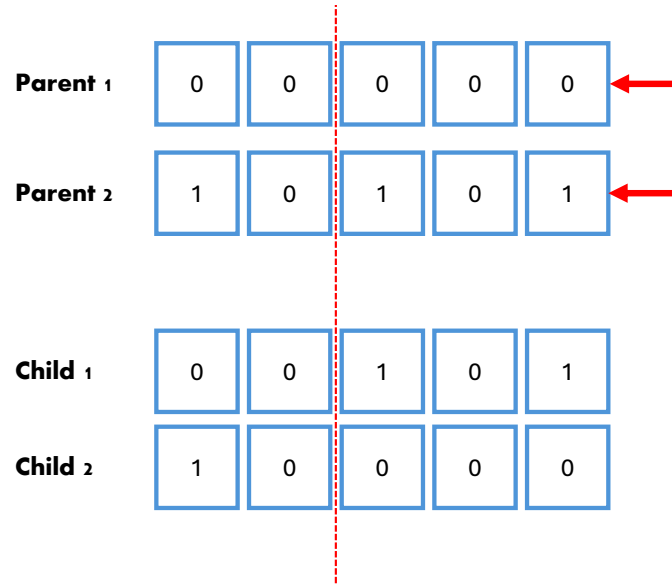


Figure 2.6: One-Point Crossover

Mutation

The mutation operator is essential for maintaining genetic diversity within the population and for exploring parts of the search space that may not be reachable through crossover alone. Its primary purpose is to prevent the algorithm from becoming trapped in local optima, thereby avoiding premature convergence [89]. Mutation is applied after the crossover step and works by introducing small random changes to selected genes in the offspring. These changes can slightly modify one or more parameters of a solution, creating new variations that may improve overall population performance [89]. Typically, only a few genes are mutated in each individual, and the mutation rate is kept low to maintain the stability of the evolutionary process while still allowing exploration. The exact implementation of mutation depends on the type of encoding used. For binary-coded chromosomes, mutation is performed by randomly flipping selected bits in the chromosome, turning 0s into 1s and vice versa (Figure 2.7), which can create new genetic combinations that were not present in the parents. For real-valued chromosomes, mutation is applied by adding a small random value to selected genes, allowing the algorithm to explore nearby regions of the search space and fine-tune solutions. In the case of permutation encoding, used for combinatorial problems, mutation may involve operations such as swapping, reversing, or inserting elements within the chromosome to generate new feasible solutions. Although mutation can sometimes temporarily reduce the fitness of an individual,

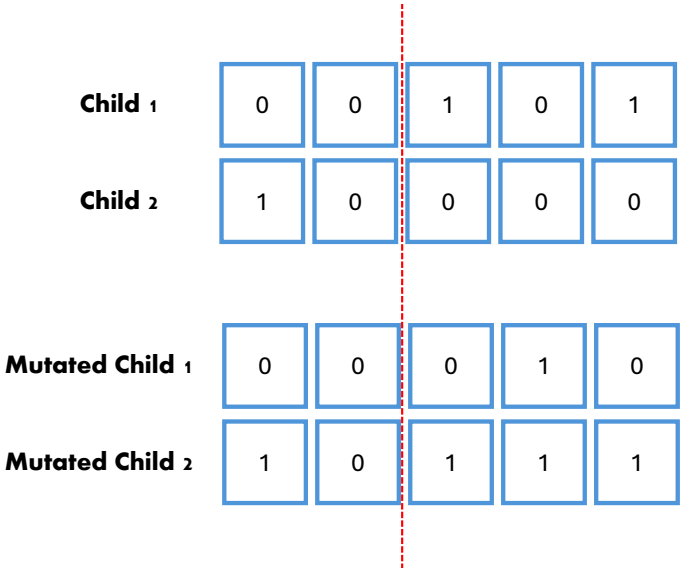


Figure 2.7: Binary coded chromosomes

it is crucial for preserving diversity in the population and enabling the discovery

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of new, potentially better solutions. Combined with selection and crossover, mutation ensures that the population continually evolves toward higher-quality solutions while avoiding premature stagnation.

Termination

The final step of the Genetic Algorithm is termination, which determines when the evolutionary process should stop. Unlike natural evolution, which continues indefinitely, artificial evolution must be halted at an appropriate point to produce optimal or near-optimal solutions [85]. Termination occurs when the population has converged and no longer produces offspring that are significantly different from the previous generation. To control this process, a termination criterion must be defined. Common criteria include reaching a maximum number of generations, achieving a sufficiently optimal value of the objective function for the best individual, observing a stagnation period during which the best individual remains unchanged for several generations, or detecting a loss of population diversity, often measured by the standard deviation of the fitness values across the population. By carefully defining the termination criterion, the GA can balance computational effort with solution quality, ensuring that the algorithm provides reliable results within a reasonable time.

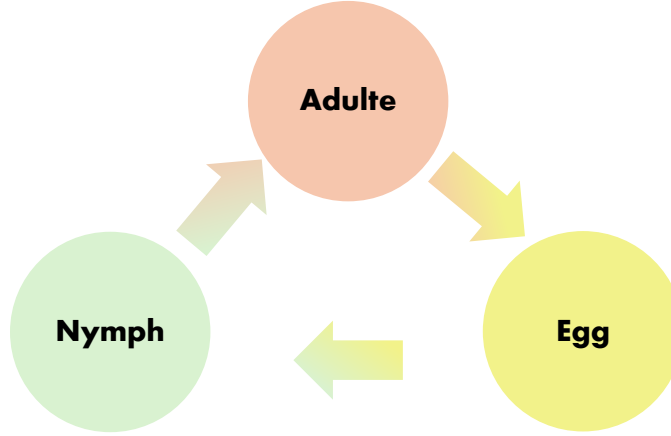
2.4.2 Grasshopper Optimization Algorithm (GOA)

Swarm intelligence (SI) emerges from the systematic study of collective behaviors observed in groups of social organisms [90]. This discipline examines how simple local interactions among individuals can give rise to complex, coordinated group dynamics. Drawing inspiration from these natural phenomena, SI has facilitated the development of highly effective optimization algorithms, in which each agent explores the solution space by leveraging both its own experience and the information obtained from neighboring agents. The performance of each agent is assessed through a problem-specific fitness function, enabling the swarm to converge toward optimal solutions [89]. Among these algorithms, the Grasshopper Optimization Algorithm (GOA) has emerged as one of the most popular and widely applied approaches. The GOA algorithm is introduced in [91], a novel and intriguing swarm intelligence algorithm inspired by the foraging and swarming behavior of grasshoppers. Grasshoppers are insects (Figure 2.8a), known for their destructive impact on crop production and agriculture. Their life cycle consists of two distinct stages: the

nymph stage and adulthood. The nymph stage is characterized by small steps and moderate movements, while the adult stage involves long-range and rapid movements (Figure 2.8b) [92–94]. The mathematical model employed to simulate the



(a) Real grasshopper.



(b) Life cycle of grasshoppers.

Figure 2.8: (a) Real grasshopper and (b) life cycle of grasshoppers.

swarming behavior of grasshoppers is presented as follows:

$$X_i = S_i + G_i + A_i \quad (2.5)$$

In the above equation, X_i denotes the position of the i^{th} grasshopper, S_i represents social interaction, G_i corresponds to the gravitational force acting on the grasshopper and A_i accounts for air advection. Randomness in the equation is introduced by:

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i \quad (2.6)$$

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r_1 , r_2 , and r_3 , are uniformly distributed random numbers in the range $[0, 1]$.

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^N S(d_{ij}) \hat{d}_{ij} \quad (2.7)$$

The distance between the i^{th} and j^{th} grasshopper is calculated using [Equation 2.8](#):

$$d_{ij} = |x_j - x_i| \quad (2.8)$$

and:

$$\hat{d}_{ij} = \frac{|x_j - x_i|}{d_{ij}} \quad (2.9)$$

Furthermore, the strength of the social forces is defined by [Equation 2.10](#)

$$S = f e^{\frac{-\delta}{r}} - e^{-\delta} \quad (2.10)$$

where f represents the intensity of attraction, r represents the distance, and l denotes the attractive length scale. The social interaction between grasshoppers can be defined as attraction and repulsion. The distance is considered in the range $[0, 15]$. The attraction increases in the interval of $[2.079, 4]$ and then decreases gradually. The repulsion occurs in the range $[0, 2.079]$. When the distance between two grasshoppers is exactly 2.079, there is neither repulsion nor attraction (no force). This area is called comfort zone [\[94\]](#). Figure shows the interaction between grasshoppers with respect to comfort area.

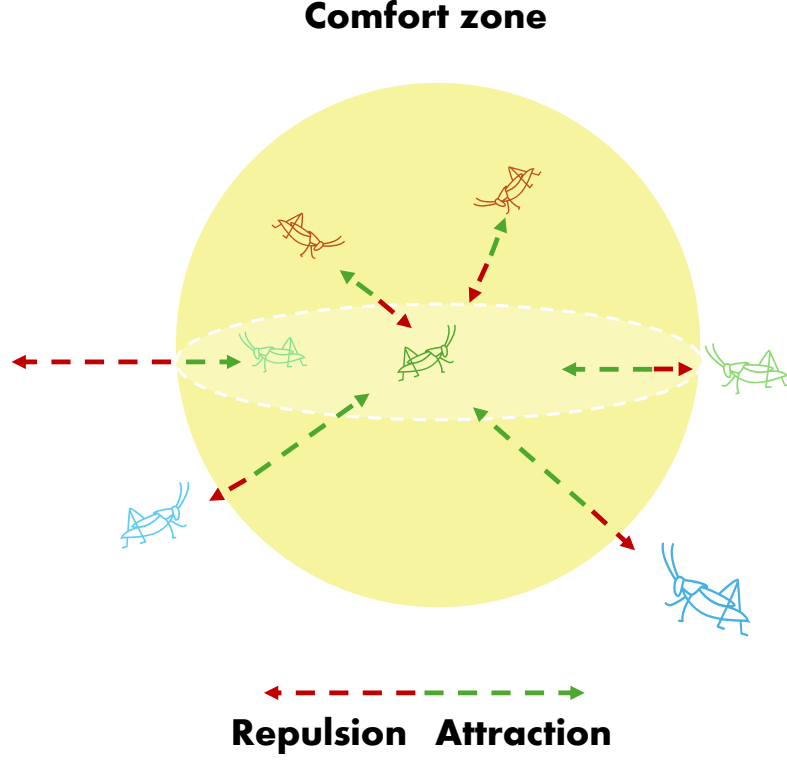


Figure 2.9: Interaction between grasshoppers with respect to comfort area.

The gravitational force component can be written as:

$$G_i = -g\hat{e}_g \quad (2.11)$$

where g represents the gravitational constant, and $\hat{e}_g$ denotes the unit vector pointing towards the center of the Earth. The component of the air advection.

$$A_i = u\hat{e}_w \quad (2.12)$$

where u is the constant drift, and $\hat{e}_w$ is the unit vector in the wind's direction. The equation is expanded by substituting the social interaction S_i , gravitational force G_i , and air advection A_i components as follows:

$$X_i = \sum_{\substack{j=1 \\ j \neq i}}^N S(|x_j - x_i|) \frac{x_j - x_i}{d_{ji}} - g\hat{e}_g + u\hat{e}_w \quad (2.13)$$

However, this mathematical model cannot be directly applied to solve optimization problems, primarily because the grasshoppers quickly reach a comfort zone, preventing the swarm from converging to a specific point. To address this issue, a modified

version of the equation is proposed for solving optimization problems as follows:

$$X_i^d = C \left(\sum_{\substack{j=1 \\ j \neq i}}^N C \frac{ub_d - lb_d}{2} S |x_j^d - x_i^d| \frac{x_j - x_i}{d_{ji}} \right) \quad (2.14)$$

+best solution found so far

where ub_d is the upper bound in the D^{th} dimension, and lb_d is the lower bound in the D^{th} dimension. The parameter C is involved in adjusting how much the grasshopper's positions change based on their current position, the position of the best grasshopper (leader), and the social forces acting on them. It plays a role in controlling the balance between exploration (searching for new areas) and exploitation (refining solutions in promising areas) during the optimization. In general, it can be mathematically represented as follows:

$$C = C_{\max} - I \frac{C_{\max} - C_{\min}}{\text{Max_iter}} \quad (2.15)$$

where $C_{\max}$ is the maximum value, $C_{\min}$ is the minimum value, I indicates the current iteration, and Max_iter is the maximum number of iterations.

2.5 Conclusion

The increasing complexity of photovoltaic systems, resulting from their nonlinear characteristics and sensitivity to environmental variations, calls for advanced modeling and control approaches to ensure reliable and efficient operation. Although conventional MPPT strategies are simple and widely implemented, their effectiveness decreases under dynamic conditions and parameter uncertainties, emphasizing the need for more flexible and robust methodologies for PV system analysis and control. Within this perspective, computational intelligence and bio-inspired optimization offer valuable alternatives to traditional techniques. Their capacity to manage uncertainty, complex parameter interactions, and varying operating conditions leads to more accurate system representation and improved control performance.

These considerations support a shift toward data-driven and adaptive modeling approaches tailored to photovoltaic applications. Accordingly, the following chapter introduces an advanced PV modeling methodology based on the integration of fuzzy logic and genetic optimization, aiming to refine the representation of PV cell behavior through adaptive parameter tuning and to provide a solid foundation for subsequent MPPT control and system optimization.

Chapter 3

Dynamic PV Modeling Using FLC and GA

3.1 Introduction

In renewable energy systems, designing robust Maximum Power Point Tracking (MPPT) controllers is essential to maximize power extraction from solar panels, particularly under unpredictable and rapidly changing climatic conditions or in the presence of partial shading [95–97]. Accurate modeling of PV arrays is critical for this purpose, as it minimizes the gap between predicted and actual performance. Traditional PV models with fixed parameters are based on equivalent electrical circuits, incorporating diodes, series resistances, and shunt resistances, with current outputs heavily dependent on solar irradiance, outdoor temperature, and wind speed [98]. These models rely on three key parameters, typically identified through analytical or numerical methods. While analytical approaches provide precise solutions, they involve solving complex, nonlinear equations, making them challenging to implement [98, 99]. As a result, researchers often turn to numerical methods, employing heuristic and metaheuristic optimization algorithms to identify these parameters by minimizing a fitness function that compares predicted and measured current outputs. Despite the advancements, fixed-parameter PV models face significant limitations. They assume constant values for key parameters, failing to capture the dynamic behavior of PV arrays under varying climatic conditions. This leads to substantial modeling errors, particularly during sudden environmental changes, and limits their adaptability in real-world scenarios. Optimization algorithms used

for fixed-parameter models often converge to local optima, resulting in inaccurate parameter identification and reduced reliability. Additionally, these models heavily depend on specific experimental datasets, which may not represent all operating conditions, further limiting their generalization and robustness. To address these challenges, researchers have proposed dynamic PV models with time-varying parameters. One approach focused on measuring thermal parameters of solar modules to improve dynamic modeling accuracy [100]. Another introduced a high-accuracy PV cell model incorporating self-heating and parameter variations, significantly enhancing modeling precision [101]. More recently, a dynamic PV model was proposed where series and shunt resistors were replaced with metallic or thermistor elements, enabling parameter variations fitted by nonlinear functions dependent on outdoor temperature [102]. While these dynamic models offer improved accuracy and adaptability, they also introduce notable drawbacks. The inclusion of nonlinear thermal parameters increases the search space and degree-of-freedom of the optimization problem, making controller synthesis more complex and computationally intensive. This complexity limits their practicality for real-time applications and increases the risk of convergence issues in optimization algorithms. Given these challenges, this chapter proposes a novel PV model with adjustable parameters that avoids nonlinear complexities. The evolution of these parameters is supervised by a fuzzy logic mechanism, where its fuzzification rules are optimally determined using the GA. Unlike fixed-parameter models, this approach dynamically adapts to changing conditions, significantly improving modeling accuracy and adaptability. The proposed PV model is validated using experimental data, demonstrating its superior performance in terms of modeling error and robustness compared to traditional fixed-parameter models.

3.2 Design of the Standard Fixed-Parameter PV Model

3.2.1 Equivalent Electrical Circuit for a PV array

In general, connecting N_s PV panels in series forms a single PV string, where each PV panel consists of N_c PV cells connected in series. Additionally, connecting N_p PV strings in parallel forms a single PV array. The primary objective of this section is to model this PV array using a fixed-parameter PV model. Typically, the PV model

is based on a nonlinear equation that relates the predicted global PV current I_m^g to the global PV voltage V_m^g . This equation is derived from an equivalent electrical circuit, which includes the following components:

- A fixed global series resistance R_s^g , where $R_s^g = \left(\frac{N_s}{N_p}\right) \cdot R_s^1$. Here, R_s^1 represents the internal and contact resistances of a PV cell.
- A fixed global shunt resistance R_p^g , where $R_p^g = \left(\frac{N_s}{N_p}\right) \cdot R_p^1$. Here, R_p^1 represents the leakage currents within a PV cell.
- A fixed diode quality factor n .

The relationship between I_m^g and V_m^g is illustrated in Figure 3.1 and expressed by Equation 3.1 [103]:

$$I_m^g = I_{ph}^g - I_{od}^g \cdot \left(-1 + \exp \left(\frac{V_m^g + R_s^g \cdot I_m^g}{n \cdot V_T^g} \right) \right) - \left(\frac{V_m^g + R_s^g \cdot I_m^g}{R_p^g} \right) \quad (3.1)$$

Where V_T^g is the global thermal voltage of the PV array, given by $V_T^g = N_s \cdot V_T^1$. The thermal voltage of a single diode V_T^1 is generated by N_c number of series-connected PV cells within a single PV panel. It is expressed as [104, 105]:

$$V_T^1 = \left(\frac{k \cdot T_c}{q} \right) \cdot N_c \quad (3.2)$$

Cell temperature T_c is determined as a function of outdoor temperature T , solar

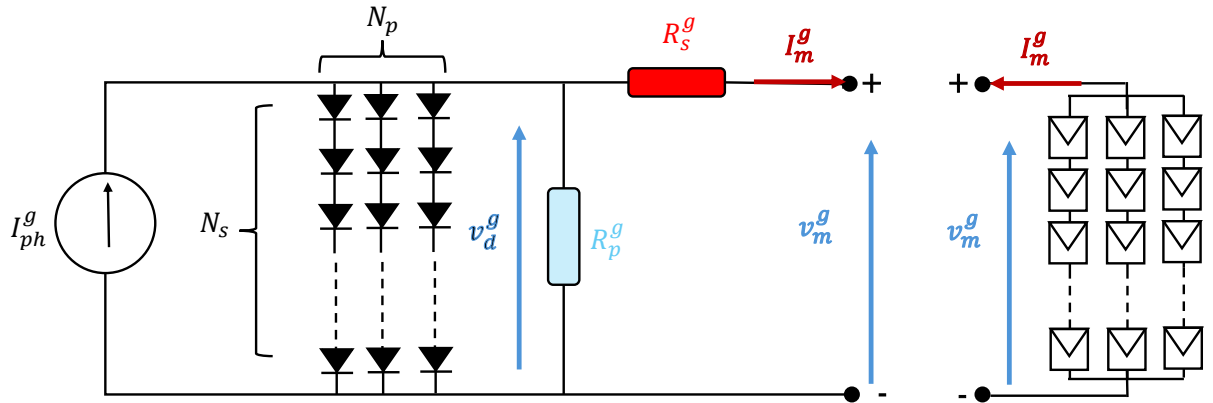


Figure 3.1: Equivalent electrical-circuit used for modelling the PV array

irradiance G , and wind speed ω using the empirical relationship [106]:

$$T_c = 1.14 \cdot (T - T_{stc}) + 0.0175 \cdot (G - 300) - K_r \cdot \omega + 30 \quad (3.3)$$

Where K_r is a positive parameter provided in the manufacturer's data sheet. The global photo-current I_{ph}^g is given by $I_{ph}^g = N_p \cdot I_{ph}^1$, where I_{ph}^1 is the photo-current corresponding to a single PV panel. It is defined by [107]:

$$I_{ph}^1 = \left(\frac{G}{G_{stc}} \right) \cdot (I_{sh,0}^1 + \alpha \cdot (T_c - T_{stc})) \quad (3.4)$$

Where $T_{stc} = 25^\circ C$ and $G_{stc} = 1000 \text{ W} \cdot \text{m}^{-2}$ are the nominal outdoor temperature and nominal solar irradiance under Standard Test Conditions (STC), respectively. The parameter α is the temperature coefficient of the nominal short-circuit current $I_{sh,0}^1$ for a single PV panel.

Moreover, the global reverse saturation current I_{od}^g is defined by $I_{od}^g = N_p \cdot I_{od}^1$, where I_{od}^1 is the reverse saturation current of the diode corresponding to a single diode. It can be derived from the datasheet information as [107]:

$$I_{od}^1 = I_{sr}^1 \cdot \left(\frac{T_c}{T_{stc}} \right)^{3/n} \cdot \exp \left(\frac{q \cdot E_g}{k \cdot n} \cdot \left(\frac{1}{T_{stc}} - \frac{1}{T_c} \right) \right) \quad (3.5)$$

where E_g is the band-gap energy of the semiconductor across the diode and I_{sr}^1 is the diode current for a single diode. It is given by [107]:

$$I_{sr}^1 = \frac{I_{sh,0}^1 + \alpha \cdot (T_c - T_{stc})}{-1 + \exp \left(\frac{V_{oc}^1 + \beta \cdot (T_c - T_{stc})}{n \cdot V_T^1} \right)} \quad (3.6)$$

where V_{oc}^1 is the open-circuit voltage for a single PV panel, and β is the temperature coefficient corresponding the monocrystalline technology of the PV panel.

3.2.2 Analytical solution based on LambertW for predicted global current computation

LambertW Function

The Lambert W function, also known as the product logarithm, is a special mathematical function defined as the inverse of we^w . In other words, if $z = we^w$, then $w = W(z)$. This function is particularly useful for solving equations where the unknown variable appears both in the base and in the exponent, a situation often encountered in physics, engineering, and control problems [108]. The Lambert W function can take on different values depending on the range of the input, but in most engineering applications the principal solution, denoted $W(x)$, is sufficient [109]. Because of this property, the function has been applied in many areas

such as diode and circuit modeling, combinatorics, population dynamics, and non-linear system [110]. In photovoltaic (PV) modeling, the Lambert W function is especially valuable because it allows the nonlinear current–voltage relationship to be expressed in an explicit analytical form, making it possible to compute the PV current more accurately and thereby improve the precision of global PV models. In the following subsection, we present how this function is applied to reformulate the PV current–voltage equation and to determine the predicted global PV current.

Application of the Lambert W Function to PV Current Evaluation

The primary objective of this work is to enhance the accuracy of the global PV model to faithfully replicate the actual behavior of the PV array. This accuracy hinges not only on the proper optimization of the three key parameters mentioned earlier but also on determining the exact root of the nonlinear function (f), derived from Equation 3.1 and expressed as:

$$f(I_m^g) = I_m^g - I_{ph}^g + I_{od}^g \cdot \left(-1 + \exp \left(\frac{V_m^g + R_s^g \cdot I_m^g}{n \cdot V_T^g} \right) \right) + \left(\frac{V_m^g + R_s^g \cdot I_m^g}{R_p^g} \right) \quad (3.7)$$

The resulting root represents the best predicted global PV current vector I_m^g . Its computation requires substituting the vector V_m^g with the actual global PV voltage V_{pv}^g and reformulating Equation 3.1 in the general form:

$$Z = W(X) \cdot e^{W(X)} \quad (3.8)$$

Z is the argument of the real function $W(X)$, and $e^{W(X)}$ includes the real vector X . This vector presents the solution of Equation 3.7, expressed in the general form:

$$X = \text{lambertW}(Z) \quad (3.9)$$

From mathematical developments of Equation 3.1 in accordance with the general form above, we can obtain [111, 112]

$$X = \left(\frac{R_s^g \cdot R_p^g}{n \cdot V_T^g \cdot (R_p^g + R_s^g)} \right) \cdot I_{od}^g \cdot \exp \left(\frac{V_m^g + R_s^g \cdot I_m^g}{n \cdot V_T^g} \right) \quad (3.10)$$

$$Z = \left(\frac{R_s^g \cdot R_p^g}{n \cdot V_T^g \cdot (R_p^g + R_s^g)} \right) \cdot I_{od}^g \cdot \exp \left(\frac{R_s^g \cdot R_p^g}{n \cdot V_T^g \cdot (R_p^g + R_s^g)} \left(I_{ph}^g + I_{od}^g + \frac{V_m^g}{R_s^g} \right) \right) \quad (3.11)$$

The predicted global PV current $\hat{I}_m^g$ is finally expressed as [95, 102]

$$\hat{I}_m^g = \frac{R_p^g \cdot (I_{ph}^g + I_{od}^g) - V_m^g}{R_p^g + R_s^g} - \frac{n \cdot V_T^g}{R_s^g} \cdot \text{LambertW}(Z) \quad (3.12)$$

3.2.3 Constrained optimization problem for identifying fixed parameters of the conventional PV model

Once the analytical determination of the predicted global current $\hat{I}_m^g$ is completed, it is necessary to compare it with the corresponding measured current vector I_{pv}^g at each sample point (k). This comparison allows the definition of a fitness function to be minimized, such as the Mean Squared Error (MSE), Integral Time Absolute Error (ITAE), or similar criterion. As this choice is not a central contribution of the present work, the MSE criterion is adopted as the fitness to be minimize. Furthermore, while numerous heuristic and metaheuristic algorithms are capable of solving this modeling problem effectively, the GA among is chosen as the optimizer for this study. This choice also falls outside the contribution of this work and was made due to its established effectiveness in handling such optimization tasks. The PV model design with fixed parameters can be formulated as the following constrained optimization problem [113]:

$$\min_{\substack{n_{\min} \leq n \leq n_{\max} \\ R_{s\min}^g \leq R_s^g \leq R_{s\max}^g \\ R_{p\min}^g \leq R_p^g \leq R_{p\max}^g}} J = \frac{1}{N} \cdot \sum_{k=1}^N \left(\hat{I}_m^g(k, n, R_s^g, R_p^g) - I_{pv}^g(k) \right)^2 \quad (3.13)$$

where N is the number of total samples collected during the experimental test. Finally, the optimal resulting three fixed parameters n^* , R_s^{g*} , and R_p^{g*} also lead to determine the global diode voltage V_d^g where $V_d^g = V_m^g + R_s^{g*} \cdot I_m^g$ (see Figure 3.1).

3.3 Design of the proposed adjustable-Parameters PV Model

The proposed methodology is illustrated in Figure 3.2. Initially, real-time input data measurements are normalized and fuzzified using predefined membership functions. A primary fuzzy inference system, equipped with user-defined fuzzification rules, computes three normalized parameters of the global PV model through defuzzification step using corresponding membership functions. These outputs are denormalized and, combined with the input dataset, used to compute the initial predicted global PV current using Equation 3.12. The MSE criterion is calculated by comparing the predicted global PV current, resulting from each fuzzification rule,

with the actual global measured PV current. The GA minimizes the total MSEs, updating the initial fuzzification rules accordingly. The updated fuzzification rules are reorganized in descending order of their MSE contributions, retaining only those with the lowest MSE values for the next GA generation. This iterative process continues until the final optimal fuzzy mechanism is achieved.

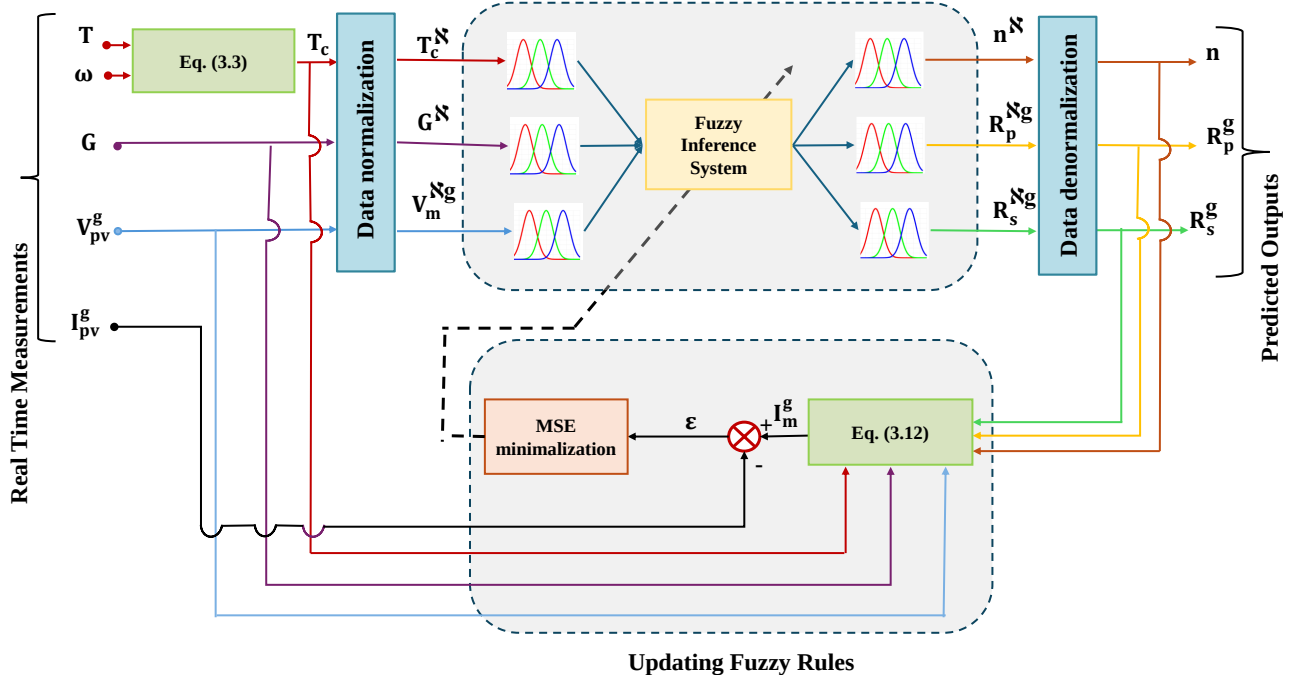


Figure 3.2: Three adjustable extraction parameters for global PV model using the proposed fuzzy mechanism

This last one will be used to supervise the evolution of each adjustable parameter of the proposed global PV model under varying climatic conditions. A key aspect of this approach is the GA-based updating of fuzzification rules in the inference system, ensuring continuous refinement and optimization of the model.

3.3.1 GA-based updating of fuzzification rules in the proposed fuzzy mechanism

Fuzzy model structure

The fuzzy model takes the normalized input vector $X^N = (G^N, T_c^N, V_m^N)^T$, derived from the real measurement vector $X = (G, T_c, V_m^g)^T$ and its lower and upper bound

vectors X_{min} and X_{max} using Equation 3.14:

$$X^{\aleph} = f^{\aleph}(X) = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (3.14)$$

Here, $G^{\aleph}, T_c^{\aleph}$ and $V_m^{\aleph g}$ are the normalized solar irradiance, normalized cell temperature and normalized global PV voltage respectively. The proposed fuzzy model predicts the normalized output vector $Y^{\aleph} = (n^{\aleph}, R_s^{\aleph g}, R_p^{\aleph g})^T$, where:

- $n^{\aleph}$ is the normalized predicted diode quality factor,
- $R_s^{\aleph g}$ is the normalized predicted global series resistance,
- $R_p^{\aleph g}$ is the normalized global shunt resistance.

The denormalized vector $Y^{\mathfrak{D}}$ is derived from $Y^{\aleph}$ and its lower and upper bound vectors $\min(Y)$ and $\max(Y)$, computed by Equation 3.15:

$$Y^{\mathfrak{D}} = f^{\mathfrak{D}}(Y^{\aleph}) = \min(Y) + Y^{\aleph} \cdot (\max(Y) - \min(Y)) \quad (3.15)$$

The lower bound $\min(Y)$ vector has the user-preselected constants $n_{min}^{\aleph}$, $R_{s_{min}}^{\aleph g}$ and $R_{p_{min}}^{\aleph g}$, while the upper bound vector $\max(Y)$ includes the user-preselected constants $n_{max}^{\aleph}$, $R_{s_{max}}^{\aleph g}$ and $R_{p_{max}}^{\aleph g}$.

Fuzzification of normalized inputs

Each component of the normalized input vector $X^{\aleph}$ is fuzzified using five membership functions, corresponding to the linguistic states: **Big Small** ($BS,1$), **Small** ($S,2$), **Medium** ($M,3$), **High** ($H,4$), and **Big High** ($BH,5$). The membership functions for the normalized inputs $G^{\aleph}, T_c^{\aleph}$ and $V_m^{\aleph g}$ are denoted $\mu_{G^{\aleph}}, \mu_{T_c^{\aleph}}$ and $\mu_{V_m^{\aleph g}}$ respectively.

Fuzzy inference system

The fuzzy inference system contains a set of fuzzification rules, each rule R_i is initially set by the user. The general form of the i^{th} fuzzification rule and j^{th} linguistic state is:

$$R_i : \text{If } G^{\aleph} \text{ is } \left\{ \mu_{G^{\aleph}}^{(i,j)} \right\} \text{ and } T_c^{\aleph} \text{ is } \left\{ \mu_{T_c^{\aleph}}^{(i,j)} \right\} \text{ and } V_m^{\aleph g} \text{ is } \left\{ \mu_{V_m^{\aleph g}}^{(i,j)} \right\}, \quad (3.16)$$

$$\text{then } n^{\aleph} \text{ is } \left\{ \mu_{n^{\aleph}}^{(i,j)} \right\} \text{ and } R_p^{\aleph g} \text{ is } \left\{ \mu_{R_p^{\aleph g}}^{(i,j)} \right\} \text{ and } R_s^{\aleph g} \text{ is } \left\{ \mu_{R_s^{\aleph g}}^{(i,j)} \right\}$$

Here:

- $\mu_{G^{\aleph}}^{(i,j)}$, $\mu_{T_c^{\aleph}}^{(i,j)}$ and $\mu_{V_m^{\aleph g}}^{(i,j)}$ are the degrees of membership of the inputs $G^{\aleph}$, $T_c^{\aleph}$ and $V_m^{\aleph g}$, respectively, for the i^{th} fuzzification rule and j^{th} linguistic state,
- $\mu_{n^{\aleph g}}^{(i,j)}$, $\mu_{R_p^{g\aleph}}^{(i,j)}$ and $\mu_{R_s^{g\aleph}}^{(i,j)}$ are the degrees of membership of the outputs $n^{\aleph}$, $R_p^{g\aleph}$ and $R_s^{g\aleph}$, respectively, for the i^{th} fuzzification rule and j^{th} linguistic state.

where $j = 1, 2, 3, 4, 5$ is the linguistic state index and $i = 1, \dots, 125$ is the fuzzification rule index.

Defuzzification of outputs

The defuzzified outputs are computed using the **center of gravity method**:

$$n^{\aleph} = \frac{\sum_{i=1}^r \left(\sum_{j=1}^5 \left(\mu_{G^{\aleph}}^{(i,j)} \cdot \mu_{T_c^{\aleph}}^{(i,j)} \cdot \mu_{V_m^{\aleph g}}^{(i,j)} \cdot \mu_{n^{\aleph g}}^{(i,j)} \cdot n_i^{\aleph} \right) \right)}{\sum_{i=1}^r \left(\sum_{j=1}^5 \left(\mu_{G^{\aleph}}^{(i,j)} \cdot \mu_{T_c^{\aleph}}^{(i,j)} \cdot \mu_{V_m^{\aleph g}}^{(i,j)} \right) \right)} \quad (3.17)$$

$$R_p^{g\aleph} = \frac{\sum_{i=1}^r \left(\sum_{j=1}^5 \left(\mu_{G^{\aleph}}^{(i,j)} \cdot \mu_{T_c^{\aleph}}^{(i,j)} \cdot \mu_{V_m^{\aleph g}}^{(i,j)} \cdot \mu_{R_p^{g\aleph}}^{(i,j)} \cdot R_{p,i}^{g\aleph} \right) \right)}{\sum_{i=1}^r \left(\sum_{j=1}^5 \left(\mu_{G^{\aleph}}^{(i,j)} \cdot \mu_{T_c^{\aleph}}^{(i,j)} \cdot \mu_{V_m^{\aleph g}}^{(i,j)} \right) \right)} \quad (3.18)$$

$$R_s^{g\aleph} = \frac{\sum_{i=1}^r \left(\sum_{j=1}^5 \left(\mu_{G^{\aleph}}^{(i,j)} \cdot \mu_{T_c^{\aleph}}^{(i,j)} \cdot \mu_{V_m^{\aleph g}}^{(i,j)} \cdot \mu_{R_s^{g\aleph}}^{(i,j)} \cdot R_{s,i}^{g\aleph} \right) \right)}{\sum_{i=1}^r \left(\sum_{j=1}^5 \left(\mu_{G^{\aleph}}^{(i,j)} \cdot \mu_{T_c^{\aleph}}^{(i,j)} \cdot \mu_{V_m^{\aleph g}}^{(i,j)} \right) \right)} \quad (3.19)$$

Here:

- $n_i^{\aleph}$, $R_{p,i}^{g\aleph}$ and $R_{s,i}^{g\aleph}$ are the normalized output values of $n^{\aleph}$, $R_p^{g\aleph}$ and $R_s^{g\aleph}$ for the i^{th} fuzzification rule,
- r is the total number of the fuzzification rules, $r = 125$.

GA for fuzzification rule optimization

The GA is used to optimize the fuzzification rules from minimizing the MSE criterion corresponding each fuzzification rule R_i where each MSE is generated from comparing the predicted output $I_{m,i}^g$ and the real measured output I_{pv}^g . Here, $I_{m,i}^g$ is computed using the denormalized outputs n , R_p^g and R_s^g of each fuzzification rule R_i and the real inputs G , T_c and V_m^g using [Equation 3.12](#).

Encoding and Optimization of Fuzzy Rules

Each fuzzy rule R_i is encoded as a chromosome in the GA. The chromosome for the i^{th} fuzzification rule given by: $[G_i^N, T_{c_i}^N, V_{m_i}^{Ng}, n_i^N, R_{p,i}^{gN}, R_{s,i}^{gN}]$, where the first three components $G_i^N, T_{c_i}^N$ and $V_{m_i}^{Ng}$ are fixed combinations (*e.g.*, 111, 112, ..., 555), while the last three components $n_i^N, R_{p,i}^{gN}$ and $R_{s,i}^{gN}$ are optimized by the GA. This algorithm searches for the optimal combination of output states among all possible combinations (*e.g.*, (BS)(BS)(BS), (BS)(BS)(BS), ..., (BH)(BH)(BH). This involves optimizing three integer variables within the lower bound vector $L_B = [1 \ 1 \ 1]^T$, and the upper bound $U_B = [5 \ 5 \ 5]^T$.

Reduction of Fuzzy Rules

To reduce the number of fuzzification rules, the GA evaluates the MSE contribution of each rule. The rules are ranked in descending order of their MSE contributions, and only the top rules are retained for the next generation. This ensures that the final fuzzy model has a reduced number of rules while maintaining high accuracy.

3.3.2 Formulation of the optimization problem

The optimization problem can be formulated as:

$$\begin{aligned} \text{Minimize } J &= \frac{1}{N} \cdot \sum_{k=1}^N \left\{ \hat{I}_m^g(k) - I_{pv}^g(k) \right\}^2 \\ \text{Subject to: } &\left\{ \mu_{n^N}^{(j)}, \mu_{R_p^{gN}}^{(j)}, \mu_{R_s^{gN}}^{(j)} \right\} \in \{1, 2, 3, 4, 5\} \end{aligned} \quad (3.20)$$

3.3.3 Experimental test description

The experimental test was conducted using a set of PV panels installed on the roof of the faculty at Yildiz University, Istanbul, Turkey [107, 113]. The PV panels included three types: thin-film, monocrystalline, and polycrystalline. This study focuses on monocrystalline panels, as the other types yielded similar results. The PV array consisted of three panels connected in series to achieve the desired current and voltage levels. Initially, modeling was performed using an equivalent electrical circuit with fixed parameters optimized by the GA algorithm. Subsequently, an equivalent electrical circuit with adjustable parameters was employed, where parameters were supervised by the proposed fuzzy mechanism based on fuzzification rule updating using the GA. The modeling phase utilized a subset of 300 samples, while the validation phase used a separate subset of 200 samples. Data were collected hourly

over a one-month period, starting at 9 a.m. on September 9th, 2024, resulting in 500 samples of total current I_{pv}^g and voltage V_{pv}^g , solar irradiance G (measured using a Kipp-Zonen CMP21 pyranometer), outdoor temperature T (measured using a Campbell CS215 thermocouple), and wind speed ω (measured using a tachymeter). Figure 3.3 illustrates the experimental setup, including the various measuring instruments [107, 113].

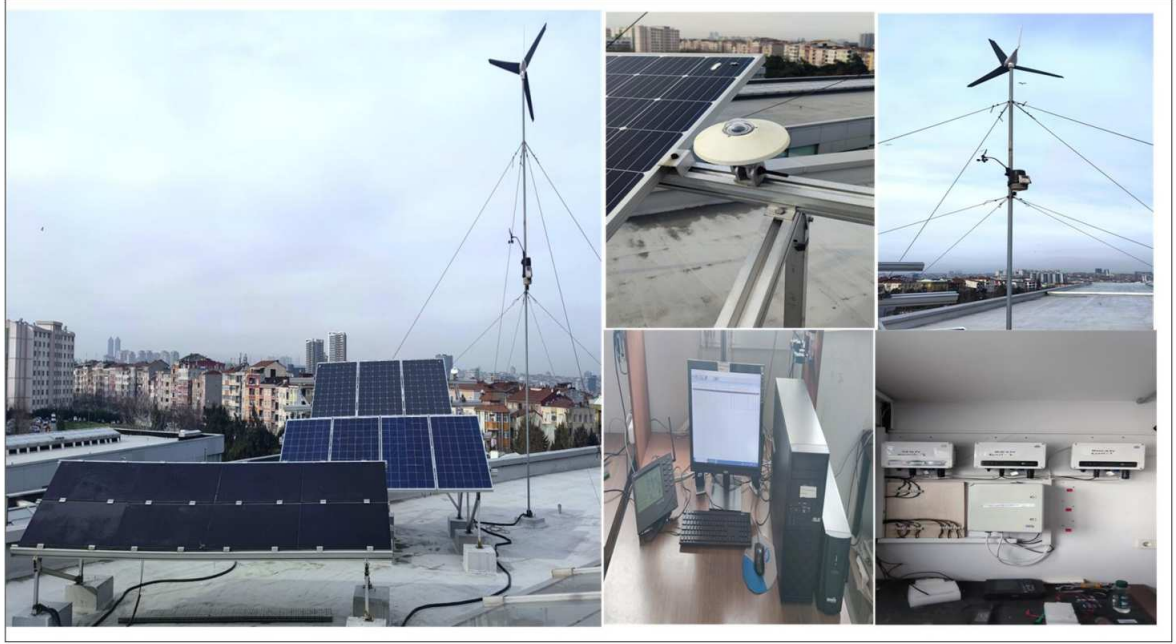


Figure 3.3: PV panels and measuring equipment used in the experimental test

The minimum and maximum values recorded for each measurement during the one-month period are summarized in Table 3.1 given below.

From the upper and lower limits summarized in Table 3.1, it is evident that STC

Table 3.1: Minimum and Maximum Limits Recorded for All Real-Time Measurements During One Month

	I_{PV}^g (A)	V_{PV}^g (V)	G ($\text{W}\cdot\text{m}^{-2}$)	T ($^{\circ}\text{C}$)	ω ($\text{m}\cdot\text{s}^{-1}$)
Minimum value	0	1.0042	0	13.600	0.2133
Maximum value	8.2634	102.25	759.47	32.712	26.658

conditions were not achieved during the specified period. Since the performance

assessment of any control strategy must be conducted under STC, the goal is to design an efficient equivalent electrical circuit that can ensure accurate predictions not only under STC conditions but also for any random variations in the aforementioned conditions.

3.3.4 Computation of the fixed parameters of the standard PV model

The datasheet for a single PV panel based on monocrystalline technology is summarized in [Table 3.2](#) below. The primary objective is to design a model that accurately

Table 3.2: Data Sheet of One Monocrystalline PV Panel Based on Polycrystalline Technology

Parameter	Value	Unit
P_{stc}^1	915.564	W
V_{stc}^1	99.33	V
$V_{oc,stc}^1$	119.82	V
I_{stc}^1	9.22	A
$I_{sc,stc}^1$	9.71	A
α	0.04	% / °C
β	-0.32	% / °C
K_r	1.509	—

describes the behavior of the PV array utilizing the monocrystalline technology. Due to the stochastic nature of the GA algorithm, it is run multiple times to optimally determine the three key fixed parameters of the equivalent electrical circuit. The first dataset, comprising 300 samples, was used for parameter identification. The GA tuning parameters are summarized in [Table 3.3](#) below. The search space for the constrained optimization problem was selected after several GA runs. Extensions were performed when the solution became stuck in saturated constraints. The most

Table 3.3: Genetic Algorithm Parameter Settings

Parameters	Value
Population size	20
Plot function	@gaplotbestf
Max. number of generations	50
Mutation function	@mutationadaptfeasible
Crossover function	@selectiontournament
Selection function	[0.1, 1.1]
Number of elite counts	2
Crossover fraction	0.8
Stall generation limit	20
Function tolerance	10^{-6}

appropriate choice to avoid saturation is as follows:

$$\begin{aligned}
0.56 &\leq n \leq 1.45 \\
0.1 &\leq R_s^g \leq 1.5 \\
1500 &\leq R_p^g \leq 2500
\end{aligned} \tag{3.21}$$

3.3.5 Computation of adjustable parameters for the proposed PV model

In this design, the proposed fuzzy mechanism consists of three normalized inputs, three normalized outputs, and five membership functions for each input and output. The sigmoid function was chosen in each membership function for the following linguistic states: (BS) , (S) , (M) , (H) , and (BH) . For the fuzzification rules, the three normalized inputs are kept by all possible fixed combinations (*e.g.*, 111, 112, ..., 555), while the three normalized outputs are kept by (111, 112, ..., 555). The GA tuning parameters are conserved as those mentioned in Table 3.3, and only the top 10 fuzzification rules corresponding the lowest MSE values are retained for the next generation are given in Table 3.4.

Table 3.4: Optimal Rule Updates Using Genetic Algorithms

Rule #	Irradiance	Temperature	Voltage	R_s	R_p	n
1	BS	BS	BS	S	S	S
2	S	BS	BS	S	S	S
3	M	BS	BS	S	S	M
4	H	BS	BS	BS	M	S
5	BH	BS	BS	M	M	BS
6	BS	S	BS	BS	S	S
7	S	S	BS	S	S	S
8	M	S	BS	S	M	M
9	H	S	BS	M	S	S
10	BH	BS	S	S	M	BS

The minimization process based on GA consistently achieves significant reductions in MSE across numerous runs. The best result yields the lowest MSE value of **0.025** (see [Figure 3.4](#)), representing a substantial improvement compared to the MSE obtained by the fixed-parameter PV model. This corresponds to an improvement rate of approximately **93.77%**, highlighting the effectiveness and value of the proposed approach.

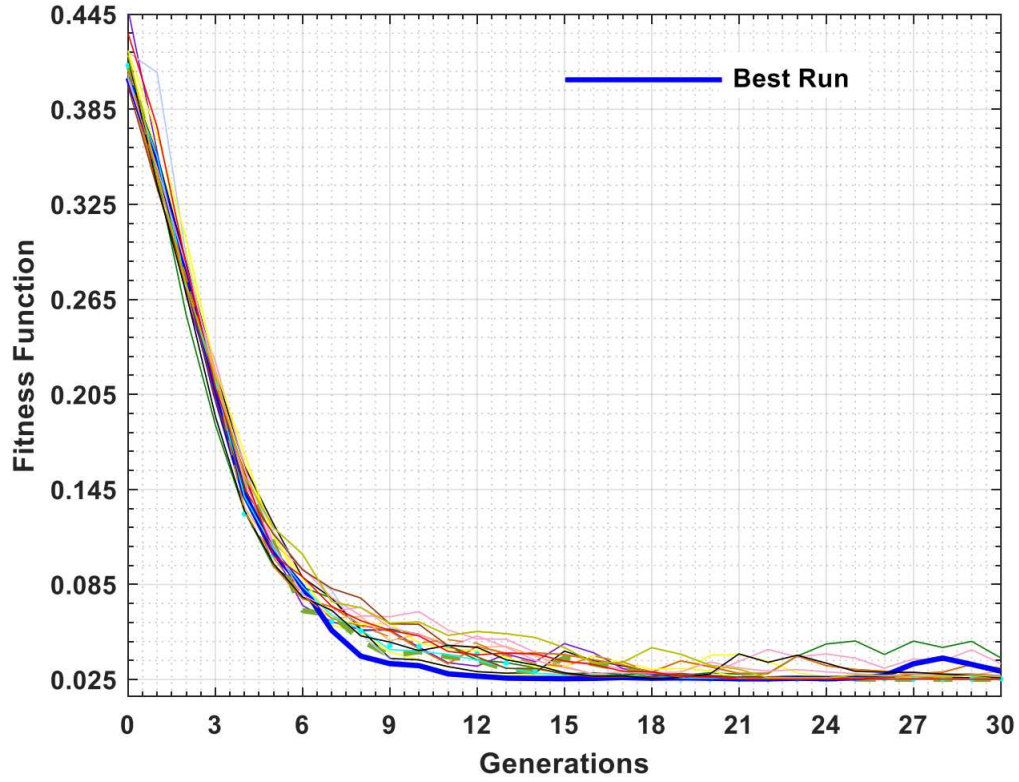


Figure 3.4: Best MSE minimization using the GA algorithm

3.3.6 Validation of the Optimal GA Solution

The optimal solution obtained by the GA algorithm provides the best prediction of the global PV current, which is compared with the actual current for the 300 samples. Figure 3.5 illustrates the comparison between predicted and actual global PV currents, also depicts the corresponding modeling accuracy achieved during the parameter identification process for the PV model with adjustable parameters.

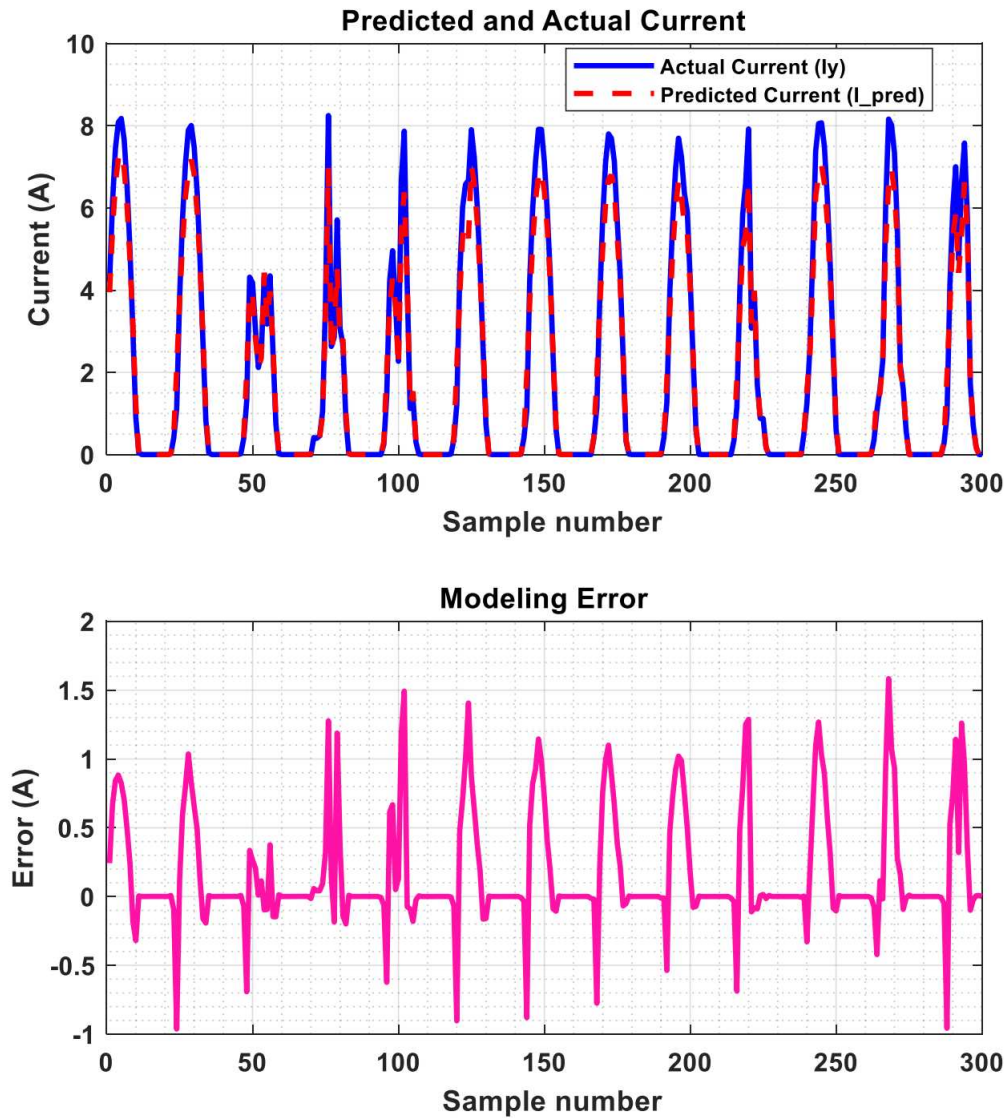


Figure 3.5: Actual and predicted global PV currents and modeling error provided during Fuzzy Model Design

Figure 3.6 illustrates the evolution of each model parameter during the validation phase. The results reveal significant fluctuations in the model parameters, demonstrating that the actual behavior of the PV array cannot be effectively captured by a model with fixed parameters.

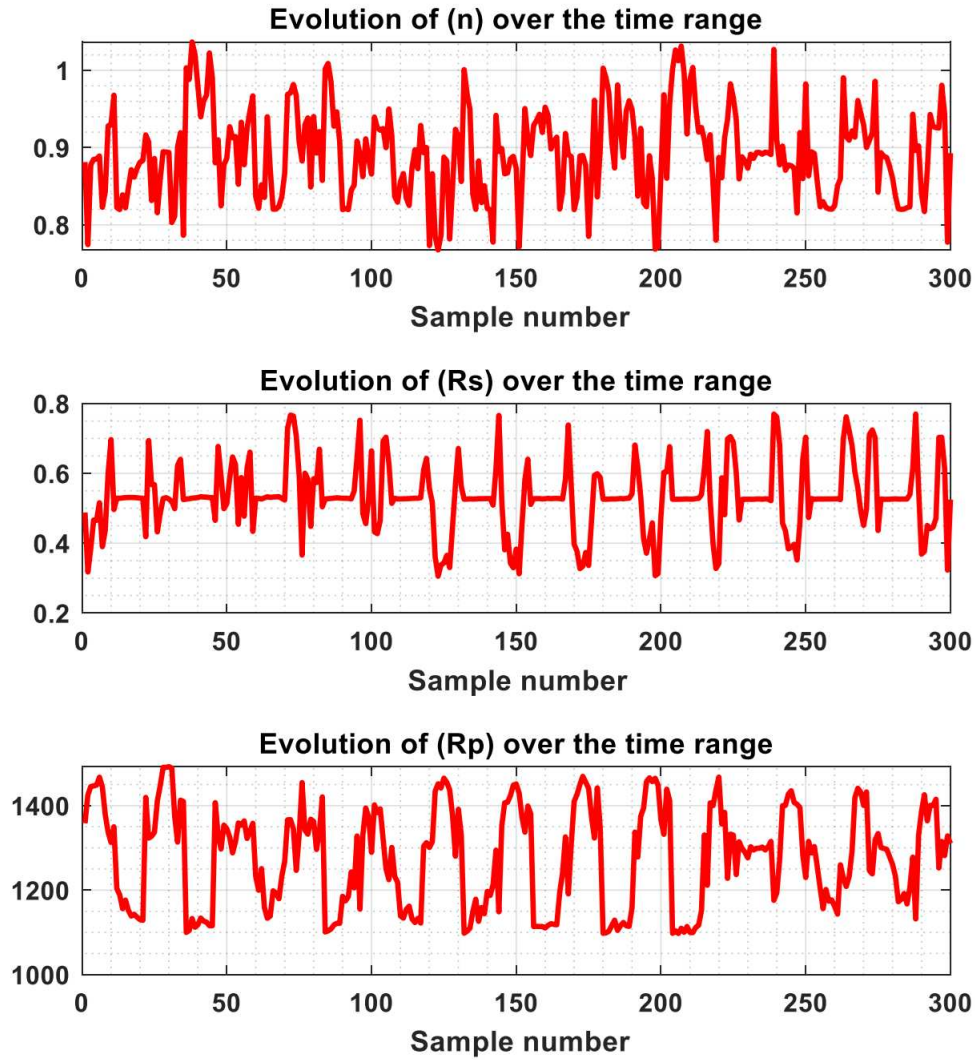


Figure 3.6: Evolution of three adjustable parameters during Fuzzy Model Design

Figure 3.7 illustrates the membership functions Gaussian shapes of the optimum fuzzy system designed. The membership functions represent the fuzzy sets for the input or output variables of the system, used by the GA to achieve the best performance for a specific application. Each membership function is typically plotted as a curve on a graph, where the x - axis represents the range of the input or output variable, and the y - axis represents the degree of membership, ranging from 0 to 1.

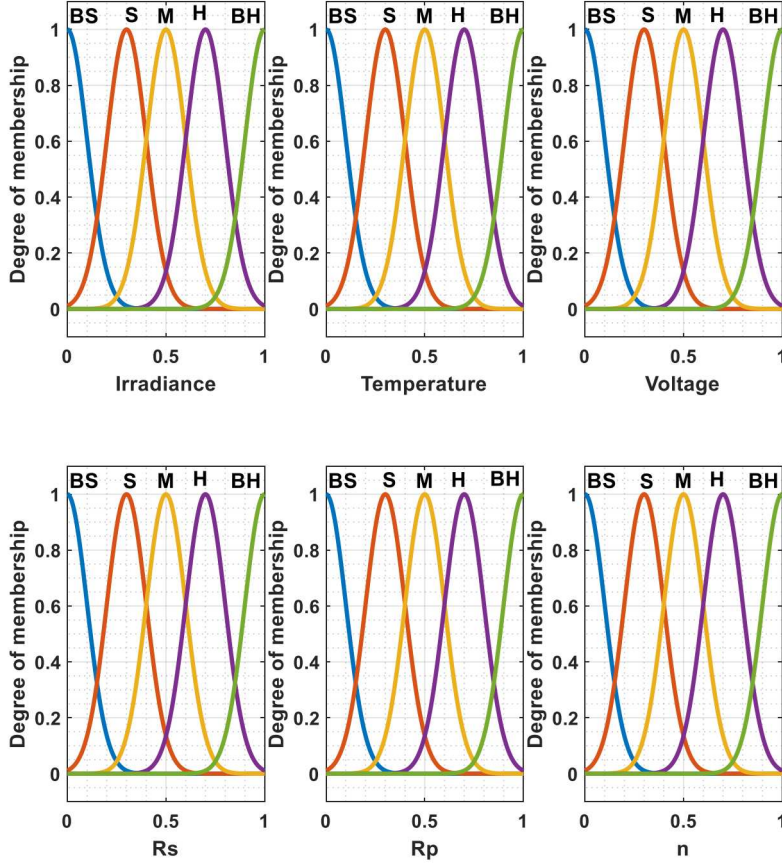


Figure 3.7: Membership functions of the fuzzy system: Gaussian Shapes

Figure 3.8 presents a 3D surface plot illustrating the nonlinear input-output mapping of the proposed fuzzy logic system, where the x - and y -axes represent normalized solar irradiance (G^N) and cell temperature (T_c^N), while the z -axis denotes the predicted normalized global series resistance (R_s^{Ng}), the predicted normalized shunt resistance R_p^{Ng} and the predicted normalized diode ideal factor n^N . For the case of the normalized global series resistance R_s^{Ng} , the surface exhibits a piecewise-continuous topology with distinct gradients, reflecting the system's adaptive response to dynamic climatic conditions. For instance, at low irradiance ($G^N = 0.2$) and temperature ($T_c^N = 0.3$), the series resistance R_s^{Ng} converges to ~ 0.15 (normalized), while at high irradiance ($G^N = 0.8$) and temperature ($T_c^N = 0.7$), it peaks at ~ 0.45 , demonstrating a 200% increase. This variability underscores the inadequacy of fixed-parameter models, which assume a constant R_s^{Ng} (e.g., 0.82Ω as per GA-optimized baseline). Sharp transitions near ($G^N = 0.5$, $T_c^N = 0.5$) indicate rule activation thresholds, validated by the 93.77% MSE reduction achieved through GA-optimized fuzzy rules. The surface's smooth interpolation between linguistic states (BS to BH)

confirms the system's robustness in handling stochastic environmental fluctuations, aligning with experimental validation results where parameter adaptability reduced modeling errors to **0.025** MSE compared to **0.41** MSE for fixed-parameter models.

Figure 3.8 depicts the nonlinear relationship between two normalized input variables (e.g., solar irradiance G^N and cell temperature T_c^N) and one denormalized output parameter (e.g., series resistance R_s^{Ng}) of the fuzzy logic system, showcasing piecewise-continuous slopes with peaks and valleys that reflect rule-dominated regions (e.g., high irradiance/low temperature) and smooth transitions between linguistic states. The surface's sharp edges indicate boundaries where membership functions overlap minimally, while flat regions reveal insensitivity to certain input variations, aligning with PV saturation effects. The absence of erratic oscillations confirms the GA-optimized rule set's robustness (Table 3.6), avoiding overfitting and generalizing well to unseen data, as validated by the low MSE in Table 3.5. This visualization underscores the fuzzy mechanism's ability to dynamically adapt PV parameters to climatic changes, bridging empirical data with theoretical models while maintaining interpretability and accuracy.

All Surface Plots for Irradiance, Temperature, and Voltage

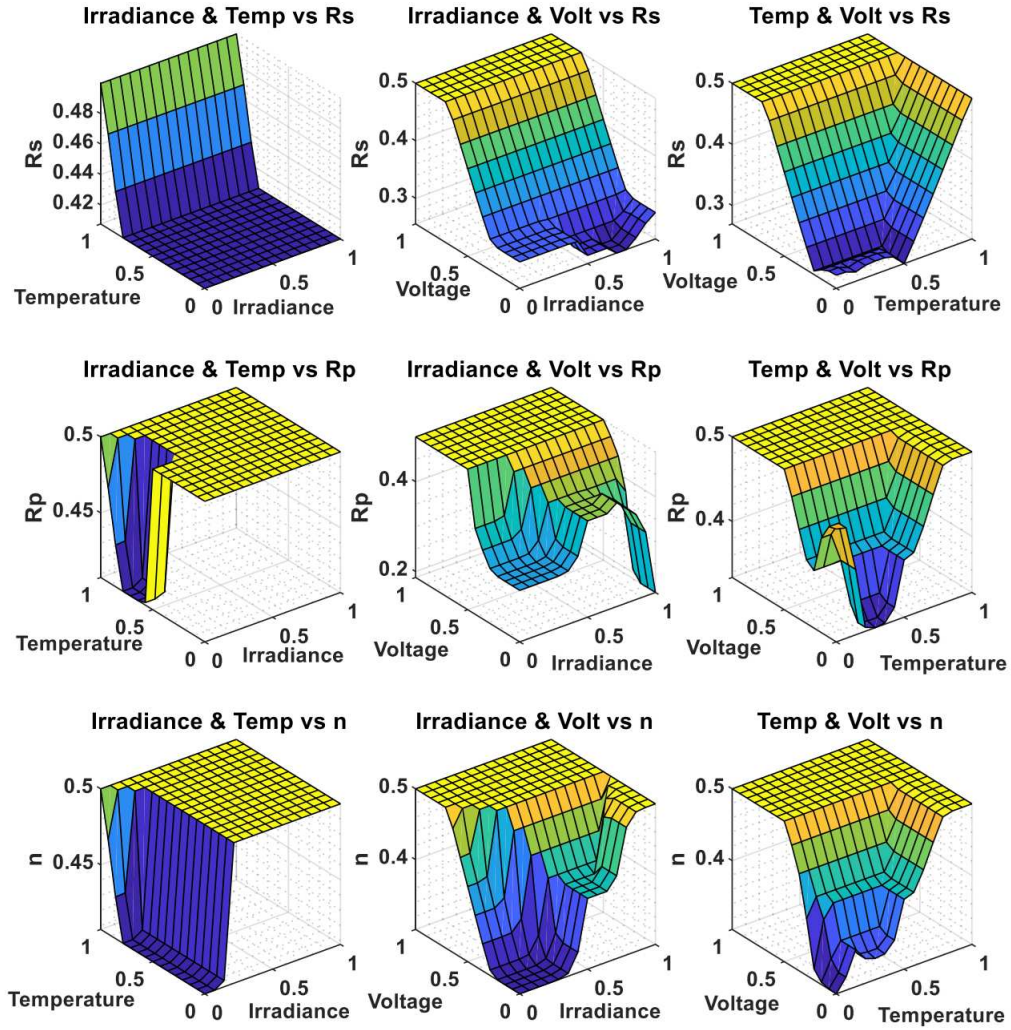


Figure 3.8: 3D surface plot of fuzzy logic system input-output mapping

3.3.7 Validation of the Fuzzy PV Model

The Fuzzy model is reconstructed using the optimal rules derived from the GA algorithm. To evaluate its accuracy and generalization capability, the model is tested on a second dataset comprising 200 additional samples. During this validation phase, the performance of the PV model with adjustable parameters is assessed to ensure its ability to accurately predict the behavior of the PV array under varying conditions. Figure 3.9 illustrates the evolution of each model parameter during the validation phase. The results reveal significant fluctuations in the model parameters, demonstrating that the actual behavior of the PV array cannot be effectively captured by

a model with fixed parameters. In contrast, the proposed PV model, supervised by the Fuzzy with GA-based updates, provides a more accurate representation of the PV array's performance. This is clearly demonstrated in [Figure 3.10](#), where the predicted global PV current closely aligns the actual measurements, even for new data points not included in the parameter identification step. Also, it presents a comparison of the modeling errors between the two PV models: one with fixed parameters and the other with adjustable parameters. The results clearly demonstrate that the proposed PV model with adjustable parameters achieves the lowest error, confirming its superiority in addressing this type of modeling problem.

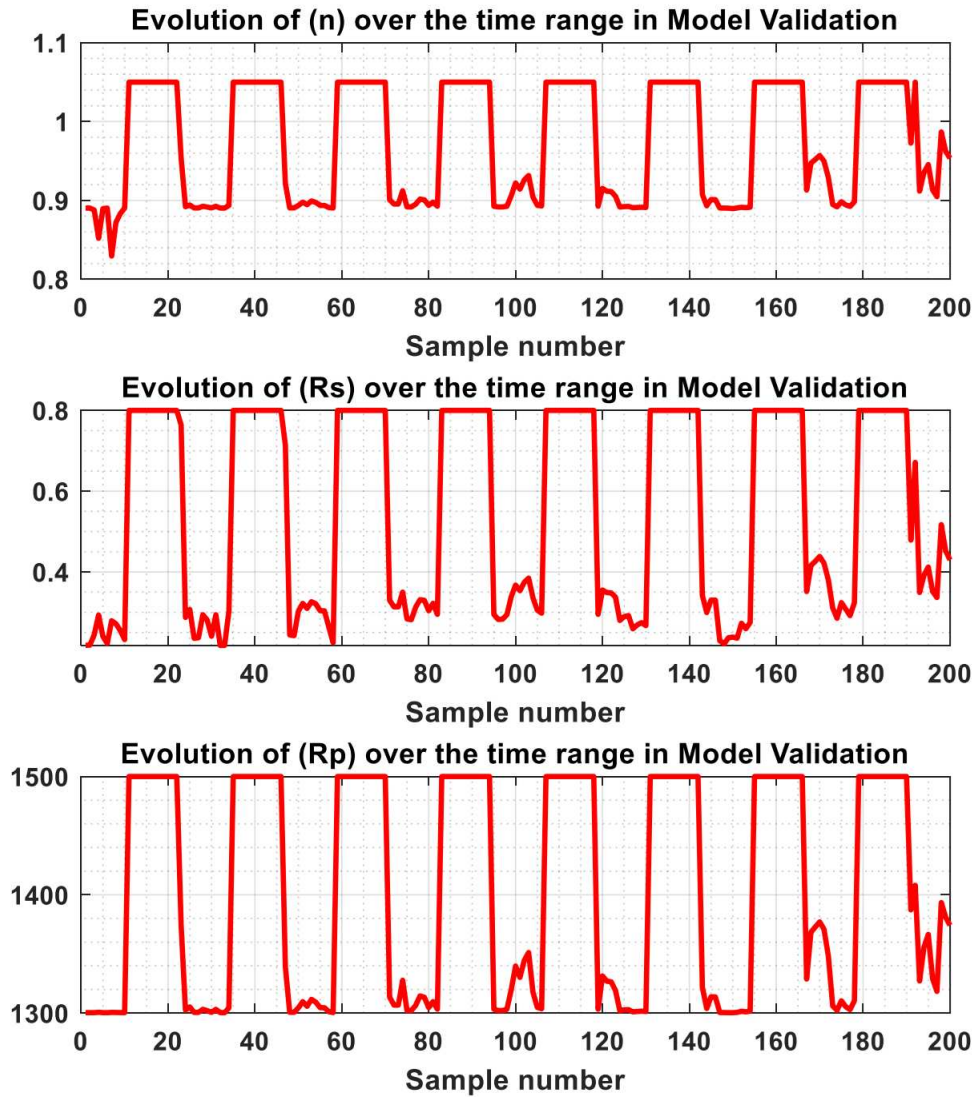


Figure 3.9: Evolution of three adjustable parameters during Fuzzy model validation

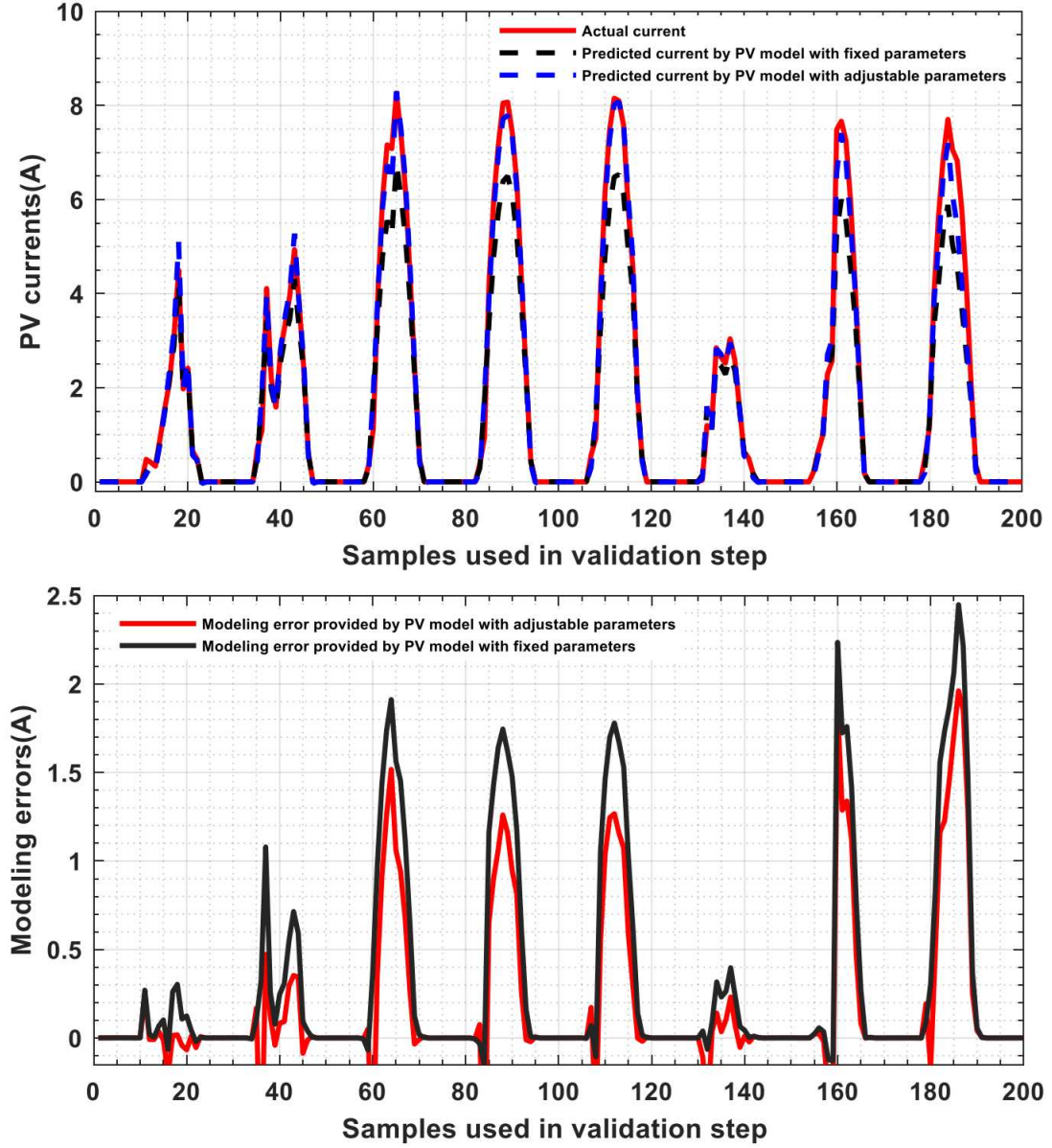


Figure 3.10: Comparison of Predicted Global PV Currents and Modeling Errors during Fuzzy Model Validation

3.3.8 Performance Robustness and Design Justifications

The proposed three-adjustable-parameter PV model achieves a notable improvement in accurately representing not only monocrystalline solar panels but also polycrystalline and thin-film technologies. This enhanced performance is primarily attributed to the fuzzy-based mechanism governing the real-time evolution of the

model parameters. However, despite these promising results, it is essential to assess the robustness and reliability of the model under different conditions and sample sizes. Such an evaluation ensures that the proposed approach is not only effective in controlled settings but also maintains consistent performance in practical applications.

Training Sample Size Robustness

To evaluate the robustness of the parameter identification stage, an empirical analysis was conducted by varying the number of training samples from 50 to 300, while reserving 200 samples for validation. The objective of this analysis was to determine the minimum number of samples required to ensure stable model performance under different operating conditions.

The results, summarized in Table [Table 3.5](#), indicate that the model's mean squared error (MSE) decreases as the number of training samples increases. Specifically, the training MSE decreases from 0.042 with 50 samples to 0.025 with 250–300 samples, corresponding to an improvement of approximately 93.77%. Beyond 250 samples, the training error plateaus at 0.025, suggesting that additional data provides only marginal improvements.

Table 3.5: Model Performance Across Varying Training Sample Sizes

Training Samples	Training MSE	Validation MSE
50	0.042	0.045
100	0.035	0.038
150	0.029	0.032
200	0.026	0.028
250	0.025	0.027
300	0.025	0.026

Moreover, the validation MSE closely follows the training MSE, with values ranging between 0.026 and 0.028 across all cases. This consistency confirms that the model generalizes well to unseen data, rather than overfitting to the training set.

The analysis demonstrates that robust performance is achieved with 200–250 training samples, striking a balance between accuracy and efficiency. This finding

highlights the practicality of the proposed model for real-world deployment, as it can maintain reliable performance without requiring excessively large datasets.

Optimality of Fuzzy Rule Count

An important aspect of the proposed fuzzy-based PV model lies in the choice of the number of fuzzy rules. In this work, 125 rules were generated by using five membership functions (MFs) per input. To validate whether this configuration is truly optimal, we compared it against other rule counts, ranging from 27 (3 MF/input) to 343 (7 MF/input). The results are summarized in Table [Table 3.6](#).

Table 3.6: Rule Count vs. Performance

Number of Rules (MF/input)	Training MSE	Validation MSE
27 (3 MF/input)	0.041	0.044
64 (4 MF/input)	0.033	0.036
125 (5 MF/input)	0.025	0.026
216 (6 MF/input)	0.024	0.025
343 (7 MF/input)	0.023	0.024

Based on an exhaustive evaluation of fuzzy rule counts ranging from 27 to 343 rules, corresponding to 3 to 7 membership functions per input, the configuration of 125 rules (5 membership functions per input) was identified as the optimal architecture for the system. This selection achieves the most favorable balance between model accuracy and computational efficiency, as evidenced by its attainment of the lowest Mean Squared Error (MSE) of 0.025 on the training set and 0.026 on the validation set. Configurations with fewer rules, such as 27 or 64, were found to underfit the data, resulting in a significant performance degradation of 30-60% in MSE. Conversely, while systems with a higher rule count (216 or 343) yielded marginal MSE improvements of less than 1%, this minimal gain was offset by a substantial 2 to 3-fold increase in computational cost and slower convergence. The robustness of the 125-rule system is further reinforced by its comprehensive coverage of the input domain and the subsequent application of a Genetic Algorithm, which prunes the rule base to retain only the ten most impactful rules, thereby enhancing interpretability and efficiency without compromising predictive performance.

Generalizability Across PV Technologies

The fuzzy mechanism's stability across sample sizes and rule configurations confirms its adaptability to eventual existing of polycrystalline and thin-film panels, where parameter dynamics may differ. The GA-optimized rules ensure efficient performance even with limited data.

As a final conclusion, the proposed model achieves stable parameter identification with 200–250 training samples and 125 fuzzy rules, balancing accuracy and computational efficiency. This makes it viable for diverse PV technologies under real-world conditions.

3.4 Conclusion

This work introduced a novel modeling approach for PV arrays, particularly those utilizing monocrystalline technologies, though applicable to other types as well. The proposed method relies on a PV model with adjustable and time-varying parameters, where the evolution of each parameter is supervised by a Fuzzy model. The rules were determined by the GA algorithm to minimize the MSE criterion between the actual and predicted currents. Unlike traditional fixed-parameter models, which often yield suboptimal modeling errors, the proposed PV model demonstrated superior performance during validation with real experimental measurements. The results confirmed that the proposed approach, combining Fuzzy with GA-based updates, provides a more accurate and reliable representation of the actual PV array's behavior. Moreover, this modeling approach offers a parametric framework that will be invaluable for future researchers in synthesizing MPPT controllers. It also facilitates comprehensive frequency analysis and robustness studies of the closed-loop system. In contrast, pure fuzzy models lack such parametric capabilities, limiting their utility for the closed-loop robustness analysis, frequency response evaluations, and similar studies. This chapter focused on GA and Fuzzy logic-based optimization of PV systems, while the next chapter continues to improve MPPT performance through the real-time implementation of the Grasshopper Optimization Algorithm (GOA), aiming for more robust and efficient power extraction under dynamic operating conditions.

Chapter 4

A GOA-Tuned TID Controller For Enhanced P&O MPPT

4.1 Introduction

In general, the tracking of the maximum power point in photovoltaic (PV) systems depends on the MPPT algorithm and the control circuit. This control circuit typically employs a DC–DC converter which is considered as a variable resistance [114]. Among the various MPPT methods, the Perturb and Observe (P&O) algorithm is widely used due to its simplicity and ease of implementation [115]. This algorithm operates by introducing small perturbations into the system and observing their effect in order to drive the operating point towards the maximum power point (MPP). However, the drawback of this algorithm is that the PV operating point fluctuates around the MPP, thus reducing the amount of extractable energy [116]. Furthermore, if solar irradiance changes rapidly, the P&O algorithm not only fails to track the actual MPP but also causes the operating point to oscillate around it, resulting in a noticeable waste of available energy.

Improving the stability and dynamic behavior of PV systems largely depends on the use of a secondary control loop. This additional loop provides smoother operation and greater stability, though it also increases system complexity. In direct MPPT methods such as the P&O algorithm, the duty cycle of the DC–DC converter is directly perturbed [117]. Although this method ensures faster response, it typically leads to oscillations around the MPP. By contrast, the indirect approach regulates a reference voltage through a secondary control loop, prioritizing stabil-

ity and precision, which makes it more suitable for applications requiring minimal fluctuations [118].

In this context, this chapter focuses on the use of a DC–DC boost converter in combination with an advanced voltage controller. A small-signal model of the MPPT system is developed using MATLAB’s Identification Toolbox to provide a simplified and accurate representation of the system dynamics. Building on this model, a Tilted Integral Derivative (TID) controller is employed, with its parameters tuned using the Grasshopper Optimization Algorithm (GOA). The controller is designed to minimize the error between the reference voltage and the measured voltage, thereby ensuring effective regulation and enhanced robustness.

The proposed modeling and control strategy are validated through experimental data collected from the *Centre de Développement des Énergies Renouvelables (CDER)*, Ghardaïa, Algeria, demonstrating the practical relevance of this approach for improving PV system performance under varying environmental and load conditions.

4.2 PV Panel Specifications and P-V , I–V Characteristic Curves

The photovoltaic module used in this study is the **AEG PQ10/40/01**, which provides a nominal power output of 38.4 W under standard test conditions (STC: irradiance of 1000 W m^{-2} at 25°C). Table 4.1 details the complete specifications of the PV module.

A PV emulator was employed to simulate the behavior of the module using (Equation 1.5). The characteristic curve of the PV module was plotted with Figure 4.1 illustrating the experimental results obtained at different irradiance levels.

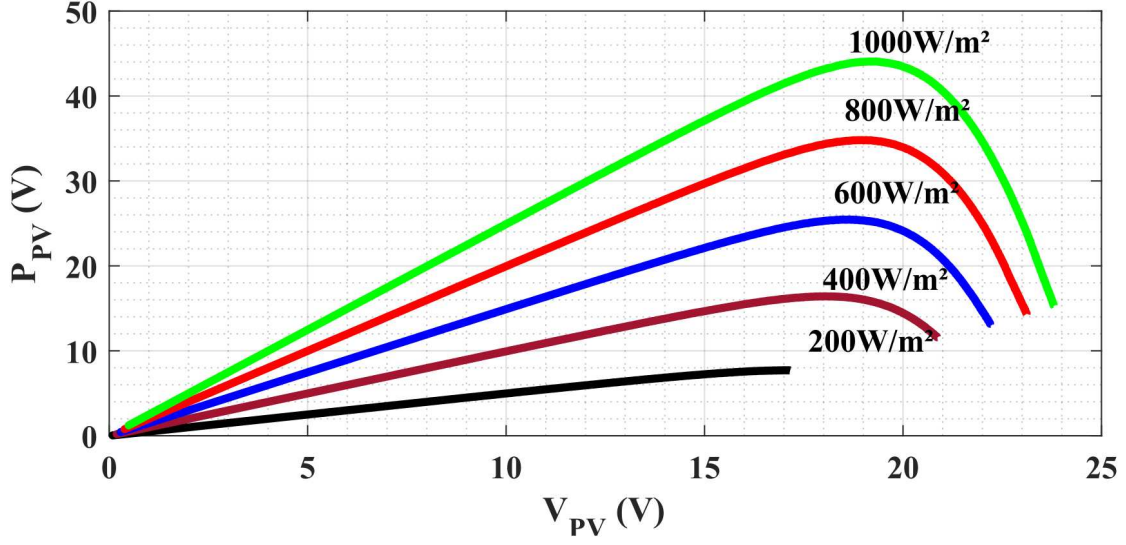
4.3 Global System Identification

The literature reports a wide range of approaches to photovoltaic (PV) system identification, characterized by varying degrees of complexity and applicability. White-box approaches are based on physical laws and equivalent circuit models to describe the system’s behavior [119], Whereas black-box approaches depend solely

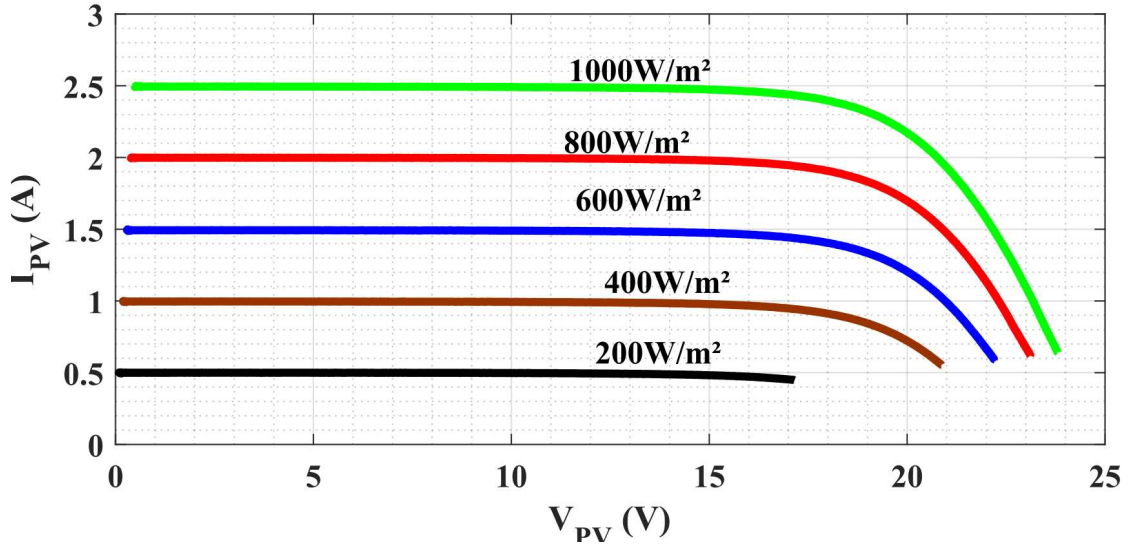
Table 4.1: Technical specifications of AEG PQ10/40/01 PV module

Parameter	Value
Maximum Power (P_{max})	38.4 W
Open Circuit Voltage (V_{oc})	21.6 V
Short Circuit Current (I_{sc})	2.55 A
Voltage at Maximum Power (V_{mp})	17.3 V
Current at Maximum Power (I_{mp})	2.22 A
Temperature Coefficient of V_{oc}	$-0.34 \text{ V } ^\circ\text{C}^{-1}$
Temperature Coefficient of I_{sc}	$0.05 \% ^\circ\text{C}^{-1}$
Number of Cells	36

on experimental input-output data, they avoid any direct reliance on underlying physical models [120]. Between these two approaches, grey-box methods integrate simplified physical models with parameter estimation techniques to enhance modeling accuracy [121]. Moreover, optimization-driven techniques employ numerical or bio-inspired algorithms to identify system parameters [122], while AI and soft computing methods, such as neural networks and fuzzy logic, enable adaptive and data-driven modeling [123]. Finally, small-signal models are obtained by linearizing the nonlinear PV system dynamics around a steady-state operating point, making them particularly valuable for control design and stability analysis [124]. In this work, a black-box small-signal identification approach is adopted, where experimental data are used to derive a linearized representation of the PV system dynamics. Generally, tuning the voltage controller depends on a precise linear small-signal model that reflects the real-world behavior of the solar system. Given the nonlinear nature of actual system dynamics, the small-signal approach becomes essential to achieve the required linearization around the maximum power point. Figure 4.2 illustrates the resulting closed-loop system, where the linear small-signal model $G(s)$ and TID voltage controller $K(s)$ are integrated through the indirect P&O algorithm. Unlike conventional analytical approaches that rely on converter equations and linearization around a theoretical operating point, the small-signal model in this study was obtained experimentally through a black-box identification process using MATLAB's System Identification Toolbox. In this approach, the entire PV system comprising the PV module, boost converter, and load is considered as a



(a) P-V (Power-Voltage) characteristic



(b) I-V (Current-Voltage) characteristic

Figure 4.1: Real experimental PV module characteristics

single dynamic entity. The model parameters are identified directly from measured input-output data, where the duty cycle perturbation serves as the input and the PV voltage perturbation as the output. This allows the model to inherently capture the real dynamic interactions among system components, including parasitic

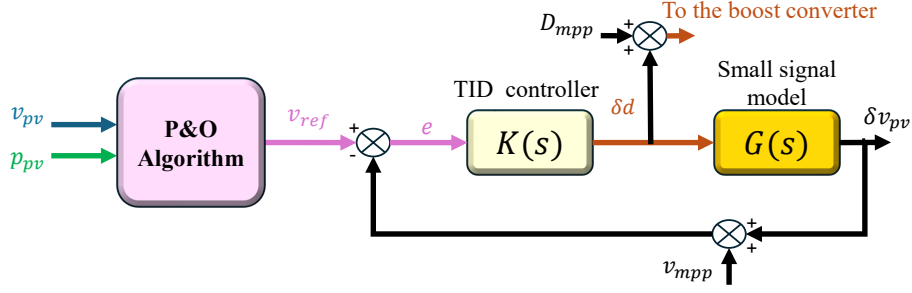


Figure 4.2: Closed Loop System Based On The Small Signal Model And The TID Controller

effects and nonlinearities that are often neglected in analytical derivations. The proposed method therefore represents a practical approach to obtaining an accurate small-signal transfer function for PV systems.

4.3.1 Small Signal Disturbance

According to the maximum power transfer theory, maximum power is transferred from the source to the load when the load impedance matches the source impedance [125]. This is achieved by adjusting the duty cycle of the boost converter. The duty cycle corresponding to the MPP can be calculated using the following equation:

$$D_{mpp} = 1 - \sqrt{\frac{R_{mpp}}{R_{Load}}} \quad (4.1)$$

R_{mpp} represents the resistance of the PV panel at the (MPP) for a specific irradiance and temperature, R_{load} is the load connected to the output of the boost converter, and D_{mpp} is the duty cycle of the boost converter at the MPP.

The linearization of the overall model enables the design of the desired voltage controller and facilitates the stability analysis of the closed-loop system according to the following steps [126]:

- Define state variables and input variables.
- Identify the operating point around which linearization has to be carried out.
- Introduce a small perturbation in the input variable, which results in perturbations in all system variables.

After repeating this process 9 times, using Equation 4.2 vary the amplitude (A_p) and frequency (f_p) of the sine wave that disturbs the duty cycle as represented

in Figure 4.3 This will lead to 9 different system variables being observed, each corresponding to a change in the disturbance parameters.

$$D_{opt} = A_p \sin(2\pi f_p) + D_{mpp} \quad (4.2)$$

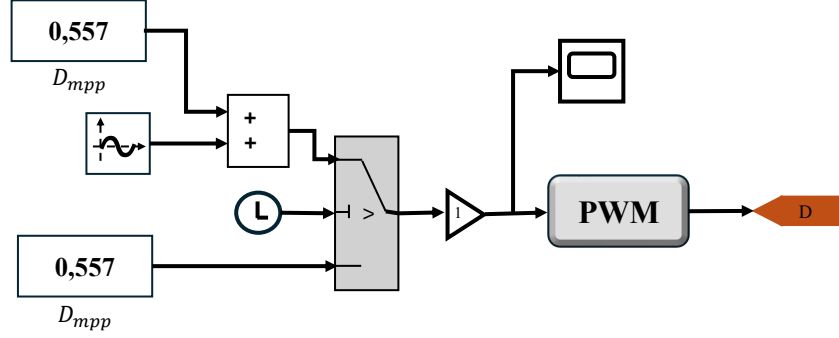


Figure 4.3: Sine Wave-Based Duty Cycle Distribution

4.3.2 Small Signal Transfer Function

The process of using MATLAB's Identification Toolbox was employed to derive the small-signal transfer function based on nine different input-output signal sets, each consisting of the input duty cycle and the corresponding output PV voltage. These nine input-output signals were obtained through a combination of PV emulator tests and real-world experimental measurements.

The goal is to obtain a small-signal transfer function that relates the perturbation in PV voltage δv_{pv} to the perturbation in the duty cycle δd . This transfer function is expressed as:

$$G(s) = \frac{\delta v_{pv}}{\delta d} \quad (4.3)$$

The sigma variable represents the perturbation value added to the constant steady-state value of the state variable, as represented in Equation 4.4. This allows for analysis of the system's dynamic behavior and the derivation of its small-signal model, which is essential for understanding the system's response to small variations in the input.

$$\begin{cases} v_{pv}(t) = v_{mpp} + \delta v_{pv}(t) \\ d(t) = D_{mpp} + \delta d(t) \end{cases} \quad (4.4)$$

Using the steady-state data, the transfer function of the linear small-signal model is derived to associate the duty cycle variation δd with the PV voltage change δv_{pv} .

MATLAB's Identification Toolbox is employed to process the input and output signals, represented as vectors.

Using the steady-state data, the transfer function of the linear small-signal model is derived to associate the duty cycle variation δd , with the PV voltage change δV_{pv} . MATLAB's Identification Toolbox is employed to process the input and output signals, represented as vectors. However, since the objective is to obtain a small-signal transfer function, the optimal D_{mpp} and V_{mpp} values are subtracted from the corresponding signals to isolate the perturbations according to the [Equation 4.5](#).

$$\begin{cases} \delta v_{pv}(t) = v_{pv}(t) - v_{mpp} \\ \delta d(t) = d(t) - D_{mpp} \end{cases} \quad (4.5)$$

The desired linear small-signal model requires the following procedures:

- Open MATLAB's System Identification Toolbox interface.
- Click on Time-Domain Data to upload the perturbed signals.
- Create input-output data objects representing the duty cycle perturbation as the input and the PV voltage perturbation as the output.
- Select a transfer function model structure.
- Specify the number of poles and zeros for the transfer function model.
- Select the Gauss-Newton method to iteratively evaluate the transfer function parameters, ensuring the best fit between the predicted and actual system outputs. Validate the model by assessing the fit and ensuring it captures the system's dynamics accurately.
- Repeat the process for the nine signals, exploring various combinations of poles and zeros to find the best representation for the system's behavior.

4.4 Controller Structure

The TID (Tilt-Integral-Derivative) controller is integrated in the photovoltaic system to enhance the dynamic performance and steady-state accuracy of Maximum Power Point tracking. Unlike conventional controllers, the TID architecture provides enhanced robustness against nonlinearities and rapid irradiance variations in

real-world PV systems. By optimizing the controller's tuning parameters through the derived small-signal model, the proposed design mitigates oscillations near the MPP while maintaining fast convergence. The TID controller is a closed-loop adjustable compensator characterized by three control parameters K_t , K_i , K_d , and an additional tuning parameter n [127]. The TID controller follows a structure similar to the PID controller, but with the proportional term replaced by a tilted proportional behavior [128]. For the TID controller, the optimal value of n typically lies between 2 and 3 [129].

A block diagram of the TID controller is presented in Figure 4.4.

Mathematically, it can be represented as:

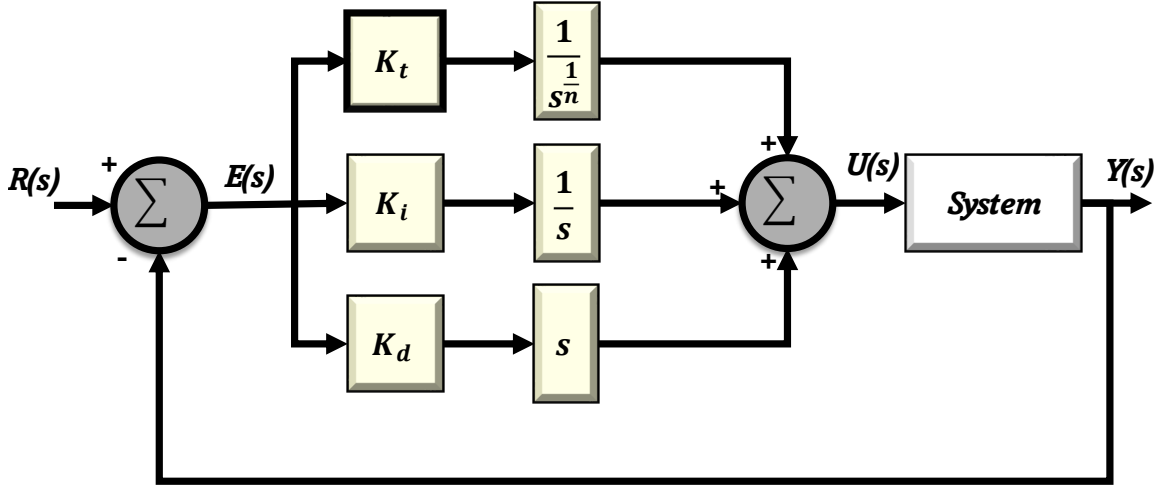


Figure 4.4: Structure of TID Controller in a Closed Loop System

$$U_{TID}(s) = K_{TID}(s, \theta) E_{TID}(s) \quad (4.6)$$

$$E_{TID}(s) = R_{TID}(s, \theta) Y_{TID}(s) \quad (4.7)$$

where $K_{TID}(s, \theta)$ represents the transfer function of the TID controller in the complex domain, with the parameter vector $\theta \in \mathbb{R}^4$. The transfer function $G_{TID}(s, \theta)$ is mathematically given by:

$$K_{TID}(s, \theta) = \frac{K_t}{s^{1/n}} + \frac{K_i}{s} + K_d s \quad (4.8)$$

where $\theta = [K_t \ K_i \ K_d \ n]$. TID control provides a high level of flexibility in its control parameters, which is expected to result in enhanced performance, including easier adjustment, improved rejection ratios, and reduced sensitivity to variations in plant parameters on the closed-loop response [127].

4.5 Results and Discussion

While the proposed P&O-TID-GOA strategy demonstrates superior performance over the conventional P&O method, it is acknowledged that the field of MPPT encompasses a wide range of advanced controllers, including nonlinear, synergetic, and artificial intelligence-based techniques. A comprehensive comparative analysis with these diverse approaches remains a valuable direction for future work. The present study establishes the viability and performance of the experimentally-tuned TID controller as a robust and high-performance alternative within the model-based control paradigm, particularly for systems where the implementation complexity of AI-driven methods is a concern.

4.5.1 Small-Signal Transfer Function validation

The duty cycle's behavior under perturbed conditions was evaluated based on real-world measurements acquired from the CDER Ghardaïa test site. The following [Figure 4.5](#) and [Figure 4.6](#) illustrate the response of the duty cycle under disturbance. After repeating the process 9 times, each with a sine wave varying the amplitude and frequency as described in [Equation 4.3](#). Consequently, nine different system behaviors were observed, each corresponding to specific disturbance parameters. The duty cycle and the resulting $v_{pv}(t)$ signals were used to extract the small perturbations, as described in [section 4.3](#). Then, the MATLAB Identification Toolbox was utilized to process the input-output vectors and estimate the system's transfer function. For each of the nine perturbation signals, the System Identification Toolbox was applied to estimate a transfer function model by varying the number of poles and zeros. [Figures 4.7](#), [Figure 4.8](#) illustrate the model validation results for each signal. These results confirm that the identification procedure was systematically applied to all test cases.

[Figure 4.9](#) illustrates the best simulated δv_{pv} response obtained for Signal 1, highlighting the close agreement between the identified transfer function and the measured data. [Table 4.2](#) below summarizes the best-fit data obtained for various input signals, detailing the frequency, amplitude, and the number of poles and zeros used during the identification process. Among the trials, Signal 1 with a frequency of 0.01 Hz, an amplitude of 1, 3 poles, and 1 zero achieved the highest fit percentage of 92.66%. This result indicates that the transfer function corresponding to Signal 1 most accurately represents the system's dynamics.

The associated transfer function is derived using the identified parameters and

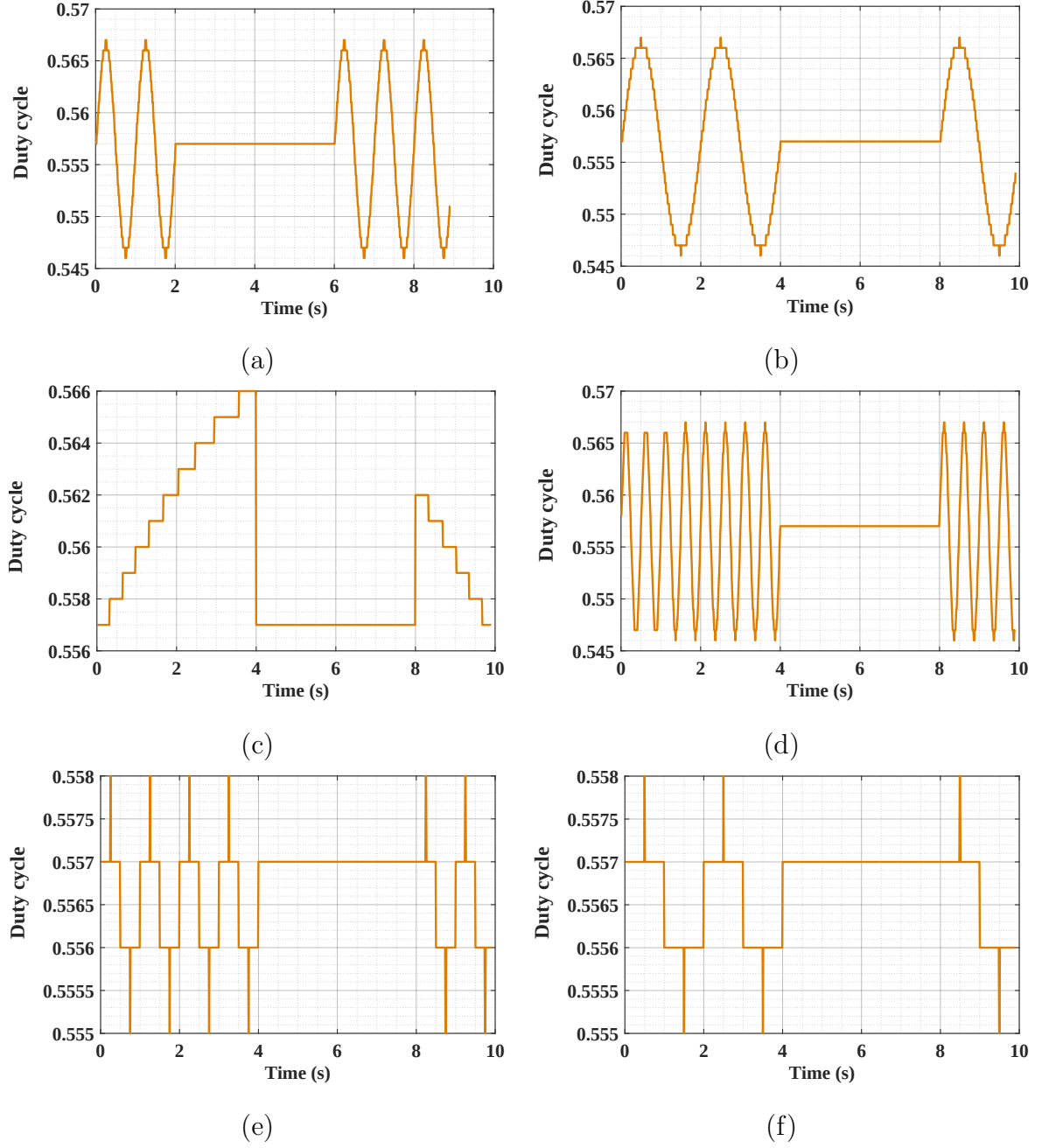


Figure 4.5: Response of the Duty Cycle to Sine Wave Disturbances of signals 1-6

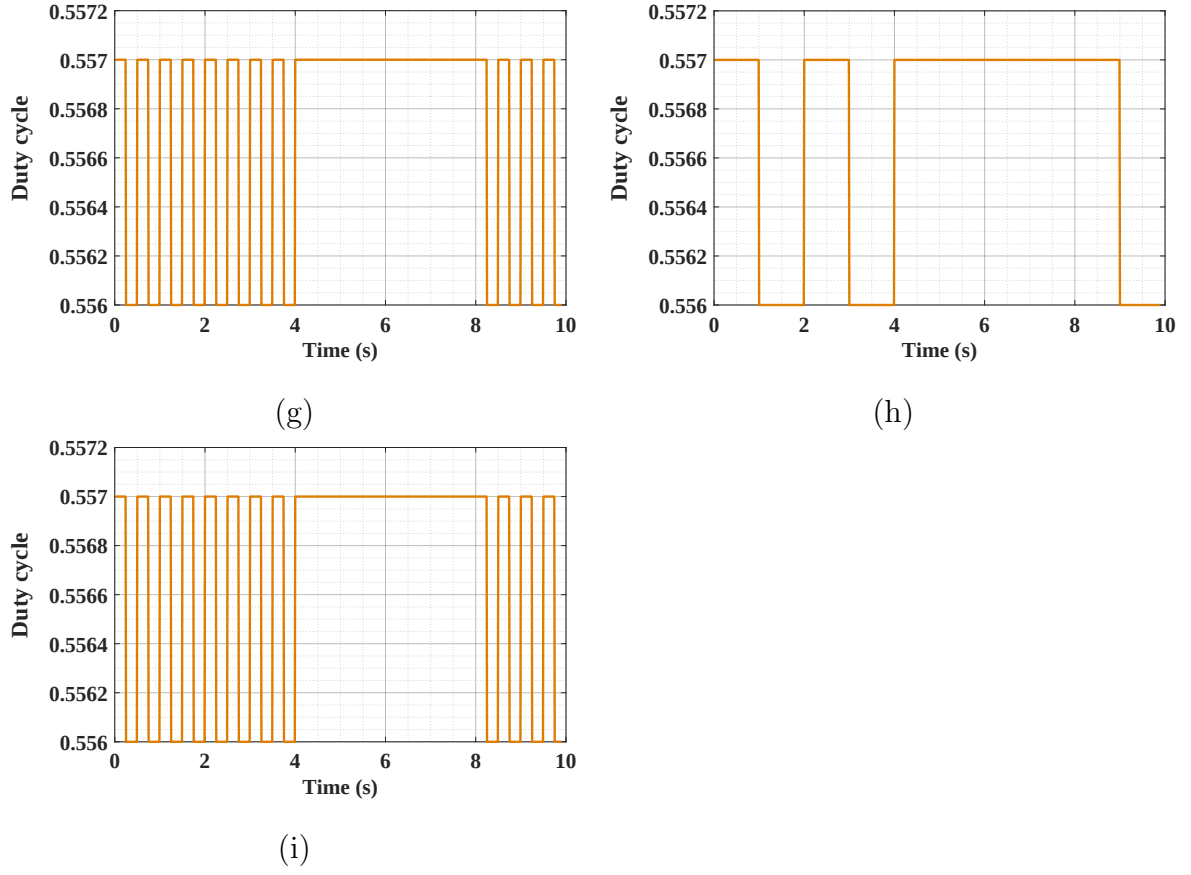


Figure 4.6: Response of the Duty Cycle to Sine Wave Disturbances of signals 7–9

Signal	1	2	3	4	5	6	7	8	9
Amplitude	0.01	0.01	0.01	0.01	0.001	0.001	0.0001	0.0001	0.00001
Frequency (Hz)	1	0.5	0.05	2	1	0.5	2	0.5	2
Poles	3	4	3	3	3	3	4	3	–
Zeros	1	2	2	3	2	2	3	1	–
Best Fit (%)	92.66	61.56	83.50	76.18	20.99	16.61	28.13	2.23	–

Table 4.2: Best-Fit Data Obtained for Various Input Signals

Chapter 4. A GOA-Tuned TID Controller For Enhanced P&O MPPT

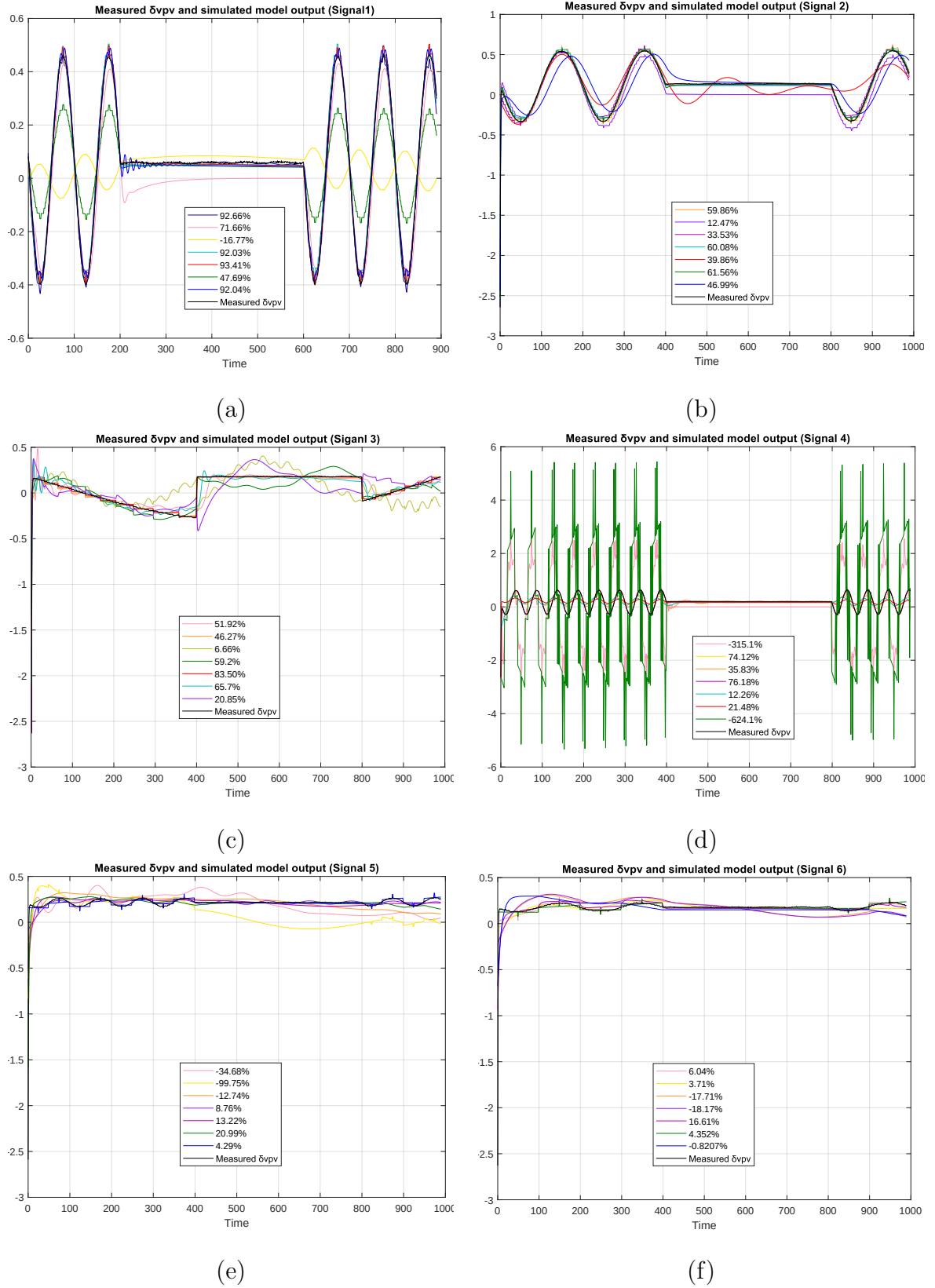
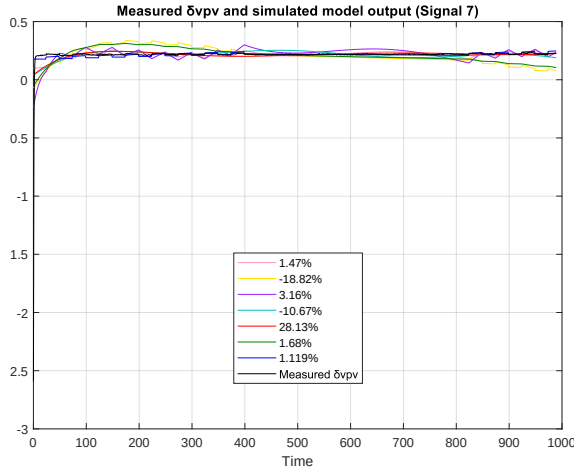
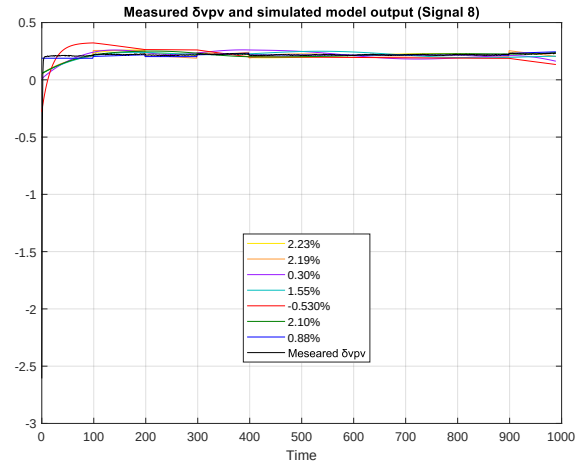


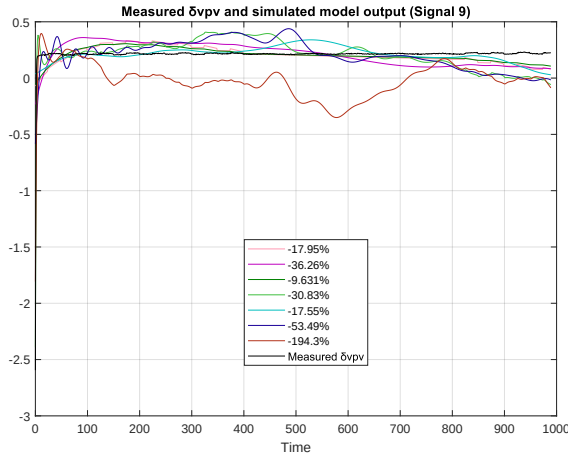
Figure 4.7: Validation results of the identified transfer functions for perturbation signals 1–6 using MATLAB's System Identification Toolbox.



(g)

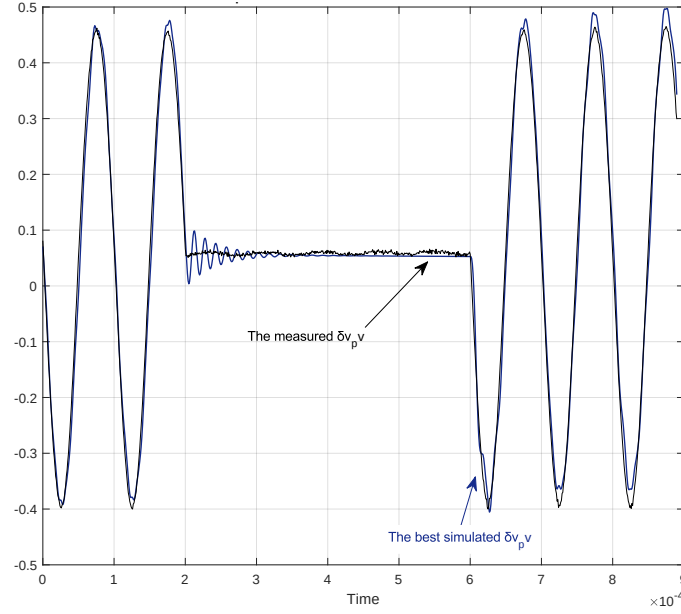


(h)



(i)

Figure 4.8: Validation results of the identified transfer functions for perturbation signals 7–9 using MATLAB’s System Identification Toolbox.


 Figure 4.9: Best simulated output δv_{pv}

represents the relationship between the PV voltage perturbation and the duty cycle perturbation . Given by:

$$G(s) = \frac{-10.81s - 0.02606}{s^3 + 0.05917s^2 + 0.2602s + 9.765 \times 10^{-5}} \quad (4.9)$$

4.5.2 TID-GOA Optimization

The TID controller was integrated into the photovoltaic system to enhance the efficiency of Maximum Power Point (MPP) tracking. To achieve optimal performance, the controller parameters $[K_t, K_i, K_d, n]$ were fine-tuned by minimizing the Mean Square Error (MSE) performance index using the Grasshopper Optimization Algorithm (GOA) as represented in Equation 4.11, as illustrated in Figure 4.10. The optimized controller parameters were then employed within the P&O MPPT strategy to extract the maximum power from the PV panel and improve its overall performance.

In this study, the cost function employed is the Mean Squared Error (MSE).

$$J = \text{Fitness} = \text{MSE} = \frac{1}{N} \sum_{i=1}^N \text{Error}^2 \quad (4.10)$$

$$\text{Minimize}(J) \quad (4.11)$$

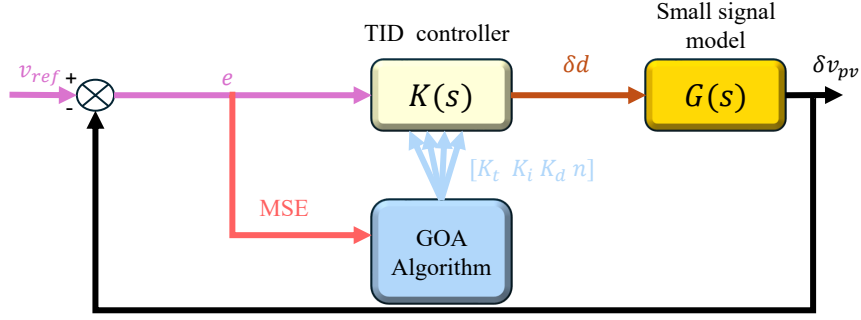


Figure 4.10: TID Control for PV Voltage Regulation Using GOA-Based Tuning

Equation 4.11 is a constrained non-linear optimization problem where $\theta(x)$ is a function of upper and lower bounds with the optimization variables (K_T, K_I, K_D, n) , and x is given by:

$$x = \left[K_{t_{\min}} \quad K_{t_{\max}} \quad K_{i_{\min}} \quad K_{i_{\max}} \quad K_{d_{\min}} \quad K_{d_{\max}} \quad n_{\min} \quad n_{\max} \right]^T, \quad x \in \mathbb{R}^8 \quad (4.12)$$

The subscripts min and max denote minimum and maximum bounds, respectively. The parameters of the Grasshopper Optimization Algorithm (GOA) used in this study are detailed in Table 4.3. These parameters are essential for defining the search space and the behavior of the grasshoppers during the optimization. The

Table 4.3: Parameters of the Grasshopper Optimization Algorithm

f	l	d	Max_iter	$c_{\max}$	$c_{\min}$	N
0.5	1.5	4	100	1	0.00004	30

convergence behavior of the Grasshopper Optimization Algorithm (GOA) for tuning the TID controller parameters was assessed over 100 iterations and repeated across 20 independent trials to ensure result consistency, as depicted in Figure 4.11. Figure 4.11 also presents the flowchart of the GOA used to optimize the TID controller parameters $[K_t, K_i, K_d, n]$. The algorithm begins by initializing the parameters $(N, D, ub_d, lb_d, f, l, c_{\max}, c_{\min}, Max_iter)$. A population of N grasshoppers is then randomly distributed within the solution space, where each position vector represents a potential set of controller parameters.

In each iteration, the Mean Squared Error (MSE) is computed for every candidate solution, and the population is sorted to identify the individual with the lowest MSE. The coefficient c , which governs the influence of neighboring grasshoppers, is

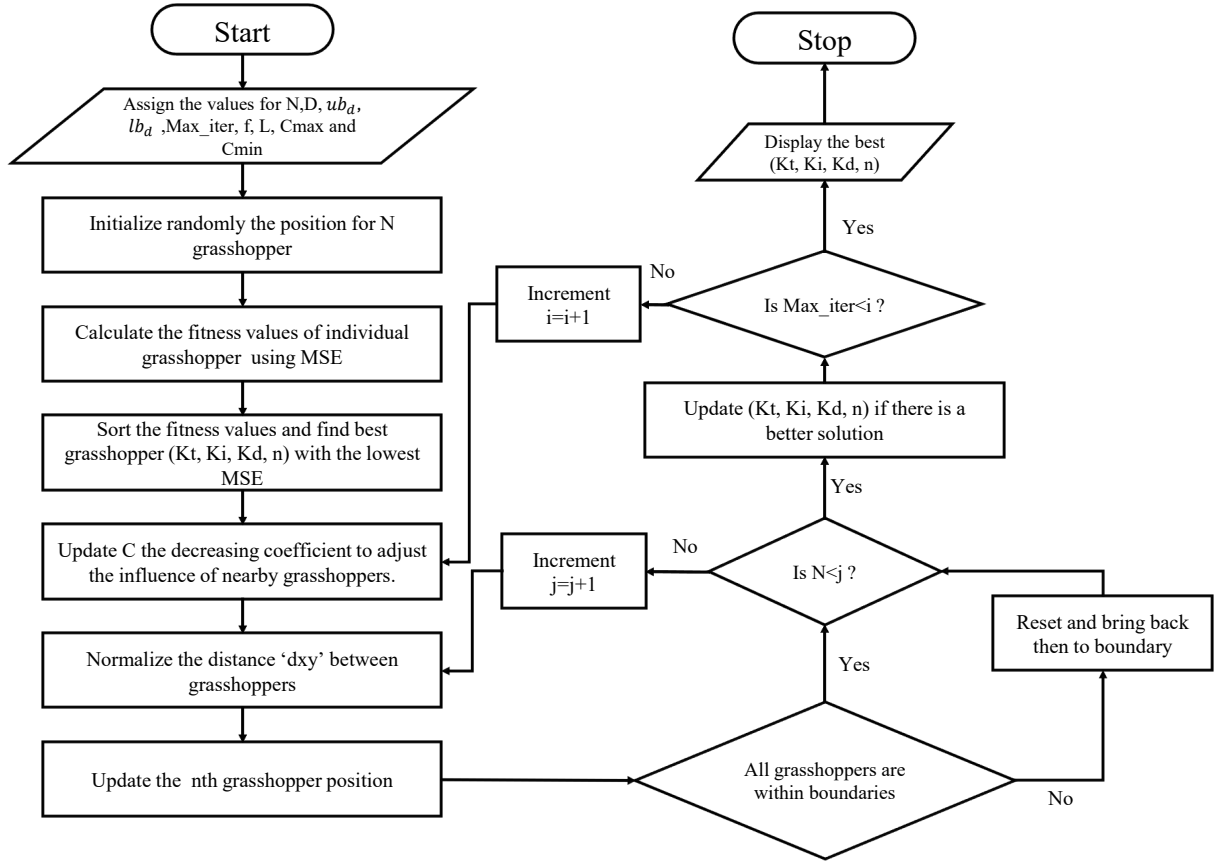
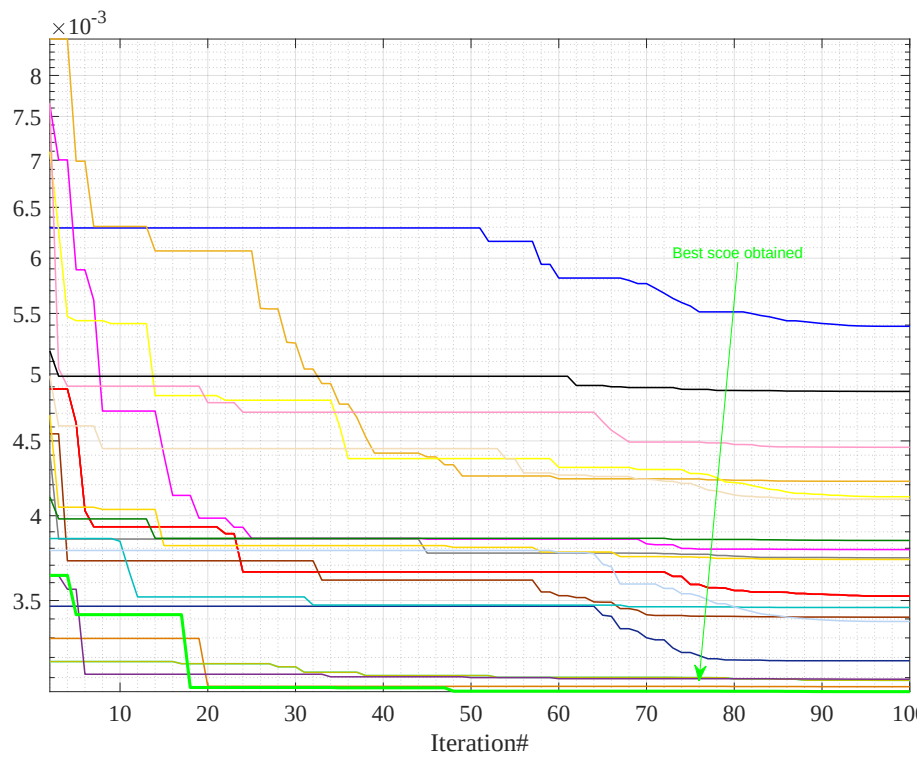


Figure 4.11: Flowchart of the GOA Algorithm

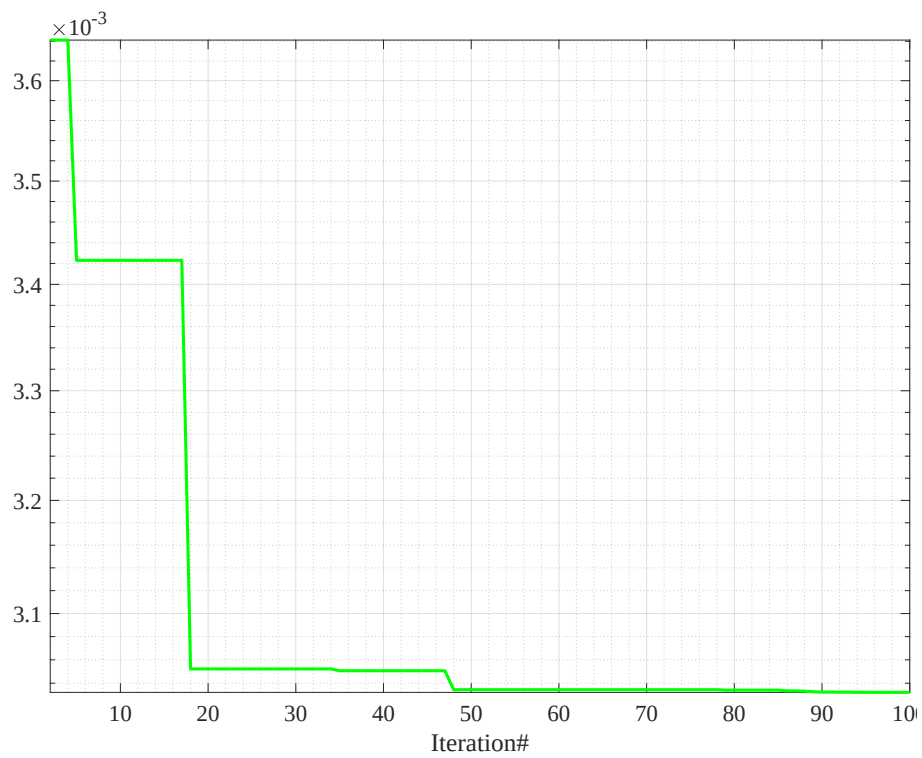
updated dynamically to maintain a balance between exploration and exploitation. Distances between grasshoppers are normalized to preserve search boundaries.

Subsequently, each grasshopper's position is updated by taking into account both the current global best and the influence of neighboring individuals. Boundary conditions are enforced at every step to ensure the solutions remain within the defined search space. This iterative process continues until the maximum number of iterations (Max_iter) is reached. The algorithm ultimately outputs the best-performing parameter combination identified through the swarm's coordinated search.

The convergence curve shown in Figure 4.12a demonstrates that the GOA effectively minimizes the Mean Squared Error (MSE) over successive iterations, with the MSE decreasing from approximately 8×10^3 to around 3×10^3 by the 100th iteration.



(a) MSE Convergence over 20 Trials



(b) Best Trial Selection (Trial 19)

Figure 4.12: Convergence curve of GOA.

Figure 4.12b highlights that Trial 19 achieved the best performance in optimizing the TID controller parameters. Based on these results, the optimal values of the TID controller parameters are summarized in Table 4.4. Table 4.4

Table 4.4: GOA-Optimized TID Controller Parameters

Trial	K_T	K_I	K_D	n	MSE
1	742.8532	173.9924	8.386933	2.858939	0.0035244
2	738.1383	714.7358	9.316082	2.227941	0.0053899
3	999.9758	54.72642	9.506784	2.240420	0.0042228
4	1000.0000	221.6819	9.593738	2.451636	0.0037923
5	993.9176	783.3805	9.879785	3.000000	0.0030868
6	745.0951	711.1271	8.937159	2.646307	0.0041213
7	1000.0000	400.1556	9.679422	2.696521	0.0034094
8	1000.0000	173.8265	9.649093	2.185883	0.0044550
9	1000.0000	814.7997	10.43139	2.176313	0.0048646
10	1000.0000	408.3072	9.660901	2.965492	0.0030560
11	939.9487	54.46693	9.190817	2.909477	0.0030962
12	999.9779	502.6255	9.811508	2.526100	0.0037433
13	965.6246	437.5715	9.548765	2.887761	0.0031834
14	1000.0000	171.5612	9.520963	2.887476	0.0030922
15	999.9897	13.85388	9.410035	2.589335	0.0034620
16	1000.0000	463.6883	9.776067	2.523892	0.0037338
17	999.9996	458.6483	9.794017	2.468648	0.0038472
18	865.6842	748.2452	9.375614	2.925331	0.0033864
19	827.5340	190.6007	9.529580	2.943650	0.0030322
20	855.7463	512.9122	9.297447	2.482648	0.0041053

presents the optimal values obtained for the TID controller parameters. Among the 20 iterations, the best result was achieved at iteration 19, where the Mean Squared Error (MSE) was minimized to 0.0030322. This outcome indicates that the Grasshopper Optimization Algorithm (GOA) effectively converged to an optimal

solution for tuning the TID controller within the specified iteration limit. These optimized parameters were subsequently tested in an experimental setup, confirming the practical applicability and performance enhancement offered by the GOA-tuned TID controller.

4.6 Experimental Setup and Test Validation

To evaluate the performance of the GOA-optimized TID controller in a photovoltaic system, an experimental hardware setup was implemented, as illustrated in Figure 4.13. The validation employed a real-time hardware configuration consisting of an AEG PQ10/40/01 PV panel (38.4 W at STC), a DC-DC boost converter (2.25 mH inductor, 470 μ F capacitors), and a variable resistive load (25 Ω to 50 Ω), controlled by a LAUNCHXL-F28379D DSP implementing the P&O_TID_GOA algorithm. Dynamic irradiance profiles (Figure 4.15) and a step load reduction from 50 Ω to 25 Ω at $t = 12$ s (Figure 4.16) were applied to simulate real-world operating conditions. The proposed control strategy demonstrated superior perfor-

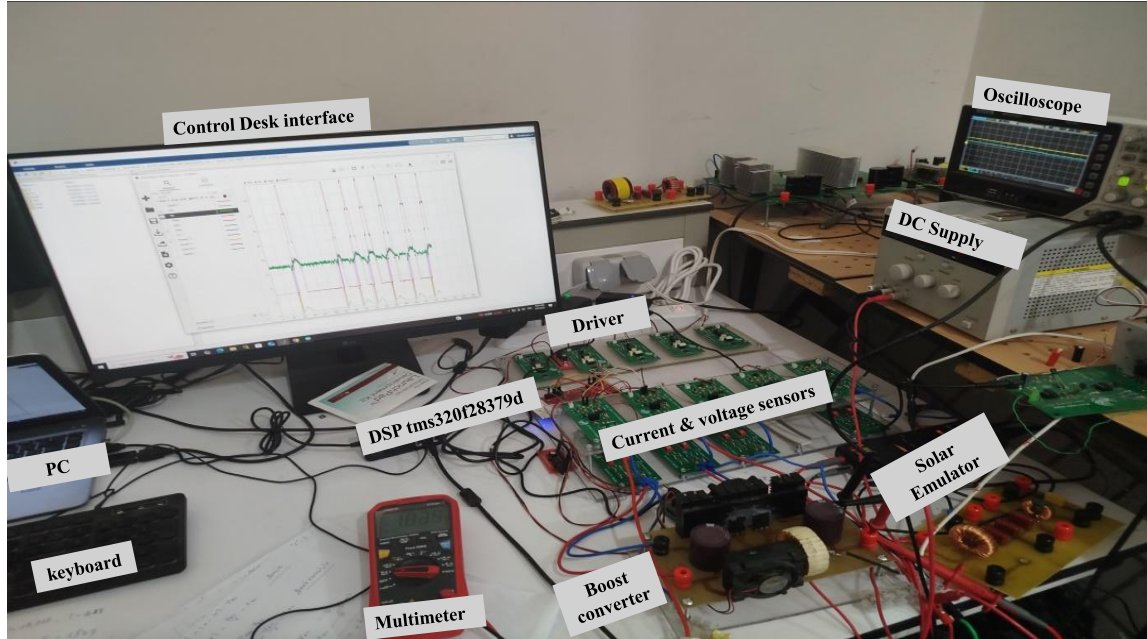


Figure 4.13: Experimental Test Including The Real-Time Implementation of The TID and P&O

mance, with V_{in} stabilizing at 17.3 V (± 0.2 V) within 0.5 s after the load transient, while I_{in} remained steady at 2.22 A (± 0.02 A), yielding near-ripple-free power out-

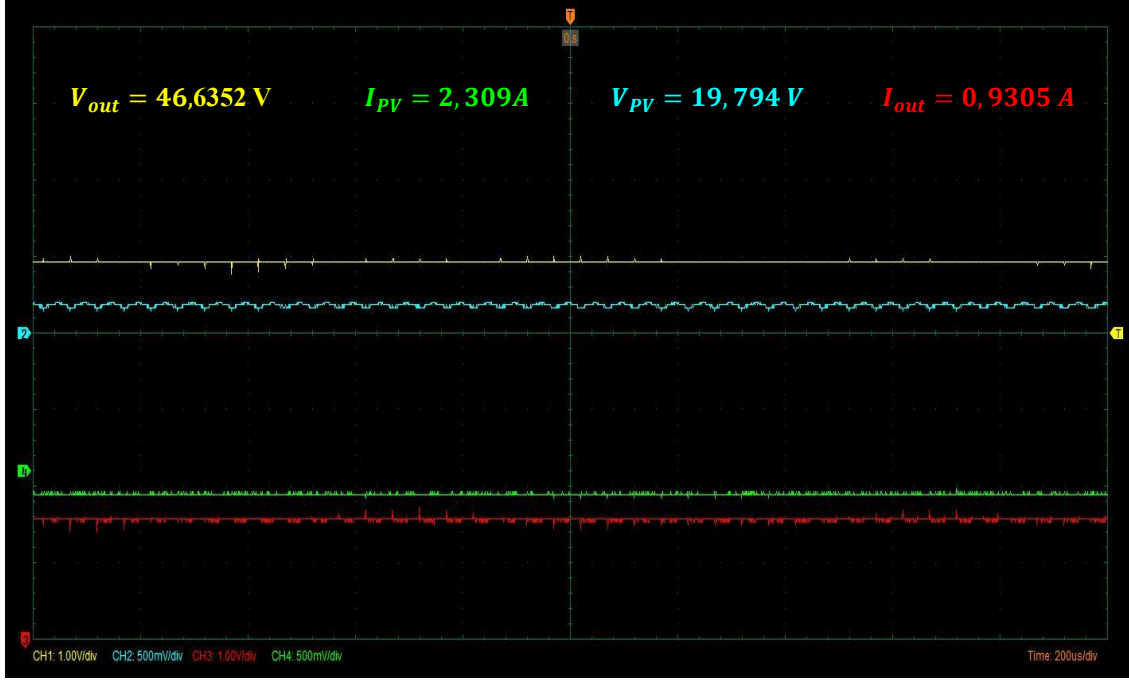


Figure 4.14: Experimental Test Including The Real-Time Implementation of The TID at STC

put ($38.4 \text{ W} \pm 0.4 \text{ W}$, 98.8 % efficiency). The TID controller's optimized parameters ($K_t = 827.53$, $K_i = 190.60$, $K_d = 9.53$, $n = 2.94$) enabled precise duty cycle regulation ($55 \% \pm 0.5 \%$), minimizing switching losses and preventing inductor core saturation. In contrast, the conventional P&O algorithm exhibited severe oscillations (V_{in} : 15 V to 19 V, I_{in} : 2.1 A to 2.4 A, duty cycle: 40 % to 60 %), causing audible inductor ringing, MOSFET overheating, and capacitor stress from high-frequency current surges. The DSP's high-resolution PWM (150 MHz clock) ensured accurate timing for the TID's derivative action. Figures [Figure 4.17](#) and [Figure 4.18](#) highlight the stark performance contrast: while the conventional P&O struggled with instability during the load transient, the P&O-TID-GOA maintained tight regulation, protecting converter components from thermal stress and EMI. The results confirm that the cascaded P&O-TID architecture not only enhances dynamic response but also ensures long-term system reliability, whereas fixed-step P&O risks component degradation and catastrophic failure in practical applications.

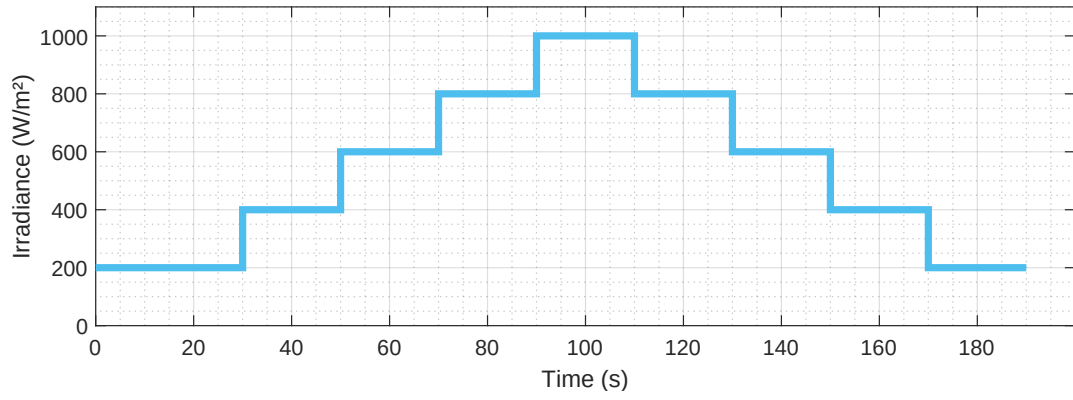


Figure 4.15: Irradiance Profile

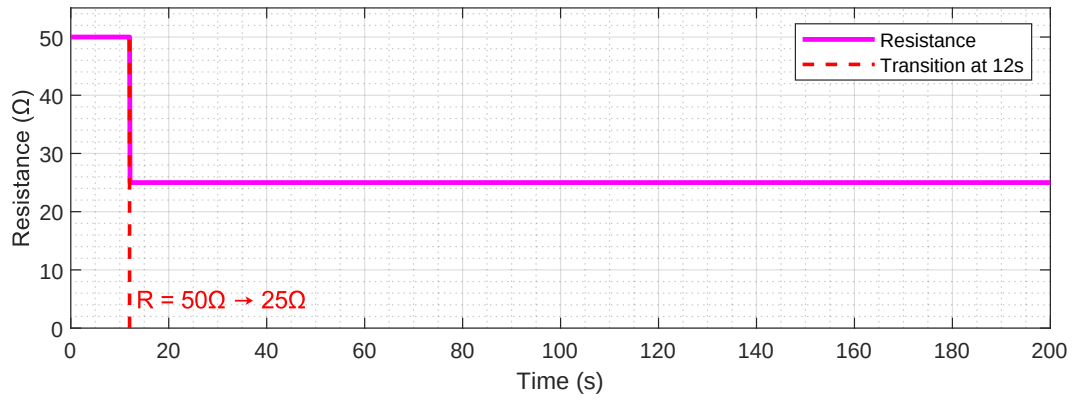


Figure 4.16: load Profile

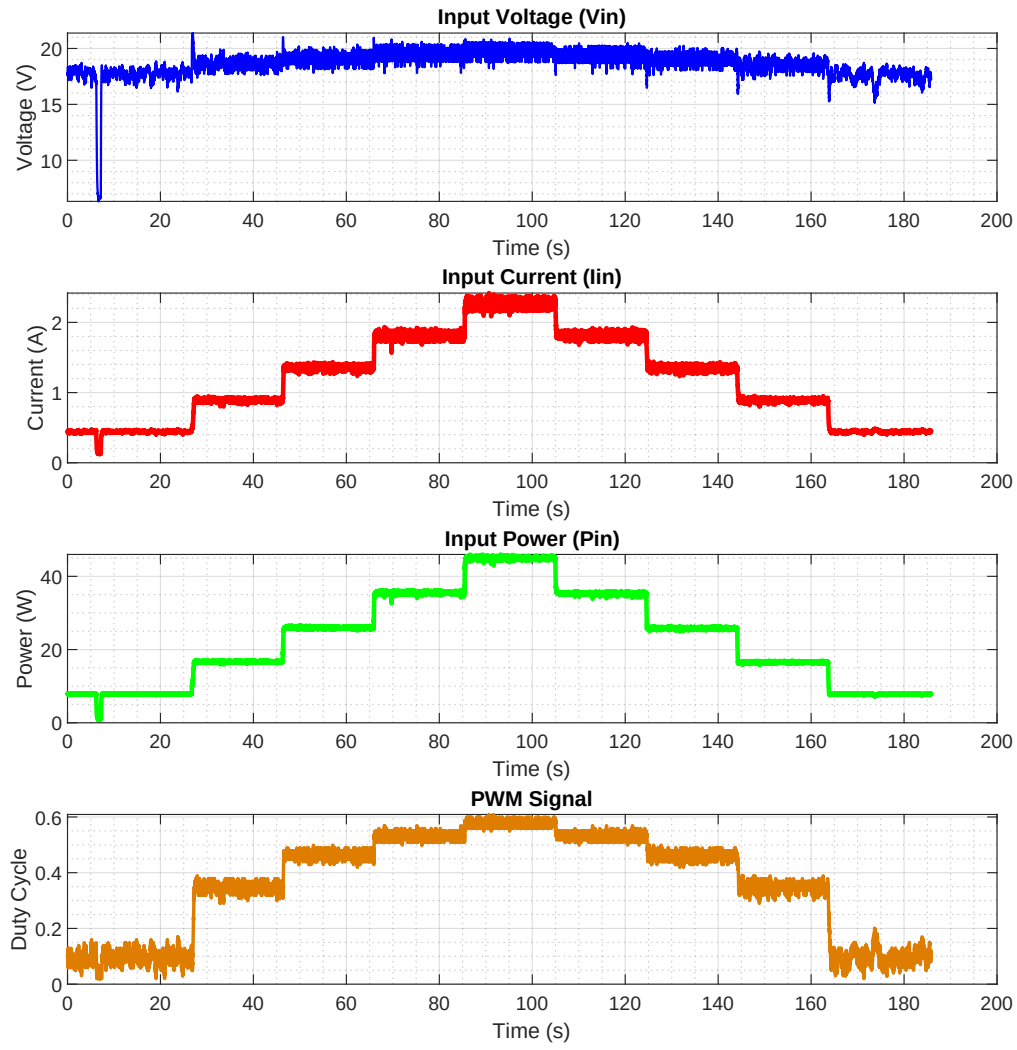


Figure 4.17: MPPT performance of the standard direct P&O

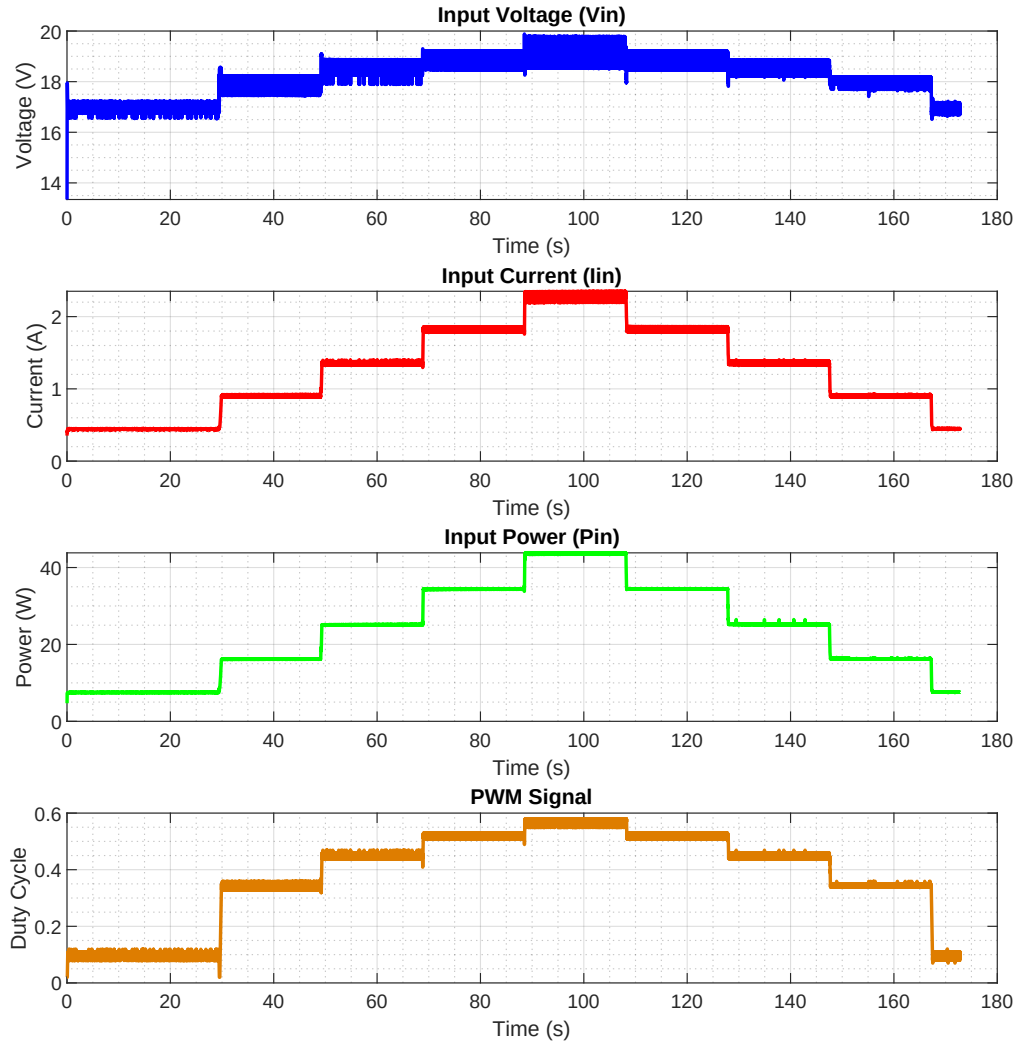


Figure 4.18: MPPT performance of the proposed P&O-TID-GOA

Accordingly, the experimental results depicted especially in Figures [Figure 4.17](#) and [Figure 4.18](#) reveal a stark contrast between the proposed P&O_TID_GOA control strategy and the conventional P&O algorithm when subjected to sudden load and solar irradiance variations. Under the abrupt load change from $50\ \Omega$ to $25\ \Omega$ at $t = 12$ sec, the conventional P&O method exhibits severe instability, with the PV input voltage (V_{in}) plunging from 17.3 V to nearly 15 V before oscillating wildly within a 2 V range, reflecting an inability to maintain steady-state operation. These voltage fluctuations induce corresponding points in the input current (I_{in}), which jumps erratically between 2.1 A and 2.4 A, causing excessive stress on the boost converter's inductor and MOSFET, evidenced by audible switching noise and increased thermal dissipation. The poorly regulated PWM signal, swinging chaotically between 40% and 60% duty cycle, further destabilizes the converter's output, leading to a power ripple of ± 5 W around the MPP and inefficient energy transfer. In contrast, the P&O_TID_GOA controller demonstrates exceptional stability, with V_{in} settling smoothly to 17.3 V within 0.5 sec post-disturbance and I_{in} maintaining a steady 2.22 A, thanks to the TID controller's optimized parameters ($K_t = 827.53$, $K_i = 190.60$, $K_d = 9.53$, $n = 2.94$). The GOA-tuned TID ensures the PWM signal adjusts with precision, keeping the duty cycle ripple-free at approximately 55%, which in turn minimizes switching losses in the MOSFET and reduces core losses in the 2.25 mH inductor. The input power (P_{in}) remains tightly regulated at 38.4 W, with less than 1% deviation, showcasing near-ideal MPPT efficiency (98.8%). Physically, this stability translates to cooler operation of the DSP (LAUNCHXL-F28379D) and reduced electromagnetic interference (EMI) from the boost converter, critical for long-term reliability. The conventional P&O's erratic behavior, however, risks overheating the converter's 470 μ F output capacitor due to high-frequency current surges and could eventually degrade the PV panel's junction integrity from repeated voltage spikes. This experiment underscores that the indirect control architecture, leveraging cascaded P&O and TID loops, not only enhances dynamic response but also safeguards hardware integrity, whereas reliance on fixed-step P&O compromises both performance and system longevity. As a result of this experimental study, several key practical implications can be drawn. The proposed control strategy enhances hardware reliability by ensuring stable voltage and current responses, which in turn reduce electrical and thermal stress on power electronic components such as MOSFETs, inductors, and capacitors, thereby extending their operational lifetime. In addition, the negligible power ripple improves energy efficiency by enabling operation closer to the maximum power point, thus maximiz-

ing the harvested photovoltaic energy. Moreover, the controller demonstrates robust performance under load transients and variations in solar irradiance, confirming its suitability for real-world applications. In contrast, the conventional fixed-step P&O algorithm introduces persistent oscillations around the MPP, which increase electrical stress and power losses and may accelerate component degradation, ultimately reducing system reliability.

4.7 Conclusion

This study introduces an advanced P&O-TID-GOA control strategy to enhance the performance of PV systems by addressing key limitations of conventional MPPT techniques, which typically suffer from steady-state power ripples and slow transient response during rapid irradiance or load variations. These limitations arise because traditional methods cannot adapt quickly to changing operating points, resulting in energy losses and voltage oscillations around the Maximum Power Point (MPP). The first major contribution is the experimental identification of a small-signal model for the complete PV system comprising an AEG PQ10/40/01 panel, DC-DC boost converter, and variable load using MATLAB's Identification Toolbox. This black-box approach eliminates the need for complex analytical modeling, relying solely on measured duty cycle and PV voltage data to derive an accurate transfer function. The second contribution involves the synthesis and real-time implementation of a TID controller, optimized via the GOA to minimize tracking errors and ensure robust voltage regulation. The experimental results show that the proposed strategy achieves approximately 98.8% MPPT efficiency, with lower power ripple and faster response than the conventional P&O under changing operating conditions. Future work will explore model-free TID tuning, online adaptive control, and applications to multi-string PV systems, aiming to overcome the current study's main limitations. Specifically, the present implementation relies on an experimentally identified small-signal model and offline GOA-based parameter tuning, which may limit adaptability under rapidly changing irradiance and load conditions. By integrating experimental modeling, metaheuristic optimization, and advanced control theory, this study provides a practical and effective approach for improving solar energy harvesting in real-world conditions. It is acknowledged that the current study uses a fixed-parameter TID controller based on a model identified at a nominal operating point.

General Conclusion

The reliable and efficient operation of photovoltaic (PV) systems under dynamically varying environmental and operating conditions fundamentally relies on the development of accurate modeling methodologies and high-performance control strategies. Accordingly, this PhD Thesis investigates two closely related challenges: the inability of conventional fixed-parameter PV models to accurately capture climatic variability, and the performance limitations of widely adopted MPPT methods especially the Perturb and Observe (P&O) algorithm under fast irradiance and load dynamics. The study was conducted in an experimental context with a strong focus on realism, robustness, and practical feasibility, aiming to narrow the gap between theoretical developments and the operational behavior of real photovoltaic systems.

Conventional photovoltaic (PV) modeling approaches are based on equivalent electrical circuits with fixed parameters identified using analytical or numerical techniques. Although mathematically rigorous, these models often fail to accurately capture PV behavior under varying irradiance and temperature, resulting in modeling errors that propagate into control design and performance evaluation. On the control side, despite its widespread adoption for its simplicity, the P&O MPPT algorithm inherently suffers from steady-state oscillations around the MPP and degraded dynamic behavior under fast irradiance variations, especially when implemented through direct duty-cycle perturbation. These shortcomings result in increased power losses, voltage fluctuations, and reduced overall efficiency. In addition, analytical small-signal models used in controller design are derived under simplifying assumptions that ignore parasitic elements and nonlinearities, limiting their validity in real experimental implementations.

To address these limitations, this thesis proposes an integrated modeling and control framework, with the main contributions summarized as follows:

Modeling side

General Conclusion

- The fuzzy model's training performance requires only about 300 samples, as smaller datasets yield high MSE, while at 300 samples the MSE drops to 0.025, beyond which additional training data provides only marginal improvement.
- The validation performed with 200 samples yields an MSE closely matching the training MSE obtained with 300 samples, demonstrating strong consistency between training and validation and confirming that the model generalizes well to unseen data rather than overfitting.
- The optimal solution obtained by the GA algorithm achieves accurate global PV current prediction, demonstrating robust performance under stochastic environmental fluctuations and reducing the modeling error to 0.025 MSE compared with 0.41 MSE for fixed-parameter models, in agreement with experimental validation.
- The results confirm that the proposed approach, combining a Fuzzy model with GA-based parameter updates, provides a more accurate and reliable representation of the actual PV array behavior than traditional fixed-parameter models.

Control side

- The small-signal transfer function was estimated using MATLAB's Identification Toolbox by applying perturbed duty cycles and PV voltages, while varying the number of poles and zeros for each case, until achieving a maximum fit of 93.41%.
- The tuning of the TID controller using the Grasshopper Optimization Algorithm (GOA) yielded its best result at iteration 19, where the Mean Squared Error (MSE) was minimized to 0.0030322. Over successive iterations, the GOA effectively reduced the MSE from approximately 8×10^3 to around 3×10^3 by the 100th iteration, demonstrating robust convergence within the specified iteration limit.
- The experimental evaluation highlights the superiority of the P&O-TID-GOA control strategy over the conventional P&O algorithm under sudden load and irradiance variations. While the conventional P&O exhibited severe voltage and current oscillations and power ripples, the GOA-tuned TID parameters ensured tight regulation of input power at 38.4 W, corresponding to near-ideal MPPT efficiency of 98.8%.

General Conclusion

Despite the encouraging results obtained, several research perspectives naturally emerge from this work:

- Explore alternative supervisory mechanisms, such as neuro-fuzzy models or Fuzzy-based GOA updates, to enhance interpretability and reduce computational demands, while extending the proposed modeling framework to other photovoltaic technologies to broaden its applicability.
- Implement an online GOA-based re-tuning strategy for TID controller parameters to accommodate dynamic operating conditions, thereby reducing reliance on fixed-parameter models.
- Apply the proposed approach to multi-string PV systems to broaden its practical applicability.

The contributions of this PhD thesis provide a significant step toward bridging the gap between theoretical PV modeling and practical control implementation. By integrating advanced fuzzy-based modeling, metaheuristic optimization, and experimental validation, this work demonstrates that accurate representation of PV array behavior and high-performance MPPT control can be achieved under realistic, dynamic conditions. The outcomes of this research not only highlight the potential of intelligent modeling and optimization techniques for enhancing PV system efficiency but also lay a solid foundation for future developments in adaptive, resilient, and scalable photovoltaic energy systems. Ultimately, the insights gained herein contribute to the ongoing efforts to maximize renewable energy utilization while ensuring system reliability and operational excellence.

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شهادة ترخيص بالتصحيح والايذاع

انا الأستاذ

زقاوي عبدالله

بصفتي المشرف المسؤول عن تصحيح مذكرة تخرج دكتوراه المعنونة بـ:

Contribution to the MPPT Algorithms by integrating bio-inspired optimization in photovoltaic systems

من انجاز الطالبة

ساسى زهور اسمهان

التي نوقشت/قيمت بتاريخ

30 جوان 2026

اشهد ان الطالبة قد قامت بالتعديلات والتصحيحات المطلوبة من طرف لجنة المناقشة وقد تم التحقق من ذلك من طرفنا

وقد استوفت جميع الشروط المطلوبة .

مصادقة رئيس القسم

امضاء المسؤول عن التصحيح

