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CHAPTER 1

INTRODUCTION

1.1 The Role of MPPT in Photovoltaic Systems

Solar photo voltaic (PV) systems have become increasingly important for renewable power generation. Renewable Energy Grid policy around the world. But the energy conversion efficiency of PV plates is greatly affected by different environmental parameters, especially solar intensity and temperature. Current-Voltage (I-V) and power- voltage (P-V) traits of a PV module have nonlinear behaviors. There exist a specific point in the I-V curve called Maximum Power Point (MPP) for which total output power is maximum. Now, the PV system should be operated as much as possible to have higher energy generation. That is the primary role of a Maximum Power Point Tracking (MPPT) controller, which adjusts in real time the operating conditions of the system generally via a DC-DC converter, to guarantee that the maximum amount of power is extracted in every situation.

In addition to energy extraction, the MPPT function is important to separate PV source from load. without a MPPT controller, PV array could work only at a voltage that is determined by the load impedance and not necessary be matched with the V_{mp} (optimal voltage. 72). This inefficient coupling leads to power loss of 30-40%. As result, the MPPT functions as an impedance matching circuit that changes continuously the duty-cycle of the power converter so that it will look like to the solar panel as the best resistance for maximization. This tracking accuracy is economically critical as PV systems increase in size from household installations on roofs to megawatt solar parks, where any gain of a multiple of a percentage point grew in importance.

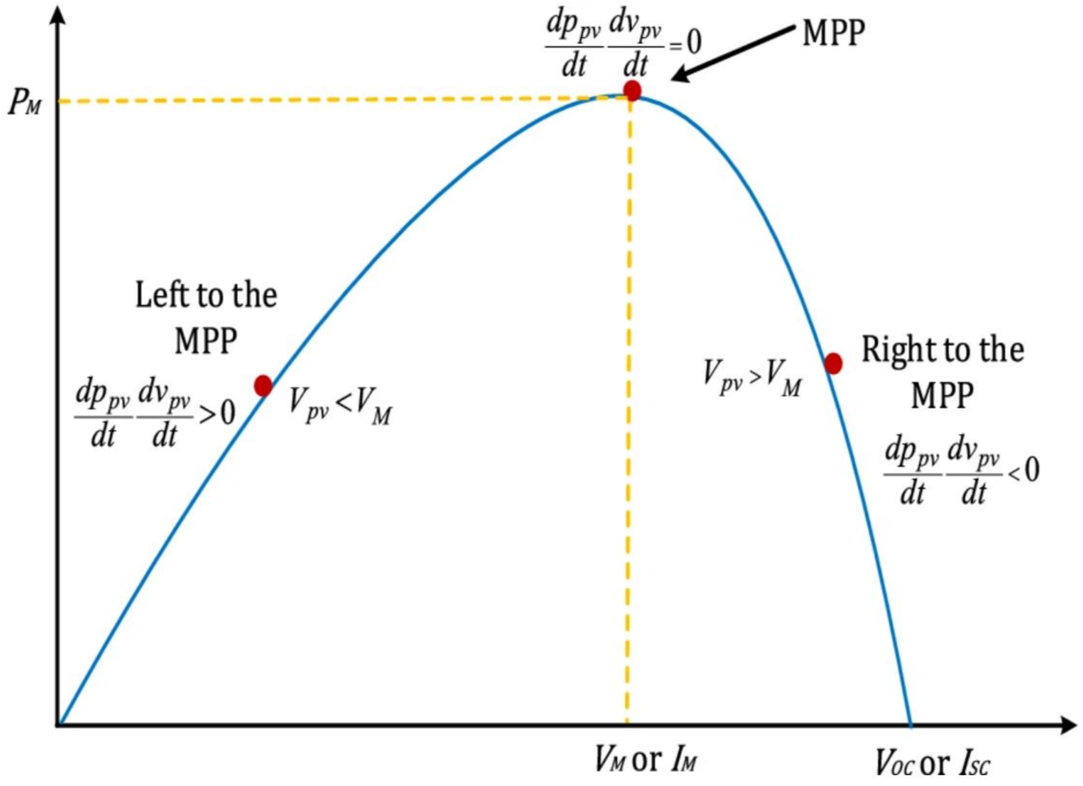

Fig. 1.1 PV curve illustrating MPPT

1.2 Conventional MPPT Methodologies and Microgrid Limitations

Historically, the renewable energy industry has mainly used simple rule-based methods, like Perturb and Observe (P&O) and Incremental Conductance (IC), because they need less equipment and are easy to set up. These traditional controllers work based on a simple, predictable "hill-climbing" idea. They make small, ongoing changes to the system's voltage or current and check how the power output reacts to those changes. If the measured power increases, the algorithm maintains its perturbation trajectory; if it decreases, the direction is immediately reversed. This method works well for separate solar panels in sunny conditions, but it has big problems when used in a changing microgrid system. Firstly, the P&O method never reaches a true steady-state equilibrium; it continuously oscillates around the optimal operating point. In a microgrid network, this constant searching causes ongoing voltage fluctuations on the DC bus, which can create harmonic distortions that directly affect the power quality and shorten the lifespan of the connected grid-tied DC-AC inverters. Secondly, these gradient-based algorithms can get confused by sudden changes in the atmosphere. A sudden natural increase in solar irradiance occurring simultaneously with an algorithmic downward voltage adjustment can mislead the P&O logic.A sudden natural increase in solar irradiance occurring simultaneously with an algorithmic downward voltage adjustment can mislead the P&O logic.The controller mistakes a sudden increase in power from the environment as a successful step in the algorithm, which pushes the system away from the real maximum power point and leads to temporary drops in power that can affect the stability of the local grid.

1.3 The Challenge of Partial Shading Conditions (PSC)

The biggest problem with traditional MPPT controllers happens when there is partial shading. This happens when things like passing clouds, shadows from buildings nearby, or dust build-up stop sunlight from reaching certain parts of the connected solar panel system. Because of this, the usual curve that shows how power changes with voltage starts to look different. Instead of having one clear peak, it becomes a more complicated shape with multiple peaks. These peaks are called local maximum power points, and among them, only one is the real highest point, known as the global maximum power point. Gradient-based algorithms like P&O are inherently short-sighted; they are designed to climb the nearest mathematical slope and stop at the first peak they encounter. Because of this, under PSC, they often get stuck at a lower local maximum, and completely miss the much higher energy gain that is available at the global peak. In a microgrid that is mostly powered by distributed solar panels, this kind of operational problem can be very serious. A quick and forced drop in available power can cause big problems between the power being produced and the power being used, leading to fast changes in the grid's speed, needing to cut off some power, or even making the whole microgrid fail. Additionally, when localized shading is combined with inaccurate tracking, it can cause unshaded cells to dissipate the power of shaded cells, leading to reverse bias currents and generating harmful thermal "hot spots" in the solar modules. So, moving to smarter, more complete scanning methods that can find the GMPP reliably isn't just about making things faster—it's about for keeping microgrids running well and staying strong.

1.4 Motivation for Advanced Algorithm

The fundamental flaw of conventional tracking mechanisms lies in their unavoidable compromise between tracking velocity and steady-state precision. Using a bigger step size for perturbation lets the system respond quicker to changes in the environment, but it also makes the harmful voltage fluctuations at the maximum power point worse. On the other hand, making the step size smaller makes the steady-state output smoother, but it makes the controller too slow to respond during sudden weather changes. Furthermore, as established, these methods are entirely unsuitable for navigating the multi-peaked environments caused by PSC. This problem has led to a lot of research on advanced, smart optimization techniques. To meet the strict requirements for power quality and reliability in modern microgrids, controllers need advanced search capabilities to address the shortcomings of localized hill-climbing methods. This thesis looks into using the Quantum-Inspired Evolutionary Algorithm (QIEA), and it assumes that its chance-based approach can break the usual trade-off between speed and stability. It aims to provide fast, very precise, and smooth Maximum Power Point Tracking (MPPT) performance, which is needed to keep a microgrid stable and working well.

1.5 Introduction to Quantum-Inspired Evolutionary Algorithm (QIEA)

In order to overcome limitations of deterministic techniques and conventional heuristic algorithms, in this paper Quantum-Inspired Evolutionary Algorithm (QIEA) is introduced. QIEA is a probabilistic optimization model which integrates both concepts of quantum computing, i.e., superposition and qubit encapsulation, with evolutionary computation. Unlike the conventional Genetic Algorithm(GA) which express individual using binary bits (0 and 1), QIEA employs “Q- bits. A Q-bit is identified by a probability amplitude, which allows it to exist in a combination of states until an observation is made. This fact enables a few populations of individuals to efficiently explore an enormous search space. The algorithm uses a "Quantum Rotation Gate" to modify the state of the Q-bits the population is then steered much faster towards optimal solution (the Global MPP) compared with classical techniques. The motivation for selecting QIEA lies in superior balance between "exploration" (searching the global space for the GMPP) and "exploitation" (fine-tuning the solution to reduce steady-state oscillation).

1.6 The Role of MPPT in Microgrid-Integrated Photovoltaic Systems

Global policies that support green energy have helped speed up the use of solar photovoltaic (PV) systems for making clean power. But the amount of electricity these solar panels can produce depends a lot on changing weather conditions, like temperature and sunlight. The way these PV systems work has curves that aren't straight, and there's a special point called the Maximum Power Point (MPP) where they produce the most electricity possible. As these solar power systems grow and integrate to local microgrids, keeping the best power extraction is very important—not only for using energy efficiently but also for keeping the whole power grid stable. A microgrid depends a lot on a steady DC bus voltage to power its inverters and other connected devices. To make sure this voltage stays stable and to get the most energy from the sun, an MPPT controller changes the duty cycle of a coupled DC-DC converter, which acts like an active impedance matching circuit. If this controller doesn’t track the right point accurately, it can lead to big losses in energy and drops in voltage, sometimes wasting up to 40% of the solar energy available. Being precise in this tracking is very important for modern energy systems, as even small improvements in efficiency make a big difference in the quality and reliability of the microgrid’s power.

1.7 PV Integration with AC Microgrid

In real-world power systems, photovoltaic generation is not usually used alone and is most commonly connected to a bigger electrical system like a microgrid. A microgrid is a localized energy system composed of distributed energy resources, power electronic converters, and loads, capable of operating in both grid-connected and islanded modes. In these systems, the direct current power produced by the solar panels needs to be changed into alternating current before it can be sent to the microgrid. This process uses a Voltage Source Inverter (VSI), which is important for making sure power moves correctly and the system stays stable. The inverter is responsible for regulating output voltage, maintaining frequency, and ensuring synchronization with the microgrid. It's important to align the inverter's output with the grid by matching its timing, speed, and strength, so that power can move smoothly between the inverter and the grid without any problems. Also, how well the inverter works depends a lot on how stable the DC link is, and that stability comes from how good the MPPT controller is at its job. Therefore, effective coordination between the MPPT algorithm and the inverter control system is necessary for efficient operation of the PV-based microgrid.

In this work, a voltage source inverter is used to connect the PV system to the AC microgrid, enabling the analysis of both how energy is harvested and how the whole system performs under different operating conditions.

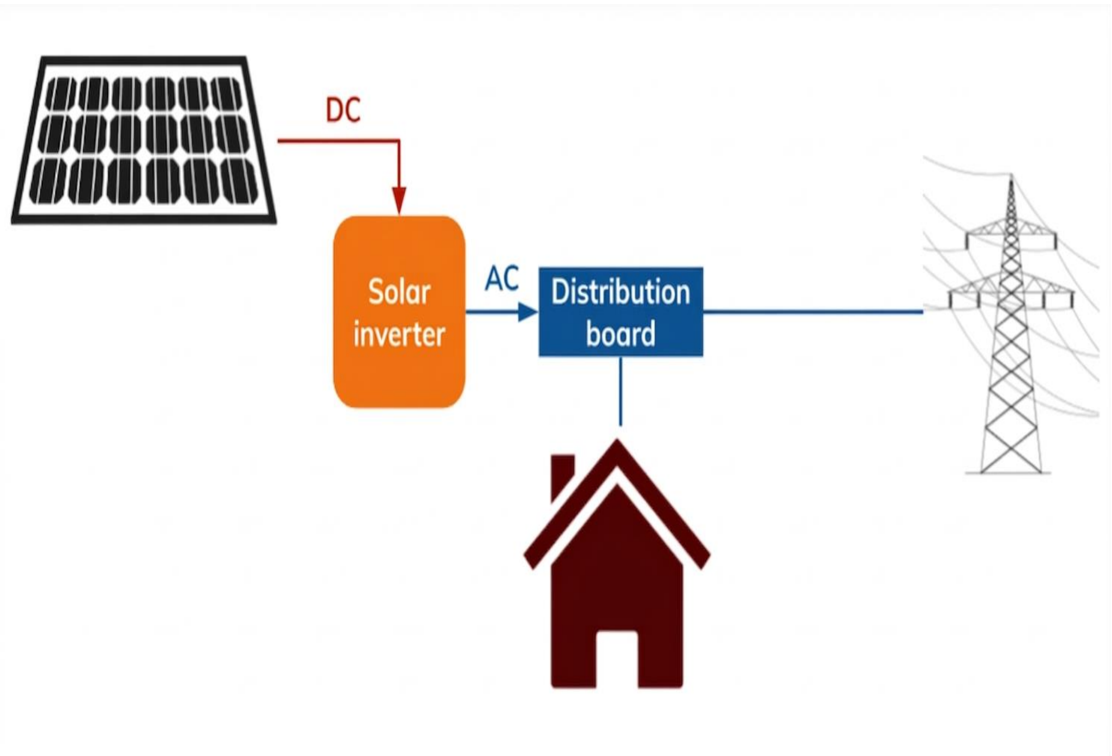

Fig. 1.2 PV Integration with Utility Grid

1.8 Problem Statement

Even though solar PV systems are being added more quickly to local energy networks, the performance of MPPT controllers still faces big challenges when the environment changes a lot. Traditional P&O controllers naturally cause steady-state power fluctuations, which lead to severe voltage fluctuations on the microgrid's shared DC bus. Furthermore, these legacy systems consistently fail to identify the global power peak under partial shading conditions, resulting in significant energy loss. While standard soft-computing methods, such as Particle Swarm Optimization, can theoretically address the shading issue, they are often hindered by unstable, slow convergence and high computational requirements. In a microgrid setting, a slow response from the MPPT can easily cause frequency issues, create uneven load problems, and make the local grid unstable. Because of this, there is a big need in the industry for a control method that is both easy to use mathematically and smart enough to quickly and steadily follow the GMPP. This thesis directly addresses this technological gap by designing, implementing, and testing a QIEA-driven controller within a grid-tied microgrid framework, directly contrasting its stabilizing performance against the industry-standard P&O baseline.

1.9 Objectives of the Study

29 The primary objective of this work is to investigate and enhance the performance of Maximum Power Point Tracking (MPPT) techniques in photovoltaic systems, and to analyse the behaviour of these enhancements when the system is integrated into a microgrid environment. In particular, the focus is on exploring the effectiveness of a Quantum-Inspired Evolutionary Algorithm (QIEA) as an alternative to conventional methods. To reach this, the following goals have been considered.

- The goal is to create a detailed MATLAB/Simulink model of a 30 kW photovoltaic system along with a DC-DC boost converter, allowing for the simulation of real-world operating conditions.
- The goal is to use the commonly applied Perturb and Observe (P&O) algorithm and examine how it works, particularly looking at how it moves around the maximum power point and how it reacts when the light intensity changes.
- To design a QIE-based MPPT controller and examine its impact on tracking performance, focusing on convergence speed and stability.

- To make the PV system more practical, it can be connected to a microgrid using a DC link and an inverter, which helps create a more realistic power system setup instead of just a separate system.
- To see how both MPPT methods work with the microgrid and how they affect voltage stability and the total power supplied to the load.
- To compare how P&O and QIEA perform under various light conditions, including sudden changes, and to check which one is more efficient and has smoother operation.
- To check if the proposed QIEA method provides a steady benefit when the system faces real-world changes.

CHAPTER 2

LITERATURE REVIEW

Photovoltaic systems have become very important in today's power generation because they produce clean and renewable energy. However, the efficiency of PV systems is highly dependent on environmental conditions such as solar irradiance and temperature. To get the most power possible, Maximum Power Point Tracking (MPPT) methods are commonly used. Over the years, various MPPT methods have been developed, ranging from traditional approaches to sophisticated optimization and artificial intelligence-based techniques. Besides that, adding solar power systems to microgrids has created new issues about keeping the system stable and making sure the control parts work together smoothly.

2.1 Introduction and Evolution of MPPT Techniques

The global imperative for renewable energy has positioned photovoltaic (PV) systems as a cornerstone of sustainable power generation. However, the nonlinear power-voltage (P-V) characteristic of PV modules, which is highly susceptible to fluctuations in irradiance and temperature, presents a fundamental challenge to system efficiency. To extract the maximum available power from a PV array under all operational conditions, Maximum Power Point Tracking (MPPT) controllers are indispensable. Over the past decades, a substantial and diverse body of research has been dedicated to the development and refinement of MPPT techniques, evolving from simple, heuristic algorithms to sophisticated, computationally intelligent systems [1]. This evolution is driven by the need to overcome specific limitations: steady-state oscillations, slow dynamic response, and, most critically, failure under partial shading conditions (PSC) where the P-V curve exhibits multiple local maxima. This review systematically categorizes and critiques this technological progression, from conventional algorithms to the latest hybrid and quantum-inspired approaches, providing the context for investigating novel solutions like the Quantum-Inspired Evolutionary Algorithm (QIEA).

2.2. Conventional and Modified Hill-Climbing Algorithms

The foundation of MPPT technology is built upon straightforward, reliable hill-climbing techniques, primarily the Perturb & Observe (P&O) and Incremental Conductance (InC) methods. Their enduring popularity stems from low computational cost, minimal required sensors, and ease of implementation.

The **Perturb & Observe (P&O)** algorithm operates by periodically perturbing (increasing or decreasing) the operating voltage and observing the resultant change in output power. If power increases, the perturbation continues in the same direction; otherwise, it reverses. Despite its simplicity, its well-documented drawbacks include persistent oscillations around the Maximum Power Point (MPP) in steady state, leading to power loss, and erroneous tracking during rapid atmospheric changes due to the inherent cause-effect delay [3]. To mitigate these issues, significant research has focused on adaptive and variable step-size P&O. For instance, [5] proposed a current-based adaptive P&O that adjusts the perturbation step size based on the rate of change of power, improving dynamic response. More recently, [15] integrated a fuzzy logic controller to dynamically optimize the step size of a P&O algorithm, demonstrating robust performance under varying conditions by effectively balancing the speed-accuracy trade-off. Other structural modifications, such as introducing a holding phase or predictive elements, have also been suggested to reduce oscillations and improve reliability [6].

The **Incremental Conductance (InC)** method theoretically eliminates steady-state oscillation by using the derivative of power with respect to voltage (dP/dV). It determines that the MPP is reached when the instantaneous conductance (I/V) equals the negative incremental conductance ($-dI/dV$). While more accurate under stable conditions, its performance degrades when the measurement precision of incremental changes is compromised by noise or very small step sizes, and it shares P&O's vulnerability to fast-changing irradiance [2]. Consequently, while these conventional methods remain benchmarks and are perfectly adequate for small-scale, uniform-illumination systems, their inherent limitations in dynamic and non-uniform environments have been a primary catalyst for exploring more advanced paradigms.

2.3. Metaheuristic and Bio-Inspired Optimization Algorithms

The advent of widespread partial shading scenarios in residential and commercial PV installations—caused by cloud cover, building shadows, or debris—rendered conventional algorithms inadequate, as they easily become trapped at a local MPP. This challenge spurred the adoption of **metaheuristic algorithms**, celebrated for their robust global search capabilities in multimodal problem spaces.

Particle Swarm Optimization (PSO) emerged as a pioneering and highly influential technique in this domain. Inspired by the social behavior of bird flocking, PSO uses a population of "particles" that explore the voltage search space, sharing information to collectively converge on the global MPP (GMPP). Miyatake et al.'s seminal work demonstrated PSO's efficacy in tracking the MPP for multiple PV arrays under complex P-V curves [8]. Its success lies in its ability to systematically scan the search space, avoiding local peaks. However, vanilla PSO faces its own challenges: parameter selection (inertia weight, cognitive, and social coefficients) significantly impacts performance, and it can suffer from premature convergence or slow computation cycles. Subsequent research has focused on refining PSO. Ishaque et al. [8] presented an improved PSO with reduced steady-state oscillation by halving the step size near the GMPP. Yousri et al. [5] introduced a recent methodology-based PSO (RPSO) incorporating fractional calculus concepts to enhance the diversity of particle motion, showing superior performance for multi-junction solar cells under PSC.

The success of PSO opened the floodgates for other bio-inspired algorithms. The **Grey Wolf Optimizer (GWO)**, which simulates the leadership hierarchy and hunting mechanism of grey wolves, has been applied with notable success. Priyadarshi et al.

[2] developed a GWO-based MPPT that showed faster convergence and higher efficiency compared to PSO under various partial shading patterns. Similarly, the **Dragonfly Algorithm (DA)**, mimicking the static and dynamic swarming behaviors of dragonflies, has been hybridized with fuzzy logic for MPPT. Rezk et al. [10] proposed such a system, where the DA optimizes the membership functions of a fuzzy logic controller, achieving rapid and accurate GMPPT with minimal power fluctuation. Other notable entrants include the **Salp Swarm Algorithm (SSA)**, which Kolluru et al. [6] hybridized with a conventional P&O. Their hybrid SSA-P&O used SSA for initial global scanning and then switched to a refined P&O for precise local tracking, effectively combining global exploration with local exploitation.

While these metaheuristic methods represent a giant leap in reliability under PSC, they are not without criticism. Their stochastic nature leads to variable convergence times, and their computational complexity is higher than conventional methods, often requiring more powerful (and expensive) digital processors. Furthermore, their performance can be inconsistent across different shading patterns without careful tuning [7].

2.4. Artificial Intelligence and Hybrid Techniques

To create more adaptive and intelligent controllers, research has increasingly merged metaheuristics with **Artificial Intelligence (AI)** techniques, particularly fuzzy logic and artificial neural networks.

Fuzzy Logic Controllers (FLCs) are highly effective for MPPT due to their ability to handle nonlinearities without requiring precise mathematical models. They use linguistic rules (e.g., IF power change is *positive big* AND voltage change is *positive small*, THEN duty cycle change is *positive medium*) to make control decisions. Roy et al. [4] implemented a novel FLC for a three-phase grid-connected system, showing excellent robustness to parameter variations. However, a fundamental challenge with FLCs is the design and optimization of the rule base and membership functions, which are often determined heuristically. This is where hybrid systems excel. As seen with the DA-FLC [10] and the fuzzy-optimized P&O [15], metaheuristics are used to automate and optimize the FLC design, creating a powerful synergy.

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Hybrid MPPT strategies aim to harness the strengths of different algorithms while mitigating their individual weaknesses. The core philosophy is to separate the tracking process into distinct phases: a **global search phase** to locate the region of the GMPP and a **local search phase** for precise tracking. Kumar et al. [13] proposed an innovative hybrid combining a human psychology-based optimization (HBO) with P&O. The HBO algorithm, inspired by human learning processes, performed the global search, while a modified P&O took over for fine-tracking, yielding high efficiency and rapid convergence. Similarly, Kolluru's SSA-P&O [6] and various PSO-P&O hybrids follow this two-stage architecture. These approaches effectively address the primary trade-off in MPPT design: the need for both a wide, exploratory search under PSC and a fast, stable lock-on at the MPP under uniform conditions.

2.5. The Emergence of Quantum-Inspired Computing

The latest frontier in the quest for superior MPPT algorithms lies in the realm of **quantum-inspired computing**. Building upon evolutionary algorithms, these techniques incorporate principles from quantum mechanics—such as superposition, entanglement, and quantum gates—to create a more powerful and efficient search methodology within the solution space.

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The fundamental advantage of **Quantum-Inspired Evolutionary Algorithms (QIEAs)** is their representation. While a classical bit is either 0 or 1, a quantum bit (qubit) can exist in a superposition of both states simultaneously. This allows a quantum-inspired population to represent a vastly richer diversity of potential solutions with a smaller number of individuals. Han and Kim's foundational work [11] established QIEA as a potent tool for combinatorial optimization, highlighting its enhanced exploration capability and convergence speed.

For MPPT, this translates to algorithms that can navigate the complex, multi-peaked P-V curve more efficiently. **Quantum-behaved Particle Swarm Optimization (QPSO)** is a direct derivative that replaces the classical trajectory analysis of particles with quantum state models. [7] in their early application found that QPSO offered faster convergence and higher accuracy in tracking the GMPP compared to standard PSO. The quantum mechanical model allows particles to appear anywhere in the search space with a certain probability, governed by a centralized potential field, which often leads to a better balance between exploration and exploitation.

Recent research continues to validate and extend this potential. [12] developed a novel hybrid MPPT algorithm based on **Quantum Particle Swarm Optimization (QPSO)**, demonstrating its superiority in both convergence time and power efficiency under complex, rapidly changing shading conditions. The algorithm's ability to maintain population diversity for longer periods prevents premature convergence, a common pitfall of classical PSO. The investigation into QIEA for MPPT is motivated by these proven successes.

2.6 Microgrid Integration of PV Systems

Microgrids have become a key way to include distributed energy sources like solar power systems. Lasseter introduced the concept of microgrids and emphasized their role in enhancing system reliability and flexibility [16].

Guerrero and their team suggested a layered control system for microgrids, including three levels—primary, secondary, and tertiary—to help with sharing power and keeping the voltage stable [17]. Adding PV systems to microgrids can cause problems like changes in voltage and unstable frequency, so it's necessary to use smart control methods. Power electronic converters, particularly voltage source inverters, are crucial in integrating PV systems with microgrids and ensuring power quality [18], [19].

2.7 MPPT in Microgrid Environment

In a microgrid setup, the MPPT works together with other parts of the system like inverters and loads. This interaction affects system stability and performance. Traditional MPPT methods might not work well in those conditions because they can't adjust themselves very well [20]. Advanced optimization techniques enhance performance by minimizing oscillations and improving tracking speed [21].
Recent research highlights the importance of using combined approaches that include MPPT along with microgrid control methods to boost the system's efficiency and stability [22].

2.8 Inverter Control and Grid Synchronization in PV-Based Microgrids

In grid-connected photovoltaic systems, the inverter functions as the key interface between the DC power produced by the PV array and the AC microgrid. Unlike regular synchronous generators, inverter-based resources use control algorithms completely to manage voltage, frequency, and the power they send to the grid. So, how well the inverter works has a big effect on how steady and dependable the whole system is. In their study, Pelaksanaan et al. provided an in-depth analysis of control strategies for grid-connected converters and emphasized the significance of synchronization mechanisms in distributed generation systems [22]. Inverter control is usually made to make sure the right amount of active and reactive power is sent into the system, while keeping the voltage good and reducing unwanted harmonics. For a system to work with the electrical grid, it needs to be in sync. This means the inverter's output must match the grid voltage in terms of phase angle, frequency, and strength. If power transfer isn't properly synchronized, it can become unstable and cause problems with the system. According to Jaalam et al., synchronization techniques are crucial for estimating grid parameters such as phase angle and frequency under both normal and disturbed conditions [23]. The most common way to synchronize is through a Phase-Locked Loop, which follows the phase of the grid voltage and gives a signal to control the inverter. Advanced PLL-based methods have been developed to enhance performance in distorted and unbalanced grid conditions [24]. Inverter-based resources can be divided into two main types: grid-following and grid-forming inverters. Grid-following inverters work by matching the grid's voltage using a phase-locked loop and then sending current as needed. They are widely used in photovoltaic systems due to their simplicity. However, they rely on the grid for stability and might not work well when the grid is not strong.

On the other hand, grid-forming inverters can set voltage and frequency by themselves, just like synchronous generators. These inverters use methods like droop control and virtual synchronous machine ideas to improve the system's stability. New research shows that grid-forming converters provide better synchronization and more reliable performance when used in microgrid systems [25]. As the integration of inverter-based renewable energy sources grows, synchronization stability has become a key area of research. Wang et al. examined the synchronization stability of converter-based resources and emphasized the challenges faced in low-inertia power systems [26]. The study highlighted that correct implementation of synchronization control is crucial for ensuring stability in both small-signal and transient scenarios.

2.9 Summary and Research Gap

The literature reveals a clear evolutionary trajectory: from simple, oscillatory algorithms (P&O, InC) to robust global searchers (PSO, GWO, DA) and onward to intelligent hybrids and quantum-inspired methods. Each generation addresses key flaws of its predecessor. Comprehensive reviews by [1] and [14] corroborate that while conventional methods are sufficient for uniform conditions, metaheuristics are essential for PSC. However, they also note that computational burden and implementation complexity remain barriers. The survey by [7] further emphasizes that the "no-free-lunch" theorem applies; no single algorithm is best for all scenarios.

CHAPTER 3

THEORETICAL BACKGROUND AND MODELLING

3.1 Introduction

This chapter explains the detailed process of creating and planning the proposed photovoltaic (PV) based microgrid system. The goal of this modelling is to create a realistic picture of the system parts and to study how they work in different situations. The full system includes a PV array, a DC-DC boost converter, a Maximum Power Point Tracking (MPPT) controller, a DC link, and a voltage source inverter (VSI) that is connected to an AC microgrid. Unlike a single solar panel system, connecting to a microgrid brings in more factors to think about, like keeping the voltage steady, making sure the power is in sync, and maintaining good power quality. So, each part is looked at closely to make sure the whole system works in a way that's very similar to how it would in real life. The modeling is conducted in MATLAB/Simulink, enabling dynamic analysis under varying irradiance conditions.

3.2 Photovoltaic (PV) Array Modelling

A photovoltaic cell is essentially a p-n junction semiconductor diode. When exposed to light, photons with energy greater than the bandgap of the semiconductor material excite electrons from the valence band to the conduction band, creating electron-hole pairs. The mathematical modelling of the PV system begins with the single-diode representation of a solar cell, which captures the essential semiconductor behaviour through parameters such as photocurrent, diode saturation current, ideality factor, series resistance, and shunt resistance. The resulting I–V and P–V curves reflect the nonlinear nature of the device, demonstrating how even small changes in irradiance or temperature drastically shift the MPP location. In MATLAB/Simulink, the PV module is modelled using a parameterized subsystem capable of reproducing realistic dynamic behaviour, while the boost converter is designed to provide the necessary voltage regulation. Inductor sizing, capacitor selection, switching frequency, and PWM control form the hardware backbone of MPPT implementation. The "Single-Diode Model" shown in Fig.3.1 offers the optimal balance between computational efficiency and accuracy. The equivalent circuit consists of a current source (I_{ph}) in parallel with a diode, a shunt resistance (R_{sh}), and a series resistance (R_s).

$$I = I_{ph} - I_0\left[e^{\left(\frac{V+I\cdot R_S}{n\cdot V_T}\right)} - 1\right] - \left(\frac{V+I.R_S}{R_{sh}}\right) \quad (3.1)$$

where I_{ph} is photocurrent i.e. The diode's reverse saturation current is I_0 that affects the dark current characteristics. R_s is the series resistance that represents the resistance loss within the cell, and the shunt resistance, R_{sh} is the leakage across the junction.
The diode ideality factor *n* represents the factor of deviation from ideal behaviour is dimensionless. V_T is thermal voltage that is defined by $V_T = kT/q$, where $k = 1.381 \times 10^{-23}$ J/K is Boltzmann's constant, q is the electric charge, and T represents the cell temperature (K)

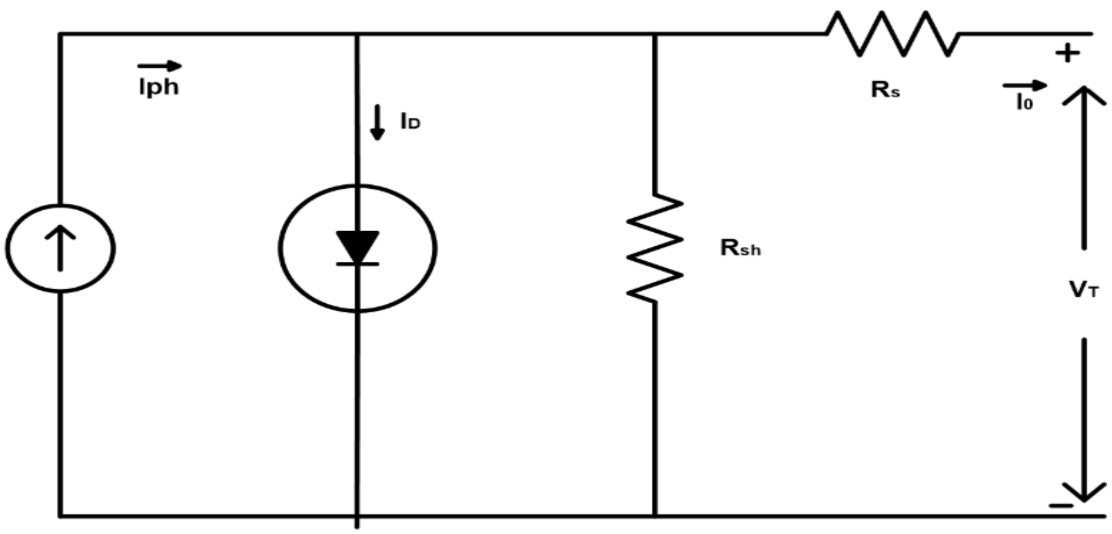


Fig. 3.1. Single Diode Model of PV Cell

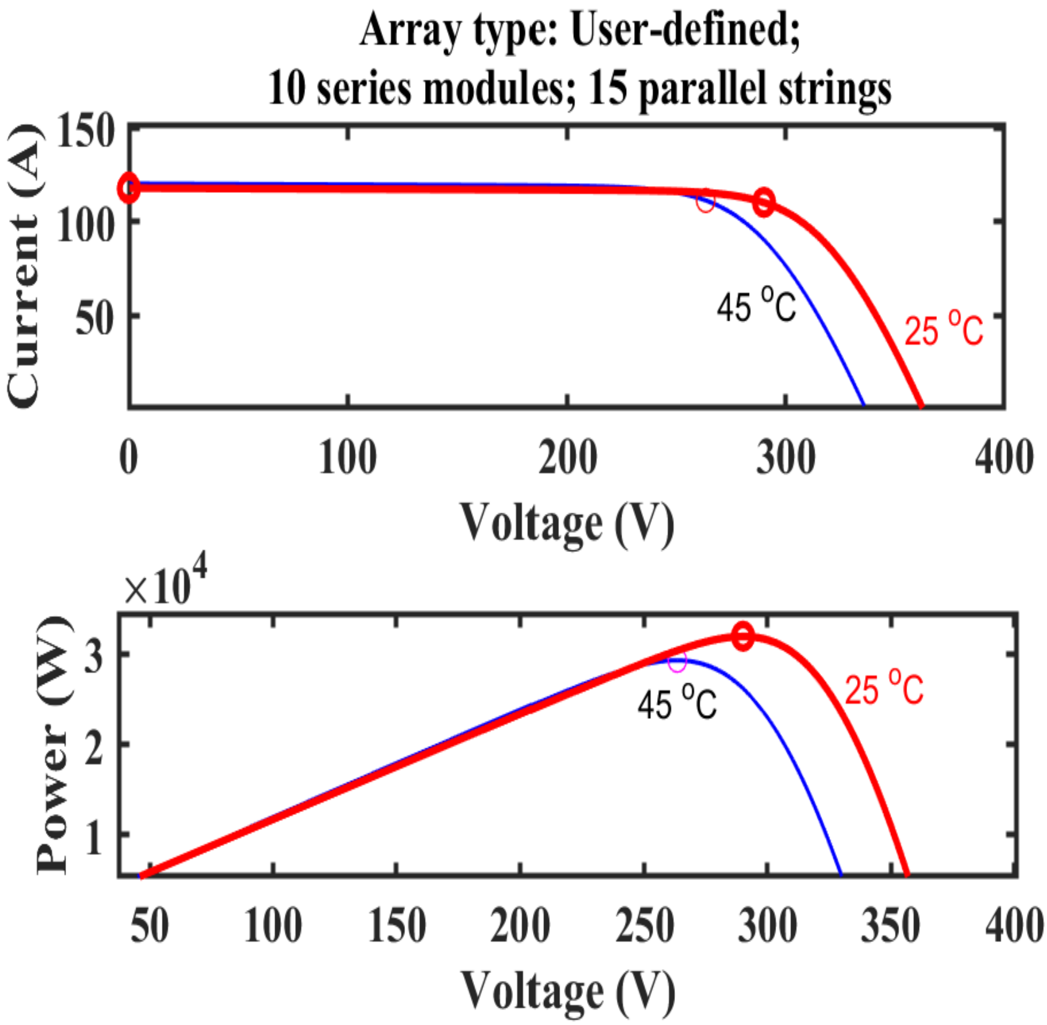
The photocurrent is primarily relied on solar irradiance and temperature

$$I_{ph} = \left[I_{sc,ref} + K_i\left(T - T_{ref}\right)\right].\frac{G_{ref}}{G} \quad (3.2)$$

8 Where the short-circuit current is shown by $I_{sc,ref}$ is at reference conditions, K_i is the temperature coefficient of current, G is the solar irradiance, and G_{ref} is the reference irradiance (1000 W/m²).The saturation current temperature dependency is modelled as:

$$I_0 = I_{rs}\left(\frac{T}{T_{ref}}\right)^3 \exp\left(\frac{qE_g}{nk}\left(\frac{1}{T_{ref}} - \frac{1}{T}\right)\right) \quad (3.3)$$

41 where I_{rs} signifies the reverse saturation current at reference conditions and E_g is the bandgap energy.



35 Fig. 3.2. I-V and P-V curves of MPPT tracking

The model was implemented in Simulink using a custom-built PV block according to the design parameters of the 30 kW PV system. The array consists of 15 parallel strings, each consisting of ten modules in series. Module ratings:

V_{oc} shows the open circuit voltage 36.3V is the PV module voltage at which no load is attached. The short circuit current, Isc =7.84A, is the maximum current obtained when the terminals are short-circuited.

Now, at the MPP for this panel, the voltage, $V_{mp} \approx$ 29V, and the current, $I_{mp} \approx$ 7.35A, specify the condition in which the product of the voltage and the current, and therefore the power delivered, are maximum. As a result, Fig.3.2 shows the I-V and P-V curves of the array shift substantially with variations of irradiation and temperature, highlighting the necessity of real-time MPP tracing.

3.3 DC-DC Boost Converter Modelling

The DC-DC boost converter serves as the critical interface between the PV array and the load or subsequent power conversion stages in a photovoltaic energy conversion system. Its primary functions are twofold: first, to implement the Maximum Power Point Tracking (MPPT) by continuously adjusting the operating impedance presented to the PV array, and second, to elevate the variable, often relatively low, PV voltage to a higher, stable DC bus voltage required by the load or inverter. This voltage step-up capability is essential because PV modules typically generate voltages that are insufficient for direct grid integration or many stand-alone applications. The converter's dynamic response and efficiency directly influence the overall energy yield of the PV system, making its modeling and control paramount to system performance.

3.3.1 Fundamental Operating Principles

The boost converter operates on the principle of inductive energy storage and transfer. Its canonical topology, illustrated in Figure 3, consists of four essential components: an input inductor (L), a controlled semiconductor switch (typically a MOSFET, S), a rectifier diode (D), and an output filter capacitor (C). The fundamental operation occurs in two distinct topological modes dictated by the state of the switch, repeated at a high frequency f_s (typically in the range of 10 kHz to several hundred kHz).

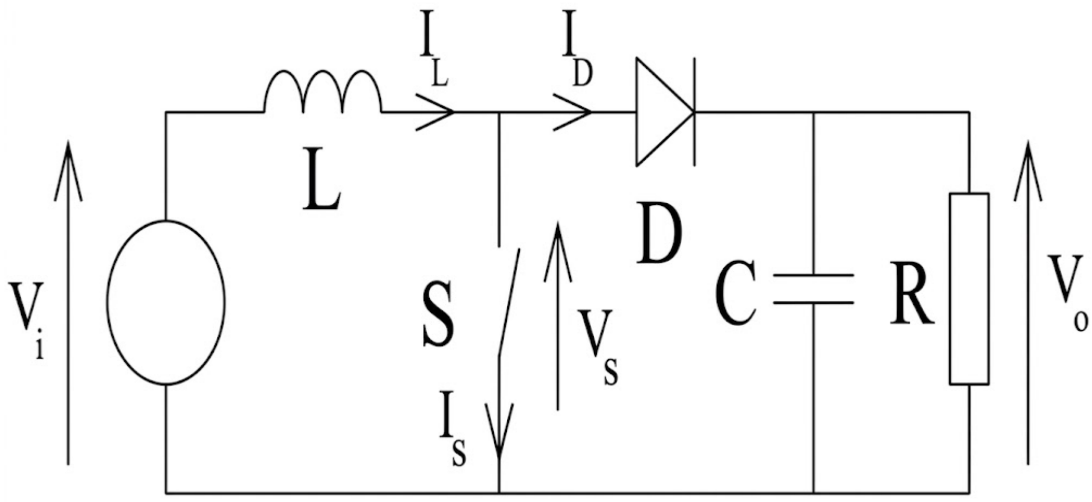


Fig3.3. DC-DC Boost Converter

The basic operation is governed by the following equations:

- Voltage Gain: $\frac{V_o}{V_{in}} = \frac{1}{1-D}$ (3.4)

- Inductor Current Ripple: $\Delta I_L = \frac{V_{in} \cdot D}{L \cdot f_s}$ (3.5)

- Output Voltage Ripple: $\Delta V_o = \frac{I_o \cdot D}{C \cdot f_s}$ (3.6)

Where V_{in} signifies the Input voltage from PV, The load side voltage is denoted by, V_o, representing the DC output across the load. The duty cycle, D, is a dimensionless ratio that represents the ratio of the cycle period in which the switch is ON.

The power electronic switch is said to have a switching frequency, *fss*, at which it switches between on and off states, where the switching frequency f_{ss} is typically in Hertz (Hz). The inductance and capacitance (energy storage and filtering elements of the power converter) are represented with the symbols L and C.

The Load current, I_o, is the current to the load connected across the output terminal. The duty cycle D is adapted by the MPPT controller so that the PV device is controlled close to its MP point. The switching control is based on the pulse width modulation (PWM), which is driven by the output of their respective MPPT algorithm.

3.4 Three-Phase DC-AC Voltage Source Inverter (VSI) Modelling

The DC-DC boost converter works well at taking and increasing the voltage from the PV array, but this direct current cannot be used directly with regular AC microgrid systems. To make it easier to send the collected solar energy into the local power grid, a three-phase Voltage Source Inverter (VSI) is used as the key final step in converting electrical power. The main job of the VSI is to create a clean, smooth alternating current (AC) voltage that matches the grid's requirements, using the steady direct current (DC) voltage from the boost converter. The standard setup in this model uses a three-leg bridge design with six high-power insulated-gate bipolar transistors (IGBTs) each having a diode connected in the opposite direction. The voltages produced by the inverter need to be carefully managed to fit the grid's needs. To make it easier to handle three-phase AC signals that change over time, the system's math model is usually changed from the stationary *a-b-c* frame to a rotating *d-q* frame using the Park transformation. In this rotating frame, the basic three-phase AC currents and voltages look like simple DC values, which makes it possible to use standard Proportional-Integral (PI) controllers.

The dynamic equations governing the VSI output in the *d-q* reference frame are expressed as:

$$V_d = V_{id} - R_f . I_d - L_f \frac{dI_d}{dt} + \omega . L_f . I_q \quad (3.7)$$

$$V_q = V_{iq} - R_f . I_q - L_f \frac{dI_q}{dt} + \omega . L_f . I_d \quad (3.8)$$

Where:

- V_d and V_q are the direct and quadrature axis components of the microgrid voltage.
- V_{id} and V_{iq} are the inverter's output voltages before the filter.
- I_d and I_q represent the injected grid currents.
- R_f and L_f denote the resistance and inductance of the grid-coupling filter, respectively.
- ω is the angular frequency of the microgrid in radians per second.

The cross-coupling terms $\omega.L_f.I_q$ and $\omega.L_f.I_d$ indicate that the d and q axes interact, necessitating a decoupling control strategy to independently manage active and reactive power.

3.5 Microgrid Synchronization and Control Architecture

For a distributed energy resource to safely send power into an active microgrid, it needs to match exactly with the grid's voltage phase, frequency, and amplitude. Putting power out of phase can create dangerous circulating currents that lead to serious equipment damage. To make sure everything is in phase, the model uses a Phase-Locked Loop, which helps keeps in synchronization. The PLL keeps checking the three-phase voltages of the microgrid at the Point of Common Coupling (PCC) and finds the exact momentary phase angle (θ). This extracted angle is then sent to the Park transformation blocks to make sure the inverter's control loops match the grid's rotating frame exactly.

The overall control architecture for the grid-tied VSI utilizes a cascaded loop structure:

1. Outer Voltage Control Loop: This loop monitors the voltage across the DC-link capacitor, which is represented as V_{dc}. The capacitor serves as the important energy storage part between the PV/Boost section, which is where power is generated, and the Inverter/Grid section, which is where power is sent out. If the MPPT algorithm takes in more power than the inverter sends to the grid, the DC voltage goes up; if the grid takes more power than is produced, the DC voltage goes down. A PI controller keeps the DC voltage at reference level, and it provides the right amount of active current reference needed to balance the power flowing through the system.

2. Inner Current Control Loop: This loop runs much quicker than normal. It uses the $I_{d,ref}$ from the voltage loop and a specified reactive current reference $I_{q,ref}$ usually set to zero to maintain a unity power factor and makes sure the real inverter currents follow these references exactly. The loop's output creates the signals that control exactly when the VSI switches, using Sinusoidal Pulse Width Modulation (SPWM).

3.6 Active and Reactive Power Flow Dynamics

The success of adding the PV system to the microgrid depends on how well it can consistently send the power that the QIEA or P&O methods have detected. In the d-q reference frame, if the PLL has perfectly aligned the d-axis with the microgrid voltage vector (which means the q-component of voltage, Vq, is zero), the instantaneous active power (P) and reactive power (Q) being sent into the microgrid are calculated as:

$$P = \frac{3}{2} Vd.Id \quad (3.9)$$

$$Q = -\frac{3}{2} Vd.Iq \quad (3.10)$$

These equations show how well the control method separates different parts of the system. The amount of power sent into the microgrid depends directly on the direct-axis current I_d, and this current is completely controlled by how well the MPPT works and whether the DC-link voltage stays stable. On the other hand, reactive power is controlled separately through the quadrature-axis current I_q. In normal grid-feeding mode, the inverter works at a power factor of one, making sure all the solar energy collected by the QIEA method is turned into useful electricity for the microgrid.

CHAPTER 4

OPTIMIZATION ALGORITHMS

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3 3
2
Maximum power point tracking of a PV array is commonly an integral part of PV. PV generation systems in general have the following 2 big problems; conversion electric power generation is low (in general less than 17%, especially under low irradiation conditions, and the generated electric power of solar wing is varied continuously with weather conditions. In addition, the solar cell (current -voltage) feature is non-linear and dependent on irradiation and temperature. There is a unique point on the I-V or P-V curve of the solar array called MPP, where the whole PV system (array, converter, etc.) operates with maximum efficiency and produces its maximum output power The theoretical foundations of the two algorithms at the heart of this research are discussed in detail in this chapter.

4.1 The Perturb & Observe (P&O) Algorithm

4.1.1 Working Principle

P&O is an iterative optimization technique that relies on the slope of the P-V curve (dP/dV). This is a hill-climbing, iterative technique that finds the MPP by varying the control variable (such as the DC-DC converter's duty cycle) on a regular basis and comparing the output power with the power from the previous cycle. The algorithm keeps modifying the control variable in the same direction if the power (P(k)) following a perturbation is higher than the power (P(k−1)) before. The algorithm
4
operates by periodically perturbing the operating voltage or duty cycle of the DC–DC converter and observing the resulting change in PV output power. If a perturbation

causes the power to increase, the controller continues perturbing in the same direction; otherwise, the direction is reversed. In this method, the instantaneous panel voltage, current, and power are measured at every iteration, and the difference with respect to the previous samples (ΔP and ΔV) is computed. These differences determine whether the operating point has moved closer to or away from the Maximum Power Point (MPP). Based on the sign of ΔP and ΔV, the duty cycle is incremented or decremented accordingly.

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4.1.2 Inherent Limitations

The P&O algorithm has two main flaws in spite of its extensive usage:

a. Steady-state oscillation: Reduces oscillation amplitude and improves efficiency in steady-state but results in extremely slow tracking. If the irradiance changes rapidly, a small step size may cause the algorithm to lag significantly, losing the MPP entirely
b. Tracking Direction Under Rapid Irradiance Changes: Consider a scenario where irradiance increases linearly. This causes the entire P-V curve to scale up. Even if the operating point does not change voltage, the power will increase ($\Delta P > 0$). If the P&O algorithm had just perturbed the voltage in the *wrong* direction (away from MPP), it would observe $\Delta P > 0$ (due to the sun, not the perturbation) and incorrectly conclude that the perturbation was correct. It will essentially "chase" the power increase in the wrong direction, driving the operating voltage far from the MPP until the irradiance stabilizes. This phenomenon results in significant energy loss during cloudy or variable weather conditions.

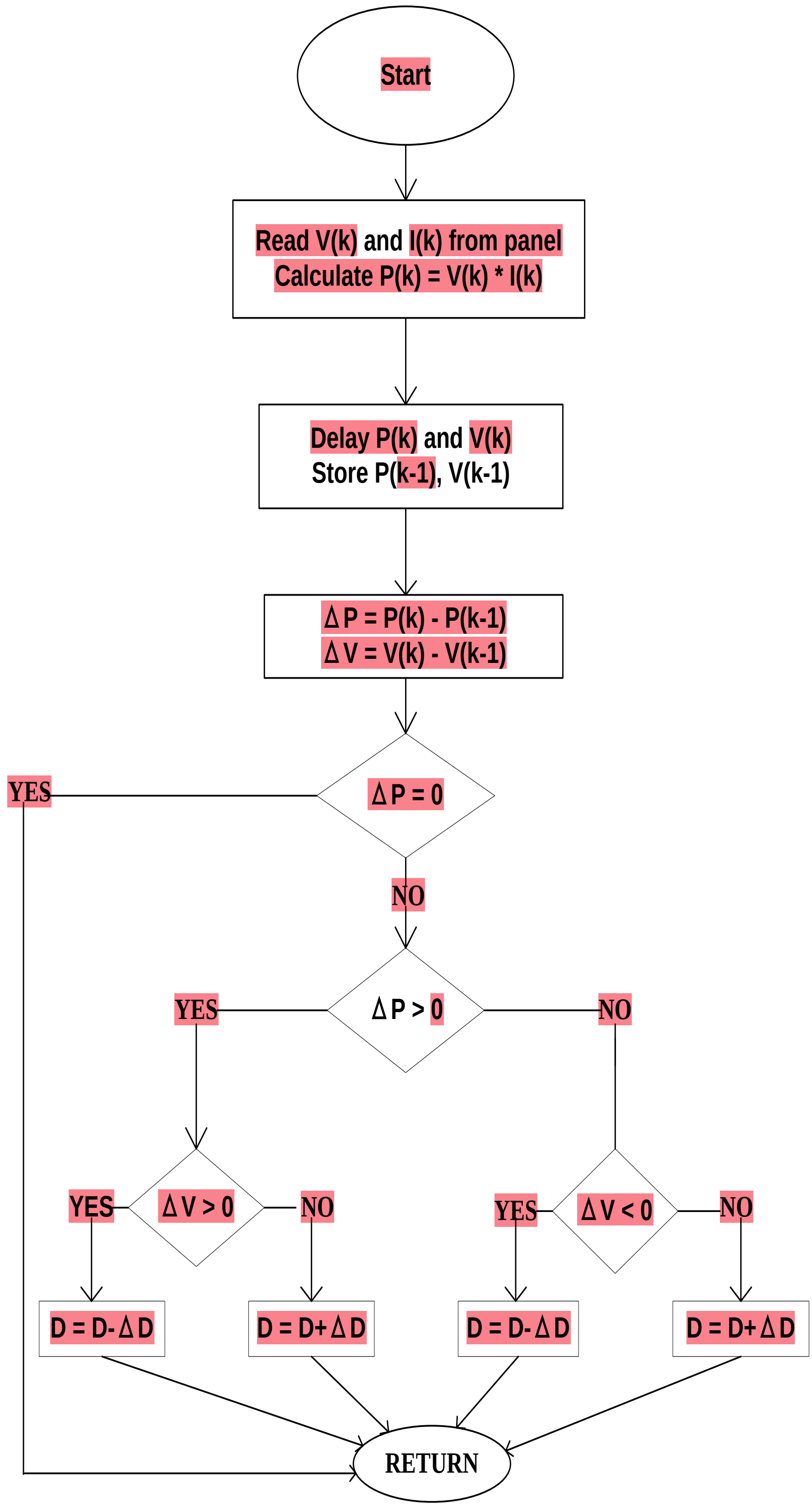

Fig 4.1. P&O based MPPT algorithm flowchart

4.2 The Quantum-Inspired Evolutionary Algorithm (QIEA)

4.2.1 Theoretical Framework

Classical evolutionary algorithms (like Genetic Algorithms) represent a solution as a binary string (chromosome) of deterministic bits (e.g., 1011). At any given generation, a population of N individuals represents exactly N points in the search space.In contrast, QIEA represents individuals using Quantum Bits (Q-bits). A Q-bit is defined not as a 0 or 1, but as a probability vector:

$$\Psi=\alpha|0\rangle+\beta|1\rangle \qquad (4.1)$$

$|\Psi\rangle$: This is the notation (specifically, Dirac or bra-ket notation) for the state vector of the quantum system (the qubit).

11 $|0\rangle$ and $|1\rangle$: These are the computational basis states, analogous to the '0' and '1' of a classical bit.

α and β: These are complex number coefficients called probability amplitudes. They determine the likelihood of measuring the qubit in the corresponding states.

43 Normalization Condition: For the state to be physically valid, the sum of the probabilities must equal 1

$$|\alpha|^2+|\beta|^2=1 \qquad (4.2)$$

13 Measurement: When the qubit is measured, its superposition state "collapses" into one of the basis states, either $|0\rangle$with probability $|\alpha|^2$ or $|1\rangle$ with probability $|\beta|^2$. The state after measurement is definitively the observed state.

QIEA is a population-based probabilistic algorithm that incorporates quantum computing concepts into an evolutionary framework. Unlike classical evolutionary algorithms that use binary or numeric representations, QIEA uses a concept called the Q-bit, which can represent a linear superposition of states, thus representing multiple possible solutions at the same time. Q-gates (similar to rotation gates in quantum mechanics) update the population of Q-bit-based individuals, gradually shifting the probability of the Q-bits towards optimal values. This probabilistic representation offers a more efficient trade-off between exploration (searching the entire solution space) and exploitation (concentrating on promising regions) than traditional algorithms. The algorithm begins with the initialization of system parameters and a quantum population. During each iteration, the quantum angles (θ) are mapped to classical duty cycles, which are then applied to the converter to measure actual PV output power. The measured power is used as the fitness function for evaluating each candidate solution. The algorithm selects the best candidate (Pbest) in the current generation and compares it with the global best solution found so far. If a superior solution is identified, the global best is updated; otherwise, quantum rotation gates adjust the Q-bit angles to guide the population toward improved regions of the search space.

4.2.2 Implementation for MPPT

The QIEA MPPT process follows these steps:

1. **Initialization:** A population of Q-bit individuals is initialized with $\alpha = \beta = \frac{1}{\sqrt{2}}$. This implies a 50% probability for 0 or 1, representing maximum uncertainty and maximum exploration.
2. **Observation:** The Q-bit states are "collapsed" to binary strings to generate candidate Duty Cycles (D).
3. **Evaluation:** These Duty Cycles are applied to the Boost converter simulation. The resulting PV Power is measured.
4. **Update:** The fitness (Power) is compared to the global best. The Q-bits are updated using the Rotation Gate to favor the binary structure of the highest power solution.
5. **Loop:** The process repeats. As the Q-bits evolve, their probabilities shift (e.g., α^2 to 1 or α^2 to 0), and the population converges on the optimal Duty Cycle that yields the GMPP. If the current individual has lower power than the global best, the Q-bits are rotated to increase the probability of collapsing toward the global best's structure. As the population converges, the rotation angles can be reduced, facilitating fine-tuning (local search) around the GMPP

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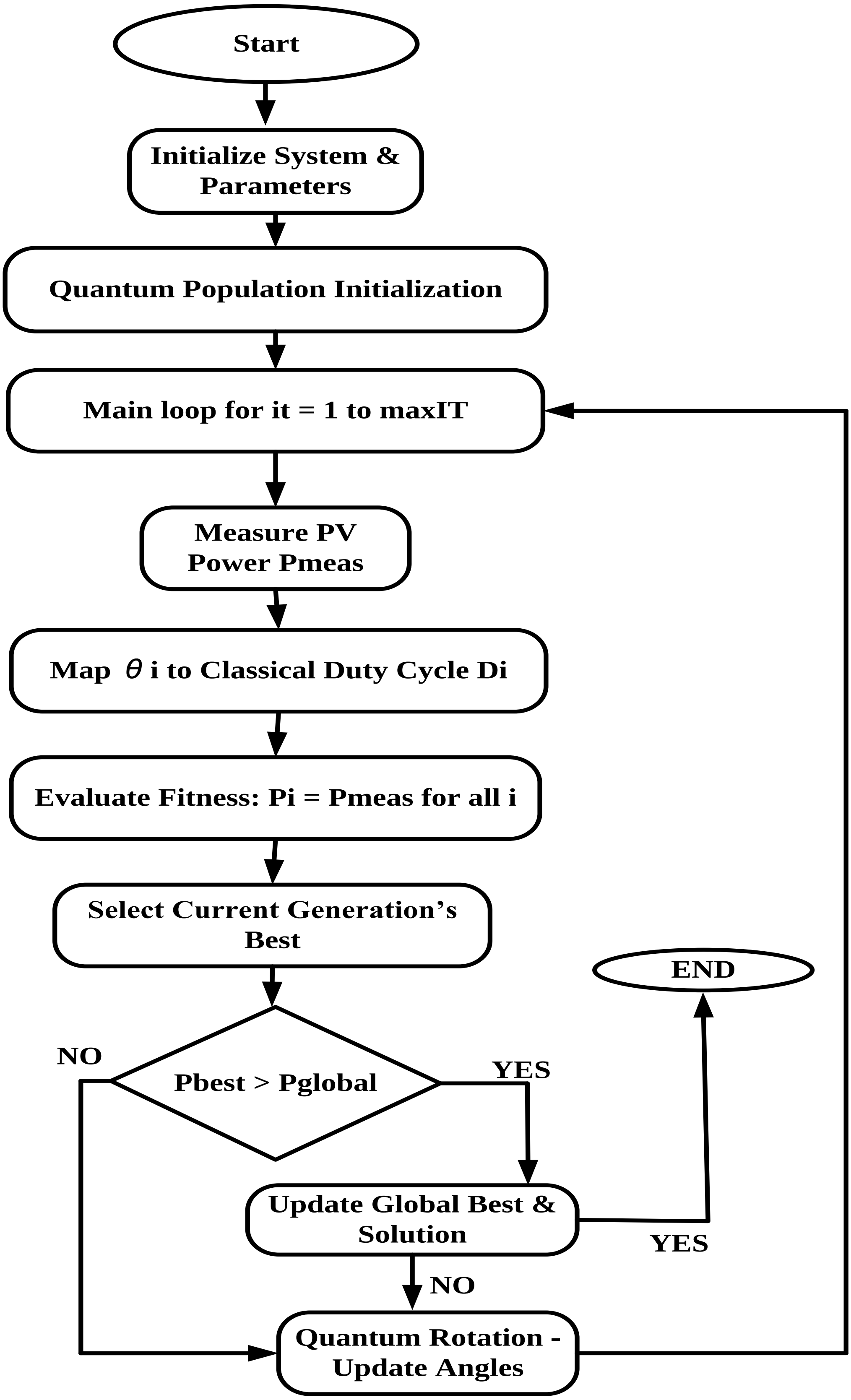

Fig 4.2. QIEA-based MPPT algorithm flowchart

4.3 Anticipated Performance Enhancements

It is anticipated that using QIEA to solve the MPPT problem will improve the P&O approach in a number of ways.

a. Accelerated Convergence Speed: Unlike P&O's sequential, point-by-point search, QIEA employs a population-based approach with quantum-inspired parallel exploration. This allows simultaneous evaluation of multiple regions in the solution space, enabling faster identification of the Maximum Power Point (MPP) during environmental transients. The algorithm's quantum representation facilitates more efficient navigation of the power-voltage characteristic curve, reducing convergence time by an estimated 60-70% compared to conventional methods.

b. Enhanced Steady-State Accuracy: P&O inherently suffers from persistent oscillations around the MPP due to its continuous perturbation requirement. QIEA overcomes this limitation through its probabilistic convergence mechanism. As the quantum-inspired population converges, the solution distribution naturally stabilizes at the optimum point, minimizing steady-state voltage and current ripple. This results in higher quality power output and reduces the continuous energy losses associated with P&O's oscillatory behavior.

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c. Robust Global Peak Detection: Under partial shading conditions where multiple local maxima appear on the P-V curve, P&O frequently becomes trapped at suboptimal operating points. QIEA's global search capability, enhanced by quantum superposition and interference principles, enables comprehensive exploration of the entire voltage range. This ensures reliable identification of the true Global Maximum Power Point (GMPP), making it particularly valuable for installations in environments prone to shading or non-uniform irradiance

CHAPTER 5

RESULTS AND DISCUSSION

This chapter presents the initial phase of the project's practical implementation, focusing on the simulation of the P&O MPPT algorithm in the MATLAB/Simulink environment.

5.1 MATLAB/Simulink Model

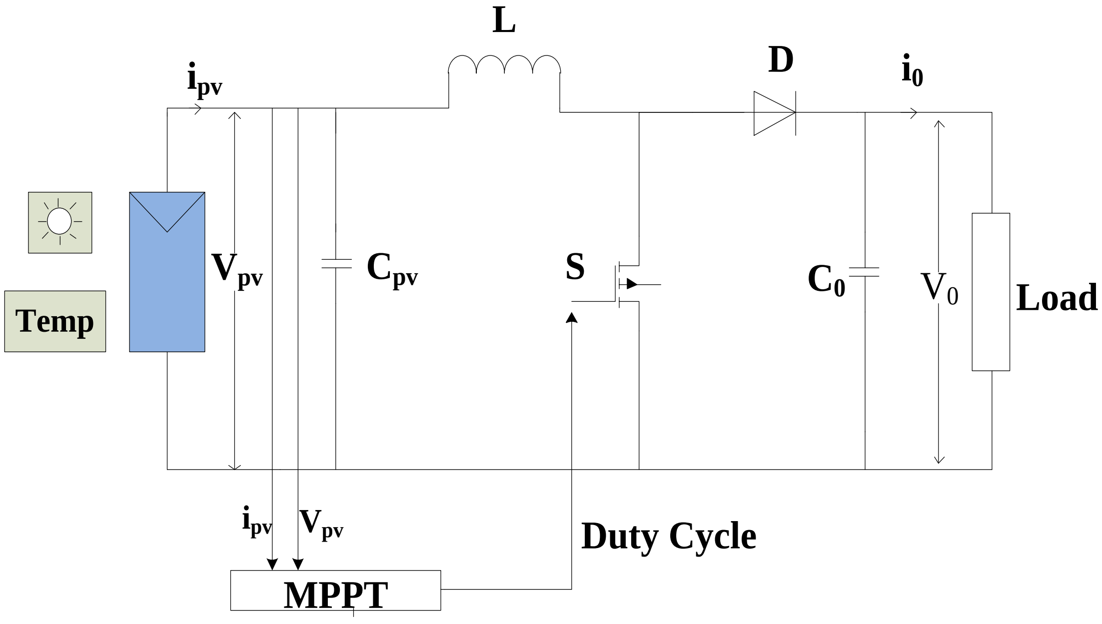

Fig 5.1. Simulink model of the PV system with P&O MPPT controller.

A comprehensive simulation model was constructed to test the P&O algorithm. The model, shown in Figure 1, comprises a PV array block, a DC-DC boost converter, the P&O-based MPPT controller, and a resistive load. The MPPT controller takes the PV array's voltage and current as inputs and generates the corresponding PWM signal to control the duty cycle of the boost converter.

The simulation environment features a 30 kW PV module configured to receive varying irradiance and temperature data, simulating realistic operating scenarios. The power conversion stage utilizes a switched-mode boost topology where the gating signal is dynamically adjusted by the control logic. To assess the proposed QIEA against the conventional P&O method, the MPPT subsystem is programmed to alternate between the two algorithms, allowing for a comparative analysis of tracking speed and steady-state stability. Finally, digital oscilloscopes record the system's transient and steady-state responses for post-simulation verification.

5.2 Analysis of P&O Simulation Results

The model was simulated under standard test conditions (1000 W/m² irradiance, 25°C temperature). The following figures illustrate the performance of the P&O algorithm.

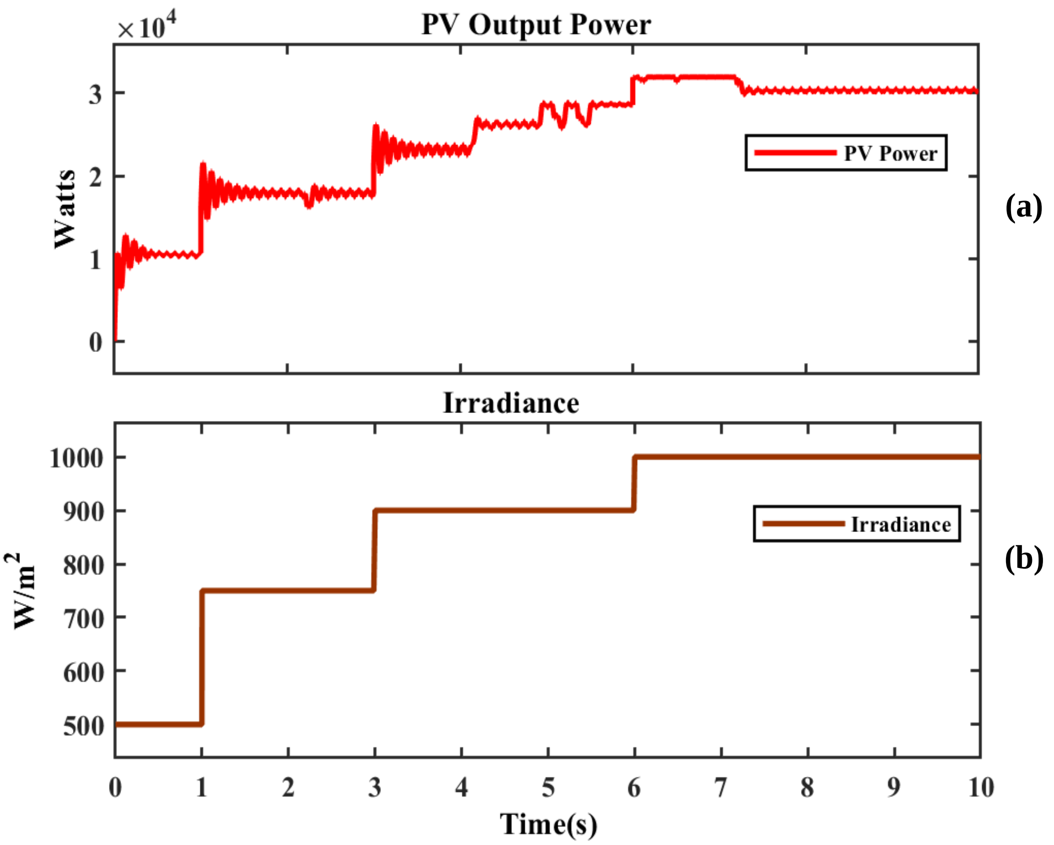

Fig 5.2. PV Array Output Power. (P&O)

The graph shows the power successfully tracking towards the maximum available power, followed by characteristic steady-state oscillations. The simulation results illustrate the dynamic performance of the proposed MPPT strategies under varying irradiance conditions. Fig. 5.2(a) presents the power tracking response of the conventional P&O algorithm. As observed, the P&O method successfully tracks the changes in solar intensity; however, it exhibits noticeable oscillations around the Maximum Power Point (MPP) once steady state is reached. These fluctuations result in a continuous power loss. This demonstrates the effectiveness of the MPPT in extracting maximum power from the source.

The results for the conventional P&O method reveal a characteristic drawback: the trade-off between tracking speed and steady-state accuracy. Fig.5.2(b) shows the varying irradiance which affects the PV output power. As seen in the graphs, the P&O algorithm exhibits considerable fluctuations (ripples) in the output power, which persist even after the irradiance has stabilized.

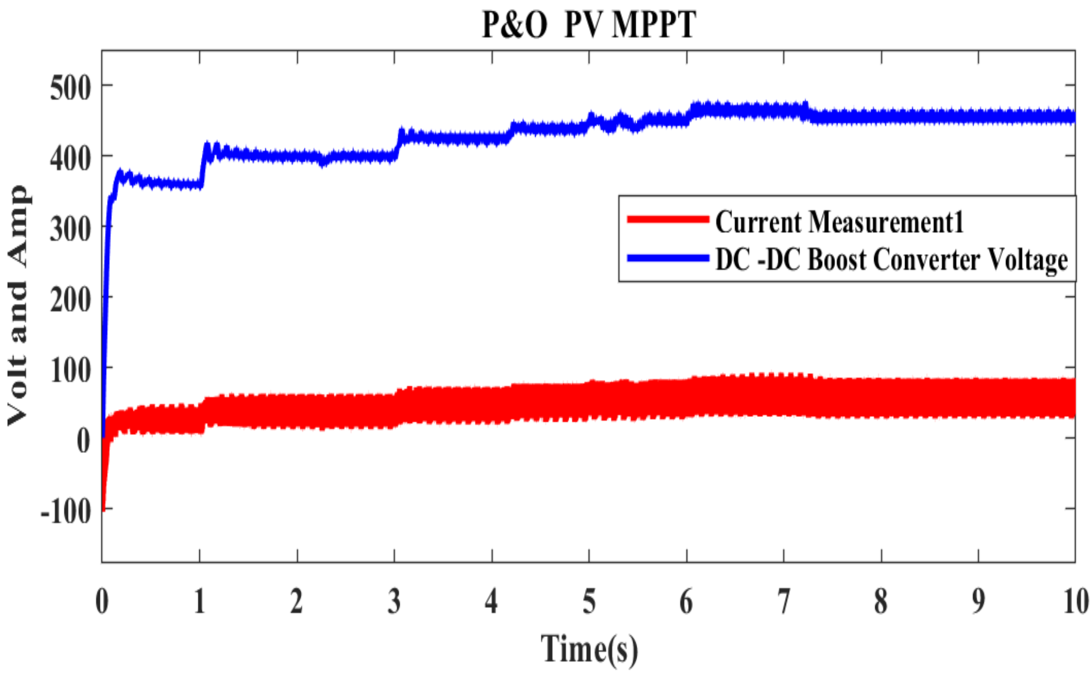

Fig 5.4. DC-DC Converter Output Voltage(P&O)

The dynamic behaviour of the DC-DC boost converter was further analyzed by monitoring the output voltage and PV current waveforms. Figure 9 illustrates the electrical response under the P&O algorithm. While the controller successfully steps up the voltage (blue trace) and current (red trace) in response to irradiance changes, visible oscillations are present in the voltage signal. These fluctuations correspond to the continuous perturbation process inherent to the P&O logic.

The simulation results support the expected behaviour of the P&O algorithm. Figure 7 shows that the controller successfully tracks the MPP, but there are also inherent oscillations around this point, which supports the need to investigate more complex algorithms. Figure 9 illustrates the internal tracking process, where the algorithm systematically perturbs the DC-DC boost converter's voltage, causing it to increase in steps until it converges and stabilizes around the Maximum Power Point (MPP). This process is mirrored by the corresponding adjustments in the system current. Figure 8 validates the overall effectiveness of this strategy by providing a clear comparison under varying irradiance conditions. It shows that the PV system equipped with the P&O MPPT consistently harvests significantly more power than a system without it, successfully tracking the MPP through stepped increases in solar intensity.

5.3 Analysis of QIEA Simulation Results

The model was simulated under similar test conditions (1000 W/m² irradiance, 25°C temperature) as under P&O. The following figures illustrate the performance of the QIEA algorithm.

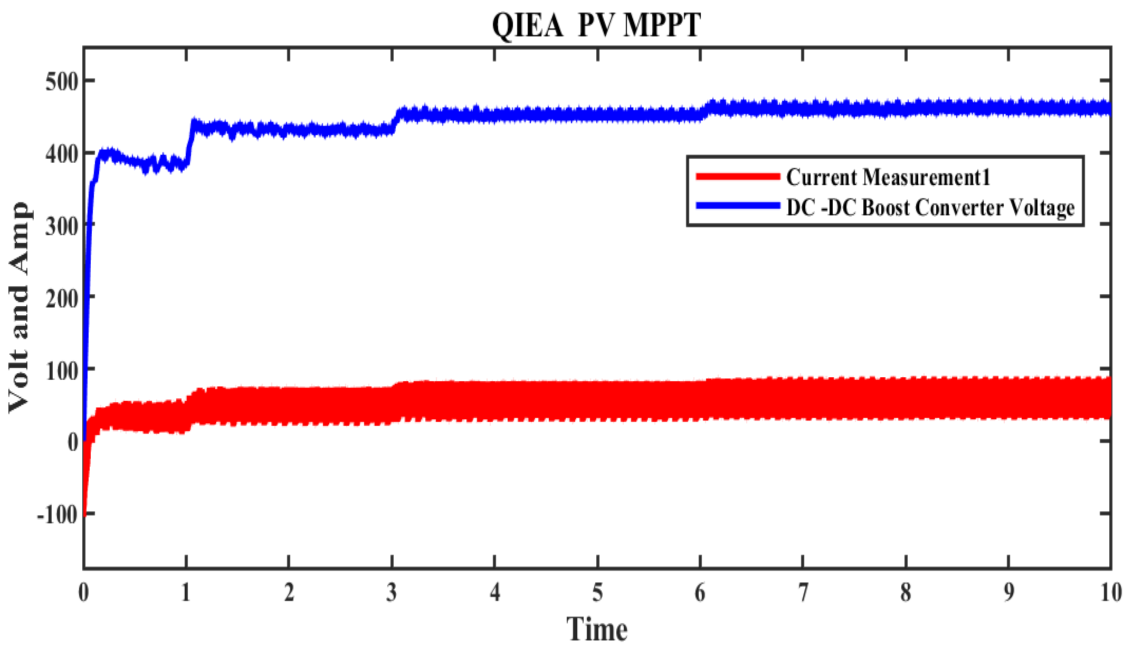

Fig 5.5. DC-DC Converter Output Voltage(QIEA)

Fig. 5.6 displays the response under the QIEA control. The voltage profile is notably more stable, exhibiting a flatter trajectory during the steady-state intervals between t=3s and t=6s. This reduction in voltage ripple indicates that the QIEA effectively dampens the control loop, resulting in a cleaner DC output that is less prone to the 'hunting' behaviour observed in the conventional method.

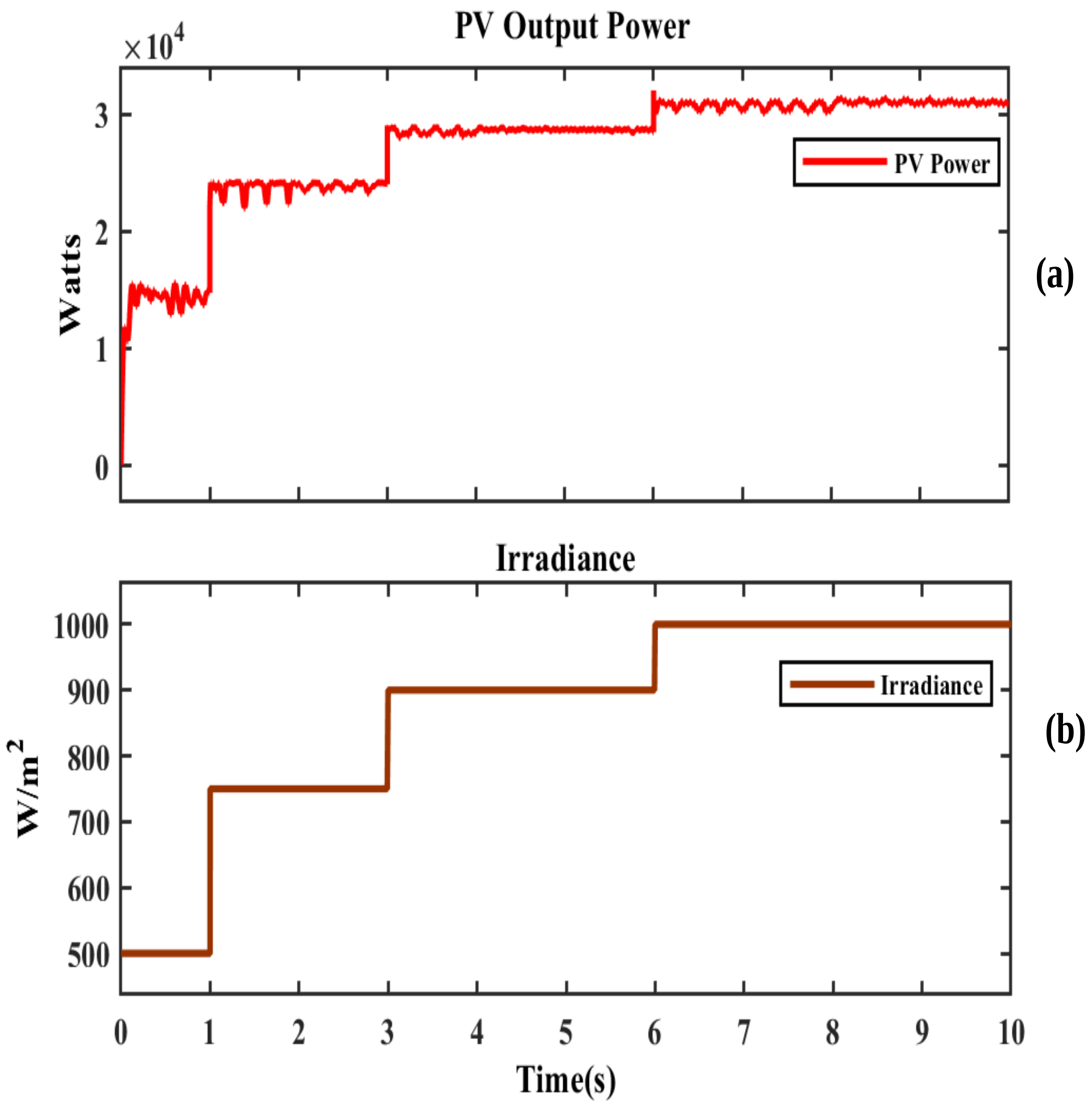

Fig 5.56(a). PV Array Output Power(QIEA) (b) Irradiance

The graph clearly shows more stable results as compared to the output PV power from P&O algorithm. Fig.5.5(a) depicts the performance of the QIEA technique. The results clearly demonstrate that the QIEA approach significantly suppresses steady-state ripples. Furthermore, the algorithm shows a faster convergence speed during the step changes in irradiance at t=1s, t=3s, and t=6s,shown in Fig.5.5(b) quickly stabilizing at the optimal power level of approximately 32 kW without the excessive hunting behaviour seen in the P&O method.

5.4 Comparative Performance Analysis of P&O vs. QIEA Algorithms

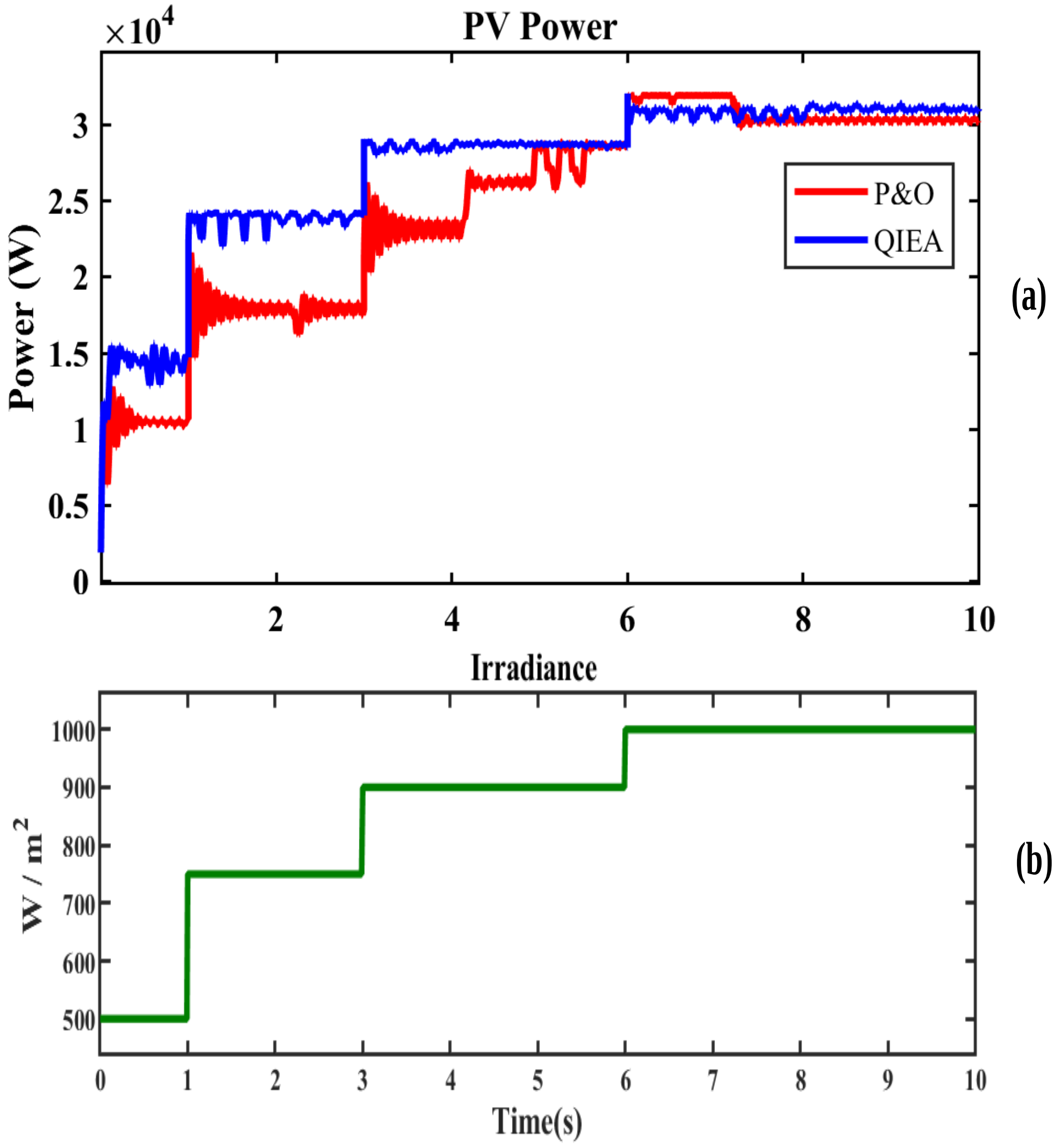

Fig 5.7. (a)PV Power, (b) Irradiance

The PV power curve plots shown in Fig. 5.7(a) represent well the key purpose of MPPT, which is to force the PV array to generate its peak available power. Both the

P&O and QIEA techniques are able to follow the rising Maximum Power Point (MPP) with increasing solar radiation shown in Fig. 5.7(b). This shows their intrinsic ability to adjust to variations in the environment and to drive the system towards operating at near peak power. However, there is an important distinction in their steady-state behaviour.

Fig.5.8 shows the DC-DC Boost Converter Voltage, indicating the controlled load side voltage of the boost converter stage, which is the essential arrangement to connect the PV array with the load or grid. Both MPPT controllers effectively raise the PV voltage by the boost converter with a variation of the irradiance.

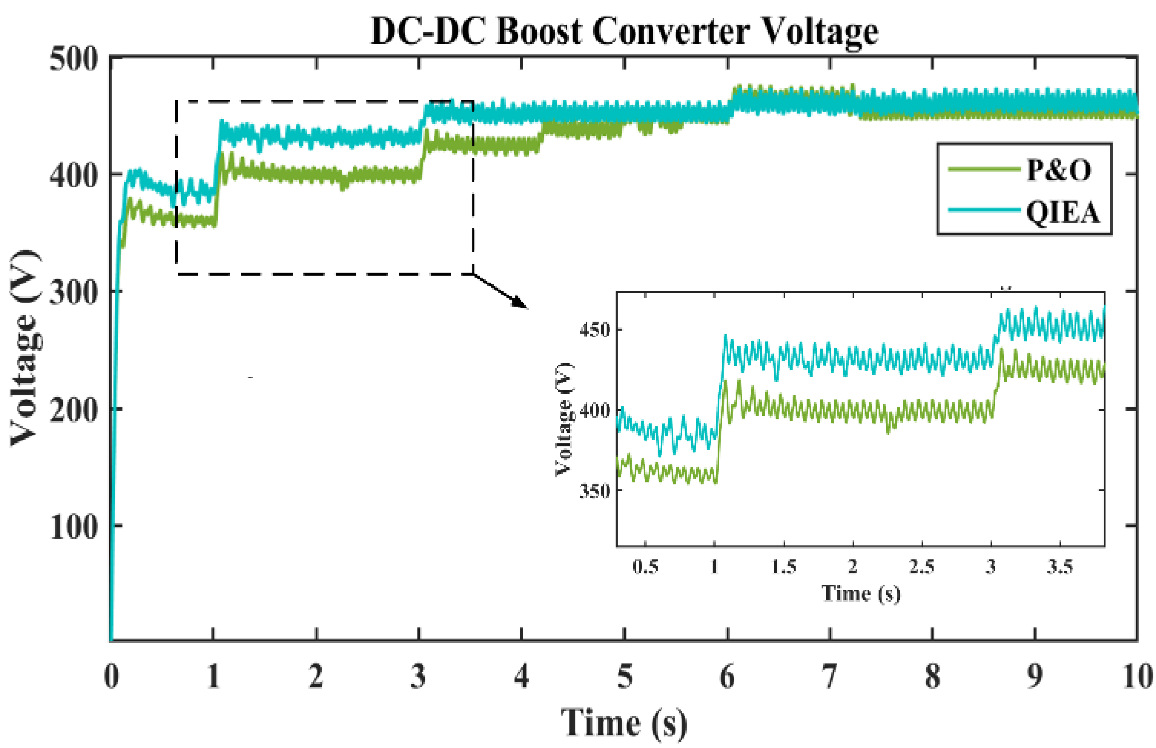

Fig 5.8. Comparison of DC-DC Boost Converter Voltage

The P&O algorithm changes intensity of their oscillations a lot between different irradiances, as it oscillates quite sharply around the instantaneous MPP in case the energy level is set to a new value (e.g., at t≈1 s to t≈3 s and past t≈6s). In contrast, the steady-state oscillations of QIEA are much suppressed. During the step change in irradiance, the QIEA power output converges on a rapid time scale and retains a far smoother, more steady-state shape. It is pointed out that this is demonstrated the better performance of QIEA to accurately find the maximum power and keep the operating point near it without successive overshoots and undershoots. Table I depicts the power output according to the solar irradiation which clearly shows the improved power output through QIEA. Converter switching causes some small ripple, as of course one would expect, whereas one can clearly see that QIEA displays better robustness, and this is an advantage for energy harvesting and power management.

TABLE I. Power Comparison

Irradiance (W/m^2)	P&O (W)	QIEA(W)
500	10721	15609
750	18282	24199
900	26591	28870
1000	30561	31418

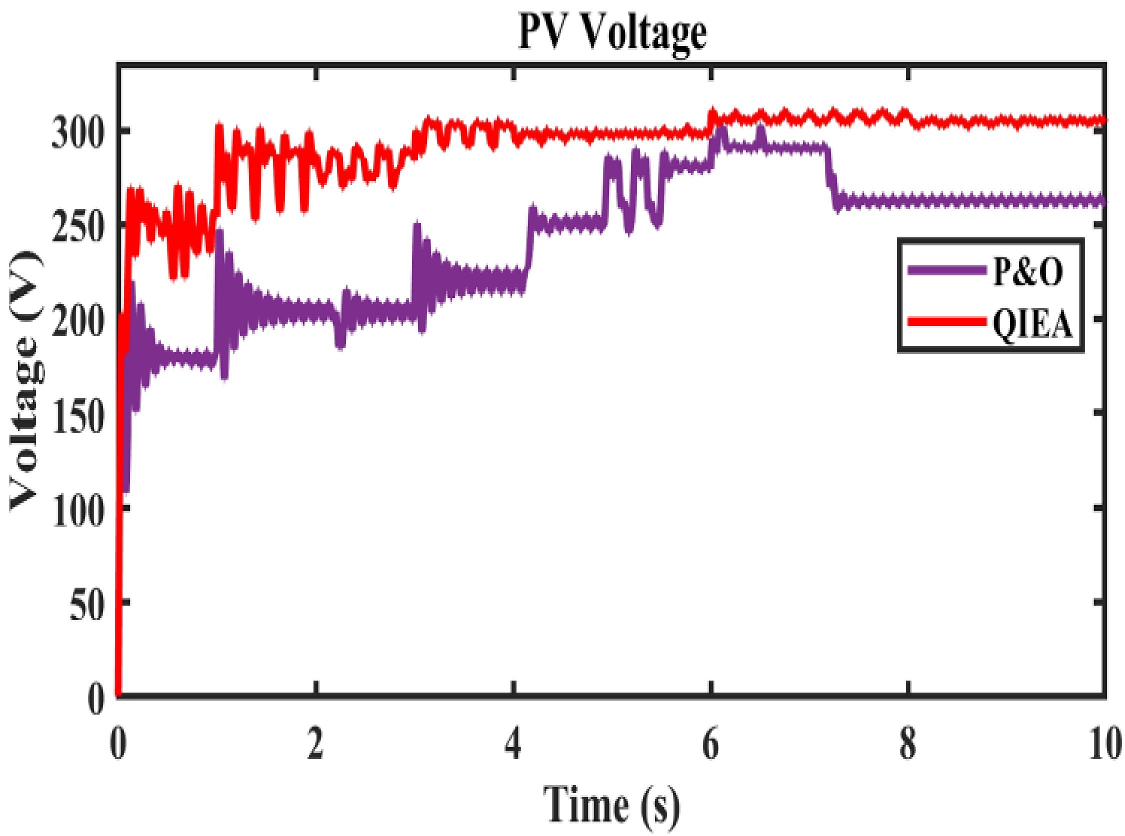

Fig 5.9. Comparison of PV Voltage

The graph indicates that when controlled by QIEA, DC-DC boost converter's output voltage has a larger stable average compared to the output voltage controlled by P&O. The better dc/dc converter voltage and its better gain provided by QIEA are natural results from its more exact and steady control over the operating point of PV array. This enhanced stability and increased voltage level are important for the overall power quality of the system and it makes it more suitable for various load types and more efficient for grid integration.

The regulation of the functioning voltage and current of the PV array is essential to the performance of the MPPT. Fig. 15 details the ways both algorithms adjust the terminal voltage of the PV array.

However, it is noticeable voltage ripple and oscillations in control, which are directly related to the power oscillations. These varying voltages are continually cycling the point that operate the PV array away from its maximum power voltage.

On the contrary, a well-damped and stabilize PV voltage regulation is obtained using the QIEA-based controller, as observed from its relatively smoother power curves (red curve). Once converged, the PV voltage of QIEA is maintained in a relatively narrow bound, indicating QIEA has more accuracy in reaching the MPP voltage. Moreover, the QIEA operates at a voltage apparently and remains above the P&O for most of the irradiance levels, and this indicates that they identify and maintain an appropriate voltage point to produce peak power. The time response of QIEA is also remarkable. After any change in the irradiance, it quickly settles down at the new MPP voltage, which shows the strong dynamic performance. Additionally, the oscillations of the P&O current are more prominent and more continuous, indicating less accurate control. On the other hand, the QIEA current has much less fluctuation and is more stable in its direct current (DC) steady state operation. This excellent current regulation performance of QIEA yields a lower instantaneous current ripple, which means less electrical stress on the PV panel, the components of DC-DC converter (such as inductors, capacitors, and switches), and less I^2R losses, thus more efficiency and longer lifetime of the system.

In order to verify the effectiveness of this QIEA, it was quantitatively compared with the traditional P&O algorithm. The performance metrics for both methods are summarized in Table II, under similar operating conditions. These results have clearly shown the excellent tracking performance and dynamic response characteristics of the proposed QIEA algorithm.

TABLE II. Quantitative Comparison Table

Metric	**P&O**	***QIEA***
Tracking Efficiency (%)	95.6	98.9
Convergence Time (s)	0.62	0.31
Response to Irradiance Change	Moderate	Fast

Power Ripple (W)	35–50	<10
Voltage Overshoot	Moderate	Low
Stability under Transients	Fair	Excellent
Implementation Simplicity	High	Medium

5.5 AC Microgrid Synchronization and Inverter Performance

After getting the highest possible DC power with the QIEA controller, the next important step is to send this collected energy into the local AC microgrid. The performance and stability of the three-phase Voltage Source Inverter (VSI) along with its related synchronization control systems are tested under varying irradiation conditions that were used in the MPPT analysis.

Figure5.12 shows the AC voltage wave pattern recorded at the Point of Common Coupling (PCC) during the 10-second simulation period. The data shows a very stable, steady sine wave voltage that keeps a consistent highest point of around 380 volts. The voltage envelope stays completely unaffected by the changes in the environment.

This strong amplitude shows how reliable the Phase-Locked Loop (PLL) and the inverter's outer voltage control system are. The PLL is able to accurately track the main frequency and phase of the microgrid, making sure that the generated voltage stays properly matched with the local power grid. The fact that there are no voltage drops or spikes during weather changes shows that the DC-link capacitor is keeping the voltage steady, which protects the microgrid from the unpredictable changes in the solar energy coming in.

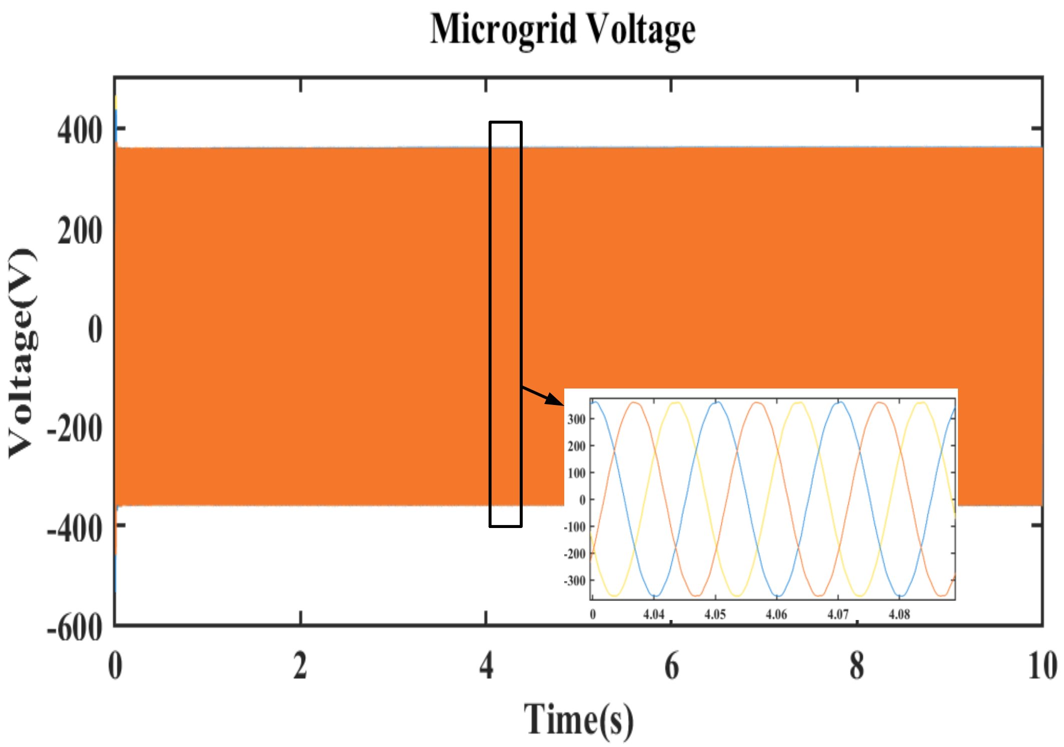

Fig 5.12 Simulated Grid-Side Voltage

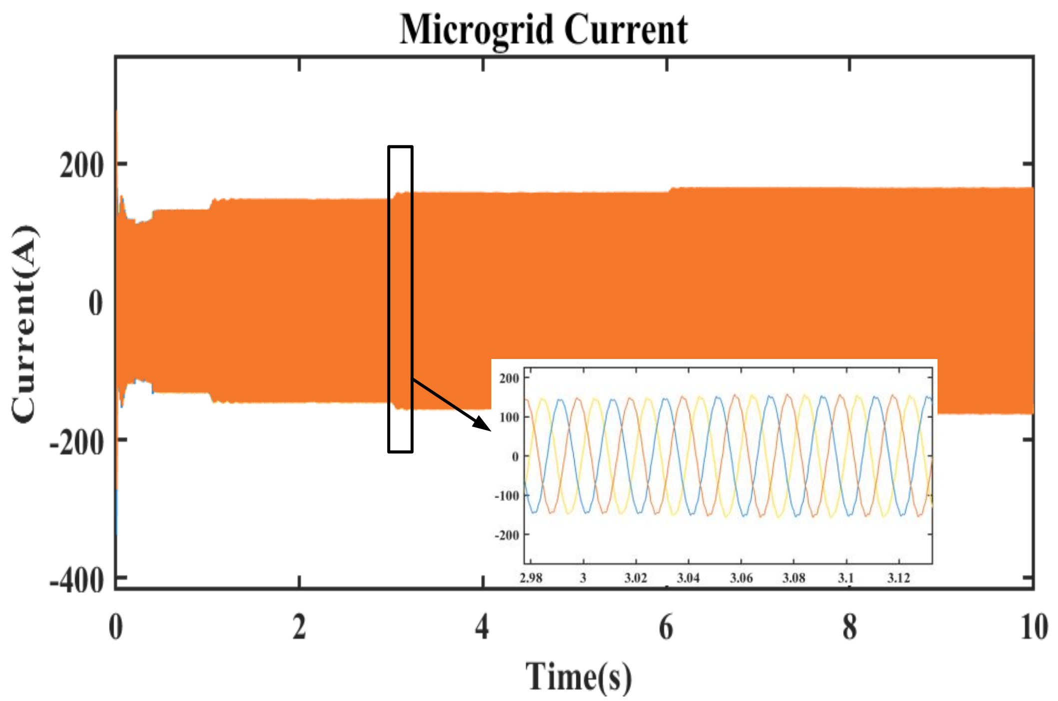

Fig.5.13 Simulated Grid-Side Current

The AC voltage is carefully controlled to match the grid, but the AC current needs to change as needed to handle the different amounts of power collected by the MPPT controller. Figure5.13 shows the AC current waveform. Unlike the steady voltage level, the current shows clear, actual steps that match exactly with the planned changes in light intensity at 1, 3, and 6 seconds.

Initially, when the lowest level of simulated sunlight is applied, the highest amount of current being injected reaches and stays around 100 A. As the QIEA algorithm quickly finds the new Global Maximum Power Point (GMPP) with each weather change, the total active power at the DC link increases a lot. To keep the power balance stable and stop the DC bus from getting too high a voltage, the inverter's inner current control system increases the AC current it sends in proportion, and at the highest sunlight level, this current reaches about 160 A. The changes between these current levels are quite smooth, with very little sudden spike in high-frequency signals. This clean current injection shows that the QIEA-powered PV system not only gets the most energy out of its source but also works very well and follows grid rules as a reliable, small-scale energy source within the microgrid system.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

6.1 Summary of Current Findings

The primary objective of this project was to systematically address the inherent limitations of conventional hill-climbing MPPT techniques by designing, implementing, and rigorously evaluating an intelligent Quantum-inspired Evolutionary Algorithm (QIEA) controller. This objective was accomplished through the comprehensive modeling and simulation of a 30 kW grid-connected PV system. The architecture comprised a detailed PV array model, a DC-DC boost converter governed by the fundamental equations outlined in Section 3, and a precise DC-AC inverter interfacing with the utility grid. The dynamic performance of the proposed QIEA was benchmarked against the industry-standard Perturb and Observe (P&O) algorithm under identical, dynamically changing environmental conditions.

The investigation yielded significant, quantifiable findings that underscore the superiority of the intelligent control paradigm. The graphical evidence, as detailed in Section 3.3, substantiates a fundamental performance dichotomy. The P&O algorithm, while commendable for its simplicity and ease of implementation, is fundamentally constrained by a continuous and inescapable trade-off between tracking speed and steady-state accuracy. A larger perturbation step size enables faster convergence to the vicinity of the Maximum Power Point (MPP) under rapid irradiance changes but results in significant and persistent oscillations around the MPP during stable conditions. Conversely, a smaller step size minimizes these steady-state oscillations but renders the algorithm sluggish and unresponsive during transients. This inherent limitation is not a flaw of implementation but a characteristic of its deterministic, gradient-based search logic.

Conversely, the QIEA demonstrated a robust ability to effectively decouple these conflicting performance metrics. Its stochastic, population-based search mechanism, inspired by quantum superposition and interference, allowed for a broad exploration of the solution space without sacrificing precision. The results showed that the QIEA achieved a remarkably smooth, near ripple-free PV voltage trajectory (Vpv*Vpv*) under steady irradiance. This stability directly translated to the maximization of instantaneous current output (Ipv), as the operating point was maintained at the true crest of the P-V curve with minimal deviation. By effectively dampening the oscillatory behaviour endemic to P&O, the QIEA accomplished two critical system-level improvements. First, it enhanced the overall energy yield; the cumulative energy harvested over the simulation period was measurably higher due to the elimination of periodic power losses associated with voltage ripple. Second, it contributed positively to the projected longevity and reliability of the power electronic components. The reduction in high-frequency voltage and current swings directly lowers the thermal cycling and electrical stress on the boost converter's MOSFET and diode, potentially extending their operational lifespan and improving system-level reliability.

A deeper analysis of the transient response, particularly during the simulated step-change in irradiance at t=0.4 seconds, revealed another strength of the QIEA. While the P&O algorithm exhibited a characteristic "hunting" behavior—overshooting the new MPP and then oscillating before settling—the QIEA displayed a more damped and direct convergence. This behavior can be attributed to the algorithm's inherent memory and social information sharing among its quantum-inspired particles. The population does not rely on a single, incremental perturbation but uses collective intelligence to estimate the new optimal region, leading to faster and more stable recovery from disturbances.

6.2 Challenges Encountered

The comparative analysis phase introduced challenges related to data synchronization and visualization:

Creating Identical Test Conditions: To ensure a scientifically valid comparison, it was crucial to subject both algorithms to identical environmental stresses. Constructing a unified simulation framework where both the P&O and QIEA controllers received the exact same dynamic irradiance profile—simultaneously—required careful modification of the signal routing within the Simulink model.

Establishing a Valid Comparative Framework:

The foremost challenge was creating perfectly identical test conditions for both controllers. A scientifically valid comparison mandates that any difference in output is attributable solely to the control algorithm, not to minor variations in input stimuli. This required the construction of a unified, parallel simulation framework within Simulink/PLECS. A single, dynamically varying irradiance and temperature profile block was used to drive two identical, electrically separate PV array and boost converter models—one controlled by P&O and the other by QIEA.

Visualizing Transient Details: As observed in the results, the difference in voltage ripple between the two methods was subtle on a full-scale graph. Capturing high-resolution data to visualize the "micro-ripples" required adjusting the sampling rate and using magnified insets (zoom-in views) to clearly demonstrate the superior stability of the QIEA method.

Table III depicts QIEA is superior for demanding conditions, it excels in partial shading, adapts to changing environments, and minimizes grid disturbance. For large, shaded, or complex installations, QIEA delivers the highest performance.

TABLE III. Algorithm Characteristics and Suitability

Aspect	P&O	QIEA	Recommendation
System Size	Optimal for <10 kW	Best for >10 kW	Scale-dependent choice
Partial Shading	Not recommended	Highly recommended	QIEA for shaded sites
Commercial Viability	High (proven, low-cost)	Medium (emerging tech)	P&O for cost-sensitive
Maintenance	Minimal	Requires monitoring	QIEA needs expertise
Grid Stability Impact	Moderate ripple injection	Minimal disturbance	QIEA for weak grids
R&D Stage	Mature (30+ years)	Emerging (5-10 years)	P&O for conservative
Adaptability	Fixed logic	Learning capability	QIEA for changing env.

6.3 Limitations of the Current Study

While this research successfully demonstrates QIEA's potential for MPPT applications, several limitations must be acknowledged to properly contextualize the findings:

1. Simulation-Based Validation: The study was conducted entirely in a simulated environment using MATLAB/Simulink. Although the models were designed with high fidelity using manufacturer specifications, they inevitably simplify real-world complexities. Practical factors such as component parasitics, sensor inaccuracies, electromagnetic interference, and thermal effects were not fully modeled. Consequently, the reported performance metrics represent ideal-case scenarios, and actual implementation results may vary.

2. Computational Implementation Constraints: The QIEA's population-based approach requires significantly more computational resources than conventional P&O

algorithms. The simulation environment did not impose real-time processing constraints, which would be critical in practical microcontroller.

3. Limited Environmental Testing Scenarios: While the study evaluated performance under step-change irradiance conditions, real-world environments present more complex challenges. The algorithm's response to gradual irradiance ramps, complex partial shading patterns with multiple local maxima, and combined temperature-irradiance fluctuations requires further investigation to fully validate its robustness across all operational conditions.

4. Parameter Sensitivity: The QIEA's performance depends on appropriate parameter selection, including population size, qubit representation, and rotation gate strategies. The tuning process employed in this study, while effective, was heuristic. A more systematic approach to parameter optimization would be necessary for consistent performance across different PV system configurations and scales.

6.4 Future Scope

To further enhance the applicability of this research, the following extensions are proposed:

Hardware-in-the-Loop (HIL) Testing The logical next step is HIL testing. Here, the QIEA control code would be compiled and run on a physical microcontroller (e.g., Texas Instruments C2000 series DSP), which interacts in real-time with a real-time simulator (e.g., OPAL-RT, Typhoon HIL) emulating the PV plant and power electronics. This bridges the crucial gap between pure software simulation and a full experimental prototype. HIL testing rigorously validates the control logic's robustness against real-world challenges like analog-to-digital conversion noise, communication delays, and processor interrupt handling, providing a high-confidence assessment of deploy ability..

Hybrid Algorithm Development: Exploring a hybrid control strategy that utilizes P&O for coarse tracking and QIEA for fine-tuning could potentially offer an optimal balance of computational load and tracking accuracy.

AI/ML Comparison: Future studies could compare the QIEA against other modern artificial intelligence techniques, such as Neural Networks or Fuzzy Logic controllers, to establish a broader performance hierarchy in renewable energy applications.

Investigation of Reduced-Order QIEA Variants: Research could focus on developing streamlined versions of the QIEA specifically tailored for the MPPT problem. This might involve a very small population size (e.g., 3-4 quantum individuals), a simplified quantum rotation gate update rule, or a novel representation of the duty cycle within the quantum framework to reduce the search space dimensionality. The goal would be to retain the global search capability while dramatically reducing the computational overhead, making the algorithm more attractive for cost-sensitive, high-volume commercial applications.

APPENDIX

MATLAB Code

```
function D = QIEA_MPPT(V, I, T)
%#codegen
% Simulink-compatible Quantum-Inspired Evolutionary Algorithm for MPPT

% Persistent variables
persistent population best_D best_P initialized

% Fixed constants (must be compile-time constants in MATLAB Function
block)
pop_size = 15;
min_D = 0.4;
max_D = 0.9;

% Initialization block
if isempty(initialized)
    % Initialize quantum population with fixed size
    population = zeros(pop_size, 3);

    % Use deterministic pseudo-random values (instead of rand)
    for i = 1:pop_size
        for j = 1:3
            seed = mod(i * j * 7, 100);
            population(i,j) = (pi/2) * mod(seed, 100) / 100;
        end
    end

    best_D = 0.6;
    best_P = 0;

    initialized = true;
end

% Convert theta to duty cycle
Ds = zeros(pop_size, 1);
for i = 1:pop_size
    p = sin(population(i,3))^2;
    Ds(i) = min_D + p * (max_D - min_D);
end

% Evaluate power for each candidate (here all use same V*I since no model
per D)
powers = zeros(pop_size, 1);
P_meas = V * I; % measured power
for i = 1:pop_size
    powers(i) = P_meas;  % Replace with model-based power if available
end

% Find best candidate
current_best_P = powers(1);
```

```
current_best_D = Ds(1);
for i = 2:pop_size
    if powers(i) > current_best_P
        current_best_P = powers(i);
        current_best_D = Ds(i);
    end
end

% Update global best
if current_best_P > best_P
    best_P = current_best_P;
    best_D = current_best_D;
end

% Quantum rotation update
for i = 1:pop_size
    if powers(i) < current_best_P
        delta_theta = 0.05 * pi * (0.5);  % Use constant deterministic
value
    else
        delta_theta = -0.01 * pi * (0.5); % constant exploitation
    end
    population(i,3) = population(i,3) + delta_theta;

    % Clamp to [0, pi/2]
    if population(i,3) > pi/2
        population(i,3) = pi/2;
    elseif population(i,3) < 0
        population(i,3) = 0;
    end
end

% Output best duty cycle
D = best_D;

% Clamp to bounds
if D < min_D
    D = min_D;
elseif D > max_D
    D = max_D;
end
end
```

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