INVESTIGATION ON SOLAR PV SYSTEMS FOR MAXIMUM POWER POINT TRACKING USING EVOLUTIONARY OPTIMIZATION ALGORITHMS

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2024

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Abstract

Photo voltaic (PV) Systems which are exposed to several disturbances like temperature variation, irradiation differences, partial shading conditions etc. are the reasons for PV cells nonlinear electrical characteristics. Operating conditions of PV System need to be ensured at maximum power point for extracting maximum PV Power available due to its low efficiency. By using maximum power point tracking (MPPT) Controller with the support of power electronic this can be achieved.

Partial shading conditions (PSC) which are severe out of all disturbances to PV System due to environmental conditions effects output power extraction. Partial shading effect results in electrical characteristics with multiple maximum power point (MPP) in PV System due to bypass diode presence in shaded module. Global MPP is the one out of all MPP which can produce maximum power from PV System in case of shading conditions due to environmental disturbances and remaining all others are local MPPS. In case of remaining disturbances which create uniform shading electrical characteristics exhibit single MPP.

Useful PV Power gets wasted by getting trapped at local MPP due to the failure of conventional MPP Techniques for tracking Global MPP. In this work, modelling of partial shaded PV System by considering the effect of both shunt and series resistance has been presented and further it has been extended to different combinations of eight PV modules i.e. four series two parallel, eight series and two series four parallel PV configurations.

The simplicity of particle swarm optimization (PSO) MPPT make it more preferable for implementation but there are some limitations. The proposed work has advancements in terms of algorithm related to MPPT, named Marine Predator Algorithm (MPA), which has an objective function to maximize output power.

In this work, an analytical model of a PV system operating under PSC is developed by considering the impact of both series and shunt resistances. The investigation explores the influence of varying various parameters such as temperatures, irradiation levels, series& shunt resistances and PSC on the PV array's electrical behaviour. By comparing the proposed model with real-time data across different PSC scenarios, the research establishes the reliability of the model, showcasing its potential applicability for a wide range of PV setups and encompassing both standalone and grid-integrated systems.

The research also integrates a novel approach called the marine predator algorithm (MPA), which draws inspiration from biological meta-heuristic algorithms. This MPA methodology is implemented using MATLAB/Simulink software and validated through both simulation and hardware experimentation under various PSC, the results showcase the superior performance of the MPA in terms of convergence time, efficiency, accuracy, and power extraction.

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V.Sampath Kumar

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List of Abbreviations

2S2P	Two Series Two Parallel
2S4P	Two Series Four Parallel
4S	Four Series
4S2P	Four Series Two Parallel
6S4P	Six Series Four Parallel
8S	Eight Series
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ANN	Artificial Neural Networks
BFBIC	Boost Full-Bridge Isolated Converter
CSO	Cuckoo Search Optimization
CSP	Concentrated Solar Power
DPSO	Dual-Stage Particle Swarm Optimization
DSP	Digital Signal Processors
EGWO	Enhanced Grey Wolf Optimization
FA	Firefly Algorithm
FAD	Fish Aggregation Devices
FBPSO	Forward backward Particle Swarm Optimization
FF	Fill Factor
FOC	Fractional Open Circuit

FPA	Flower Pollination Algorithm
FSC	Fractional Short Circuit
GA	Genetic Algorithm
GHO	Grass Hopper Optimization
GMPP	Global Maximum Power Point
GSA	Gravitational Search Algorithm
GW	Giga Watts
GWO	Grey Wolf Optimization
GWp	Giga Watt Peak
HC	Hill Climbing
INC	Incremental conductance
IV	Current Voltage
LMPP	Local Maximum Power Point
MFO	Moth-Flame Optimization
MLPE	Module-Level Power Electronics
MPP	Maximum Power Point
MPPT	Maximum Power Point Tracking
MW	Mega Watt
P&O	Perturb and Observe
PLL	Phase Locked Loop
PopB	Backward Initialization of Population
PopF	Forward Initialization of Population
PS	Pattern search

PSC	Partial Shading Conditions
PSO	Particle Swarm Optimization
PV	Photovoltaic
SA	Simulated Annealing
SDM	Single Diode Model
SRA	Search and Rescue
STC	Standard Test Conditions
TCT	Total Cross Tied
TDM	Two Diode Model
WOA	Whale Optimization Algorithm

1

Introduction

1.1 Introduction

Non-conventional energy is vital for electricity production as traditional fuels diminishes and demand rises. Many countries now switch to solar photovoltaic (PV) System for power generation, enjoying advantages such as abundant, never-ending solar energy, reduced greenhouse gas emissions, and eco-friendliness. Multiple PV cells are connected in series and parallel to build PV Modules for diverse applications.

Several classic maximum power point tracking (MPPT) controllers, including incremental conductance (INC), hill climbing (HC), and perturb and observe (P&O), perform under uniform shaded circumstances effectively to track maximum power point (MPP) but these are unable to follow the global MPP (GMPP) due to partial shading conditions (PSC), resulting in wasted viable power and a reduction in PV system efficiency[1]. Some writers employed intelligence-based methodologies like fuzzy systems, which utilize a mathematical framework fuzzy logic that handles uncertainty and imprecision in decision-making and control processes. These systems are particularly effective when dealing with complex, ambiguous, or vague information. Whereas artificial neural network (ANN) computational models are influenced by human brain design and operation. They are used to model difficult relationships and patterns in data under PSC to extract maximum power from the literature[2], [3] however these techniques require sufficient training and are system dependent. Metaheuristic algorithm-based solutions are an appealing option for PV MPPT under PSC.

1.2 Solar Scenario

The vast amount of accessible solar energy makes it a powerful electricity source. In 2014, solar energy's yearly potential was 109.613 TWh which is much more than the world's total energy consumption. Solar energy technology will have enormous long-term benefits, as well as worldwide advantages. Figure 1.1 depicts the solar energy absorbed and emitted by the planet [136].

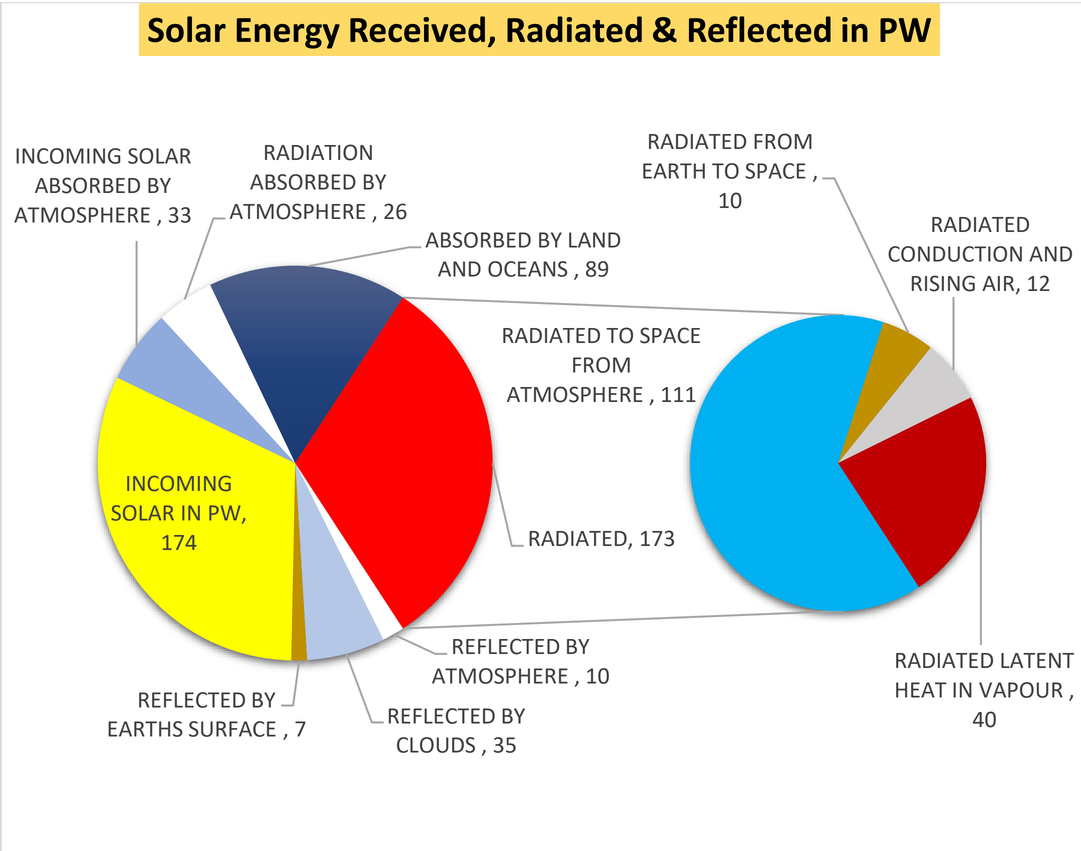


Figure 1.1. Solar Energy Received, Radiated& Reflected in PW

Solar radiation strikes the Earth in huge amount out of which 30% is reflected back into space, while the rest is absorbed by land, seas, and clouds. About 3,850 Zetta Joules (ZJ) of solar energy is absorbed by them (one Zetta represents a factor of 1021). In a year, the sun's energy reaches the planet's surface at a rate that is doubles that of all conventional energy sources combined.

1.2.1 Solar Energy

Solar energy refers to the natural light and heat emitted by the sun, which can be utilized through various technologies including PV's solar heating, and thermal energy systems. These are divided into two categories:

1) Active Technologies
2) Passive Technologies

Building Orientation, solar water heating, concentrated solar power (CSP), and PV systems are active technologies, whereas choosing favorable materials is a passive technology.

1.2.2 Solar Power Generation

Solar power is generated by turning the sun's energy into electricity, either directly or indirectly through PV or CSP systems. The installed capacity of solar power has experienced a remarkable growth, expanding over 18 times from 2.63 GW in March 2014 to reach 49.3 GW by the end of 2021. In the fiscal year 2022, India witnessed the addition of 7.4 GW of solar power capacity which also reflects a substantial increase of 335% compared to the previous year's 1.73 GW.

1.2.2.1 PV System

PV cells transform the sun's radiant energy into a flow of electrons and works on the basis of PV effect. Photons of light are used to excite electrons into a higher state, and these electrons operate as charge carriers. This phenomenon was first observed in the 19^{th} century by scientists such as Alexandre-Edmond Becquerel. The key to the PV effect lies in the unique properties of semiconductors, which form the basis of solar cell technology.

1.2.2.2 CSP Generation

CSP systems utilize lenses and tracking mechanisms to concentrate a vast amount of sunlight onto a small area, resulting in concentrated heat that is used to convert working fluid into steam to create electrical power via a turbine.

1.3 PV Power Generation

Sunlight can be directly turned into electrical energy due to the PV effect. PV systems are built by combining series and parallel PV modules. PV provides a number of benefits including no greenhouse gas emissions, no moving components and inexhaustibility. PV systems may be operated in two modes such as freestanding and grid-connected. Atmospheric conditions have a negative impact on PV system power output.

1.3.1 Growth of solar PV

PV is growing at an exponential rate all around the world and it is dominated by countries like USA, China, Germany, India and Japan. Solar power generation is expected to surpass coal as the world's highest source of electrical energy by 2050 as shown in figure 1.2.

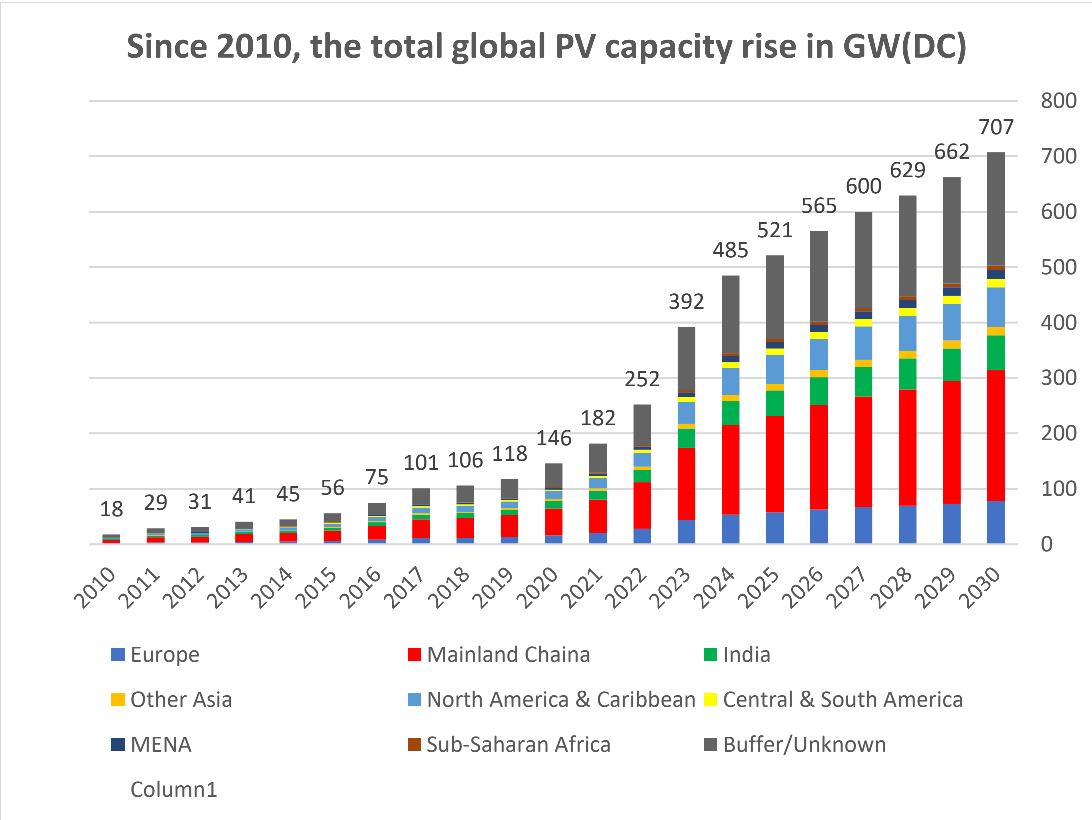


Figure 1.2. Since 2010, the total global PV capacity rise.

1.3.1.1 Growth in World

Significant solar power capacity has been included into the electricity networks of numerous nations and areas as a substitute or addition to conventional energy sources. The global growth of PVs has been remarkably dynamic with substantial variations among countries. By 2019, worldwide solar power installed capacity reached an impressive 629 GW. By early 2020, China took the lead as the top country in solar power generation with an impressive capacity of 208 GW, constituting roughly one-third of the global installed solar capacity. Moreover, over 37 countries across the globe had accumulated PV capacities exceeding one gigawatt by 2020[137].

1.3.1.2 Growth in India

In India the ministry of new and renewable energy (MNRE) looks after the renewable energy sources development. About 5,000 trillion kWh per year energy is incident over India’s land area with most parts receiving 4-7 kWh per sqm per day. As per National Institute of Solar Energy, the country's solar potential is approximately 750 GWp, assuming that 3% of unused land area could be utilized for solar PV modules. Notably, India has recently surpassed Italy, securing the 5th global position in solar power deployment. Over the past five years, solar power capacity in India has grown significantly which is increased to 49.3 GW in March 2021 from 2.6 GW in March 2014. As of now tariffs of solar power in India have become highly viable and have achieved grid equivalence. The implementation of the plug and play model has resulted in a reduction of over 75% in solar power tariffs with a record low of Rs 1.99/unit. Karnataka and Rajasthan lead in solar power capacity with 7328.86 MW and 5389.48 MW, respectively. As of December 31, 2020, the total installed solar power capacity in India stands at 37.46 GW. Additionally, there are around 36.69 GW of solar power tenders in the pipeline for which Letter of Intent (LoI) has been issued but not yet commissioned. Furthermore, tenders for approximately 18.47 GW are yet to receive the issuance of LoI. Solar power installed capacity has reached around 70.10 GW as on 30-06-2023. The capacity of 70.10 GW includes 57.22 GW from ground-mounted solar projects, 10.37 GW from rooftop solar projects, and 2.51 GW from off-grid solar projects.

1.3.2 PSC

In a photovoltaic (PV) system, solar panels are connected in series to create higher voltage output. PSC is an adverse phenomenon, where PV modules are subjected to partial shading (due to passing clouds, building shadows, bird waste etc.). When PV system is subjected to PSC, due to bypass diode operation across shaded modules its electrical characteristics exhibit multiple MPPs which are points on the current-voltage (I-V) curve where the power output is maximized.

Figure 1.3 (a) & (b) depicts PV systems with four PV modules, which are represented as four series (4S), two series two parallel (2S2P) arrangements of PV modules respectively.

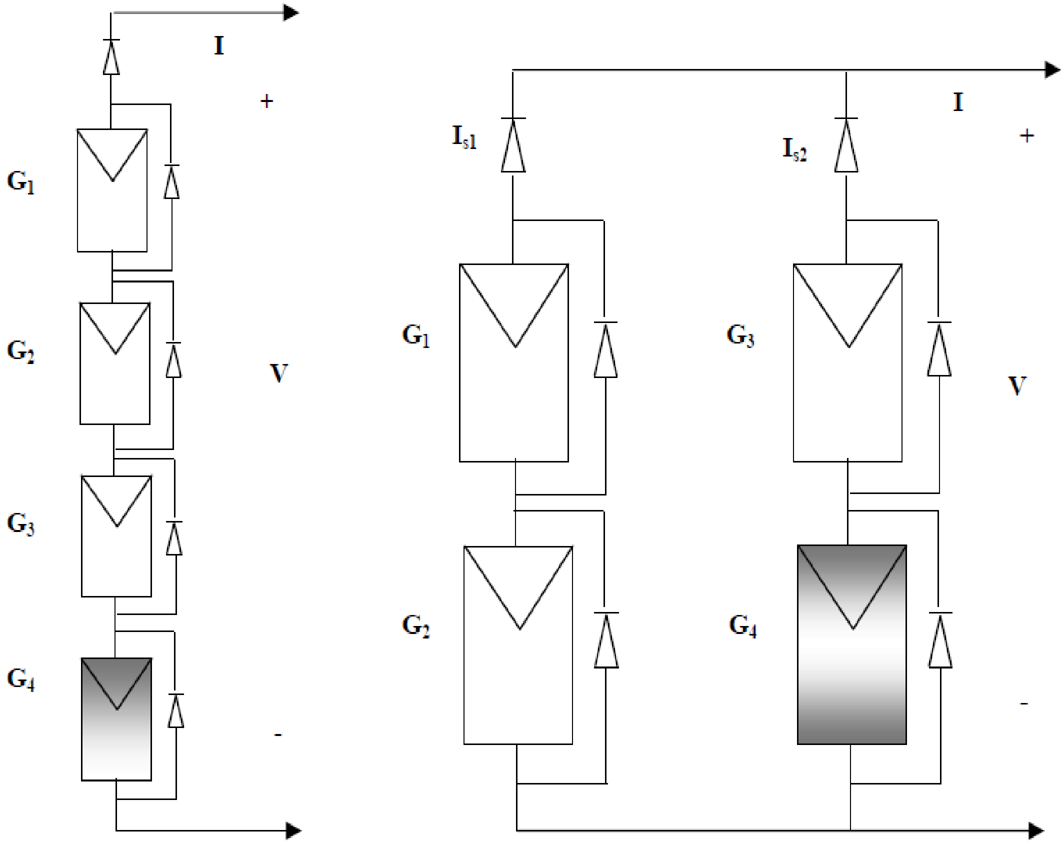


Figure 1.3. (a) PV 4S configuration (b) PV 2S2P configuration

Assume each PV module in Figure 1.3(a) receives same irradiation of 1000 W/m^2 and rating of each module is 200 W at STC (The significance of Standard Test

Conditions in facilitating fair and realistic comparisons among solar panels from different manufacturers in providing a common ground for fair and realistic comparisons. The choice of 200 watts as a benchmark ensures consistency, reliability, and meaningful insights for consumers, industry professionals, and the solar industry as a whole). As irradiation is same, bypass diodes are reverse biased resulting same current flows through all modules and electrical characteristics of PV array exhibit only single MPP. When the PV array is subjected to partial shading, module G4 receives less irradiation (500 W/m^2) while other modules in the string receives 1000 W/m^2. The module G4 acts as load instead of generator and it tries to take the current generated from unshaded modules. The bypass diode is forward biased and protects the shaded module from being damaged. Due to diversion of current by bypass diode, the electrical characteristics have multiple MPPs of which one is global MPP with more power output. If bypass diode is removed, array exhibit only one MPP, but output is drastically reduced. The blocking diodes shown in Figure 1.3(b) prevent the reverse current from other strings due to voltage mismatch between two strings.

There are numerous strategies for reducing the impact of partial shading, including as

1. MPPT Controllers

2. Reconfiguration of PV Array

3. Configurations of power electronic converter

The MPPT controller is utilized in this study to offset the effects of PSC and to harvest all of the PV power available by running at GMPP. Exploration of a Novel Algorithm for Enhancing GMPPT in PV Systems.

1. Photovoltaic Systems and Associated Challenges:

As society gravitates toward sustainable energy solutions, PV systems emerge as pivotal players in this transition. Nevertheless, these systems encounter a set of challenges that directly impact their overall efficacy. The intricacies of PV system performance are intricately tied to environmental variables such as sunlight intensity, temperature fluctuations, and instances of shading. Conventional MPPT algorithms, though effective in certain scenarios, often exhibit sluggish adaptability in dynamic environmental conditions.

2. Significance of GMPPT in PV Systems:

GMPPT represents the optimal operating point where the system generates the highest attainable power output in prevailing environmental conditions. Ensuring precise tracking of the GMPPT is imperative for maximizing energy yield and optimizing the overall performance of PV systems.

3. Limitations Inherent in Existing MPPT Algorithms:

The prevailing MPPT algorithms, including widely utilized methodologies like Perturb and Observe or Incremental Conductance, come with inherent limitations. Their responsiveness, especially during swift shifts in environmental conditions, can be sluggish. Moreover, these algorithms may encounter difficulties in scenarios involving partial shading or erratic changes in solar irradiance.

4. Unleashing the Potential of Innovative Algorithms:

Addressing the challenges outlined necessitates a paradigm shift in MPPT algorithm innovation. Novel algorithms hold the promise of delivering heightened adaptability, accelerated response times, and improved efficiency in capturing the GMPPT across diverse conditions. This research is poised to explore unconventional methodologies, drawing inspiration from varied fields or principles beyond the confines of traditional approaches.

5. Harnessing Concepts from Diverse Disciplines:

This study envisions drawing inspiration from concepts originating in fields such as artificial intelligence, optimization, or bio-inspired computing. By embracing cross-disciplinary approaches, we aim to uncover innovative strategies for GMPPT that surpass the limitations posed by current algorithms.

6. Integration of State-of-the-Art Environmental Sensing:

An instrumental aspect of elevating GMPPT algorithms involves integrating cutting-edge environmental sensors. These sensors, equipped to deliver real-time data on sunlight intensity, temperature dynamics, and patterns of shading, stand to significantly enhance the accuracy and responsiveness of the tracking algorithm.

7. Simulation and Real-World Validation Framework:

Simulations serve as a fundamental phase in the developmental journey of algorithms, providing a platform for swift prototyping and evaluation within controlled environments. However, the ultimate validation lies in the application within the real-world context. This research emphasizes a seamless transition from simulation to implementation on tangible PV system hardware, assuring the algorithm's effectiveness in authentic scenarios.

8. Anticipated Outcomes and Project Impact:

The envisaged outcomes encompass the creation of an avant-garde GMPPT algorithm showcasing superior performance compared to its predecessors. Through a meticulous blend of simulations and real-world validations, the research endeavors to demonstrate the algorithm's efficacy, adaptability, and potential for augmenting the overall energy output of PV systems. Beyond the research sphere, the anticipated impact extends to the advancement of renewable energy technology, ushering in more dependable and efficient PV systems.

So the imperative for groundbreaking innovations in GMPPT algorithms for PV systems articulates the constraints of existing approaches, proposes a multidisciplinary exploration to design pioneering algorithms, and emphasizes the integration of advanced environmental sensing. The seamless transition from simulation to tangible implementation emphasizes the practical relevance and potential transformative impact of this research endeavor.

1.3.3 MPPT

PV systems are run at MPP utilizing MPPT controllers to collect highest power under any climatic circumstances. The efficiency of power transfer is the key issue addressed by MPPT and it is determined by the amount of sunshine received and the load connected. The load characteristics and MPP both fluctuate with irradiation, and the system operates most efficiently when it is at MPP. Here the MPPT controller is used to mitigate the impacts of PSC by operating the PV system at GMPP in order to collect all available PV power.

1.3.3.1 MPPT implementation

The operational point is seldom at MPP when a load is connected directly to a PV system. The operating point of a module is determined by the impedance observed by the system and pushed towards MPP by changing impedance. To match the source's and load's impedances, DC-DC converters are used. By adjusting the converter duty ratio, the impedance observed by the module can be modified. At a specific duty ratio, the MPP will serve as the operating point. Variations in atmospheric variables as irradiance, temperature, and PSC affect the properties of the module. As a result, under such dynamically changing operating conditions, the duty ratio is not set.

MPPT controllers evaluate module voltages and currents on a regular basis and alter the duty ratio as needed. MPPT approaches like traditional PSO, GWO, MFO, and proposed MPA approaches are implemented using Arduino MEGA-2560 controller.

1.3.3.2 DC-DC Converter

To get maximum PV power, the MPPT controller's power stage uses power electronic converters such as DC-DC converters and/or inverters. There are various DC-DC converter topologies that are widely utilized for PV applications in the literature[4]. To connect the PV system and load, an MPPT is utilized in conjunction with a boost type DC-DC converter. Figure 1.4 depicts the block diagram for the MPPT controller.

1.4 Objectives of the Research Work

In response to the growing demand for sustainable energy sources, the optimization of PV systems has become a central focus. A critical aspect of this optimization involves the effective tracking of the GMPPT of PV arrays, a key factor in maximizing power output amidst changing environmental conditions. This research endeavors to tackle this challenge by conceptualizing and implementing an innovative algorithm for GMPPT in PV systems. While existing MPPT algorithms have shown effectiveness, this research aims to explore novel approaches beyond conventional methods, emphasizing adaptability and responsiveness.

1. Algorithm Innovation:

- Propose and cultivate an original GMPPT algorithm that surpasses the capabilities of current methodologies.
- Harness innovative concepts or principles, potentially from diverse fields beyond traditional MPPT approaches, to enhance adaptability and efficiency.

2. Environmental Sensing Integration:

- Integrate cutting-edge environmental sensors to capture real-time data, including sunlight intensity, temperature, and shading patterns.
- Develop algorithms for processing and interpreting sensor data to inform the novel GMPPT algorithm.

3. Simulation and Performance Evaluation:

- Implement the novel GMPPT algorithm within a simulation environment.
- Evaluate its performance under various environmental scenarios, considering factors such as rapid changes in irradiance and partial shading.

4. Comparative Analysis:

- Conduct a comprehensive comparative analysis between the novel GMPPT algorithm and established MPPT methods.
- Assess the algorithm's efficiency, adaptability, and responsiveness compared to traditional techniques.

5. Robustness and Adaptability Testing:

- Rigorously test the robustness and adaptability of the novel GMPPT algorithm under real-world conditions.

- Evaluate its ability to handle sudden changes in environmental parameters without convergence issues.

6. Integration with Hardware:

- Implement the novel GMPPT algorithm on physical PV system hardware.
- Validate its performance using real PV panels and associated components.

Requirements:

- Proficiency in algorithm design and optimization.
- Familiarity with advanced sensor technologies for environmental monitoring.
- Knowledge of PV system characteristics and behavior.
- Strong programming skills for simulation and hardware integration.
- Access to PV system components and advanced environmental sensors.

Expected Outcomes:

- The development of an innovative and effective novel GMPPT algorithm for PV systems.
- Simulation results showcasing superior performance under diverse environmental conditions.
- A comprehensive comparative analysis highlighting the advantages of the novel algorithm over traditional MPPT methods.
- Validation of the algorithm's effectiveness through its implementation on physical PV system hardware.

The successful implementation of a novel algorithm has the potential to significantly improve the efficiency and adaptability of PV systems, marking a substantial contribution to the field of renewable energy.

In PV systems, MPPT algorithms are frequently employed, but the search for the GMPPT in a PV array is still a research gap for various reasons.

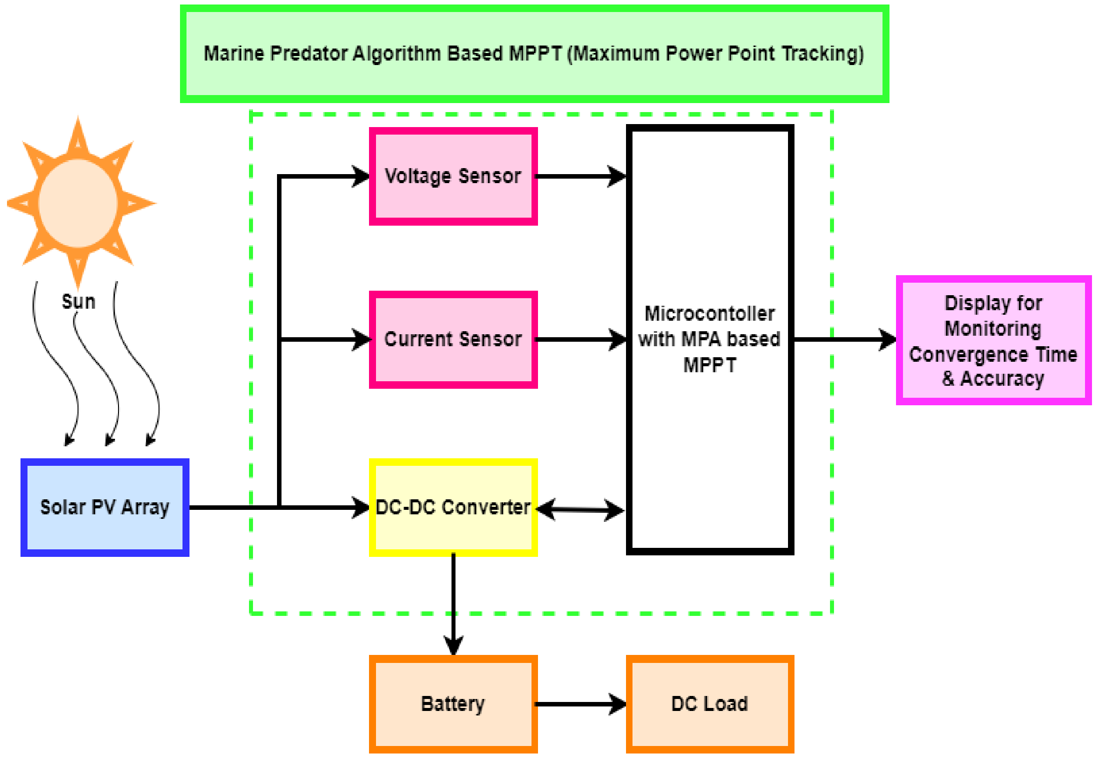


Figure 1.4. Block diagram of MPPT controller

i) MPPT hybrid technique: Researchers are exploring hybrid MPPT techniques that combine algorithms to handle changes in radiation and temperature more effectively. These hybrids improve the accuracy and speed of GMPPT.

ii) Real world conditions: MPPT algorithms often overlook real-life factors like shade, weather changes, and sign deterioration, which greatly impact GMPPT estimates. Developing algorithms to handle these complexities is an ongoing research challenge.

iii) Efficient and powerful: Researchers continually develop MPPT algorithms that are efficient in energy extraction and robust in different conditions.

iv) Objective: Ensure consistent tracking of GMPPT in various situations.

v) Challenges in hardware implementation: Real-time computation, communication latency, and control loop stability. Research aims to connect theoretical advances with practical implementation challenges.

Therefore, the search for the GMPP in PV arrays continues to be an active area of research due to real-world complexity, module variations, inter-module interaction and the pursuit of more efficient MPPTs.

For maximizing solar energy production and by consideration of research gap and research background, the following are the objectives that were met in this work:

a) Mathematical formulation of PV Model, considering single and double diode model and taking into consideration the impact of both series and shunt resistance under irradiation conditions.

b) Formulation of effective metaheuristic a search technique to monitor the PV system's overall MPPT in PSC that are constantly changing.

c) Performance Analysis and comparison of the proposed metaheuristic algorithm based MPPT algorithm with different techniques to mitigate the effect of partial shaded conditions in PV Systems.

Identifying the electrical characteristics of PV systems for irradiation, temperature, and internal parameters such series and shunt resistance variations of a PV module, as well as PSC of the 8S, 4S2P, and 2S4P configurations, addresses the first objective. Because of the bypass diode functioning across the shaded modules, under PSC, the P-V characteristics show a number of local MPPs. As illustrated in Chapter 3, the suggested model is employed to imitate higher levels of partially shaded PV systems.

The second and third objective is achieved by introducing bio-inspired marine predator algorithm (MPA) is used by controlling duty cycle of boost converter for GMPP tracking of PV panel with high precision. To demonstrate the efficacy of the MPA approach, the efficiency, power at MPP and time to track the MPP for various PSCs were calculated. The results reveal that the MPA technique achieves a high level of MPP tracking accuracy in the steady state when compared to moth flame optimization (MFO), grey wolf optimization (GWO) and particle swarm optimization (PSO) techniques, as presented in Chapter 4&5.

1.5 Organization of the Thesis

Chapter 1: Introduces solar energy and its current state in the globe and in India, as well as solar PV power generation and installation under various climatic circumstances.

Chapter 2: Provides literature review on several types of PV models, parameter extraction approaches, partly shaded condition modeling, PSC mitigation techniques, and MPPT procedures under PSC.

Chapter 3: Examines the use of a single-diode model & double diode model to analyze PV systems in PSC and partly shaded situations, taking into account the effects of both shunt and series resistances.

Chapter 4: The implementation of improved and heuristic algorithms for MPPT under constantly changing partly shadowed situations is described. The suggested MPPT approaches' tracking results are given and reviewed.

Chapter 5: The comparison of different MPPT algorithms for various PV systems subjected to different dynamically changing shade patterns is shown.

Chapter 6: The findings of this research are presented.

1.6 Summary

This chapter provides an overview of solar energy and its current state in the globe and in India. An overview of the many solar power producing systems are presented. This chapter introduces solar PV systems, the effect of PSC on solar PV systems, and several ways for mitigating the effect of PSC. Within this chapter, the concept of MPPT is discussed, along with the utilization of a DC-DC boost converter to effectively track GMPP , research background and research gaps of GMPPT are presented. Importance of GMPPT in PV power generation , formulating objectives and organization of the thesis are presented in this chapter.

2

Literature Survey

2.1 Introduction

This chapter provides a review of the literature on different types of PV systems, modeling of various types of PV cell models, and parameter extraction approaches. One of the main contributions of the thesis is modeling of PV systems under PSC; in this chapter, numerous types of modeling approaches used in the literature are explored, as well as alternative strategies to reduce the influence of PSC on PV power output. In this chapter the numerous conventional, hybrid MPPT approaches as well as artificial intelligence and metaheuristic-based MPPT strategies are all thoroughly reviewed.

2.2 Literature Survey

2.2.1 PV Systems

Prakash et al. [4] provided a comprehensive analysis of grid-connected PV system topologies and components such as PV cells, PV array topologies, filters, MPPT, power electronic converters, regulating approaches, and grid integration. Academicians working on both independent and grid-connected PV systems will find this work extremely useful. Various PV cell types, different PV configurations, impacts of PSC, structure and topologies of different inverter based PV systems, MPPT, energy storage, and grid synchronization of PV systems through phase locked loop(PLL) were briefly examined by Enrique et al. [5]. Seyedmahmoudian et al. [6] developed a freestanding PV system with the hardware concept of a PV array simulator and two batteries with electronic load for suitable PV system size selection.

Molina et al. [7] used an experimental method to illustrate the thorough characterization and dynamic nature of grid-linked systems. This research enables researchers to evaluate the impact of PV systems on the electric grid.

2.2.2 PV Modeling

Sam Koohli-Kamal et al. [8] provided a complete review on modeling of PV cells, arrays, and strings for the assessment of power system dynamic performance, as well as a new categorization of existing modeling approaches, namely circuitry and equation based methods. The author found that circuit-based modeling is simpler, whereas equation-based modeling is more accurate but requires more computation.

Sangram et al. [9] addressed the issue of insufficient PV cell fabrication data for PV system simulation. Iterative approaches are used to acquire the unknown parameters of the single diode model (SDM) and the two diode model (TDM) for PV systems. When the authors evaluated the two models, they found that the TDM is more accurate under low irradiation. Ahmed et al. [10] used MATLAB/Simulink to construct both SDM and TDM PV cell models, and parameters were calculated using an accurate technique. Under STC and changing environmental conditions, the findings of both SDM and TDM are experimentally confirmed with an ISOFOTON I-75 panel (Matlab/Simulink Module). The authors provide an accurate optimization of PV parameters in both SDM and TDM using the cuckoo search optimization(CSO) technique[11].

For PV researchers to grasp I-V curves and accurately anticipate PV system performance under external climatic circumstances, Tao Ma et al. [12] created a simple and accurate PV simulation model. Giuseppina et al. [13] provided a brief overview of several solar PV technologies, as well as an explanation of the electric behavior of various single junction PV cell types and their performance under various temperature and irradiance situations. A new TDM PV cell model with fewer parameters was developed by Chittibabu et al. [14]. The authors reduced the number of parameters for modeling a TDM PV cell from seven to four without sacrificing accuracy by neglecting the shunt and series resistance, and the findings were experimentally confirmed.

The authors in [15] developed a four-parameter TDM PV cell model that includes the shunt and series resistances, and the parameters are derived using Newton's iterative approach. This model is more accurate under low irradiance circumstances, and the authors have expanded it to include the PSC of a PV system. Adel et al. [16] suggested a seven-parameter PV cell model, with parameters collected using the Newton Raphson(NR) and Runge-Kutta(RK) methods. The accuracy is evaluated on three different types of data, and the findings are compared to the manufacturer's data sheets to confirm the correctness. The authors of [17] suggested a reduced parameter TDM PV cell model that is simple, accurate, and quick. The suggested model's correctness is confirmed by testing with six distinct PV modules types. The comparison of results with the data sheets provided by the manufacturer. Under changeable temperature and irradiation circumstances, the suggested model performs better.

2.2.3 Parameter Extraction

Parameter extraction of a PV array involves determining the key electrical characteristics that define its performance across various conditions. These parameters are vital for accurately modeling and optimizing the array's operation.

Askarzadeh et al. [18] suggested a parameter extraction approach based on the artificial bee colony (ABC) algorithm. The parameters of both the SDM and TDM models are retrieved, and the results of the ABC technique are compared, demonstrating that it beats existing approaches like genetic algorithm (GA), chaos particle swarm optimization (CPSO), simulated annealing (SA), pattern search (PS), and harmony search (HS) algorithm in terms of correctness. Vun Jack Chin et al. [19] provided a brief overview of several parameter estimate strategies for various PV cell models in the context of PV simulator applications. For parameter estimation of the sandia array performance model(SAPM) and five-parameter model, Sofiane et al. [20] employed five alternative techniques. The accuracy of all algorithms was evaluated using normalized mean absolute error (NMAE) and root mean square error (RMSE) for various climatic circumstances, and it was determined that the ABC method outperformed the others.

For parameter identification of TDM PV modules, Sandrolini et al. [21] devised a numerical technique integrating statistical and cluster analysis. Yuan et al. [22] suggested a novel parameter identification method based on a mutative-scale parallel chaos algorithm with crossover and merging operations. The performance of SDM and TDM PV modules is assessed by extracting their parameters. Ali et al. [133] provided a brief overview of SDM and TDM PV cell parameter detection methodologies. Each model's performance is evaluated, as well as its impact on the I-V and P-V curves. The model's correctness is verified by comparing it to the manufacturer's data sheet. Sudhakar Babu et al. [23] offer a TDM parameter detection approach based on the fireworks algorithm (FWA). On monocrystalline and multi-crystalline PV modules, the suggested method is tested. Finally, the authors came to the conclusion that the FWA algorithm outperforms the GA and PSO parameter extraction techniques. Prasanth et al. [24] suggested a parameter extraction approach based on a novel hybrid Bee pollinator flower pollination algorithm (BPFPA). Under various climatic circumstances, the parameters of SDM and TDM are extracted. By comparing the results to existing meta-heuristic-based approaches, the performance is better. On monocrystalline and multi-crystalline PV modules, the suggested method has been tested. Finally, the authors determined FWA algorithm out performs the GA and PSO parameter extraction approaches.

2.3 Modelling of PV System under PSC

The electrical characteristics (I-V and P-V) of the PV system are mostly depend upon atmospheric conditions like temperature changes, irradiation changes and partial shaded condition (PSC) (due to buildings, clouds and bird waste etc.) as shown in figure 2.3. Partial shaded condition is an adverse phenomenon that leads to wastage of viable power due to in accuracy associated in tracking global MPPs. Under PSC, PV characteristics exhibit multiple maxima with complex non-linearity due to bypass diode operation across the shaded module[5]. Bypass diode provides path for current flow from unshaded module and protects system from damaging due to hot spots. From literature it is noticed that there are very few contributions for analytical modeling of PV system under PSC. These works are based on certain assumptions and by neglecting shunt resistance component in current equation of the PV array. It is imperative to develop a complete analytical modeling of PV system under PSC for system analysis, to test the accuracy of different MPPT controllers under PSC and also to promote research on dynamic analysis of power converters.

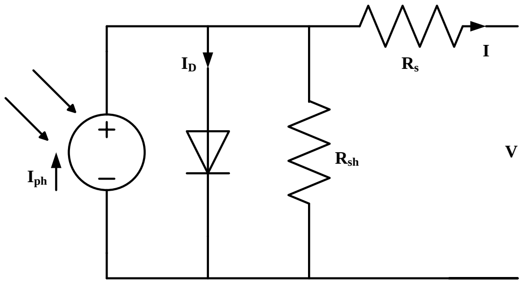


Figure 2.1. PV cell model

The PV output current is given by

$$\boldsymbol{I = I_{ph} - I_o \left[e^{\frac{q(V+IR_S)}{KTA}} - 1\right] - \frac{V+IR_S}{R_{sh}}} \tag{2.1}$$

where, I is the PV output current, V is the PV output voltage, I_{ph} is the Photocurrent of PV module, I_d is the Diode current, Io is the Reverse saturation current of diode, K represents the Boltzmann constant (1.3806503 x 10-23 J/K), q refers to the charge of an electron (1.60217646 x 10-19 C), T is the Operating temperature (K), A is the diode ideality factor, Rs is the series resistance (normally high) and Rsh is the shunt resistance (normally low).

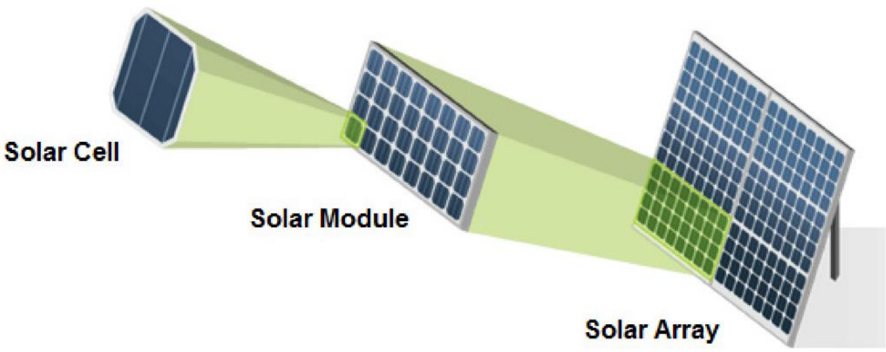


Figure 2.2. From solar cell to array

$$\boldsymbol{I_{ph} = \left(I_{sc\_STC} + k_i \Delta T\right) \frac{G}{G_{STC}}} \tag{2.2}$$

$$\boldsymbol{I_o = I_{o\_STC} \left(\frac{T_{STC}}{T}\right)^3 e\left[\frac{qE_g}{AK}\left(\frac{1}{T_{STC}} - \frac{1}{T}\right)\right]} \tag{2.3}$$

$$I_{o\_STC} = \frac{I_{sc}}{e^{\left(\frac{qV_{oc}}{AKT_{STC}}\right)}-1} \tag{2.4}$$

where, I_{SC_STC} is light generated current at Standard Test Conditions (STC), T_{STC} is the Panel Temperature at STC (25ºC), ΔT is the temperature difference between T and T_{STC} (in Kelvin), G is the surface irradiance of the cell, G_{STC} is the irradiance at STC (1000 W/m^2), K_i is short circuit current coefficient, Eg is the bandgap energy of the semiconductor, I_{O_STC} is the diode reverse saturation current at STC, I_{SC} is the Short circuit current and V_{OC} is the Open Circuit Voltage.

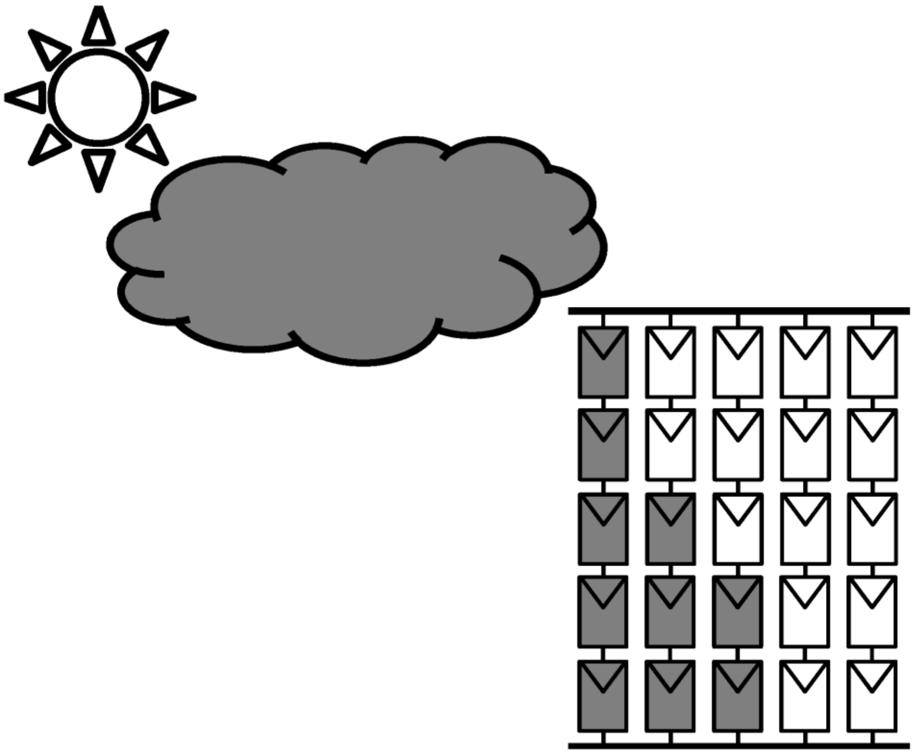


Figure 2.3. PV system under PSC caused by passing cloud

Silvertre et al. [25] investigated the impact of bypass diode design across PV modules on PV electrical characteristics under PSC. Based on a SDM, Bader et al. [26] developed analytical modeling of PV systems. The voltage equation is modeled using distinct shaded and unshaded parts, and the PV characteristic equation is given in terms of voltage equation with short circuit current component depending on irradiation receiving. By comparing PV string current with the short circuit currents of the individual PV modules, the PV system under PSC is modeled and current is calculated by adding the currents of each branch.

For the sake of simplification, the authors in this article ignored the influence of resistance components in the characteristic equation. The fuzzy logic based MPPT approach was also implemented by the authors. Based on the current equation of a SDM, Seyedmahmoudian et al. [27] established PV system modeling under PSC analytically. By comparing the PV string current with the photo current (current produced by a solar module when it is exposed to light. It's a direct result of the PV effect, where sunlight excites electrons in the semiconductor material of the module, creating a flow of current) of each module, the characteristics under PSC of PV system may be determined. The influence of series and shunt resistances is studied in this article, however the modeling is limited to a basic PV string under PSC. This does not apply to huge PV arrays with many strings. Kinattingal et al. [28] developed a SDM for PV system simulation under PSC. The module in the string that receives the most irradiation determines the maximum current. The string voltage of the PV is calculated by adjusting string current from minimum to maximum and comparing it to the photo current of each individual PV module. In addition, the system total current is calculated by aggregating the currents of the individual PV strings. PSC is used to acquire the PV system characteristics.

In [29], [30]authors proposed a PV system modelling under PSC based on SDM. The characteristic equation is written in terms of voltage by neglecting the shunt resistance component. The voltage of a PV system is calculated by adjusting the string current to the photocurrent of the module from zero with the highest irradiation and comparing it to the photocurrent of each individual PV module. The current of PV system is obtained by summation of individual PV string currents. Wang Y J et al. [31] proposed analytical modelling of PSC and PV modules oriented differently. The bypass diode is viewed in this context as a piecewise specified resistance, which offers high resistance under reverse bias condition and low resistance under forward bias condition. The PV array currents are modelled based on the resistance offered by bypass diode and the complete modelling is not shown in this work.

Seyedmahmoudian et al. [32] present a PV system modeling under PSC based on a SDM that considers the influence of shunt and series resistance. By comparing photo current to string current of each PV, the electrical properties of the PV string may be determined. This modeling is limited to a single PV string and cannot be used to represent PV arrays with many strings. MATLAB-based simulation of PV array PSC characteristics impact is suggested by Patel et al. [33]. A series assembly is formed by a subassembly with a more quantity of PV modules providing same irradiance and a set of similar subassemblies providing varying irradiances. A group of series assemblies with identical shading is formed, and the groups are then joined to form an array. The array peaks are separated by an integral multiple of 80 percent of V_{OC} module as a result of this effort.

2.3.1 Methods to Mitigate PSC Effect

Under PSC, the characteristics of PV systems are very nonlinear, resulting in power generation mismatching of individual PV Cells. To lessen the influence of PSC on PV systems, the literature has suggested three different types of methods.

1. PV Reconfiguration
2. Power electronic converter-based techniques
3. MPPT techniques

2.3.1.1 PV Reconfiguration

The primary goal of PV reconfiguration approaches in the context of mitigating PSC effects is to optimize the arrangement of PV modules to minimize shading-induced losses and maximize energy output. Here's how PV reconfiguration achieves this:

i) Shade Avoidance: PV reconfiguration aims to strategically arrange the modules in a way that minimizes the impact of shading. By rearranging or reconfiguring the layout of modules, shading on one module does not significantly affect the entire array's performance.

ii) Module Isolation: Reconfiguration can involve isolating shaded modules from unshaded ones. By segregating shaded modules from the rest of the array, their reduced performance does not affect the output of the other modules, preventing power losses.

iii) Optimal Stringing: When PV modules are connected in series to form strings, shading on one module can significantly impact the entire string's output. PV reconfiguration might involve forming strings in a way that minimizes shading's effect on each string's performance.

iv) Voltage and Current Matching: Reconfiguration can help match the voltage and current characteristics of modules more closely. Modules with similar performance characteristics are grouped together, minimizing the mismatched currents that can occur due to shading.

v) Dynamic Adjustments: In some advanced reconfiguration approaches, modules or arrays might be mechanically or electronically adjusted in response to changing shading patterns. This dynamic adaptation can ensure optimal performance as shading conditions change.

vi) Enhanced Monitoring and Control: Some reconfiguration systems incorporate monitoring and control mechanisms that detect shading events and adjust the array configuration accordingly. This real-time response maximizes energy production.

vii) Safety and Maintenance: Effective reconfiguration can also enhance safety and ease of maintenance by reducing the chances of hotspots or underperforming modules.

By implementing PV reconfiguration approaches, system designers and operators can counteract the negative effects of shading on PV systems. The ultimate achievement is a more efficient and productive PV array that maintains high energy yield even in the presence of PSC.

The authors of [34] suggest an evolutionary-based dynamic reconfiguration of PV systems with decreased processing time. The approach provided is more dependable and may be used in real time. Malathy et al. [35] provided a thorough investigation of the impact of PV array size, design, and shading pattern on PV system power generation. Belhachat et al. [36] studied how various PV system designs performed under varied PSC. The six series four parallel (6S4P) PV setup is used to evaluate the performance of all the configurations on all conceivable shading patterns. The authors determined that in most cases of PSC, the Total Cross Tied (TCT) arrangement is preferable. During the reconfiguration of a series-parallel PV array, Balato et al. [37] looked at the heating phenomena caused by bypass diode operation and hot spots reverse bias cells. A good regulation of the array operating point is required to limit the heating phenomena while simultaneously extracting PV system maximum power.

Balato et al. [38] developed a quick and simple series-parallel array reconfiguration approach that only evaluates a tiny portion of all potential configurations. The suggested Monte Carlo-based method is quick and harvests the most PV energy, mitigating the drawback of early ageing owing to the creation of hotspots. Shubhankar et al. [39] suggested a genetic algorithm-based PV reconfiguration approach for getting the most energy out of a TCT PV arrangement.

2.3.1.2 Power electronic converter-based techniques

Power electronic converter-based techniques play a crucial role in mitigating PSC adverse effects on PV systems. These techniques leverage advanced electronics to manage the power output of individual PV modules, ensuring that the system operates as efficiently as possible even in the presence of shading. Here's how power electronic converter-based techniques achieve this mitigation:

i) Module-Level Optimization: Power electronic converters, such as micro inverters and DC optimizers, are installed at the module level. They allow each module to operate independently and at its MPP, regardless of shading conditions.
ii) Individual MPPT: Each module equipped with a power electronic converter which has its own MPPT capability. This means that modules exposed to shading can adjust their voltage and current output to find their MPP, mitigating the mismatched currents caused by shading.
iii) Minimizing Mismatch Losses: Shading can lead to reduced current output from shaded modules, which can drag down the entire array's performance.

Power electronic converters ensure that each module contributes its maximum power, minimizing the power losses due to mismatched currents.

iv) Avoiding Hotspots: Shading can cause some modules to become "current sinks," leading to potential hotspots and overheating. Power electronic converters prevent this scenario by managing the output of each module to ensure safe operation.

v) Enhanced Monitoring and Control: Power electronic converter-based systems often come with monitoring and control capabilities. Operators can remotely track the performance of individual modules, identify shading events, and assess any system anomalies.

vi) Flexible Array Design: Power electronic converter-based systems offer flexibility in array design. Modules can be installed with varying orientations or in different areas of the roof, allowing the array to adapt to changing shading patterns.

vii) Fast Response: These techniques enable fast response to changing shading conditions. If a module is suddenly shaded, the associated power electronic converter can quickly adjust its operation to minimize power losses.

viii) Maximized Energy Yield: By ensuring that each module operates at its MPP, power electronic converter-based techniques improve the overall energy output of PV system, even when shading occurs.

Power electronic converter-based techniques mitigate the impact of PSC on PV systems by enabling each module to optimize its power output independently. This approach minimizes power losses, reduces hotspots, and ensures that the system operates at its highest efficiency even when some modules are shaded.

Liu et al. [40] provided a summary of several firmware and hardware-based global MPPT approaches. For limiting the effect of PSC, the author briefly described the concepts of multilevel inverter, distributed architecture, and equalizer-assisted topologies. Ramli et al. [41] briefly discussed various PSC mitigation techniques based on converter configuration, such as the conventional interleaved boost converter, single stage micro inverter, replacing a voltage source inverter with a current source inverter, and interleaved dual boost converter concept, among others.

2.3.1.3 MPPT

MPPT is a technique used to mitigate the negative effects of PSC on PV systems. MPPT ensures that a PV system operates at its MPP under varying shading conditions, thereby minimizing power losses and maximizing energy production. Here's how MPPT achieves this mitigation:

i) Optimal Power Operation: A PV module's maximum power point (MPP) is the location on its current-voltage (I-V) curve where it produces the most power. Under normal, uniform illumination, the PV system operates at its MPP. However, shading can cause modules to operate away from their MPP, leading to significant power losses.

ii) Dynamic Tracking: MPPT techniques continually track changes in shading, temperature, and other conditions. They adjust the voltage or current operating point of the PV modules to maintain them as close as possible to their MPPs, regardless of shading effects.

iii) Minimizing Mismatched Currents: In PSC, some modules may produce less current due to shading, causing a mismatch in the string or array. MPPT adjust the operating conditions of shaded modules, ensuring they contribute their maximum power output and reducing the overall impact of shading-induced mismatches.

iv) Shade Recovery: When shading changes or shifts, MPPT algorithms quickly adapt the PV system to the new conditions, helping to recover lost energy production by aligning the operating points of the modules with their updated MPPs.

v) Enhanced Energy Yield: By operating each module at its MPP, MPPT enable the PV system to capture the maximum available energy from the sunlight, even under PSC.

vi) Optimizing Power Electronics: MPPT techniques are often integrated into power electronics such as inverters, DC optimizers, or micro inverters. These devices manage the voltage or current levels to confirm that the system as a whole is performing at its MPP.

vii) Reduced Hotspots and Stress: Operating shaded modules closer to their MPPs reduces the likelihood of hotspots and other stress-related issues caused by mismatched currents.

viii) Consistent System Performance: MPPT maintains consistent power output and performance levels across the PV array, mitigating the significant drops in power that can occur with shading.

MPPT is a key technique for mitigating the effects of PSC on PV systems. By ensuring that each module operates at its MPP, MPPT minimizes power losses, prevents mismatched currents, and maximizes the overall energy yield of PV system even in challenging PSC.

The fundamental goal of MPPT is to get the most electricity out of a PV system in any weather situation. This is accomplished by duty ratio adjustment of the PV system's power electronic interface with the load. The triggering pulse of the converter is set to match the MPP of the PV system. The most significant features of any MPPT approach are listed below.

i) The precision of the MPPT controller determines the efficiency of a PV system and ability to track precise GMPP.

ii) The time required to track global MPP must be minimal.PV systems have a low efficiency because of the high tracking time, which results in a power loss.

iii) It should be effective for both uniform irradiation and PSC. The PV characteristics exhibit multiple MPPs under PSC, therefore finding the exact MPP is a challenging task.

iv) The MPPT controller should be system-independent, meaning it should work with a variety of PV systems.

v) It should be easy.

vi) It should be devoid of fluctuations in the vicinity of MPP.

vii) It should be capable of monitoring MPP in response to dynamic changes in atmospheric conditions.

For MPPT of PV systems, several types of power electronic converters are used, including as for high step-up standalone applications (One of the key functions of the three-port chopper is to perform voltage conversion. It steps up the voltage generated by the PV array to a level suitable for charging the energy storage element or supplying power to the load). Chen et al. [42] developed a three-port chopper incorporating PV system. This converter offers benefits such as high dc gain, fewer switches, and a simple control method, and the results have been tested on a 200 W PV module. Ben et al. [43] created an integrated boost converter with a simple control technique and fewer components. With 250 W prototypes, the converter has been experimentally validated. The authors of [44] presented a one panel per one module cascade idea, which aids in the provision of a high-voltage string for a dc-ac grid inverter. Different approaches of panel integrated dc-dc converters were presented by Kasper et al. [45]. The authors claim that the buck-boost converter is the most effective converter available. For MPPT implementation, Nabil et al. [46] compared the performance of alternative non-isolated and isolated DC-DC converter designs. Prakash et al. [4] reviewed the literature on several DC-AC, DC-DC converters and modified DC-AC converter topologies, that are utilized to achieve MPPT.

Provides an in-depth examination of several high gain, PV application approaches for high power dc-dc converters [47]. This converter is derived using a basic technique. To extract maximum power, Fabio et al. [48] examined the performance of micro inverter and string inverter systems for PV applications. Based on real-time data in Spain, Dez-Mediavilla et al. [49] examined the performance of central inverter and string inverter approaches for grid-type PV applications.

2.4 MPPT Techniques

MPPT is a critical technique used in PV systems that operates at its MPP under varying conditions of sunlight intensity and temperature. The PV module's MPP is the location on its I-V curve where the maximum power output is achieved.

The MPPT approaches may be divided into two groups. The first group comprises traditional tactics such as

1. P&O
2. HC
3. INC
4. Voltage in a fractional open circuit
5. Fractional current in a short circuit

1. *P&O:*

- P&O is one of the most fundamental and often used MPPT methods.
- It periodically perturbs (changes) the operating point slightly and monitors how the power output changes as a result.
- The process continues in the same direction if the power output rises; if it decreases, the algorithm reverses direction.
- P&O is effective in stable conditions but can oscillate around the MPP in rapidly changing conditions.

2. *INC:*

- A better variant of the P&O approach.
- It compares the instantaneous change in power with the instantaneous change in voltage, adjusting the operating point to maintain the maximum conductance.
- It is more suitable for environments with rapidly changing solar conditions.

3. *Fractional Open-Circuit Voltage (FOCV):*

- FOCV calculates the MPP using the PV module's open-circuit voltage.
- It's relatively simple and efficient, especially in low-to-moderate shading scenarios.

4. *Fractional Short-Circuit Current (FSCC):*

- FSCC calculates the MPP based on the PV modules short-circuit current.
- Like FOCV, it's relatively simple and can be effective in specific scenarios.

Soft computing-based MPPT approaches fall under the second group. The following are some of the MPPT approaches:

1. Fuzzy logic-based techniques
2. Techniques based on ANNs and
3. Techniques based on biology.

1. *Fuzzy logic-based techniques:*

- Fuzzy systems are a type of computational model used to handle uncertainty and imprecision in decision-making and control processes. They are particularly effective when dealing with complex systems that involve vague or incomplete information.

2. *Techniques based on ANNs:*

- ANNs are computational models inspired by how the human brain is organized and works. They are used to model complex relationships and patterns in data. ANNs consist of interconnected nodes, or "neurons," organized in layers (input, hidden, and output layers).

3. *Techniques based on biology:*

- MPPT techniques inspired by biological concepts are a relatively new and innovative approach to optimizing the performance of PV systems.
- These techniques draw inspiration from natural processes found in living organisms to improve the efficiency and adaptability of MPPT algorithms.

The role of these different MPPT techniques is to dynamically adjust the voltage and current output of the PV modules to maintain them as close as possible to their MPPs. By doing so, these methods make sure that the PV system is able to capture the most solar energy possible, even when sunlight conditions change rapidly or PSC occur. The choice of the MPPT method is influenced by a variety of variables, including the PV system's particular operating environment, accuracy requirements, and system complexity.

Benefits of MPPT in PSC:

- Continuous Adjustment: MPPT techniques continuously track changes in irradiance and shading conditions, ensuring that the PV system always operates as close to its MPP as possible.
- Optimized Output: By maintaining the array at its MPP, MPPT minimizes the negative effects of shading, preventing shaded modules from dragging down the overall output.
- Reduced Power Losses: MPPT methods prevent shaded modules from operating at points of low efficiency, minimizing power losses due to shading-induced mismatched currents.
- Enhanced Energy Production: MPPT allows the PV system to capture more energy from the available sunlight, which is especially important in regions prone to shading or cloud cover.

Under homogeneous irradiation conditions, when the PV electrical characteristics reveal standard MPPT approaches to monitor the MPP. PV systems that have undergone PSC, the electrical characteristics show many MPPs, one of which is the Global MPP and the others are Local MPPs. In this case, traditional approaches fail to trace the precise MPP and instead converge on local MPP. Because of the inability to track the Global MPP, usable PV power gets wasted. In the literature, there is a comprehensive overview of several types of MPPT approaches under uniform and PSC.

Zhu[50] presents a model of PV modules to predict the power output under PSC.Experiments of shading a single cell and shading the module in parallel with different edges and data processing are presented. The results between experiments and simulations are discussed. Robles Campos H.R[51] PV cells and bypass diodes through a single equivalent circuital representation. The model synthesizes I–V performance curves and computes junction temperatures of PV cells and bypass diodes from data that is generally available from measurements: solar irradiance, ambient temperature and wind speed. Yin Ooi Wen [52] examined and compared the performance of a PV module with a single and two diode models in relation to environmental factors like temperature and irradiance level fluctuations. For the purposes of the study, the MATLAB/Simulink environment is used to mathematically simulate the PV module and shown analyzing accuracy results of multi-crystalline and monocrystalline PV modules. A comparison study is conducted between single diode and two diode PV modules from different manufacturers and the findings are summarized.

K Sundareswaran[29] ABC for tracking GMPP under PSC by in-homogenous insolation in which problem formulation, applications and outcomes of the ABC algorithm are examined. By taking into account two alternative shading patterns, numerical simulations of two different PV configurations are performed. Concluded with the remarks of best method to find GMPP compared to the existing and also validated with experimental results. In this work presented by K Sundareswaran [28], a novel algorithm is introduced that combines PSO and P&O algorithms. This combined work is designed to effectively track the GMPP in a PV system operating under PSC. The novel method combines known PSO and P&O algorithms in a sequential manner. When properly begun, swarm intelligence's capacity for global search and the P&O method's proven capacity for convergence are linked, creating a more viable approach.

A Bouraiou[53] in Matlab/Simulink software using one diode and two diode PV Module simulation and modeling done by using two accurate and fast methods for obtaining the PV panel parameters. Under STC validation in experimental mode is done by utilizing the one diode and two diode models to bring the IV and PV characteristics on ISOFOTON I-75 panel with different temperature and irradiation conditions are presented. T Ma[54] a comprehensive literature review of PV mathematical models and determination methods is presented and the model involved in this study is then discussed and validated using previously collected data on file. A case study that on standalone PV systems to predict the operating performance is done here on a remote mode. G Ciulla [55] explains the five most recent and frequently mentioned mathematical models while presenting the many forms of PV, associated subjects, and their performances with equivalent circuits for PV modules. For each model, a description of the parameter extraction process is provided.

SMoballegh [56]the proposed formulation considers the impact of shaded conditions on the PV internal and electrical parameters, the role of by-pass diodes, and the array configurations: SP, BL, and TCT. By predicting the multiple power peaks and the corresponding voltages, this technique facilitates the online analysis of different configurations to determine the most efficient ones under a given shading condition. M Seyedmahmoudian [27] mathematical investigation of a single module's responses to constant irradiance levels. The impact of the PSC on the output of PV systems is next investigated, and modeling of the module and array under PSC is done in a more realistic scheme. The simulation of the results for the suggested multidimensional PV array configuration correlating to different partial shading levels is presented at the end.

A Bidram [57] summarizes several methods aimed at academics and practicing engineers working on PV-based power systems, it maximizes the power from shaded arrays. It also examines the key features of partial shade, such as electrical properties of PV and hot-spot occurrences. PSC control algorithms that execute GMPPT are reviewed. The implementation, complexity, cost, and tracking speed of the methods provided vary, as does their success in tracking the global maximum under varied PSC. Mansoor M[58] by utilizing search and skip method the GHO algorithm is implemented to find GMPP which reduces the computation time and achieve tracking time efficiency 99.5% under PSC. Rizzo SA[59] under quickly changing PSC and irradiance to find out GMPP ANN based MPPT technique is presented which requires intensive training with data to NN. In this paper, an ANN-based MPPT control design is presented for the estimation of the GMPP under rapidly variable irradiance and PSC. For GMPP under PSC, NN training requires large training data sets, which takes time and is resource-intensive. Hong Y-Y [60] to identify MPP in the case of non-uniform temperature and irradiance is used to create and evaluate an improvised PSO algorithm, also an improved PSC accuracy detection with 99% in GMPP detection is achieved.

Ahmed J[61] CSO algorithm which showed better accuracy when it is compared with ANN and INC when GMPP is determined using the modified levy flight function for the PV system when temperature and irradiance are changing.

PilakkatD[62] 99.5% efficiency is achieved under PSC by using ABC along with P&O for GMPP effective tracking. Zafar MH [63] 98.54% efficiency is achieved to find GMPP with 240ms average tracking time under dynamically varying conditions by considering improved GWO(IGWO) with boost full-bridge isolated converter (BFBIC). Bouakkaz[64] higher efficiency is an outcome due to stable voltage and low oscillation to track GMPP using MFO under PSC through direct control. Li X [65]under uniform irradiance to find out the GMPP a novel fuzzy logic control algorithm with parameter β having three input and one output is considered.

JavedMY [66] 99.8% efficiency under several PSC is achieved through testing by using P&O and PSO are compared with a generalized-PTS for detecting MPPT. HamzaZafar [67] novel intelligent techniques search and rescue (SRA) algorithm is applied to PV systems MPPT control in standalone. SRA results are compared against GHO, GWO, PSO, CS, and PSOGS. PS, fast varying irradiance, Islamabad city of Pakistan field atmospheric data, and experimental verification authenticate the effectiveness of MPPT controller named SRA. Xue S [68] strings in series of PV arrays which are dynamically reconfigured output is verified which is costly and the switches whose mechanical reconfiguration is done are prone to fail. Diaz Martínez [69] efficiency, partial shading with and without initial parameters, convergence speed, search space, initialization are some key issues which are taken in account and these are reviewed based on PSO methods. Da Rocha[70] by considering the boost converter in the circuit evaluation and comparison of Bat-IC, Bat-Beta and Bat P&O are done by experimental validation of Bat based MPPT techniques.

Sahlol [71] suggested method was tested on two communal COVID-19 X-ray datasets, achieving great performance while reducing computational difficulty. The COVID-19 X-ray images that make up the two datasets shared on Kaggle by international cardiothoracic radiologist, researchers, and others. Soliman[72] the nine best parameters found using the MPA are contrasted with those acquired using PV model-based alternative optimization techniques. The marketable Kyocera KC200GT and Solarex MSX60 PV panels are compared using numerical results and quantifiable data for a more accurate comparison. The MPA-based two diode PV model's efficacy is validated by comparing its current error to that of other models. With the aid of

MPA expertise, any commercial PV module may be accurately modelled, which offers a novel contribution to the PV power systems business. Suyanto[73] to determine the maximum power values, simulations were run using a variety of different approaches. The FPA is thought to be the most ideal device, having the highest output power of 140.81 watts, according to the test findings. With a maximum time of 0.02 seconds, the FPA also succeeded in becoming the fastest way of finding power. The studies final findings can be used to promote the enhancement of the smart micro grid solar panel system's performance quality.

Hemalatha[74] the suggested technique may precisely monitor the MPP and enhance FFA's tracking speed for convergence performance. The outcomes of the simulation and the maximum power analysis are used to demonstrate the effectiveness of the suggested solution for the PV system.Simulation is used to demonstrate the proposed system's efficacy. Balamurugan[75] harmonic elimination, MPPT panel reconfiguration summaries, and oscillations around the operating point of a grid-linked PV system are all influenced by shading circumstances. System dependency, real-time implementation, algorithm complexity, and convergence are all evaluated under numerous conditions. Basha[76] oscillations at MPP, algorithm complexity, sensing parameters, and tracking speed are taken into account during the comparison study under static and dynamic irradiation settings. The fill factor (FF) and maximum power extraction of the SDM PV panel and the TDM PV panel are also contrasted. The appropriateness of MPPT approaches for various converter designs are clearly demonstrated. Faramarzi [77] the statistical study found that in comparison to GA, PSO, GSA, CS, SSA, and CMA-ES, MPA is a high performance optimizer whose performance is statistically equal to that of SHADE and LSHADE-cn-EpSin.

Hadji [78] we use the GAs, by maximizing a fitness function we can obtain a solution to the perturbations effect around the MPP. So, with the proposed algorithm, the MPP is only moving to get more power, the oscillations problem around the MPP is minimized. By measuring I_{SC} and V_{OC} the proposed algorithm can follow efficiently the variation of irradiance and temperature (climatic conditions) and not P-V evolution curve. With GAs, the solution doesn’t depend on initial conditions because this method works with a population of individuals randomly generated and choose the best one. Jiang [79] this uniform technique ant colony optimization (ACO) based MPPT where accelerating convergence speed is addressed, which is significant in systems with PSC by fast irradiance change. Joisher [80] experiments are carried out with a boost converter configuration, an ET-M53695 screen, and a Arduino MEGA-2560 controller. Finally, the simulation and hardware findings are compared to those PSO and DE techniques which show superiority. Brano [81] the suggested model extracts the five distinctive parameters, such as short-circuit current, open circuit voltage, and MPP using readily available tabular data and just well-defined mathematical relationships. The absence of mathematical simplifications or other physical assumptions distinguishes this model from others. All equations utilized were acquired by a straight forward analytical approach.

Oshaba[82] by constructing two PI controllers, with PV-DC motor pumps a new MPPT has been proposed. The first is used to achieve MPPT by keeping track of adjusting the PV array's voltage and current, as well as changing the duty cycle of the DC-DC converter. Another PI controller is intended to manage the speed by altering the voltage supplied to the motor via another DC-DC converter. The proposed speed controller and MPPT design challenge is solved by an ABC to identify the optimum potential PI controller settings. Renaudineau[83] the PSO approach is used to address the real time 15 constrained optimization issue, which requires information of the actual voltage vs current curve of each solar generator. The study also discusses the practical implications of this necessity. The suggested approach's practicality and performance are experimentally tested using a prototype in laboratory. Glöser-Chahoud[84] in this work, we make the case that industrial disassembly systems should strive for better circularity levels.

Sera [85] in P&O and INC MPPT algorithms two strategies are carefully examined from both a practical implementation and mathematical standpoint. Their mathematical study finds no distinction between the two. This was substantiated by experimental testing performed in accordance with the EN 50530 standard, which revealed a difference in 0.13% efficiency in dynamic situations and as low as 0.02% in static settings. In the research conducted by Colak [86], the establishment of a solar PV power plant in the Malatya Province of Turkey was determined through the utilization of geographical information systems (GIS) technology. In this comprehensive approach, various influential factors were derived such as solar energy capacity, road infrastructure, energy transmission networks, transformer facilities, terrain incline, orientation, dam and river locations, natural gas pipelines, fault lines, land usage patterns, and residential zones.

Prasanth et al. [87] provided a comprehensive overview of several types of traditional and soft computing-based MPPT approaches. PSC is used to evaluate these speed, complexity, and dynamic tracking strategies. The benefits and drawbacks of selected MPPT approaches are discussed in general. The authors came to the conclusion that strategies based on swarm intelligence are superior in terms of speed and ability. Parameters which are constant type, measurement along with comparison type, trial and error type, mathematical calculation type, and intelligent prediction type MPPT approaches were briefly reviewed by Nabil et al. [3]. The number of sensors employed, speed, stability, and tuning were all compared by the authors. Dileep et al. [88] provided a brief overview of several soft computing-based PV system MPPT approaches. In terms of duration, complexity, ability to handle PSCs, and variables employed, these strategies are compared. Kermadi et al. [6] conducted a comparison of artificial intelligence based MPPT controllers. All MPPT controllers are put through their paces using a buck boost converter along with DC load under the identical conditions. Alireza et al. [3] divided MPPT approaches into three categories: traditional, artificial intelligence-based, and hybrid. These methods are compared in MATLAB/Simulink for a TDM-based PV panel under various irradiation circumstances. The authors of [84] briefly explored the need for MPPT as well as the many types of MPPT strategies available in the literature. These approaches are divided into three categories for comparative analysis: indirect control methods, direct control methods, and soft computing base methods. Saravanan et al. [89] provided a quick overview of several P&O strategies. Under uniform irradiation conditions in PV systems, INC approaches, intelligent MPPT techniques, and other modified PSO algorithms whereas other heuristic based algorithms for MPPT under PSC are also used. Rezaee et al. [90] reviewed PSC, old MPPT approaches, new MPPT techniques, and a metaheuristic-based methodologies overview. The authors of [6] went over all of the soft computing-based MPPT approaches in depth and compared them analytically.

The MPPT strategies used by Ahmed et al. [91] to reduce the effect of PSC on PV systems were critically reviewed. Liu et al. [40] explore the impact of PSC on PV generating systems briefly. Firm-based MPPT techniques and hardware-based MPPT techniques are the two types of GMPPT approaches. Khare et al. [92] conducted a comprehensive PSO analysis based solar PV systems applications such as size and allocation, as well as MPPT. In this study, hybrid versions of PSO algorithms are integrated with other intelligent strategies. Under homogenous irradiation settings, Kashif et al. [2] addressed several traditional and soft computing based MPPT algorithms. To address the MPPT under PSC, the authors additionally considered modified conventional approaches, artificial intelligence techniques, and PSO based MPPT strategies.

The authors of [93] divided MPPT approaches into three categories: offline, online, hybrid, and explored them briefly under uniform irradiation settings. Lina et al. [94] conducted a comprehensive review of ANN-based MPPT approaches and presented a new categorization based on input variables and control structure for these techniques. These strategies are tested in both transient and steady-state circumstances, with the findings being provided. HC and INC MPPT strategies were tested by Kjr et al. [95], who determined that both techniques fail when exposed to substantial irradiation variations.

There are some of the most regularly utilized traditional MPPT approaches. The P&O approach was suggested by the authors in [96], [97] and it is the most widely used traditional MPPT technique for PV systems. The maximum power is attained by perturbing the voltage and watching the power in this procedure. Under PSC, this approach suffers from oscillations and local maximum trapping like P&O. Sera et al. [98] presented the INC(Incremental Conductance) approach, the power derivative with respect to voltage is zero at MPP. The derivative on the left side of MPP is positive, whereas on the right side it is negative. To acquire the MPP, a tiny voltage perturbation is applied, and the accompanying current is monitored.

The incremental and instantaneous conductance's are measured and compared.INC algorithm like P&O and HC is not appropriate for PSC. The approaches of proposed fractional short circuit(FSC) and fractional open circuit(FOV) MPPT[99], [100] the PV operating point is pushed towards 0.71-0.78 V_{OC}, in FOV technology. The operating point is pushed towards 0.78-0.92 I_{SC}, in FSC approach. These methods are simple and just require one sensor. The primary disadvantage is that periodic monitoring of short circuit current and open circuit voltage disconnects power supply loads, resulting in lower efficiency and incompatibility with PSC.

Under uniform irradiation circumstances, the above-mentioned standard MPPT approaches are most commonly utilized to track MPP. There are also various modified and hybrid conventional MPPT approaches that may be used to increase the performance of traditional techniques, however they are not possible under PSC. Several authors have developed ANN-based MPPT algorithms to track PV systems MPP in the literature [91]. Some writers advocated combining hybrid ANN MPPT algorithms with traditional approaches. Though ANN monitors the MPP, it is system-dependent and requires the right training. With a bigger number of hidden layers, tracking efficiency improves while tracking speed suffers. Biology-based algorithms are the next type of soft computing, and they are often inspired by biological activities and natural evolutions. In both uniform irradiance and half shadowed circumstances, they are extensively used to track the MPP. These methods solve the drawbacks of traditional, fuzzy, and ANN-based MPPT approaches, such as MPP oscillations, system reliance, and the difficulty to trace the GMPP under PSC.

Chen et al. [101] suggest an algorithm of biological swarm chase for MPPT of PV system. The MPPT is represented by a moving target, while each module is represented by a particle. Each module has a slave controller that interacts with the master controller to obtain the MPP. With enhanced efficiency, the authors demonstrated its superiority over traditional P&O. It is demonstrated that no metaheuristic algorithm is suited for tackling all optimization problems based on a thorough literature review and the No Free Lunch Theorem. The authors of [102], [103] provided a brief overview of several bio-inspired optimization algorithms and their capacity to tackle various difficult and non-linear optimization problems in a variety of engineering applications. Kennedy J et al. [104] suggested a PSO technique based on the fish schooling behavior and the birds flocking behavior. This method is most commonly used in PV MPPT under PSC. Mirjalili et al. [105] suggested a novel population-based algorithm based on the natural hunting behavior of grey wolves. This is the most modern MPPT optimization technique for PV systems operating under PSC. Mirjalili et al. [106] suggested an unique bio-inspired optimization method inspired by humpback whale hunting behavior to solve the MPPT problem under PSC.

For MPPT of PV systems, several metaheuristic algorithms are utilized. There are various biological algorithm-based MPPT strategies in the literature to extract maximum available power under PSC, and these are further classified into evolutionary algorithms like GA, DE, and swarm intelligence-based algorithms like PSO, ACO, and ABC, among others. The Genetic Algorithm's diversity is utilized to track solar PV systems GMPP under PSC.Several writers suggested a GA and its adaptations for monitoring MPP under PSC in the literature [107]. Although it converges to GMPP, it has certain drawbacks, such as accuracy being dependent on population size and tuning factors such as mutation and crossover. For greater dependability, several writers developed hybrid MPPT algorithms that include genetic and conventional algorithms, as well as soft computing approaches [108]. DE is an evolution-based optimization technique that may be used to tackle a variety of optimization issues. Mohammad et al. [109] PV systems MPPT algorithm based on differential evolution operating in PSC and demonstrated that it outperformed the traditional HC MPPT approach. Ramli et al. [110] suggested a modified DE MPPT algorithm with a deterministic mutation operator under PSC, and the results demonstrated its superiority. Swarm based intelligence techniques for MPPT are the next subcategory of evolutionary computing-based MPPT approaches. Due to its capacity to address complicated non-linear optimization problems in various engineering applications, the PSO method is the most widely used approach to track PV systems GMPP under PSC [92]. Miyatake et al. [111] introduced MPPT algorithm based on PSO, which used decision variable as terminal voltage in PV modules. Ishaque et al. [112] suggested an MPPT algorithm that used duty cycle as a decision variable and was based on direct control PSO. Ishaque et al. [113]To reduce steady-state oscillations, an improved version of the PSO-based direct control MPPT technique employing duty cycle as the assessment variable was proposed. Liu et al. [114] suggested an MPPT algorithm PSO based using decision variable as duty cycle, here particles are initiated at preset places in the search space with equal distances. Ishaque et al. [115] suggested a deterministic PSO MPPT approach based on removing randomness from the equation of velocity decision variable as duty cycle. Mirhassani et al. [116] suggested an enhanced MPPT algorithm PSO based approach among variable sample time that took decision variable as duty cycle. Venugopalan et al. [117] devised a modified PSO based MPPT algorithm for determining duty ratio positions using the reflected impedance method. Though PSO based MPPT approaches are effective in tracking the exact MPP, oscillations at the MPP might cause problems. Because of this flaw, updated versions of PSO are being offered by some authors.

Some writers presented hybrid PSO algorithms that combine traditional and other heuristic techniques. The authors of [118] suggest a two stage MPPT approach based on P&O and PSO using voltage as the decision variable. Sundareswaran et al. [28] devised a two stage MPPT that combine benefits of P&O and PSO algorithms while taking the duty ratio into account as a decision variable. Proposed PSO and GA-based hybrid MPPT approach that combines the benefits of both algorithms[119]. Seyedmahmoudian et al. [27] devised a hybrid MPPT algorithm that incorporates both DE and PSO to execute even and odd iterations using voltage as the decision variable. Tang et al. [120] devised an unique cooperatively co-evolving PSO method for solving MPPT of large scale PV arrays, concluding that it improves output power under difficult climatic circumstances.

Authors in the literature have devised MPP approaches based on the ABC algorithm and its modified forms under PSC of PV systems. The authors of [121], [122] suggested an ABC method for MPPT approach that took into account all phases of the bee, including employer, spectator, scout bee phases, and used duty cycle as a decision variable. The authors of [29] used an upgraded version of ABC to improve tracking by removing the scout bee phase.

A firefly algorithm (FFA) is used by Sundareswaran et al. [30] for GMPP tracing under PSC in PV systems. FFA is on the intensity dependent behavior of firefly light. With reference to the firefly with the best duty cycle, other fireflies adjust until maximum power is obtained in the firefly MPPT algorithm. When the firefly MPPT algorithm was compared to traditional PSO and P&O under uneven irradiance and PSC, it demonstrated to be superior. In many engineering applications, the ACO approach is used to tackle nonlinear optimization problems. This is based on ant communication based on pheromone lay phenomenon in order to improve food source position (optimal position). Jiang et al. [123] used ACO for PV system MPPT under PSC, however this is less advantageous for individual MPPT. As a result, it is employed as a tool for determining the best tuning for the fuzzy MPPT approach. To track PV systems GMPP under PSC, Ahmed et al. [124] used a CSO based MPPT approach. This is based on the cuckoo bird's ingenuity in developing eggs in other bird nests while killing the eggs of the host bird. Cuckoo search for MPPT was successfully used under PSC, and the results demonstrated its supremacy over traditional PSO and P&O MPPT algorithms when it comes to reduced steady state error and transient fluctuations.

A grey wolf optimizer(GWO) approach based MPPT technique was proposed by Mohanty et al. [125]. The authors used an experimental setting to test their findings and compared them to current enhanced PSO and P&O MPPT approaches. The authors of [126], [127] developed a novel flower pollination algorithm (FPA) for global MPPT of PV systems under PSC. The suggested method uses dual mode search to generate appropriate randomness in each iteration. The new approach was empirically evaluated and compared to current PSO and P&O algorithms, demonstrating its superiority. Mustafa et al. [128] introduced a novel voltage current based MPPT method with the ability to verify PSC and implement the algorithm independently for uniform and PSC. The suggested approach is better than P&O algorithm in terms of efficiency and convergence time. Sundareswaran et al. [129] suggested a random search method based MPPT methodology for PV systems. Random values with particular bounds are picked in this technique, and the search for the global optimum begins. Duty cycles are picked at random in this manner, and a search procedure is used to generate GMPP. When compared to PSO approaches, the findings show that it is superior in terms of tracking speed. In [130], [131], the authors suggested hybrid MPPT approaches that combine the benefits of model based and heuristic based algorithms.

From the extensive study of the literature related to MPPT techniques in PV systems, there is still scope to work on the areas of GMPPT findings from PV Systems under PSC. The related research areas are given below.

i) Partial Shading Handling: While many GMPPT algorithms exist, addressing PSC remains a challenge. Most algorithms assume uniform irradiance, but in real world conditions, partial shading can significantly affect PV system performance.
ii) Robustness to Parameter Variations: Many GMPPT algorithms rely on accurate system parameter values. However, real world systems experience variations in environmental conditions and component characteristics, affecting the accuracy of these algorithms.
iii) Complex System Modeling: Accurately modeling PV systems under PSC is difficult due to the nonlinear behavior of PV characteristics and the dynamic interplay between series and shunt resistances.
iv) Efficiency and Convergence Speed: Some GMPPT algorithms may struggle to find the true GMPP quickly and efficiently, leading to suboptimal energy harvesting.
v) Adaptability: PV systems may operate in varying configurations, such as standalone or grid integrated setups. Existing algorithms might lack adaptability across different system types.

As mentioned, when a PV system is exposed to PSC, the electrical characteristics show many MPPs, one of which is the GMPP and the others are LMPPs. Here, the need of heuristic techniques arises, because to run PV modules at the highest efficient voltage in order to get the most available electricity out of them (MPP). Explaining the mathematical basis for multiple MPPs and how they arise under PSCs will strengthen the work for the need to employ heuristic techniques for accurate MPPT in such situations.

The mathematical relationship between voltage (V) and power (P) in a PV module is typically described by the following equation, known as the power-voltage (P-V) curve:

$$P(V) = V.I(V) \tag{2.5}$$

Where:

P (V) is the power output of the PV module at voltage (V).

I (V) is the current output of the PV module at voltage (V).

This equation essentially states that the PV module's power output is the result of multiplying its voltage by its current at a given operating point.

Now, let's illustrate how PSC introduce additional peaks and valleys in this curve. Under normal or uniform illumination conditions, the P-V curve is relatively simple, with a single well-defined peak representing the GMPP. The equation for this condition might look like this:

$$P(V) = V.I_{Max} \tag{2.6}$$

Where: I_{MAX} is the maximum current output of the PV module under uniform illumination.

However, when PSC occurs, the P-V curve becomes more complex. This is due to the fact that different parts of the PV module are operating at different voltage and current levels.

The introduction of shading can be mathematically represented by dividing the PV module into several sections, each with its own current-voltage characteristics. The overall P-V curve is nothing but the combination of these individual characteristics. Mathematically, this can be expressed as:

$$P(V) = \sum_{i=1}^{n}(V.I_i(V)) \tag{2.7}$$

Where: n is the number of sections or sub-modules in the PV array.

$I_i(V)$ is the current-voltage relationship for the (i)-th section.

In this scenario, partial shading can create multiple peaks and valleys in the P-V curve because each section operates under different illumination levels, resulting in various MPPs. These LMPPs may not necessarily coincide with the GMPP, leading to the challenge of accurately identifying the true MPP under PSC.

Graphically, in this work by plotting the P-V curve with multiple peaks and valleys representing different sections of the PV module operating at varying illumination levels. The GMPP corresponds to the highest peak on this curve, but there may be other lower peaks corresponding to LMPPs introduced by partial shading.

The MPA draws inspiration from nature, specifically the hunting behavior of marine predators, to solve optimization problems. Applying MPA to GMPPT PV systems offers several motivations:

i) **Exploration and Exploitation Balance:** MPA inherently balances exploration (searching for better solutions) and exploitation (refining known solutions), making it suitable for optimization problems with complex, multi-modal search spaces.

ii) **Meta-Heuristic Power:** MPA is a bio-inspired meta-heuristic algorithm that can potentially outperform traditional optimization methods in terms of finding optimal solutions.

iii) **Handling Multiple Peaks:** MPA's ability to mimic predator-prey dynamics can help in tackling the challenge of multiple peaks in the GMPPT problem, which can arise due to PSCs.

iv) **Robustness:** MPA's natural adaptive nature enables it to navigate changing environments and varying system conditions, which aligns well with the uncertainties and variations in PV systems.

v) **Convergence Speed:** MPA has demonstrated rapid convergence in certain scenarios, which can be crucial in real-time optimization like GMPPT.

vi) **Parallelism and Distribution:** The nature of MPA allows for parallelism and distribution, potentially leveraging modern computational resources for faster optimization.

vii) **Fewer Assumptions:** MPA can potentially require fewer assumptions about system parameters, making it more adaptable to real-world variations.

By leveraging the strengths, the proposed MPA GMPPT PV system aims to address the limitations of existing algorithms, provide a more robust, efficient, and adaptable clarification for optimizing power output in PV systems, especially under PSCs.

2.5 Summary

This chapter reviews the literature on various types of PV systems as well as modeling methodologies for PV systems under both uniform and PSCs. This chapter reviews the research on several approaches for reducing the impact of PSC on PV systems and also provides a comprehensive review of the most widely used conventional MPPT approaches, as well as other forms of soft computing and metaheuristic based MPPT strategies designed for tracking GMPP under PSC in PV systems. The literature on several hybrid MPPT approaches is also included in this chapter. Research gaps related to GMPPT finding under PSC in PV systems are discussed in detail and the importance of MPPT techniques along with the mathematical analysis is provided. To address the shortcomings of traditional and current meta-heuristic methods the proposed MPA and its motivations are explained in detail.

3

PV System Modeling in a PSC

3.1 Introduction

PV technology uses PV cells to convert sunlight's radiant energy into direct current (DC) power. PV technology is proven to be a cost-effective source of energy in the power generating sector, thanks to recent advancements. The literature has a variety of models that explain how PV cells work and behave. In order to estimate non-linear electrical properties, these models differ in computational technique, precision, number of involved factors [9], [13]. The results of modeling several types of PV cells, PV modules, and PV systems for different PV array configurations under PSC are described in this chapter. PV system electrical properties (I-V and P-V) are largely influenced by atmospheric factors like as temperature, irradiance, and PSC. Because of the inaccuracy involved with measuring GMPP, partial shading is a negative event that results in the waste of useful power. Operation of bypass diode across the module which is shaded, PV characteristics display several MPPs with complicated non-linearity under PSC [24]. Bypass diode safeguards system from damage caused by hot spots by providing a conduit for current flow from unshaded modules. Analytically PV system modeling under PSC are very few in the literature [20], [132], [27]. These presumptions are applied to the current equation of the PV module by neglecting resistance in the shunt[29], [28]. Building a thorough analytical model that accurately represents the correctness of MPPT controllers under varied PSC is essential, and supporting research on the dynamic analysis of power converters is also important [35], [45], and [48].

In this work, a single diode model (SDM) is utilized to simulate a PSC PV system, taking into account the effects of shunt resistance and series resistance.

3.2 PV Generation System

The PV system is one of the most popular and frequently utilized technology for generating electricity from the sun light. The basic principle at work in a PV generating system is utilizing a semi-conductor to convert light energy to DC electrical energy medium that conducts electricity.

3.2.1 PV effect

It is the direct conversion of solar energy into electrical energy through the use of semiconductor materials that absorb photons and release electrons. A PV cell is the most basic component of a PV system.

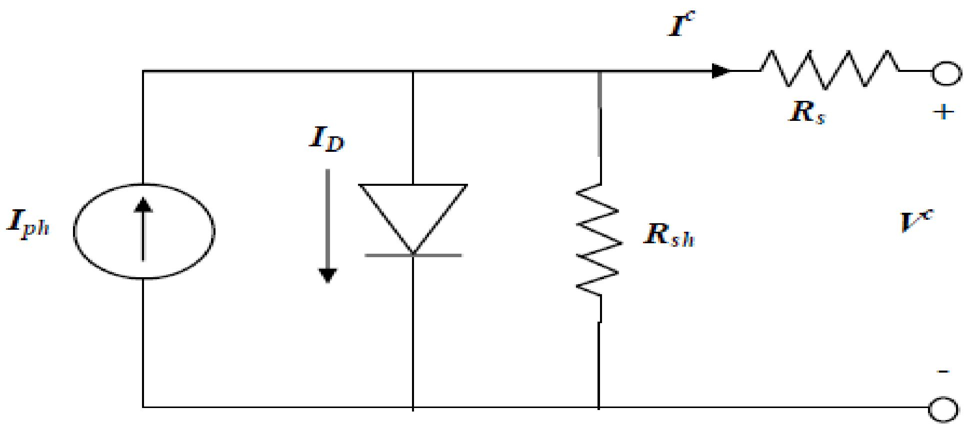
3.2.2 PV cell

The sun's radiant energy is converted into direct electricity via a PV cell. A PV cell is made up of a PN junction and a semi-conducting substance in general. Silicon is the most common semi-conducting material utilized in PV cell fabrication. PV cells are classified into numerous categories based on their materials and structure.

- Monocrystalline cells
- Polycrystalline cells
- Thin Films
- Dye-sensitized cells
- Organic solar cells
- Tandem or stacked cells
- Quantum dot solar cells

3.2.2.1 Types

The operation and behavior of PV cells are described by a number of models in the literature. In order to establish non-linear properties, these models differ in computational process, factors involved and accuracy [8], [9].



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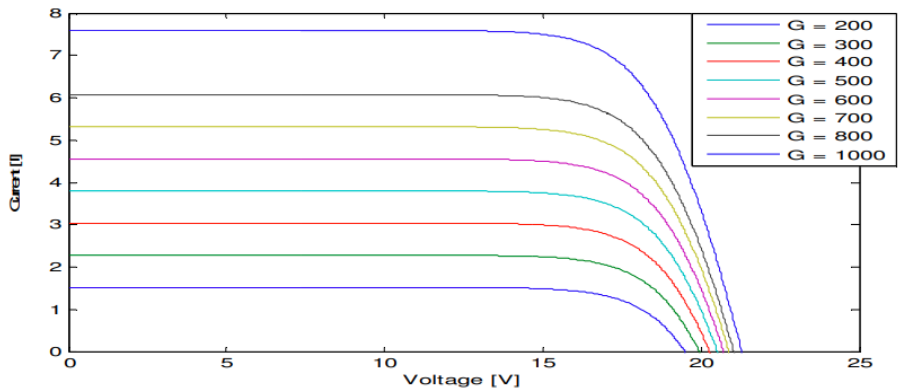

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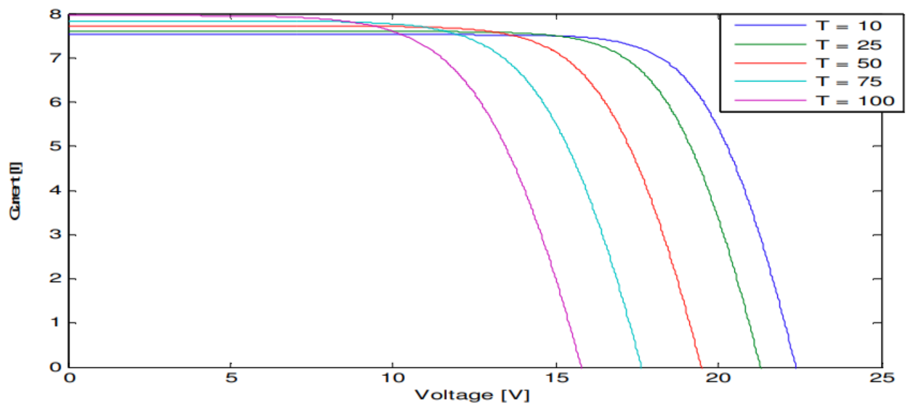

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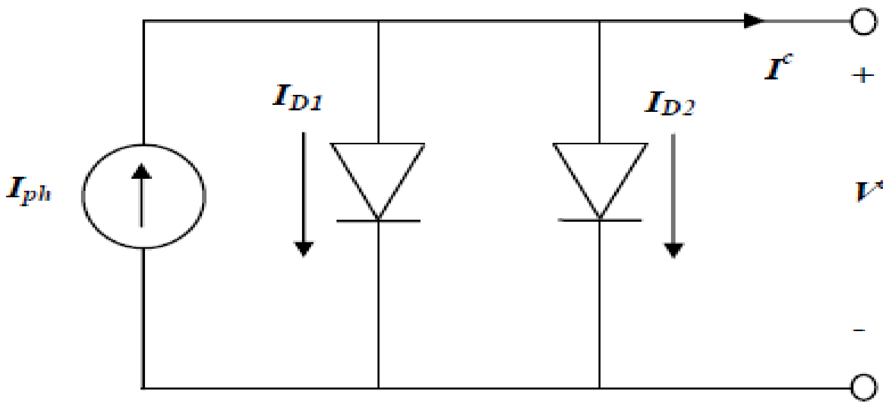
Figure 3.1. a) PV cell with a single diode b) V-I Curve during different irradiance c) V-I Curve during different temperature



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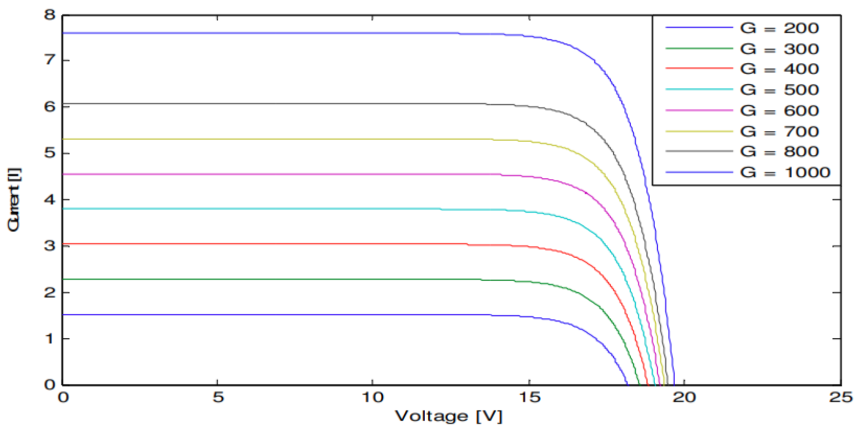

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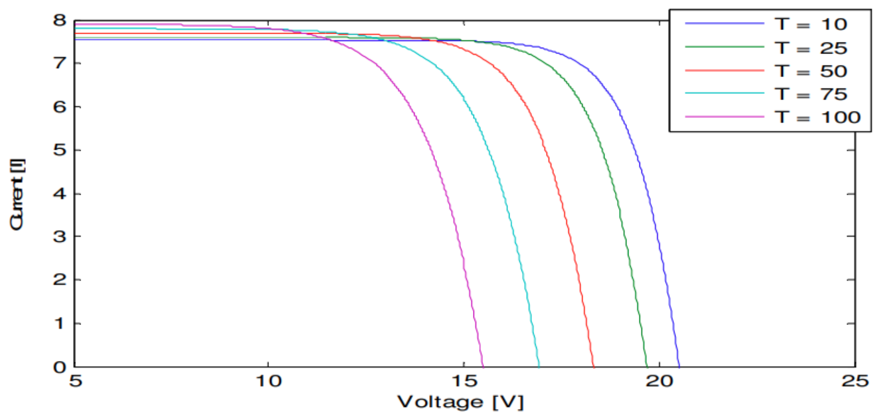


(c)

Figure 3.2. a) Two diode model PV cell b) V-I Curve during different irradiance c) V-I Curve during different temperature

3.2.2.1.1 Single diode model

The SDM is the most popular due to its ease of use and effectiveness in computing [13], based on the assumption that recombination loss in the depletion zone is small [15]. Figure 3.1.a depicts the analogous SDM PV cell model circuit. Similarly figures 3.1.b and 3.1.c show the voltage versus current (V-I) characteristics with respect to varying irradiance and temperature respectively of an SDM. On examining the curves, it is clear that with raise in irradiance, the current also rises proportionally but voltage increases very less.

The PV cell's current output is given by

$$I^c = I_{Ph} - I_o \left[e\left(\frac{q\left(V^c + I^C R_S\right)}{KTA}\right) - 1 \right] - \left(\frac{V^C + I^C R_S}{R_{Sh}}\right) \tag{3.1}$$

$$I_{ph} = \left(I_{ph\_STC} + k_i\, \Delta T\right) \frac{G}{G_{STC}} \tag{3.2}$$

$$I_o = I_{O\_STC} \left[\frac{T_{STC}}{T}\right]^3 e\left[\frac{qE_g}{AK}\left(\frac{1}{T_{STC}} - \frac{1}{T}\right)\right] \tag{3.3}$$

$$I_{0\_STC} = \frac{I_{SC\_STC}}{e\left(\frac{qV_{OC\_STC}}{AKT_{STC}}\right) - 1} \tag{3.4}$$

3.2.2.1.2 Two diode model

The TDM is the most accurate PV cell model because it takes into account recombination loss effect, which adds an extra diode in the PV cell's equivalent circuit [15]. Figure 3.2.a [14] depicts the analogous circuit of the TDM PV cell model. Similarly figures 3.2.b and 3.2.c show the voltage versus current (V-I) characteristics with respect to varying irradiance and temperature respectively of a two diode model. On examining, it is evident that the current somewhat increases as the temperature rises and cell voltage shows significant decrease in its value.

The PV cell's current output is given by

$$I = I_{Ph} - I_{01}\left[e^{\frac{qV}{KTA_1}} - 1\right] - I_{02}\left[e^{\frac{qV}{KTA_2}} - 1\right] \tag{3.5}$$

The photo current I_{PV} is given as

$$I_{ph} = \left(I_{Ph\_STC} + k_i \Delta T\right) \frac{G}{G_{STC}} \tag{3.6}$$

(3.7) and (3.8) are used to calculate the reverse saturation currents of diodes [19].

$$I_{01} = \frac{I_{SC\_STC} + K_i \Delta T}{e^{\frac{(V_{OC\_STC} + K_v \Delta T)q}{(N_S K T A_1)}} - 1} \quad (3.7)$$

$$I_{02} = \left(\frac{T^{\frac{2}{5}}}{3.77}\right) I_{01} \quad (3.8)$$

3.2.2.2 Parameter Extraction

The number of parameters in a PV cell model is proportional to the number of components in the PV cell circuit. Because of the extra diode, SDM is commonly referred to as a five-parameter model, while TDM is referred to as a seven-parameter model. Several approaches for extracting SDM and TDM parameters have been proposed in the literature [133], [20], [19]. The parameters to be retrieved and the procedure utilized to extract them differ across these methods. Kyocera KC 250GT PV module characteristics are utilized in this work for PV system modeling, and their specifications are presented in the Appendix.

3.2.3 PV Module

A single PV cell is not enough for any practical use; PV module is combination of PV cells which are linked in series.

For SDM, PV module current output is as follows:

$$I = I_{ph} - I_0 \left[e^{\frac{(V + I R_S)}{V_t}} - 1 \right] - \frac{V + I R_S}{R_{sh}} \quad (3.9)$$

$$V_t = \frac{N_S K T A}{q} \quad (3.10)$$

TDM PV module current output is stated as:

$$I = I_{ph} - I_{01} \left[e^{\frac{qv}{N_S K T A_1}} - 1 \right] - I_{02} \left[e^{\frac{qV}{N_2 K T A_2}} - 1 \right] \quad (3.11)$$

3.2.3.1 Effect of Temperature

As the temperature increases, the solar panel's output current increases exponentially but its voltage output declines linearly. In fact, the voltage drop is so predictable that it may be used to monitor temperature accurately. Heat can thus substantially reduce the solar panel's capacity to produce power.

3.2.3.2 Effect of irradiation

The PV panel current I_{Ph} is significantly impacted by changes in irradiation. Maximum power rises with irradiation because open circuit voltage V_{OC} increases marginally with increasing irradiance but short circuit current I_{SC} rises nearly linearly. PV module electrical characteristics for varying temperature and varying irradiation are presented in the results.

3.2.3.3 Effect of series resistance

The series resistance is mainly due to resistance between the metal contact and silicon (top and rear contacts) which are due to the movement of charge carriers between emitter and base. The series resistance and power output are inversely proportional. The increase in series resistance decreases power output.

3.2.3.4 Effect of shunt resistance

The shunt resistance of the solar cell is mainly due to manufacturing defects. This is generally preferred to be high, the low value of shunt resistance offers an alternate path for photo-current and minimizes the current flow through the junction of the solar cell thereby reduces the overall voltage cell. The change in shunt resistance will not have much effect on the power output of the PV module.

3.2.4 PV Array

Using connectivity topologies, a single PV module may be readily aggregated as PV array of any size. The series-parallel topology is the largest part widely used among the numerous PV array topologies. A module is made up of many cells, and strings are made up of series linked PV modules that are then connected in parallel to form an array. The required voltage determines how many PV modules are in a string, and the required current determines how many strings are in an array. Furthermore, as illustrated in Figure 3.3 [25], blocking diodes in series with each PV string are required in series-parallel setups to prevent current flows from one string to the next and bypass diodes across each module to prevent hotspots during shading.

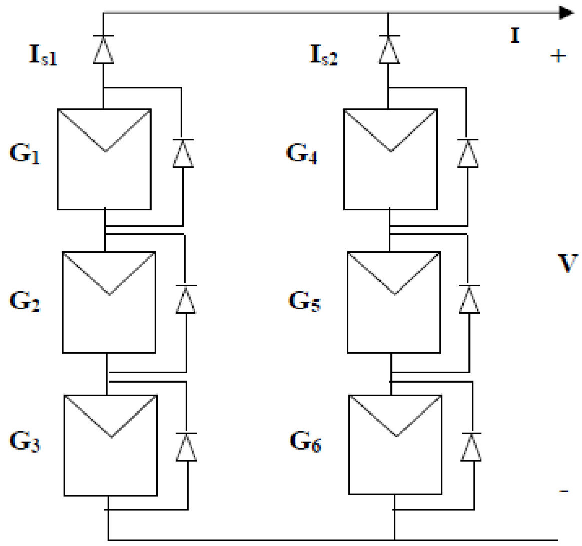


Figure 3.3. PV array with blocking and bypass diodes

3.3 PSC

The electrical properties of a PV system are mostly determined by environmental factors such as temperature, irradiance, and PSC. Because of the inaccuracy involved with measuring GMPP, partial shading is a negative event that results in the waste of useful power. Due to operation of bypass diode across the module which is shaded, PV characteristics display several maxima with complicated non-linearity under PSC [25]. Bypass diode safeguards system from damage caused by hot spots by providing a conduit for current flow from unshaded modules.

3.3.1 Partial Shaded Sub-module

Only one bypass diode is connected across the module when PV cells are connected in two groups and exposed to different levels of irradiation, a partially shaded sub module is formed. Figure 3.4 [32] shows the circuitry for a partly shaded sub-module. Sub module with r cells connected in series receives irradiance G_1 for s darkened cells and (r-s) cells receive irradiance G_2. The parameters of PV may be determined using (3.12), as well as the output current and voltage (3.13).

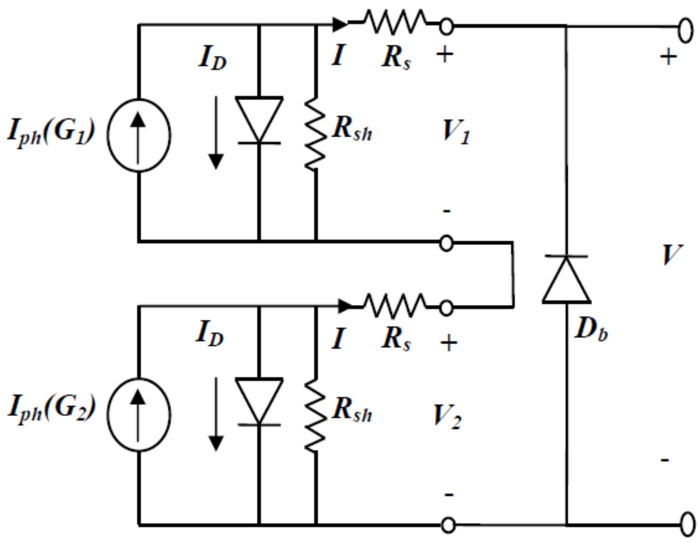


Figure 3.4. Partial shaded sub-module

$$I_{ph1} = I_{ph}(G_1), I_{ph2} = I_{ph}(G_2), N_{s1} = sN_{s1}, N_{s2} = (r - s)N_{s2} \tag{3.12}$$

Where 1 and 2 denote cells with G_1 and G_2 irradiance, respectively.

$$I = Min(I_1, I_2), V = \sum_{i=1}^{2} V(i) \tag{3.13}$$

3.3.2 Modeling of PV System under PSC using SDM

The operational point must change from the non-shaded to the shaded module due to bypass diode functioning due to PSC [33], [30], [31]. The following sequential procedures are used to describe the PV system characteristics throughout the PSC using SDM, assuming each module has one bypass diode.

For the sake of clarity, (3.9) is rewritten as follows in terms of voltage function:

$$f(V, I) = V - I_{ph}R_{sh} + I_0R_{sh}\left[e\left(\frac{V+IR_S}{V_t}\right) - I(R_s + R_{sh})\right] \tag{3.14}$$

The function V and I in equation (3.14) may be solved using Newton's iterative approach [29]. Comparing the photo current of the n_{th} module associated with the string current I_{sk} yields the voltage output of the n_{th} module as follows:

$$V^{kn} = \begin{bmatrix} V - I_{ph}^{kn}R_{sh} + I_O R_{sh}\left[e\left(\frac{V^{kn}+I_S^k R_S}{V_t}\right)\right] & \\ +I_S^k(R_s + R_{sh})I^{kn} > I_S^k & \\ 0 & I^{kn} > I_S^k \end{bmatrix} \tag{3.15}$$

Voltage of the n_{th} module of the k_{th} string is V^{kn}.

The output voltage of the K_{th} string is derived [32] by adjusting the string current I_s from zero to the module's photocurrent with better irradiation.

$$V_s^k = \sum_{n=1}^{m} V^{kn} \tag{3.16}$$

Where m is the number of modules in a string. The arithmetic total of all string currents yields the output current of PV array, which is represented by:

$$I = \sum_{k=1}^{s} I_s^k \tag{3.17}$$

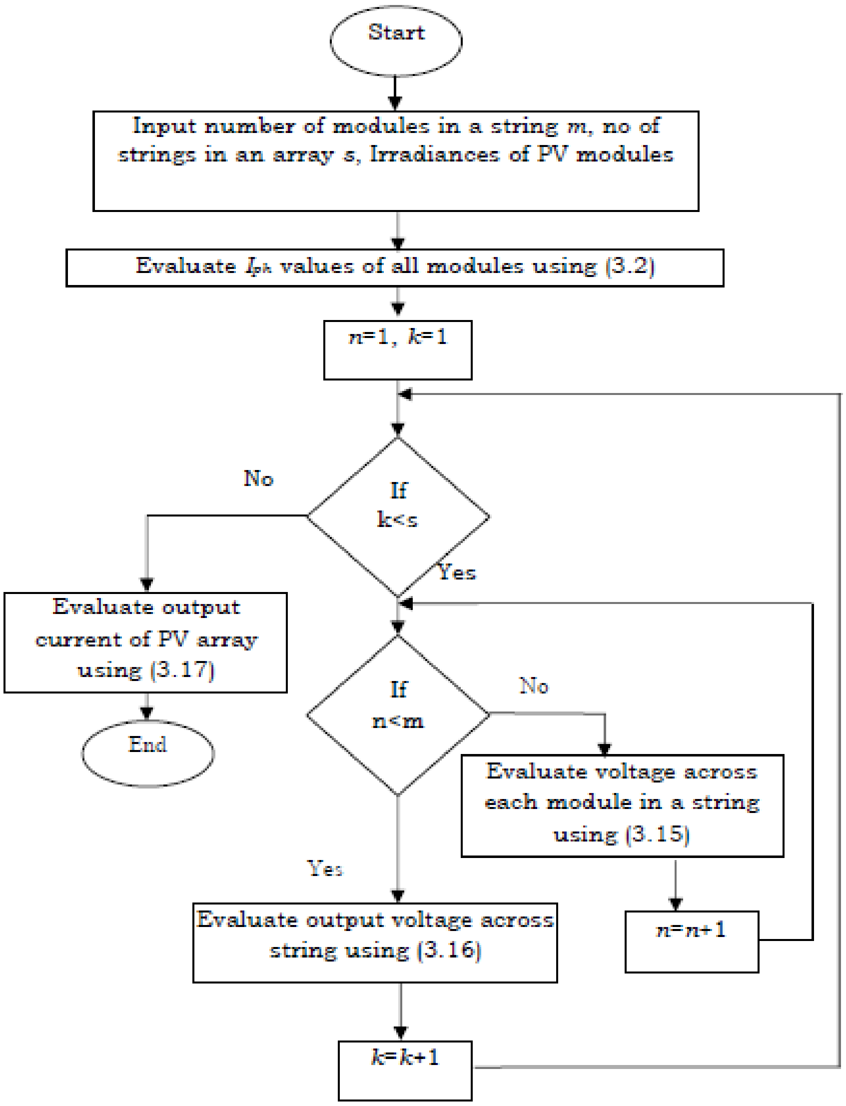
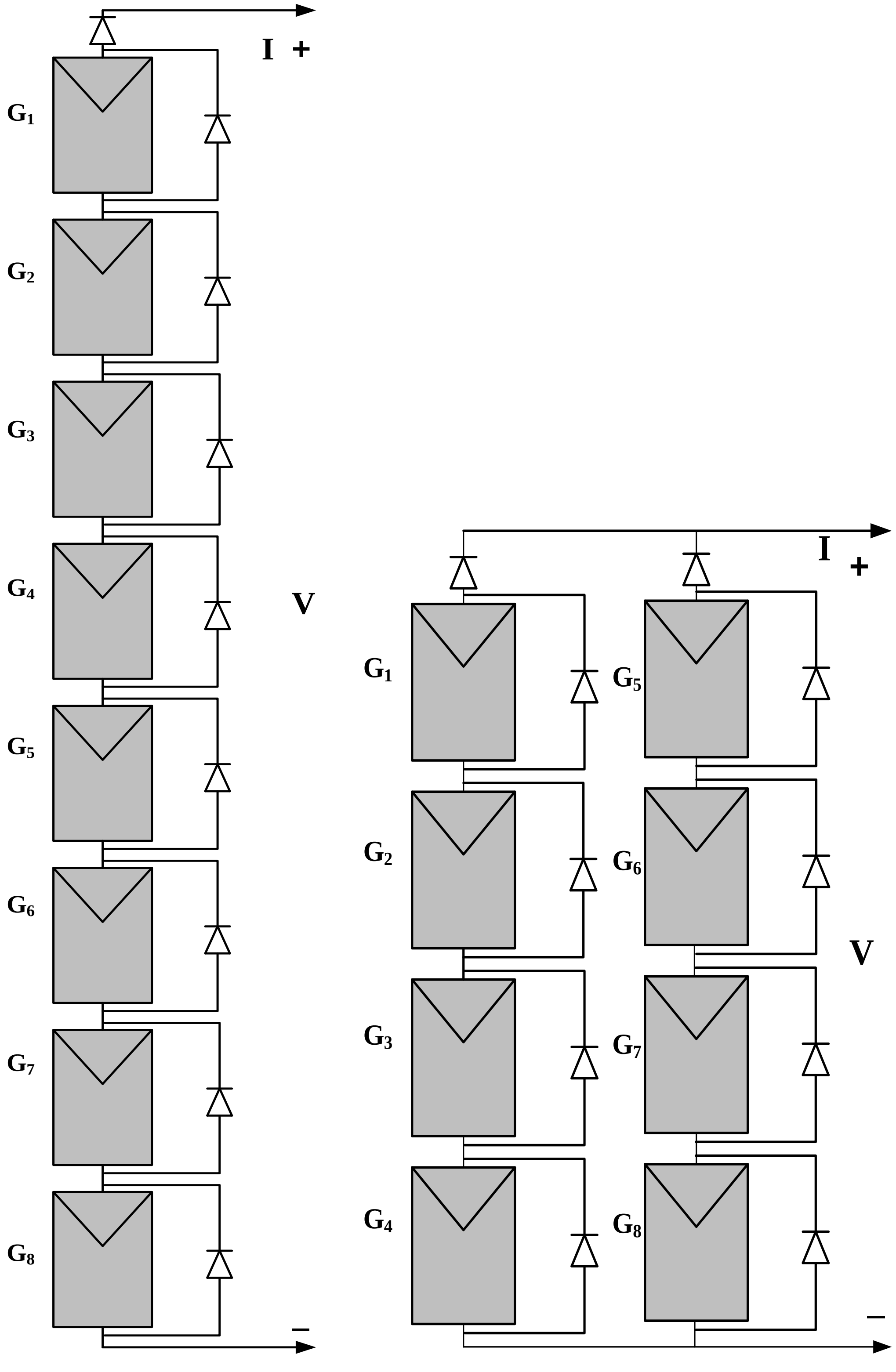
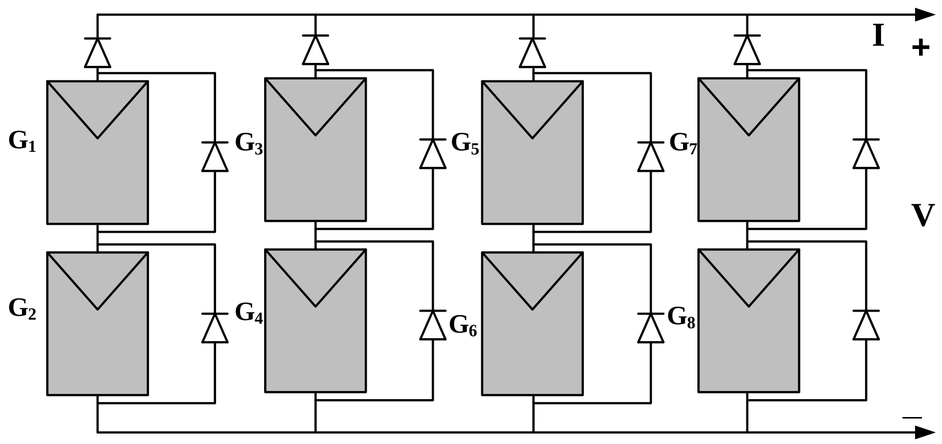


Figure 3.5. Flowchart for PV system modeling under PSC



(a) (b)



(C)

Figure 3.6. a) PV configuration in 8S b) PV configuration in 4S2P c) PV configuration in 2S4P

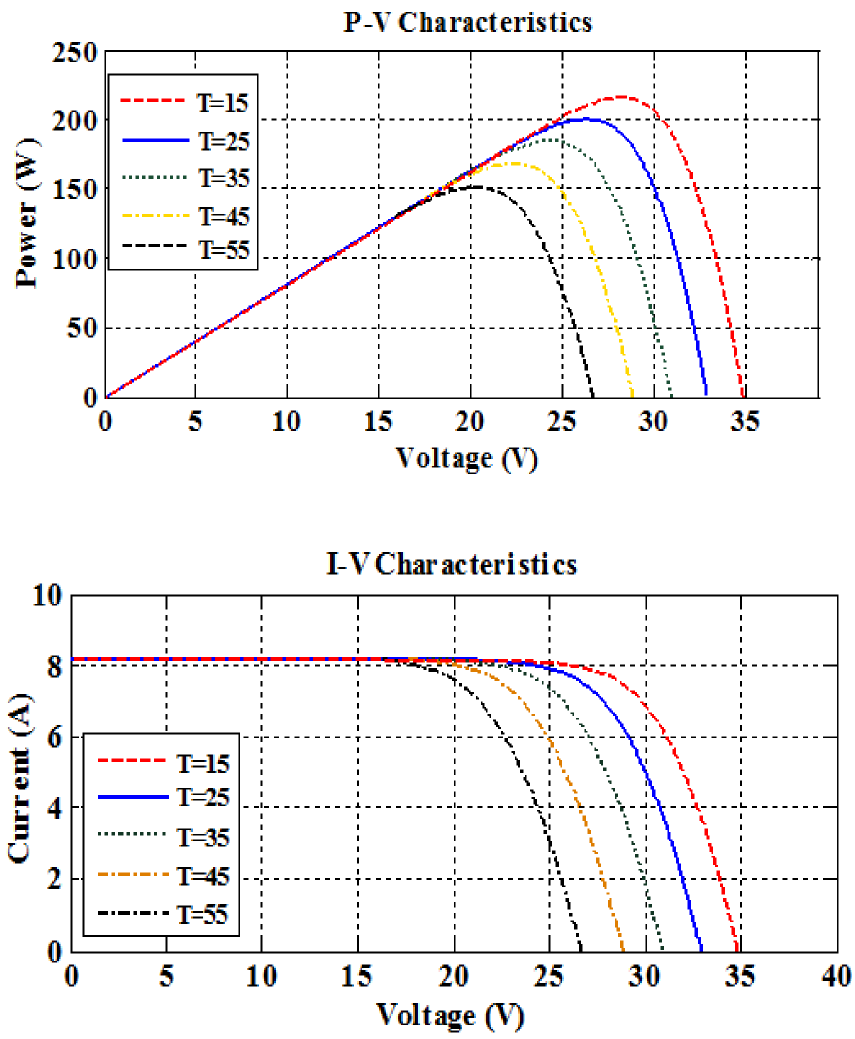
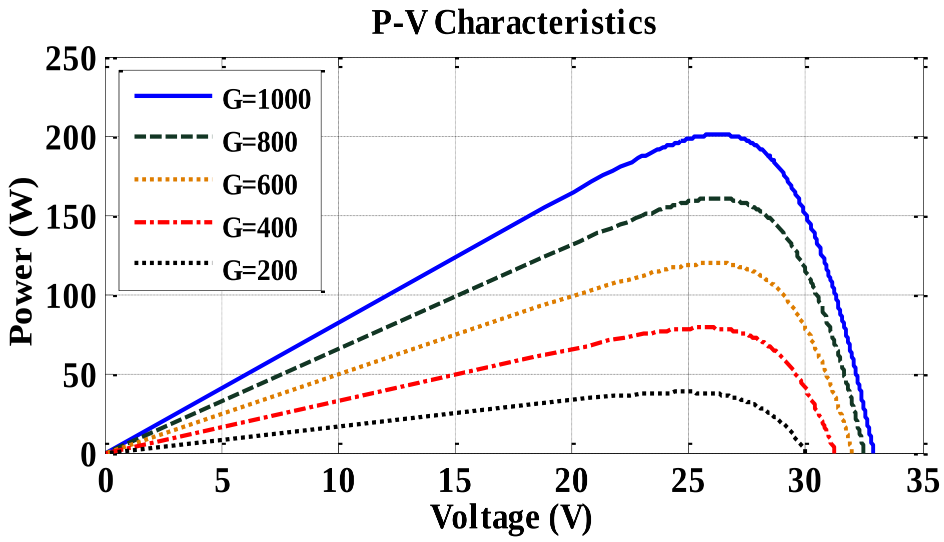


Figure 3.7. PV Module characteristics at variable temperatures

Parallel strings linked in an array are denoted by s. Figure 3.5 depicts the technique to model a PSC PV system.

3.4 PV Array Configurations

A system with 8S (Eight series), 4S2P (4 series 2 parallel), and 2S4P (2 series 4 parallel) PV Parameters is studied using PSC in this study.



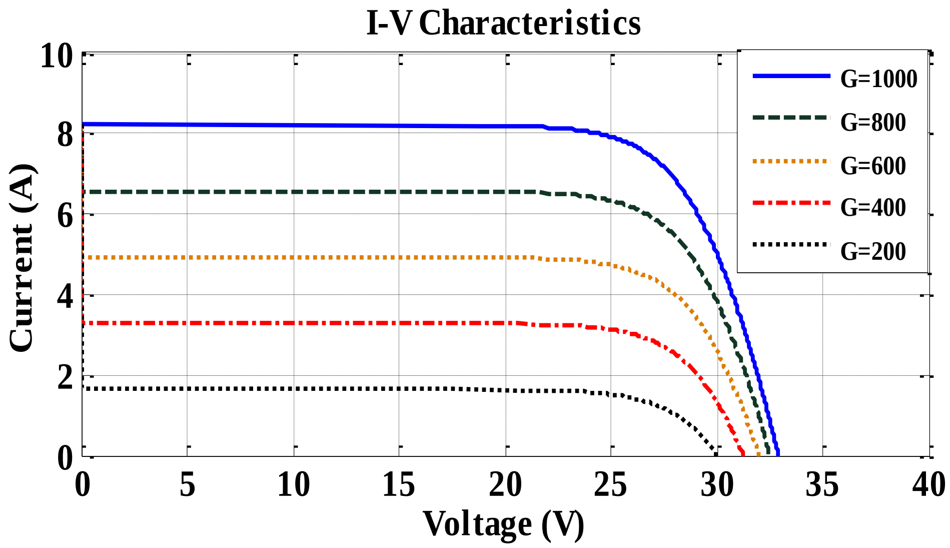


Figure 3.8. PV Module characteristics at variable irradiance

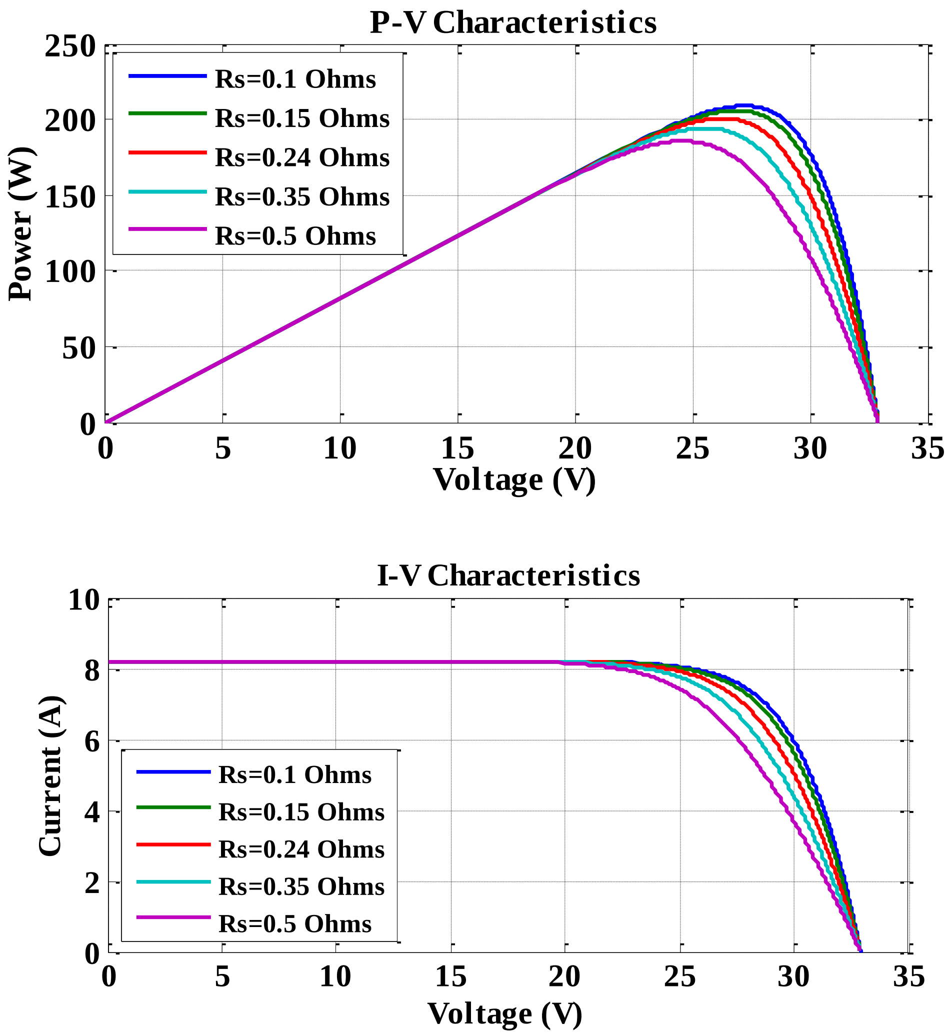
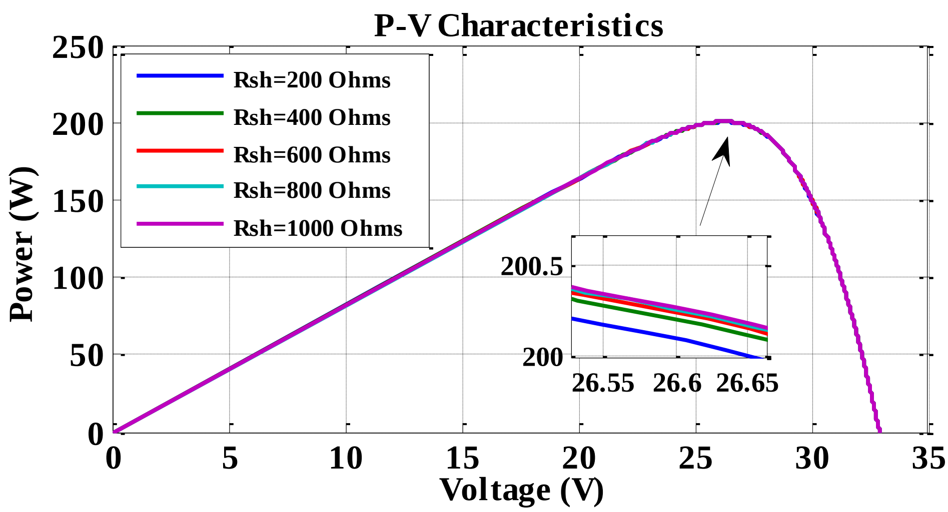


Figure 3.9. Characteristics of PV Module for changes in series resistance



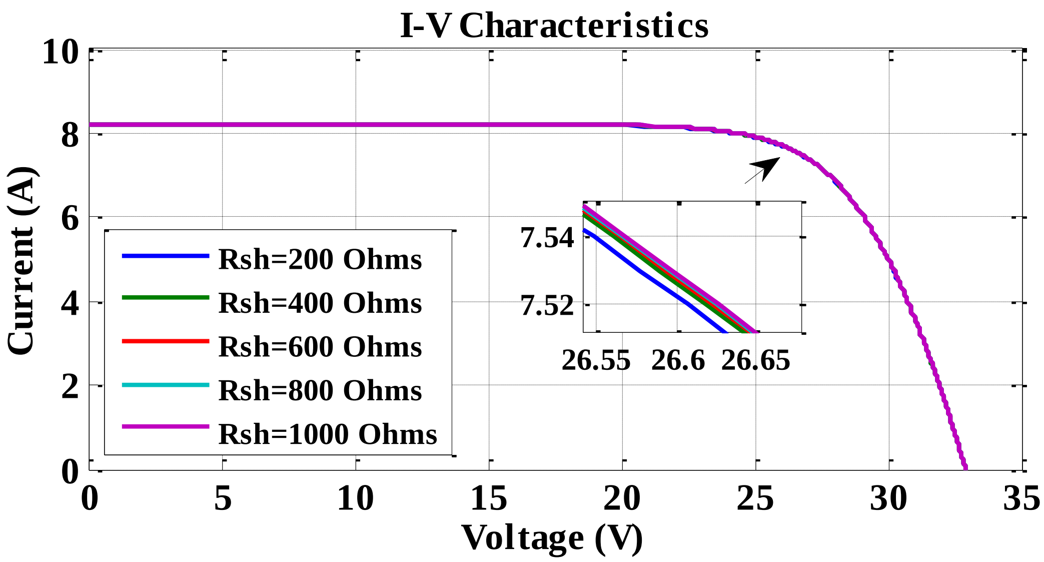


Figure 3.10. Characteristics of PV Module for changes in shunt resistance

3.5 Simulation Results

PV system electrical properties are described for all climatic variables like as temperature changes, irradiance changes, and PSC.

3.5.1 Temperature Changes

Figure 3.7 shows the PV module electrical properties at ranging temperatures as of 15°C to 55°C under uniform irradiation conditions (G_{STC}=1000 W/m^2).

As seen in the graph, short circuit current decreases somewhat as temperature rises, while open circuit voltage falls sharply, PV module maximum power also declines.

3.5.2 Irradiation Changes

Figure 3.8 shows the PV module characteristics in terms of electrical with various irradiances varies 200 W/m^2 to 1000 W/m^2 at T_{STC}=25°C.

Also, it is noticed that as irradiance increases, short circuit current increases quasi linearly and voltage increases slightly at open circuit. Therefore PV module maximum power increases with irradiation.

3.5.3 Characteristics of PV array due to changes in series resistance

The characteristics of the PV module for different values of series resistances R_S ranging from 0.1 to 0.5 ohms are depicted in Figure 3.9 From the figure, it is noticed that there is a reduction in the power output of the PV module due to the increase in series resistance.

3.5.4 Characteristics of PV array due to changes in shunt resistance

The PV module electrical characteristics for diverse values of shunt resistance R_{sh} ranging from 200 to 1000 ohms are depicted in Figure 3.10 it is observed that the impact on the power output of the module is very less because of the change in the shunt resistance.

3.5.5 8S PV configuration

The following are the shade patterns (W/m^2) for the 8S configuration of PV as shown in Figure 3.11:

1) G_1,G_2=1000 W/m^2, G_3,G_4=600 W/m^2, G_5,G_6=400 W/m^2, G_7,G_8=200 W/m^2
2) G_1=1000 W/m^2,G_2=900 W/m^2, G3=800 W/m^2, G_4=600 W/m^2, G_5=500 W/m^2, G_6=400 W/m^2, G_7=300 W/m^2, G_8=200 W/m^2

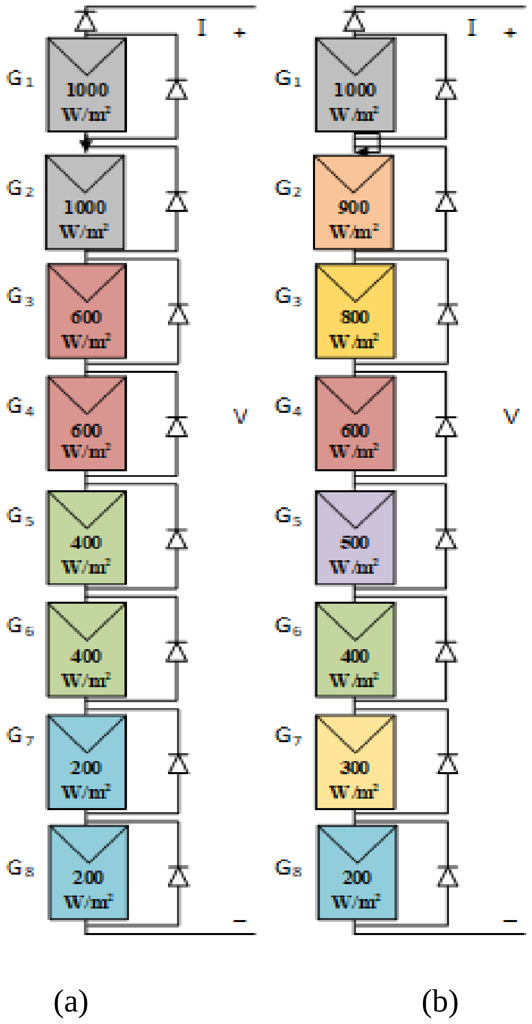


Figure 3.11. 8S PV configuration (a) Pattern I (b) Pattern II

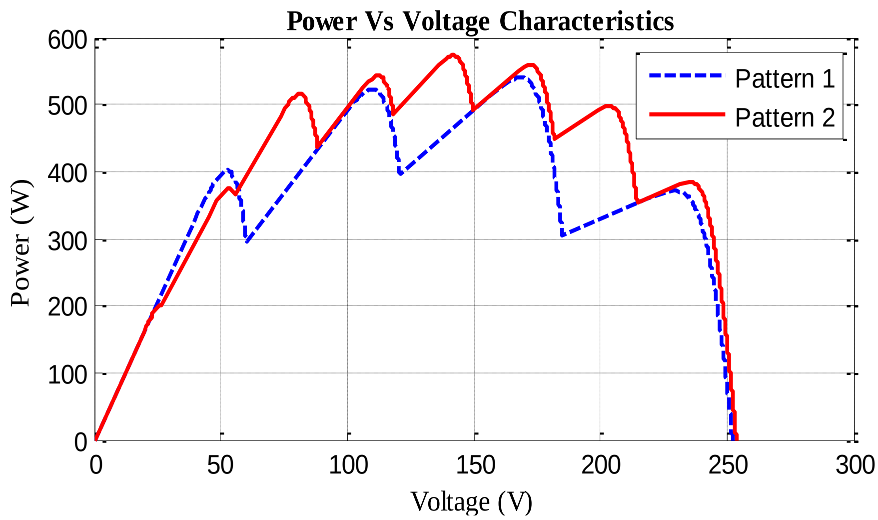


Figure 3.12. PV configuration Characteristics in 8S

Figure 3.12 shows the electrical properties of an 8S arrangement. The 8S electrical characteristics arrangement display four MPPs when exposed to pattern 1, and eight MPPs subjected to pattern 2 due to operation of bypass diode across the shaded module, as shown in the figure [139].

3.5.6 4S2P PV configuration

The following are the shade patterns (W/m^2) for the 4S2P PV configuration as shown in Figure 3.13:

3) G_1=1000 W/m^2,G_2=600 W/m^2, G3=400 W/m^2, G_4=200 W/m^2, G_5=1000 W/m^2, G_6=600 W/m^2, G_7=400 W/m^2, G_8=200 W/m^2
4) G_1=1000 W/m^2,G_2=600 W/m^2, G3=400 W/m^2, G_4=200 W/m^2, G_5=1000 W/m^2, G_6=800 W/m^2, G_7=600 W/m^2, G_8=400 W/m^2

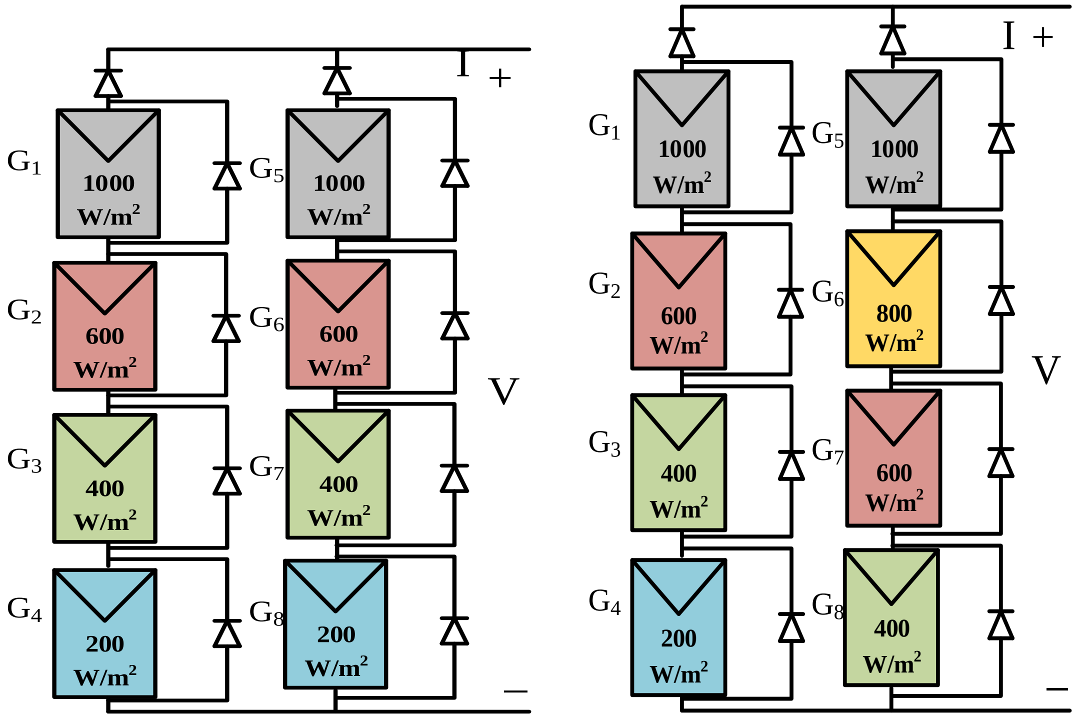


Figure 3.13. 4S2P PV configuration (a) Pattern III (b) Pattern IV

Figure 3.14 shows the electrical properties of the 4S2P arrangement. Operation of bypass diode throughout the module which is shaded, the electrical characteristics in 4S2P design display four MPPs with distinct amplitudes when subjected to patterns 3 and 4.

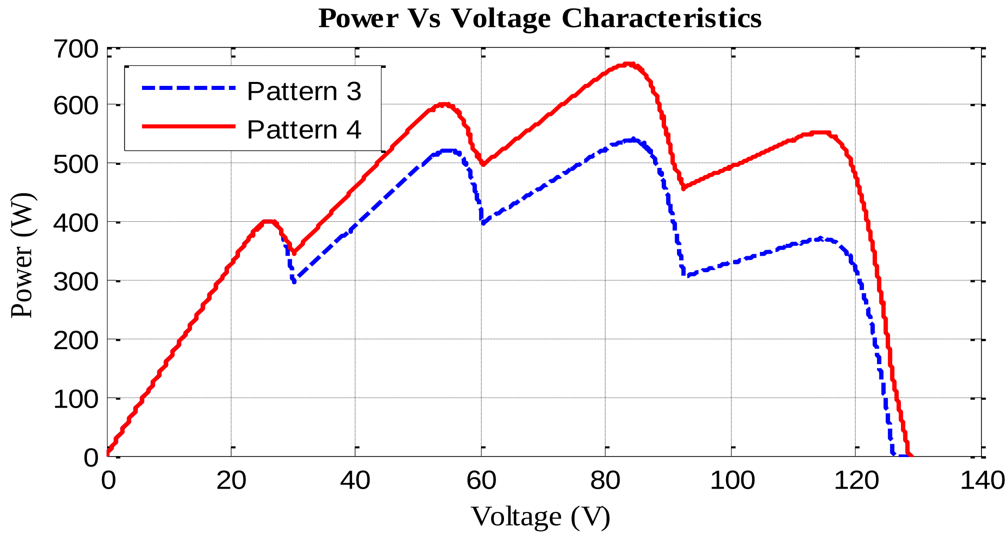
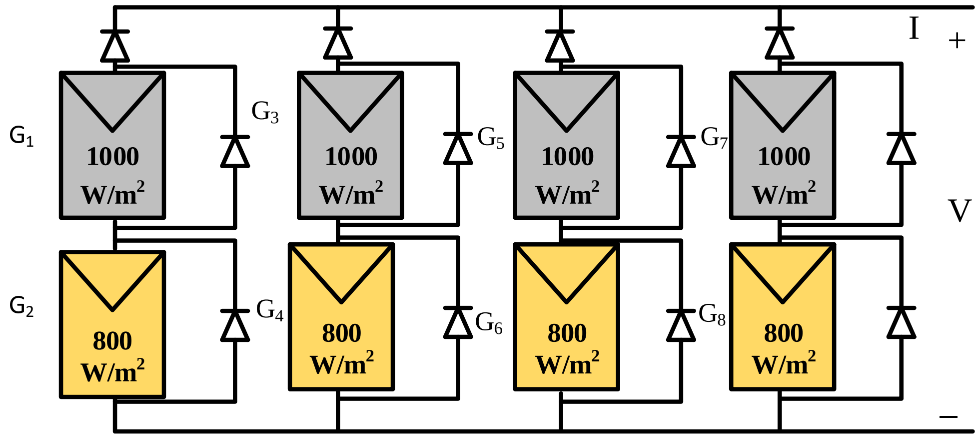


Figure 3.14. PV configuration Characteristics in 4S2P

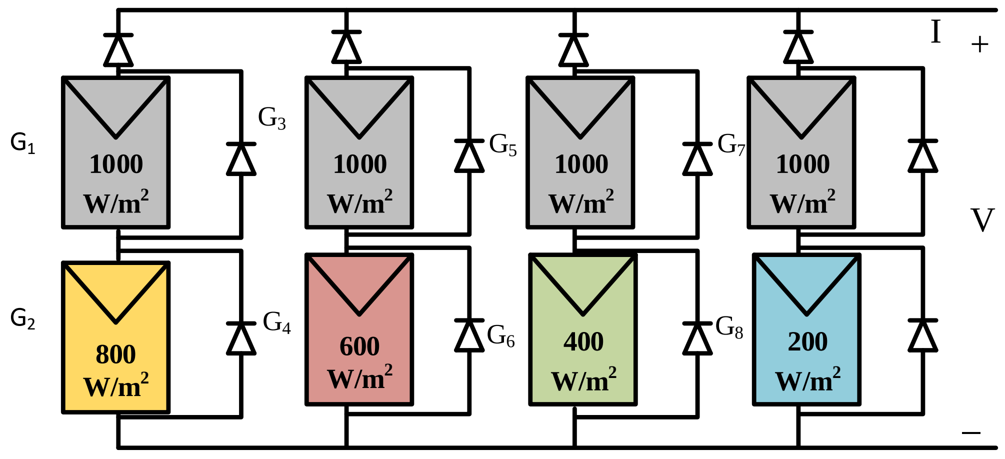
3.5.7 2S4P PV configuration

The following are the shade patterns for the 2S4P PV configuration as shown in Figure 3.15:

5) G_1=1000 W/m^2,G_2=800 W/m^2, G3=1000 W/m^2, G_4=800 W/m^2, G_5=1000 W/m^2, G_6=800 W/m^2, G_7=1000 W/m^2, G_8=800 W/m^2
6) G_1=1000 W/m^2, G_2=800 W/m^2, G3=1000 W/m^2, G_4=600 W/m^2, G_5=1000 W/m^2, G_6=400 W/m^2, G_7=1000 W/m^2, G_8=200 W/m^2



(a)



(b)

Figure 3.15. 2S4P PV configuration (a) Pattern V (b) Pattern VI

Figure 3.16 shows the electrical properties of the 2S4P arrangement. For pattern 5 and 6, the characteristics show two MPPs, one global and the other local.

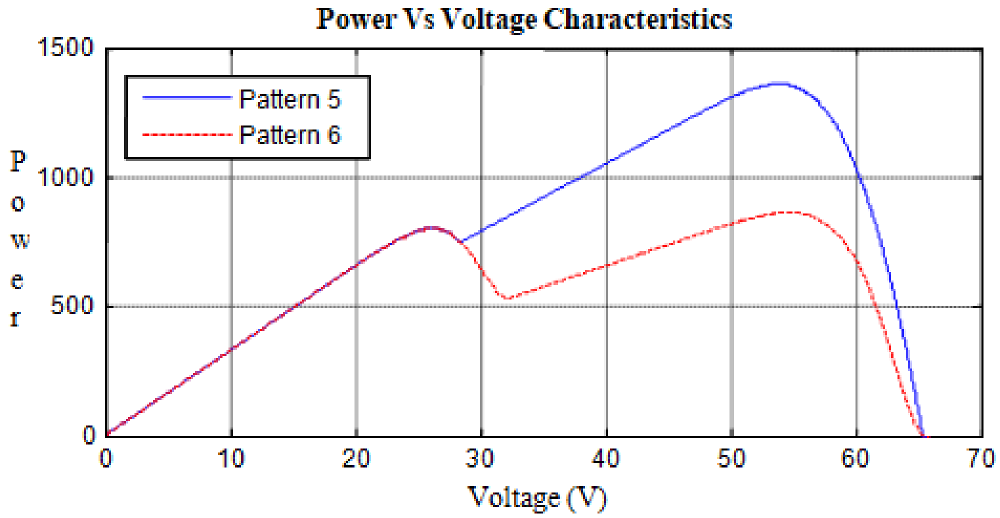


Figure 3.16. PV configuration Characteristics in 2S4P

3.6 Summary

In this chapter it is presented as an explicit systematic modeling of PV system subjected PSC taking into consideration the effect of shunt resistance and series resistance, which combines the accuracy and versatility of the SDM. PV systems electrical characteristics for irradiation, temperature variations of a PV module, and PSC are provided in this project for the 8S, 4S2P, and 2S4P configurations. Due to operation of bypass diode across the modules which are shaded, the PV characteristics show several local MPPs under PSC. The work was carried out and tested in a standalone PV system. A number of PV systems can use the proposed modeling with various array sizes under PSCs in both standalone and grid-connected applications. PV systems must be controlled at GMPP for maximum advantage, which may be accomplished with a power electronic converter in combination with a MPPT controller.

4

Application of Metaheuristic Algorithms for MPPT under PSC

4.1 Introduction

Shaded PV module bypass diode operation under PSC results multiple maxima in its electrical characteristics. The PV system must run at GMPP during PSC in order to provide its maximum output. In this chapter, recent and advanced MPPT strategies based on PSO [83], GWO [105] and MFO [138] algorithms are discussed. The mentioned algorithms are efficient with almost same convergence time as well as tracking time.

The selection of these specific metaheuristic algorithms for MPPT under PSC in this work depends on various factors and objectives which are

i) Diversity and Comparison: One common purpose for using multiple algorithms is to compare their performance. By applying several algorithms, one can evaluate which one performs better under PSC in terms of tracking the MPP of a PV system. This helps in identifying the strengths and weaknesses of each algorithm, leading to a comprehensive analysis.

ii) Robustness Testing: Different algorithms have different characteristics and robustness levels under various shading scenarios. Some algorithms may perform well in specific conditions but poorly in others, so evaluating their behaviour under partial shading provides valuable insights.

iii) Algorithm Suitability: These algorithms may be known for their ability to handle highly nonlinear and dynamic problems, making them suitable for

MPPT in PV systems subjected to PSC, which can result in nonlinear and rapidly changing power curves.

iv) Algorithm Popularity: Certain algorithms like PSO and GA have been widely used in various optimization problems, including MPPT. These well-established algorithms as benchmarks for comparison to see if newer or less conventional algorithms like DPSO, FBPSO, GWO, and MFO offer any advantages or improvements.

v) Novelty and Innovation: The selection of less common or newer algorithms (e.g., DPSO, FBPSO, GWO, and MFO) might indicate a desire to explore novel approaches and push the boundaries of what's been done before. These algorithms have unique features that could potentially enhance MPPT performance under PSC in terms of accuracy, tracking time and efficiency.

vi) Algorithm Parameter Tuning: Different algorithms have various parameters that can be adjusted to fine-tune their performance. Researchers might choose this set of algorithms to investigate the impact of parameter settings on MPPT accuracy and efficiency under PSC.

vii) Publication and Benchmarking: These algorithms that are commonly used in the field of MPPT research to ensure their work is comparable to existing literature. This helps in establishing benchmarks for the field and enables others to replicate and build upon their research.

viii) Resource Constraints: Depending on the computational resources available, these algorithms are computationally efficient and feasible for their specific experimental setup.

Overall, the purpose of selecting these metaheuristic algorithms for MPPT tracking under PSC could be a combination of factors, including the need to compare, evaluate, and understand their performance, their suitability for the problem at hand, a desire for innovation, and the desire to add to the body of already existing knowledge in the field.

The use of suggested MPPT approaches for global MPP tracking exposed to PSC for dynamically changing shading patterns for 8S, 2S4P and 4S2P arrangement of PV is discussed, and tracking results are shown.

4.2 Introduction to DPSO

4.2.1 Overview of PSO Algorithm

Kennedy et al. [98] inspired by bird flocking and fish schooling introduced a swarm intelligence-based metaheuristic algorithm. In PSO, a swarm of potential solutions (or particles) joins the search for the ideal solution after being randomly begun in the search space. The particles' collaboration and communication leads to the discovery of the best solution. In many engineering applications, identifying best solution for optimization issues PSO is utilized. Mathematically PSO method is represented by two equations that define how a particle's location and velocity are updated. Figure 4.1 shows how the particles' positions are updated.

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{4.1}$$

$$v_i^{k+1} = wv_i^k + c_1 r_1 \{P_{besti} - x_i^k\} + c_2 r_2 \{G_{best} - x_i^k\} \tag{4.2}$$

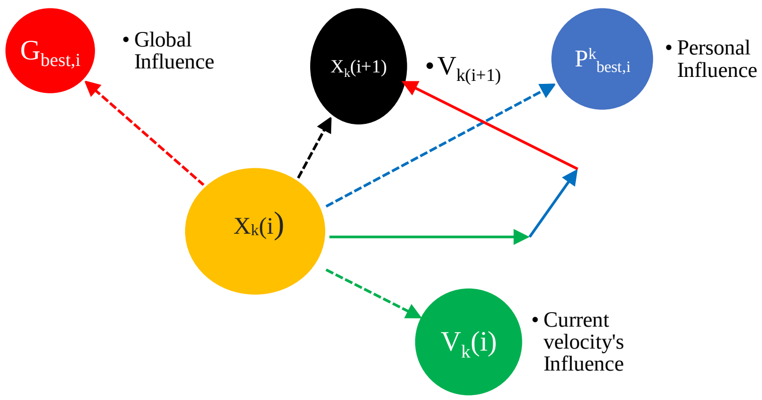


Figure 4.1. Movement of particles in search process

4.2.2 Dual-Stage PSO Algorithm

Traditional PSO algorithms randomly start populating the search space with probable solutions, which results in inconsistent monitoring of the ideal value and the possibility of convergence at local optimal points. The uniform distribution, which has equal probability intervals for all distributions, one of the most significant symmetric probability distributions, is used to resolve this issue [135]. This strategy distributes the total population evenly over the search space. The proposed DPSO method is composed of two phases.

i. Initialization

Create a population of possible solutions that is evenly distributed between the lowest and maximum limits a and b in (4.3).

$$\text{unifrnd}(a, b, N_P, n) \tag{4.3}$$

Where number of choice factors denoted by n and population size denoted by N_P.

ii. Dormant-stage

Population distributed uniformly will be assessed by the objective function and fitness value in this step, and then compares their subsequent fitness values to find the best population pair by pair. Populations with low fitness values will go dormant and will not participate in the search process. Classified local best values are said to be the best candidate solutions, with one being designated as the global best value. Then, using these values as in a traditional PSO, begin an iterative process of updating position and velocity using (4.1) and (4.2). Random numbers r_1 and r_2 are uniformly initialized in (4.1) and (4.2). This method of execution begins the search with a strong beginning estimate and converges in fewer steps and less time.

4.2.3 Parameters of DPSO

Three criteria heavily impact the DPSO search process.

1. Inertia weight (W)
2. Cognizant factor (C_1)
3. Social factor (C_2)

Particles are moved towards the optimum solution by the inertia weight W, and the cognitive and social factors C_1, C_2 are combined to form learning parameters, which are employed to sustain a suitable balance between the search process of exploration and exploitation phases. The optimal values for these parameters were found using the trial-and-error process and are listed in Table 4.1.

Table 4.1. Proposed DPSO method Parameters

Parameter	PSO	DPSO
Initial Population (Duty ratio, *d*)	Randomly between 0.1 and 0.9	Uniformly between 0.1 and 0.9
N_P	8	8
C_1	1.2	1.2
C_2	1.6	1.6
W	0.4	0.4
Termination criterion	Max No of iterations	Max No of iterations
Max number of iterations (K_{Max})	100	100

4.2.4 Application of DPSO for MPPT under PSC

In this part, to resolve the MPPT issue in PSC, DPSO is employed. The following is the whole application:

PV Power P_{MPP} is the objective function to be maximized in MPPT, while voltage is the decision variable used to monitor the maximum power[125] is the objective function.

Maximize: $P(D_i)$ (4.4)

Subjected: $0.1 \leq D_i \leq 0.9$ (4.5)

Where D_i is the duty ratio

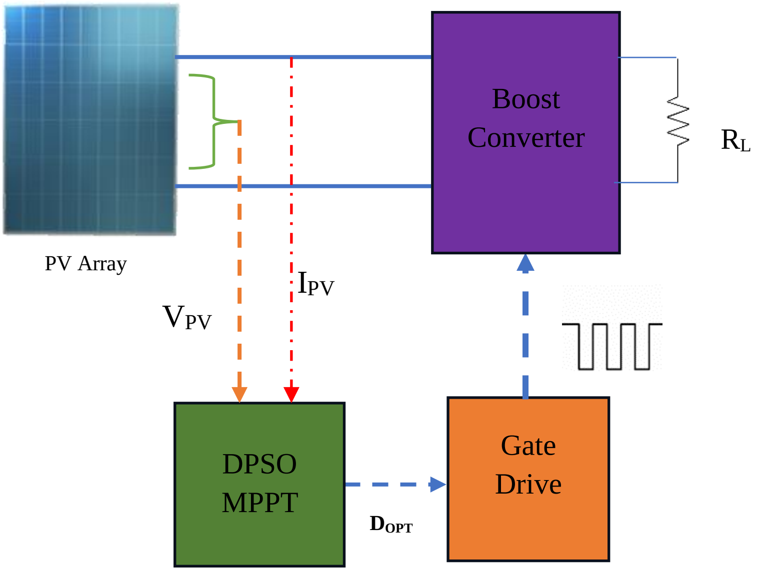


Figure 4.2. Block diagram of MPPT controller

DPSO MPPT algorithm's block diagram is given in Figure 4.2. Global MPP tracking using this algorithm will be done in sequential stages as follows:

PV array output power changes when the solar irradiation of the PV modules changes and the suggested MPPT algorithm restarts by detecting changes in output PV power (4.6). Figure 4.3 depicts the DPSO MPPT algorithm's flowchart.

$$\frac{P^K - P^{K-1}}{P^K} \geq 0.1 \tag{4.6}$$

4.2.5 Simulation Results

Simulations for 8S, 4S2P, and 2S4P configurations of PV for dynamically changing shading patterns are carried out to assess the performance of the MPPT algorithm DPSO, and tracking results of both PSO and DPSO MPPT algorithms are presented.

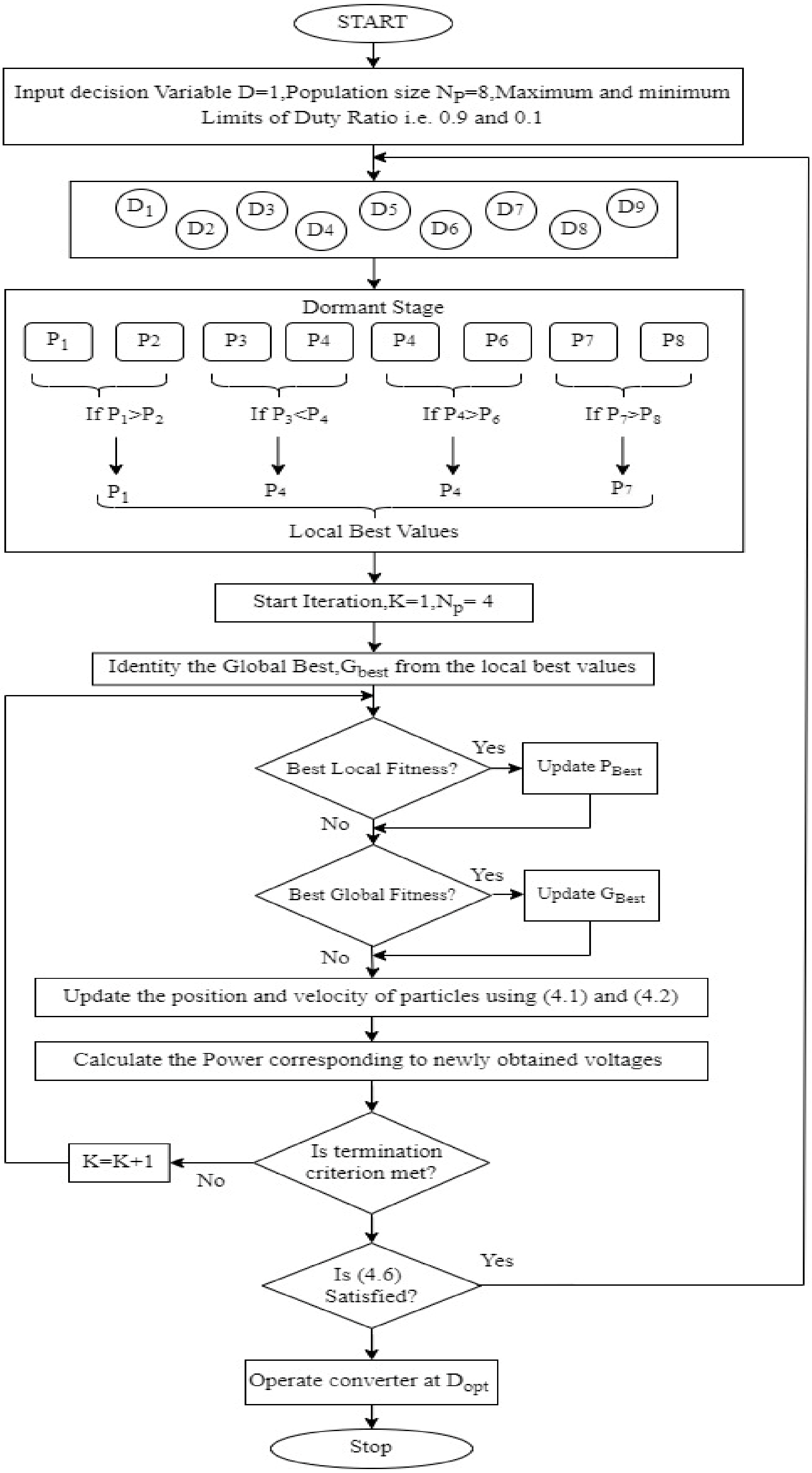


Figure 4.3. DPSO MPPT algorithm flowchart

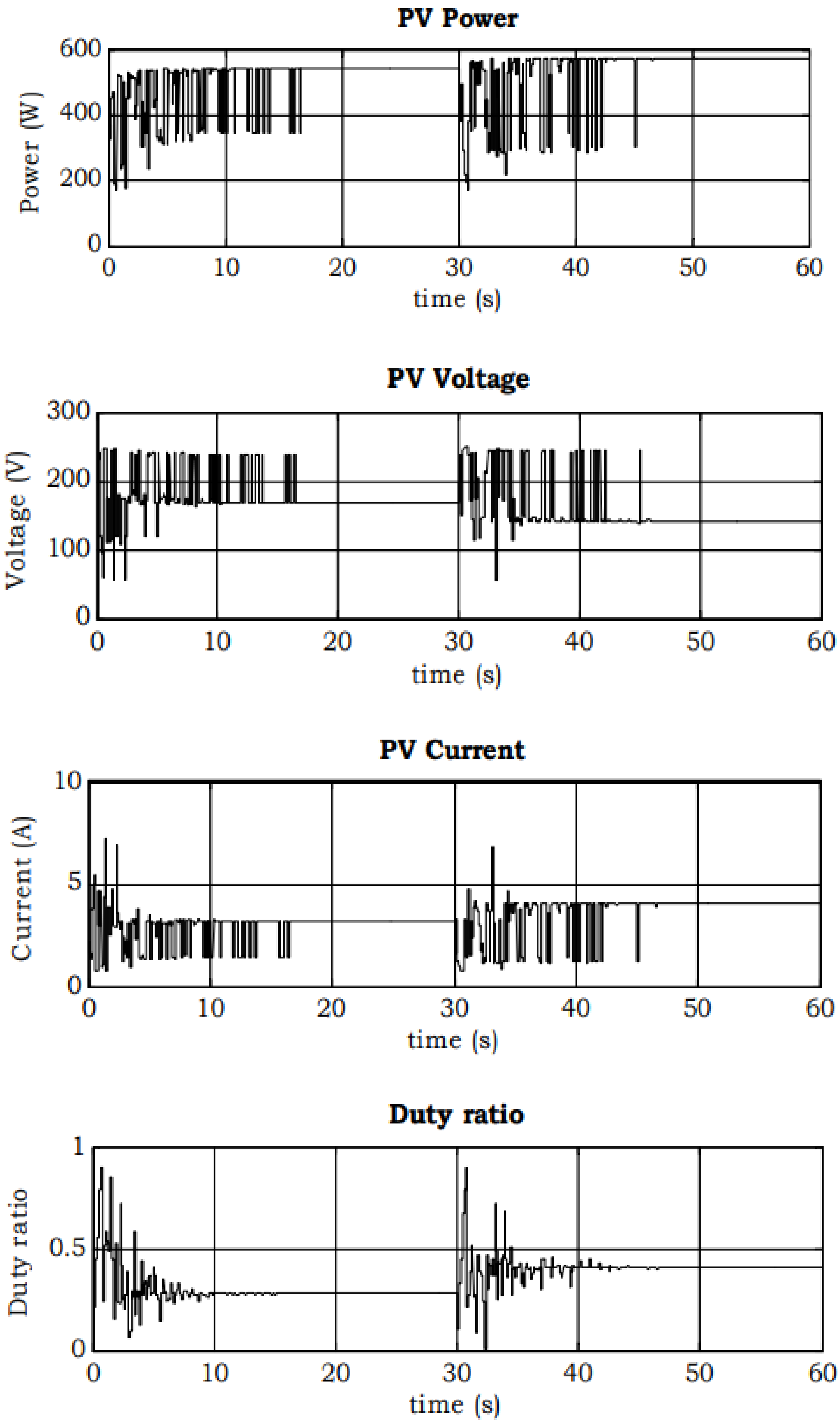


Figure 4.4. Tracking Curves of PSO MPPT Algorithm for 8S PV configuration

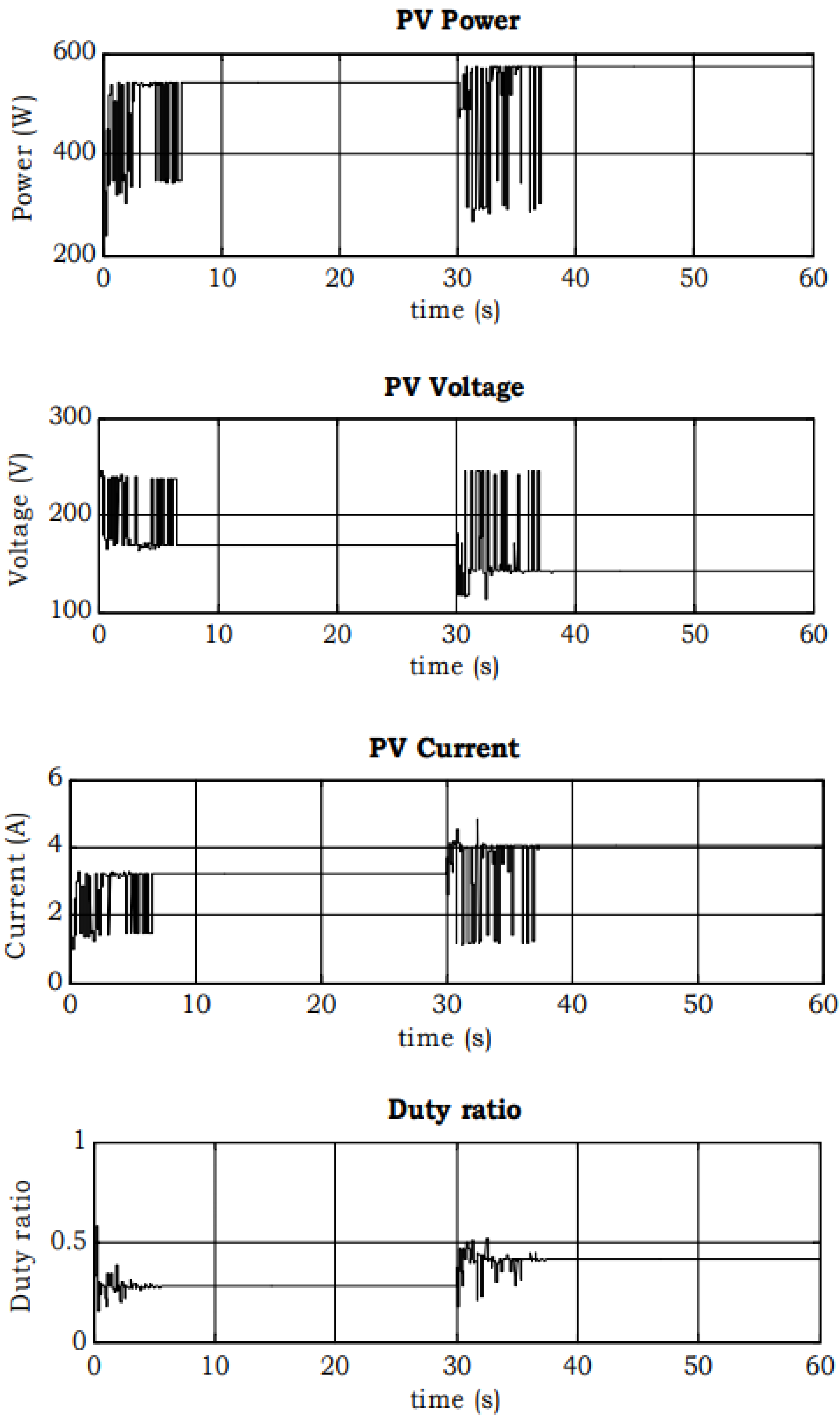


Figure 4.5. Tracking Curves of DPSO MPPT Algorithm for 8S PV configuration

4.2.5.1 Tracking curves of PSO and DPSO MPPT Algorithm for 8SPV Configuration

Operating an 8S PV system under various shade patterns allows researchers to analyze the suggested DPSO and conventional PSO MPPT algorithms' dynamic performance. From 0 to 30s Pattern 1 and from 30s Pattern 2 forward are applied to the 8S PV setup. By detecting the change in PV power, the program starts looking for changes in the shade pattern from scratch. Figures 4.4 and 4.5 demonstrates the tracking curves for the DPSO and PSO MPPT algorithms for an 8S PV system for PV power, current, voltage and duty ratio. According to the figures the suggested DPSO algorithm extracts the maximum power of 540.24 W and 573.28 W in 6.6 sec and 7.4 sec respectively. Where the maximum power of the standard PSO MPPT approach is extracted as 540.24 W and 573.28 W in 16.5 and 16.8 seconds for pattern 1 and pattern 2 respectively.

4.2.5.2 Tracking curves of PSO and DPSO MPPT Algorithm for 4S2P PV Configuration

Operating the 4S2P PV system under various shade patterns allows researchers to analyze the suggested DPSO and conventional PSO MPPT algorithms' dynamic performance. 4S2P PV arrangement from 0 to 30s Pattern 3 is applied; from 30s Pattern 4 is applied. By detecting the change in PV power, the program starts over in its search for changes in the shade pattern. The tracking curves for PV power, voltage, current, and duty ratio for a 4S2P PV system are shown in Figures 4.6 and 4.7 for the PSO and DPSO MPPT algorithms, respectively. According to the figures, the conventional PSO MPPT approach maximizes the power of 541.01 W and 669.8 W in 11.2 sec and 13.2 sec for patterns 3 and 4, while the suggested DPSO algorithm extracts the maximum power of 541.01 W and 670.35 W in 7.2 sec and 4.6 sec.

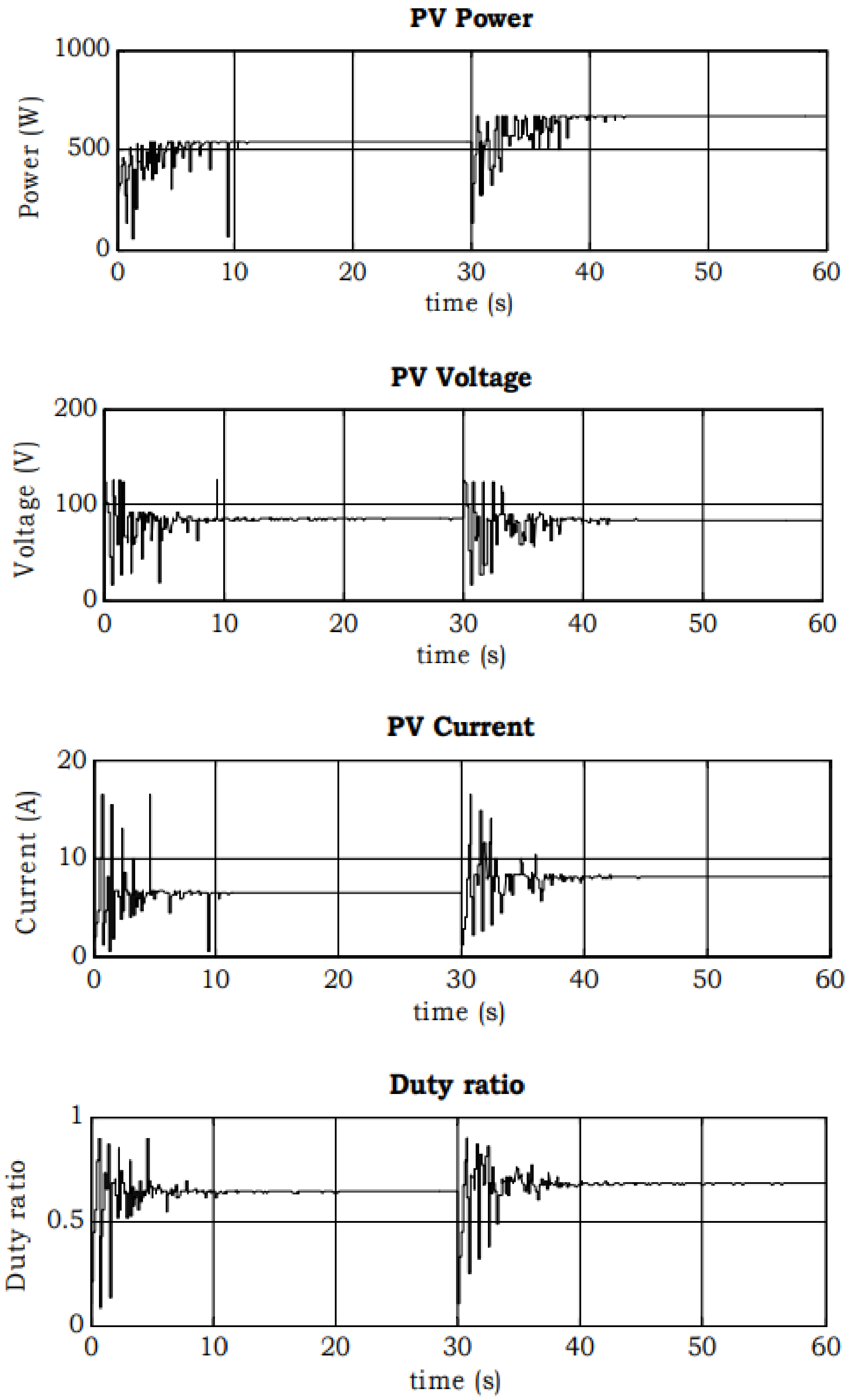


Figure 4.6. Tracking Curves of PSO MPPT Algorithm for 4S2P PV configuration

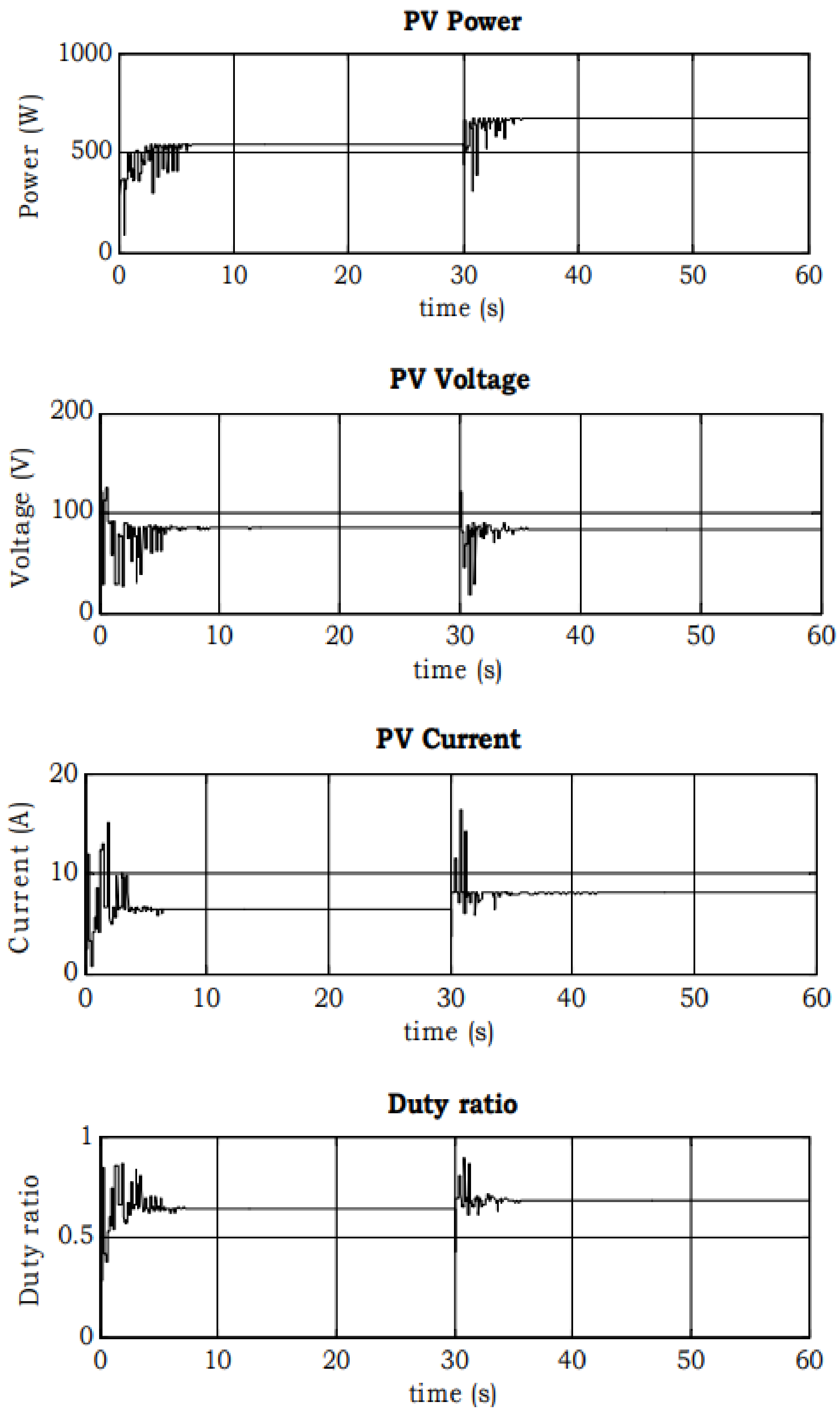


Figure 4.7. Tracking Curves of DPSO MPPT Algorithm for 4S2P PV configuration

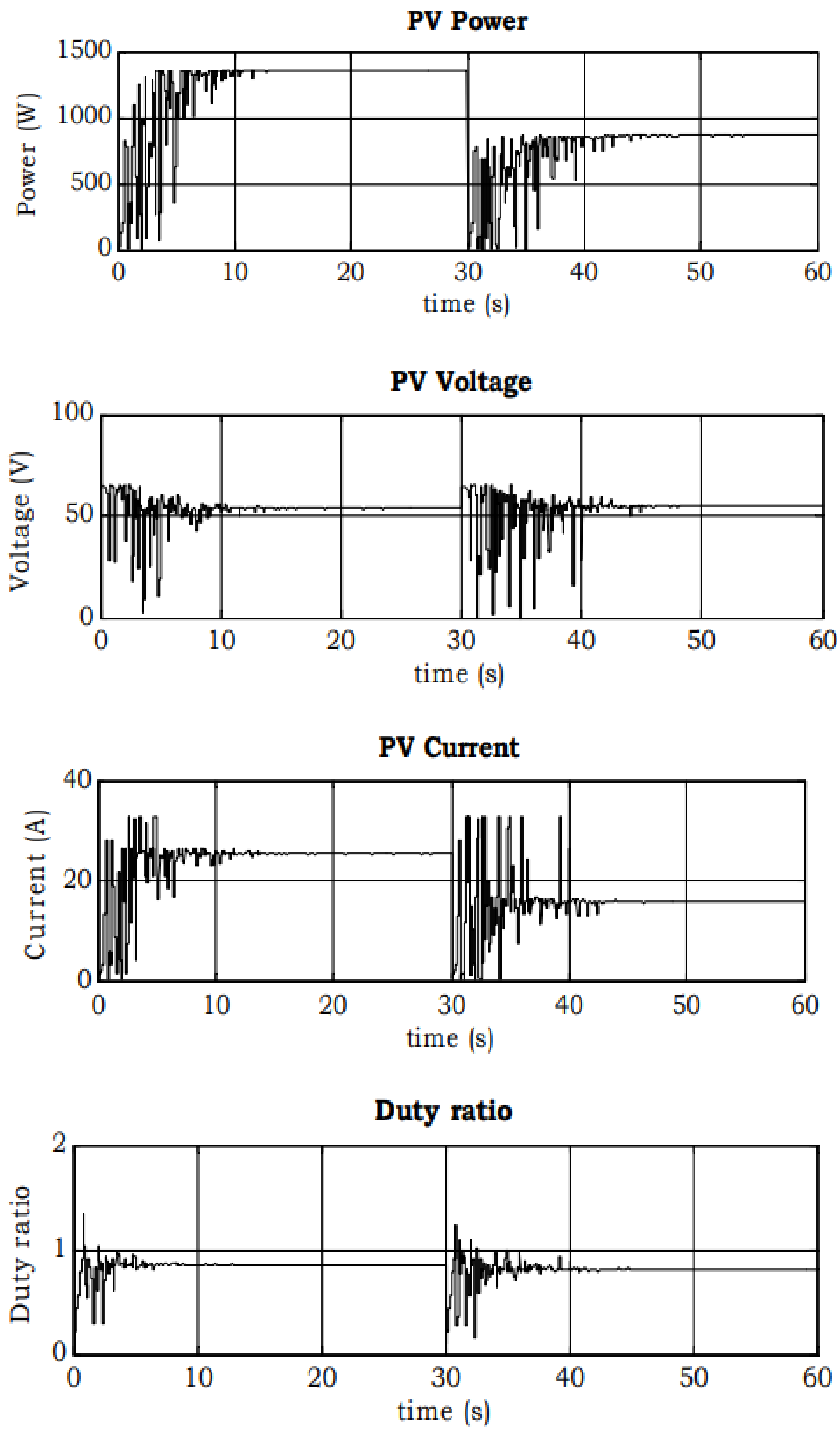


Figure 4.8. Tracking Curves of PSO MPPT Algorithm for 2S4P PV Configuration

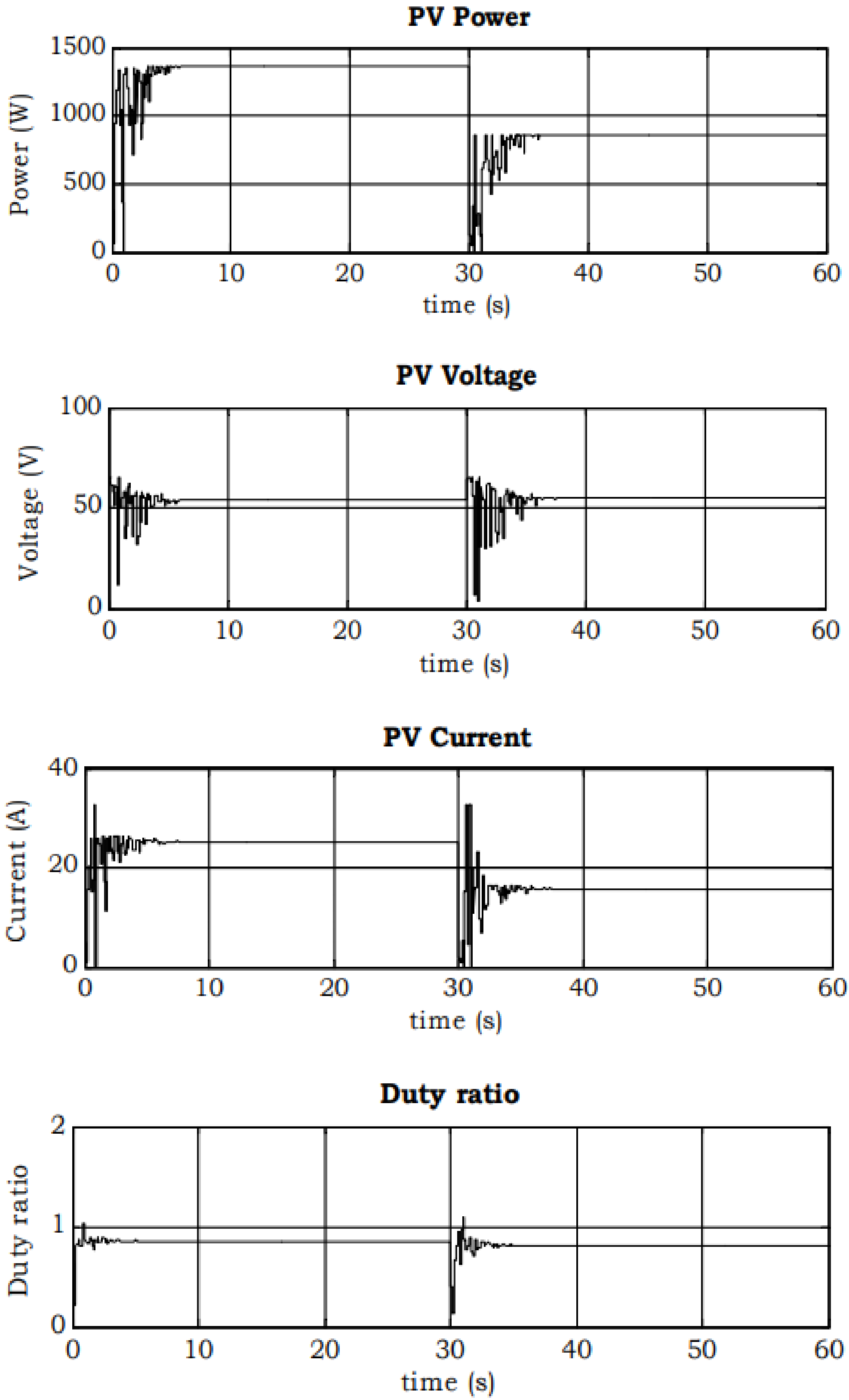


Figure 4.9. Tracking Curves of DPSO MPPT Algorithm for 2S4P PV Configuration

4.2.5.3 Tracking curves of PSO and DPSO MPPT Algorithm for 2S4P PV Configuration

Operating the 2S4PPV system under various shade patterns allows researchers to analyze the suggested DPSO and conventional PSO MPPT algorithms' dynamic performance. From 0 to 30spattern 5 and from 30s pattern 6 are applied to the 2S4P PV arrangement. By detecting the change in PV power, the program starts over in its search for changes in the shade pattern. The tracking curves for PV power, voltage, current, and duty ratio for a 2S4P PV system are shown in Figures 4.8 and 4.9 for the PSO and DPSO MPPT algorithms, respectively. The suggested DPSO algorithm extracts the maximum power of 1360.8 W and 864.8 W in 5.1 sec and 5.9 sec, whereas the standard PSO MPPT approach maximizes the power of 1360.8 W and 864.8 W in 11.7 sec and 15 sec for pattern 5 and pattern 6, respectively.

4.3 Introduction to FBPSO

4.3.1 FBPSO algorithm

A typical PSO approach begins by randomly generating a population of particles across the entire range of possibilities between the maximum and minimum boundaries. According to FBPSO, utilizing (4.7) and (4.8), in the first part of the search space, the particle population is initialized and the second part is dispersed using opposition-based learning [134].

$$PopF = a + (b - a)rand \tag{4.7}$$

$$PopB = a + b - PosF \tag{4.8}$$

Here PopF is forward population initialization and PopB is the backward population initialization and decision variable high and low restrictions are a and b.

The search mechanism in FBPSO uses a smaller population of particles. The best particles are identified by comparing the fitness ratings of the forward and backward particles. Particles that are obtained in this way are used in the search. Using (4.1) and (4.2), Particle I's position and speed are changed, correspondingly.

4.3.2 Parameters of FBPSO

Three parameters have the greatest influence on the FBPSO search process. Table 4.2 displays the numbers that were chosen for the recommended strategy along with the cognizant component (C_1), the social component (C_2), and the inertia weight (W).

Table 4.2. Proposed FBPSO method Parameters

Parameter	**FBPSO**
Initial Population (Duty ratio, d)	Termination criterion
N_P	8
C_1	1.2
C_2	1.6
W	0.4
Maximum No of iterations (K_{Max})	100
Criterion of Termination	Maximum number of iterations

4.3.3 Application of FBPSO for MPPT under PSC

In this section FBPSO is applied for MPPT problem under PSC. The detailed application is as follows:

For MPPT, PV Power GMPP is the function that must be tracked, while duty ratio is the assessment variable used to monitor the maximum power [104]. Figure 4.10 shows flowchart for FBPSO MPPT algorithm.

4.3.4 Simulation Results

Simulations are run for 8S, 4S2P, and 2S4P configurations of PV for dynamically PSC, and results evaluated the working of FBPSO MPPT algorithm.

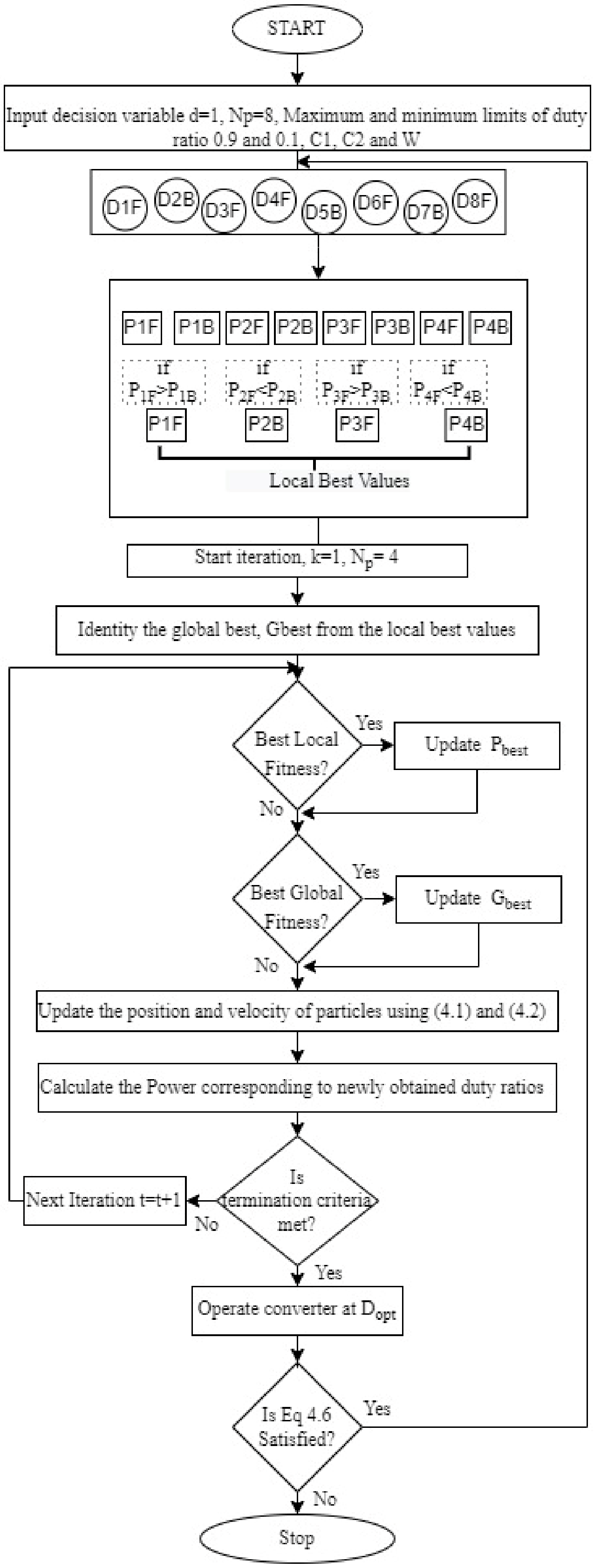


Figure 4.10. Flowchart for FBPSO MPPT algorithm

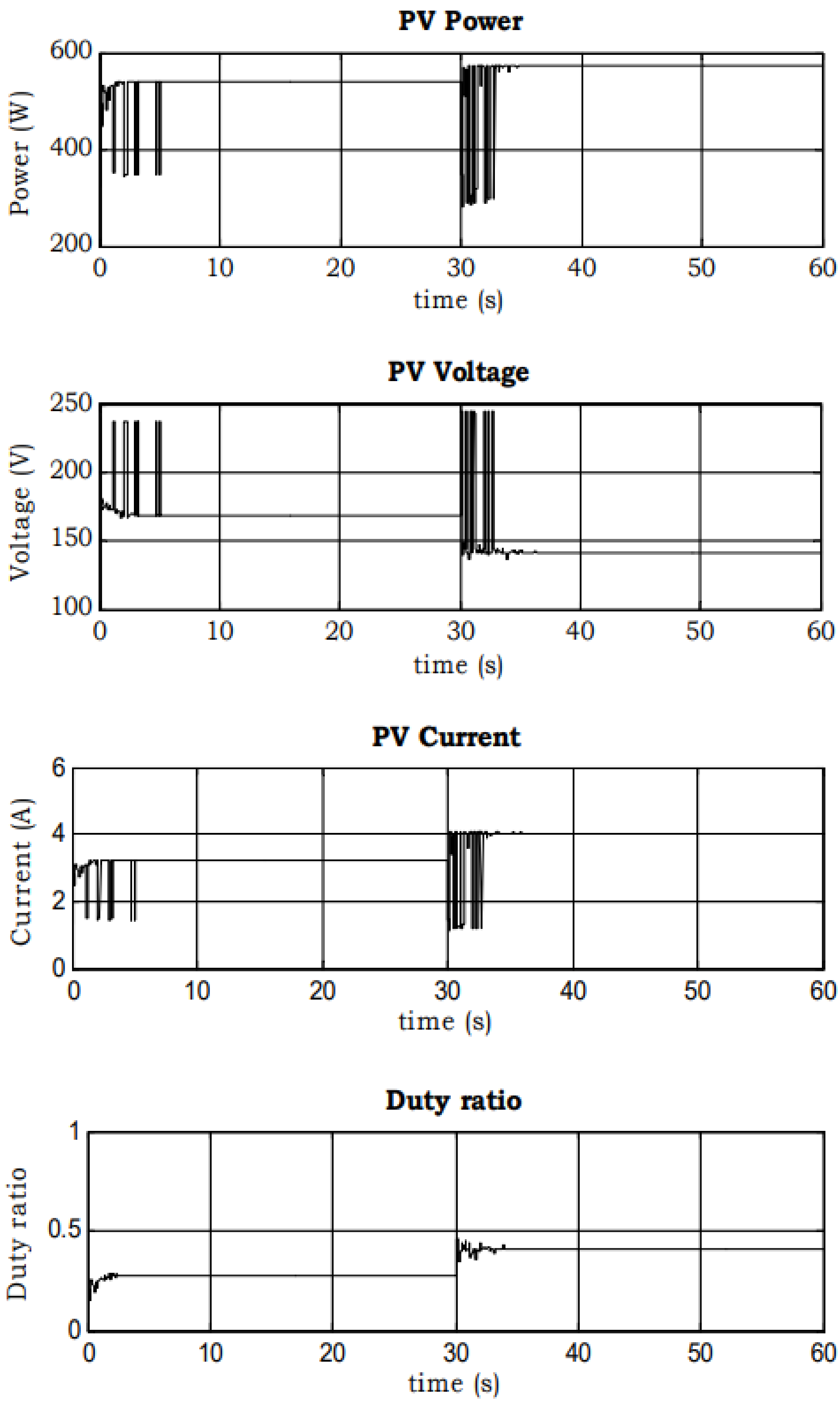


Figure 4.11. FBPSO MPPT Tracking Curves for an 8S PV setup

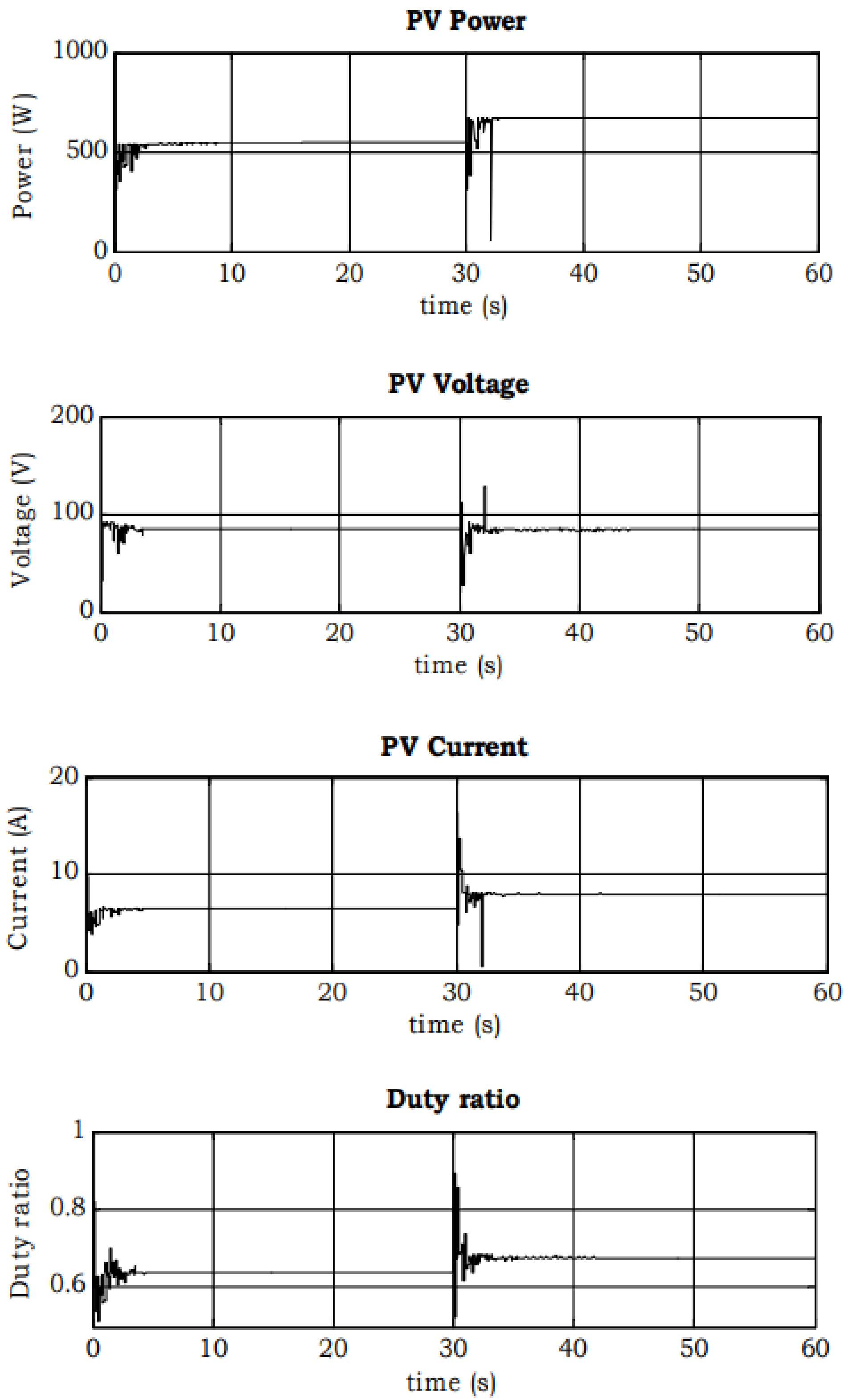


Figure 4.12. Tracking Curves of FBPSO MPPT Algorithm for 4S2P PV Configuration

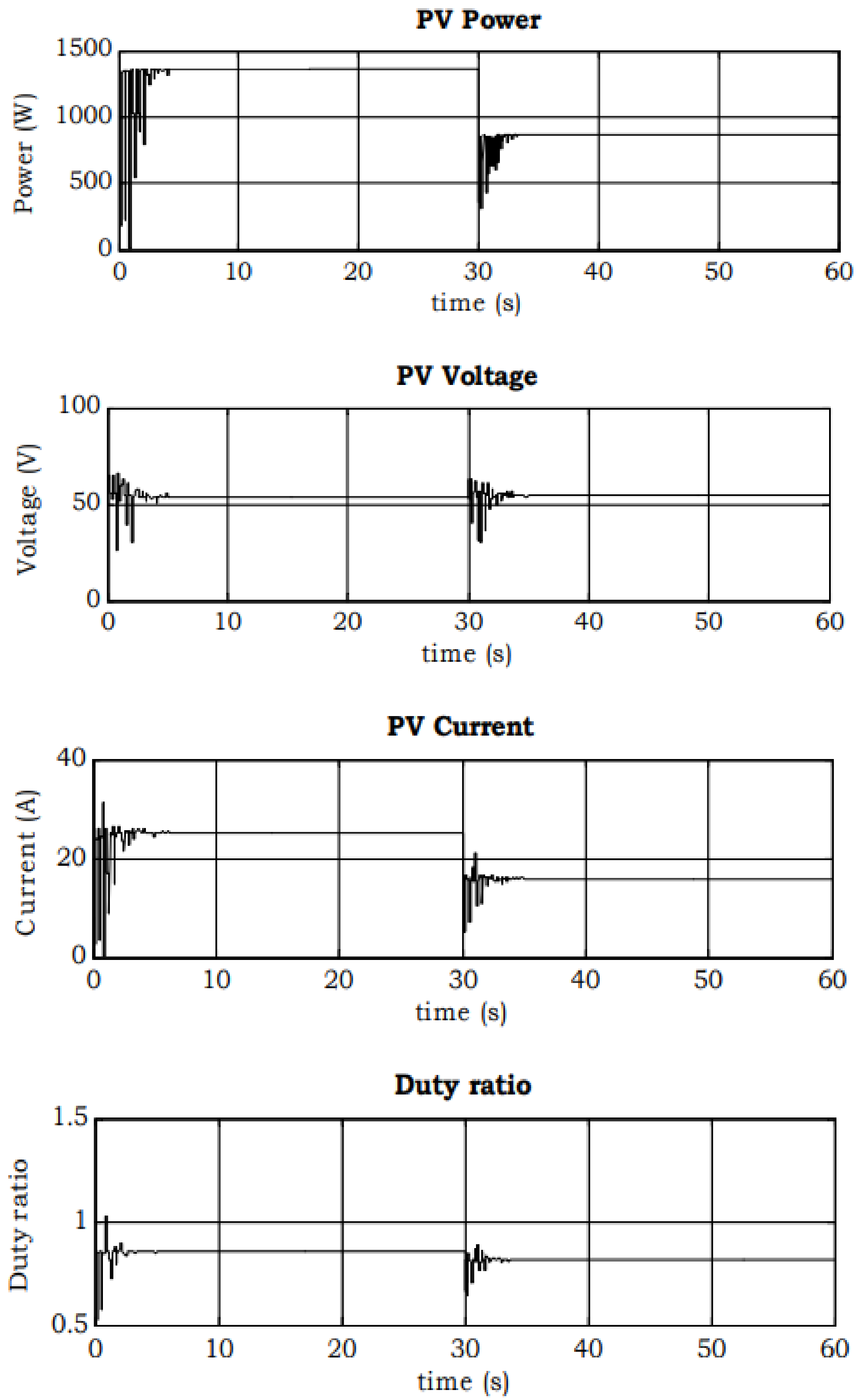


Figure 4.13. Tracking Curves of FBPSO MPPT Algorithm for 2S4P PV Configuration

4.3.4.1 FBPSO MPPT Algorithm Tracking curves of for 8S PV Configuration

The proposed FBPSO MPPT algorithm's dynamic performance is evaluated by running an 8S PV system under a variety of dynamically changing shading patterns. Figure 4.11 shows the FBPSO MPPT algorithms' tracking curves for PV power, voltage, current, and duty ratio for an 8S PV arrangement. Figure shows that the suggested FBPSO algorithm extracts the maximum power of 540.24 W and 573.28 W for patterns 1 and 2 in 5.1 sec and 4.8 sec, respectively.

4.3.4.2 Tracking curves of FBPSO MPPT Algorithm for 4S2P PV Configuration

The proposed FBPSO MPPT algorithm's dynamic performance is evaluated by running a 4S2P PV system under various dynamically varying shading patterns. Figure 4.12 shows the FBPSO MPPT algorithms' tracking curves for PV power, voltage, current, and duty ratio for a 4S2P PV system. Figure shows that for patterns 3 and 4, the proposed FBPSO algorithm extracts the maximum power of 541.01 W and 670.35 W in 3.7 sec and 3.2 sec, respectively.

4.3.4.3 Tracking curves of FBPSO MPPT Algorithm for 2S4P PV Configuration

The proposed FBPSO MPPT algorithm's dynamic performance is evaluated by running a 2S4P PV system under various dynamically varying shading patterns. Figure 4.13 shows the FBPSO MPPT algorithms' tracking curves for PV power, voltage, current, and duty ratio for a 2S4P PV system. Figure shows that for patterns 5 and 6, the proposed FBPSO algorithm extracts the maximum power of 1360.8 W and 864.8 W in 4.2 and 3.8 seconds, respectively.

4.4 GWO Algorithm

From the inspiration of grey wolves optimization problems which are nonlinear can be addressed by the brand new metaheuristic algorithm named as GWO hunting strategy and leadership structure which are naturally imitated by grey wolves [105]. The four different varieties of grey wolves found in GWO are called alpha, beta, delta, and omega. These wolves have an extremely tight social dominance hierarchy, as seen in Figure 4.14, where dominance declines from top towards bottom.

In GWO, optimization problems best solutions are provided by the wolves which are classified as belonging to the third class and also the herd's leaders. They are also subservient to other wolves and aid in decision-making[105].

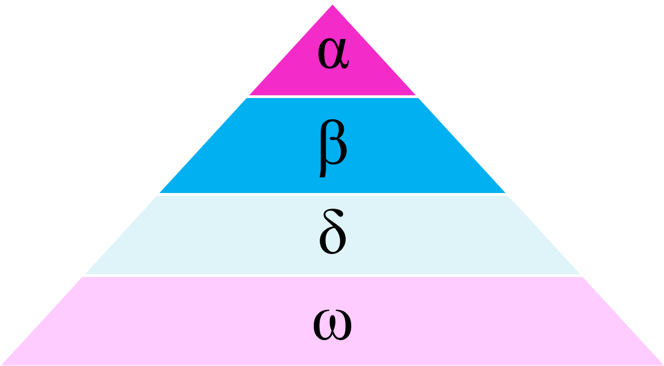
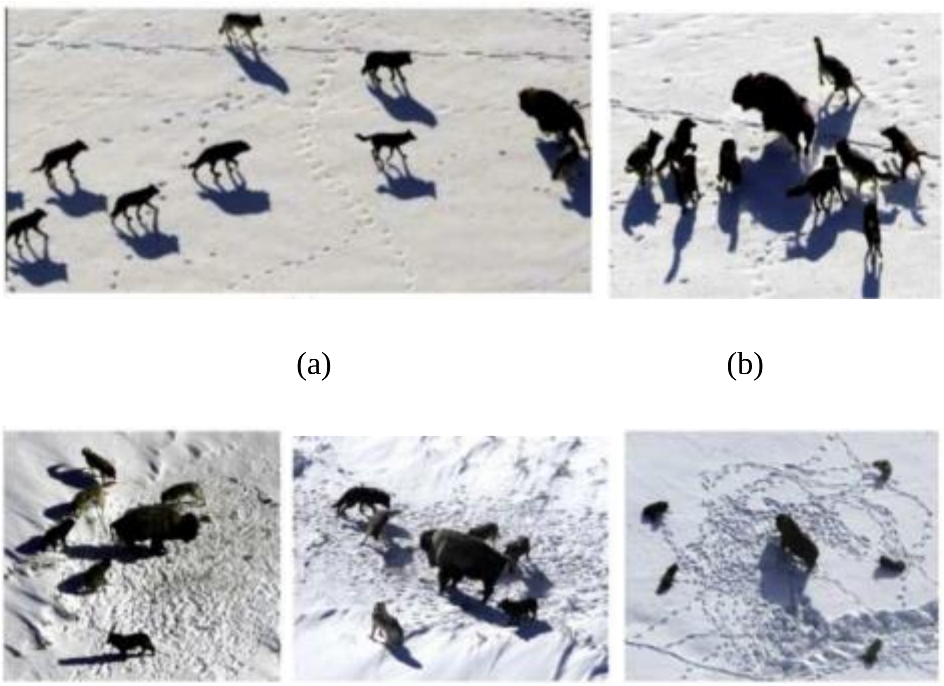


Figure 4.14. Hierarchy of grey wolves



(a) (b)

(c) (d) (e)

Figure 4.15. Grey Wolves' Hunting techniques:
a-c) Pursuing, approaching, and tracking prey; d) Encircling;
e) Attacking stationary targets

The three primary phases of hunting are looking for prey, surrounding prey, and attacking prey. The wolves' communication and collaboration results in the best answer in the shortest amount of time. Figure 4.15 depicts the grey wolves' hunting habits. GWO has a straightforward design, strong convergence speed, high accuracy, and a superior balance between the search process's exploration and exploitation phases [105].

4.4.1 Enhanced GWO algorithm

In traditional GWO, wolves yield to other wolves and make no effort to seek their prey. This increases the number of search agents in use and wastes time trying to get the best answer. The suggested Enhanced GWO algorithm totally eliminates the phase in order to expedite the search process without sacrificing the precision of the best solution. The following stages have been updated in the proposed EGWO algorithm to identify encircling and hunting behavior[105]:

i) Encircling

During the hunt, each search agent surrounds the target. The mathematical model for the encircling behavior reads as

$$D = \left|C.X_p(k) - X_{sg}(k)\right| \quad (4.9)$$

Where current iteration is represented by k

$$X_{sg}(k+1) = X_p(k) - A.D \quad (4.10)$$

$$A = 2.a.r_1 - a \quad (4.11)$$

$$C = 2.r_2 \quad (4.12)$$

Where r_1, r_2 are random values between [0, 1], A and C are coefficients to ensure a superior balance between the search process's exploration and exploitation, and over the course of repetitions, linearly declined from 2 to 0, simulating the prey's approach.

ii) Hunting

Using following equations, search agents locations are updated for each iteration in accordance with the positions of the top search agents X_α and X_β.

$$D_\alpha = \left|C_1 X_a - X_{sg}\right|, D_\beta = \left|C_2.X_\beta - X_{sg}\right| \quad (4.13)$$

$$X_1 = X_\alpha - A_1(D_\alpha), X_2 = X_\beta - A_2.\left(D_\beta\right) \tag{4.14}$$

$$X_{sg}(k+1) = \frac{X_1+X_2}{2} \tag{4.15}$$

When the prey stops moving, search agents conclude the hunt by assaulting it. Figure 4.16 displays the grey wolf' updated position.

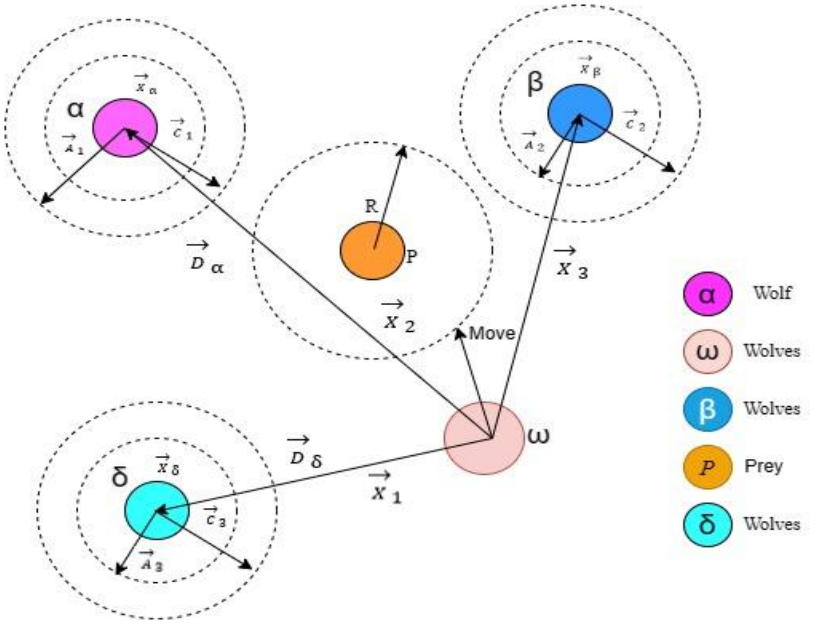


Figure 4.16. Position updating of grey wolves

In this part, EGWO address the PSC's MPP tracking difficulty. PV Power P_{MPP} is the goal function that must be maximized for MPPT, while duty ratio is the decision variable used to monitor the generated power maximum. The flowchart for EGWO MPPT algorithm illustrated in Figure 4.17, and Table 4.3 lists the method's parameters.

Table 4.3. Parameters of Proposed EGWO method

Parameter	EGWO
Initial population (Duty Ratio)	Randomly among 0.1 and 0.9
N_P	8
a	2 to 0
Maximum Number of iterations(K_{MAX})	100
Termination Criterion	Maximum Number of iterations

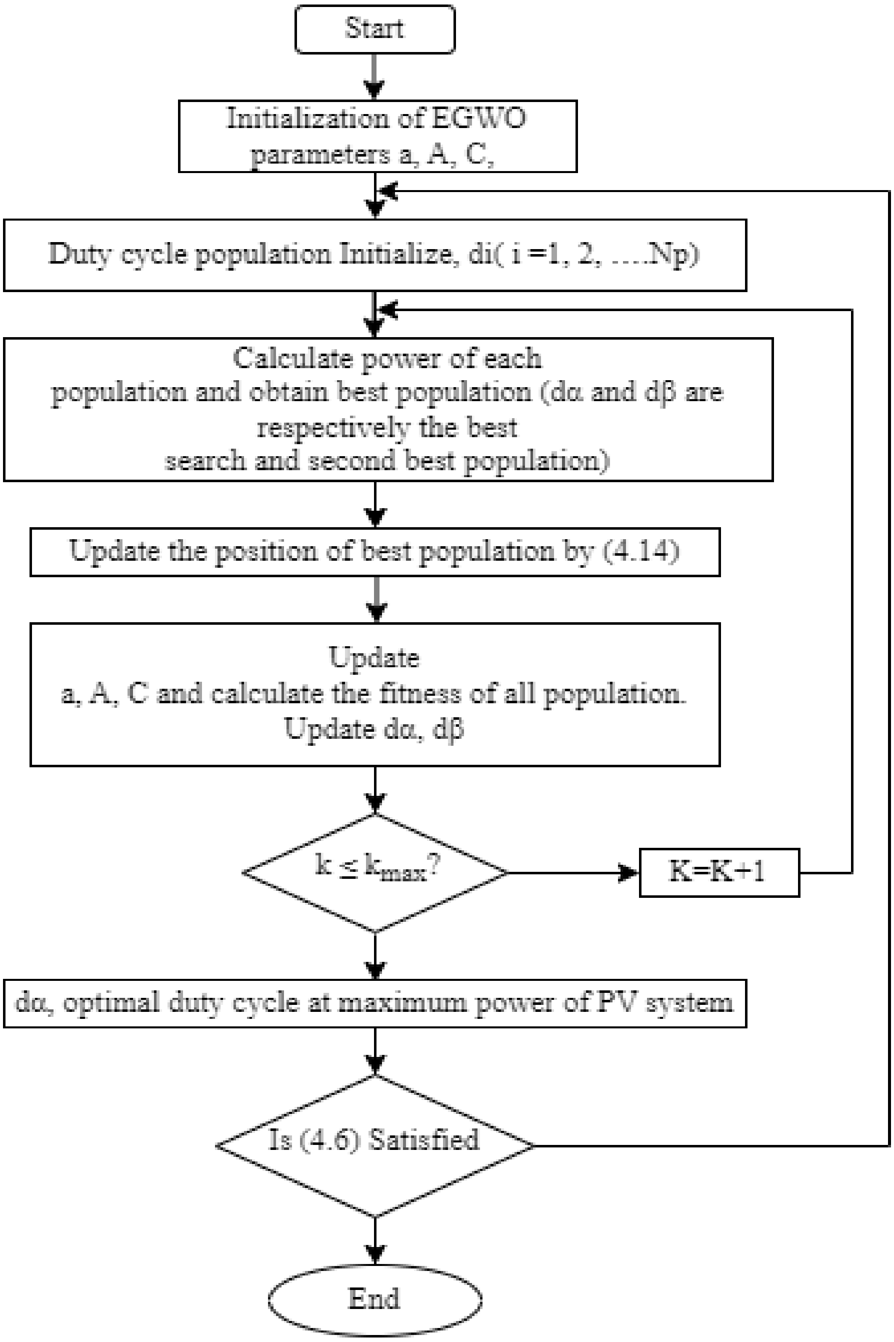


Figure 4.17. EGWO MPPT algorithm flowchart

4.5 Simulation Results

Performance evaluation of EGWO MPPT algorithm for 8S, 4S2P, and 2S4P PV configurations simulations are performed for dynamically changing shading patterns and tracking results are presented.

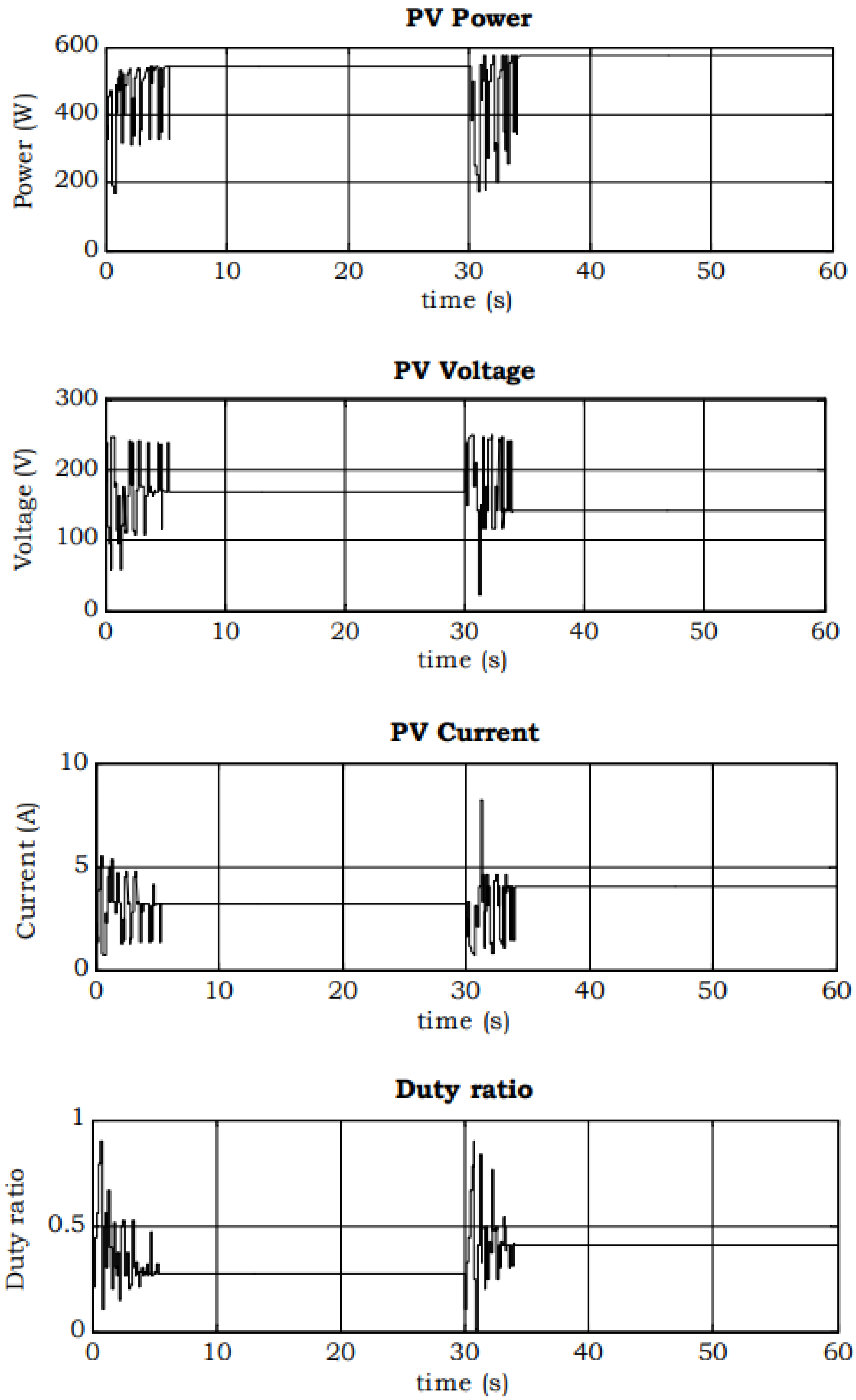


Figure 4.18. Tracking Curves of EGWO MPPT Algorithm for 8S PV configuration

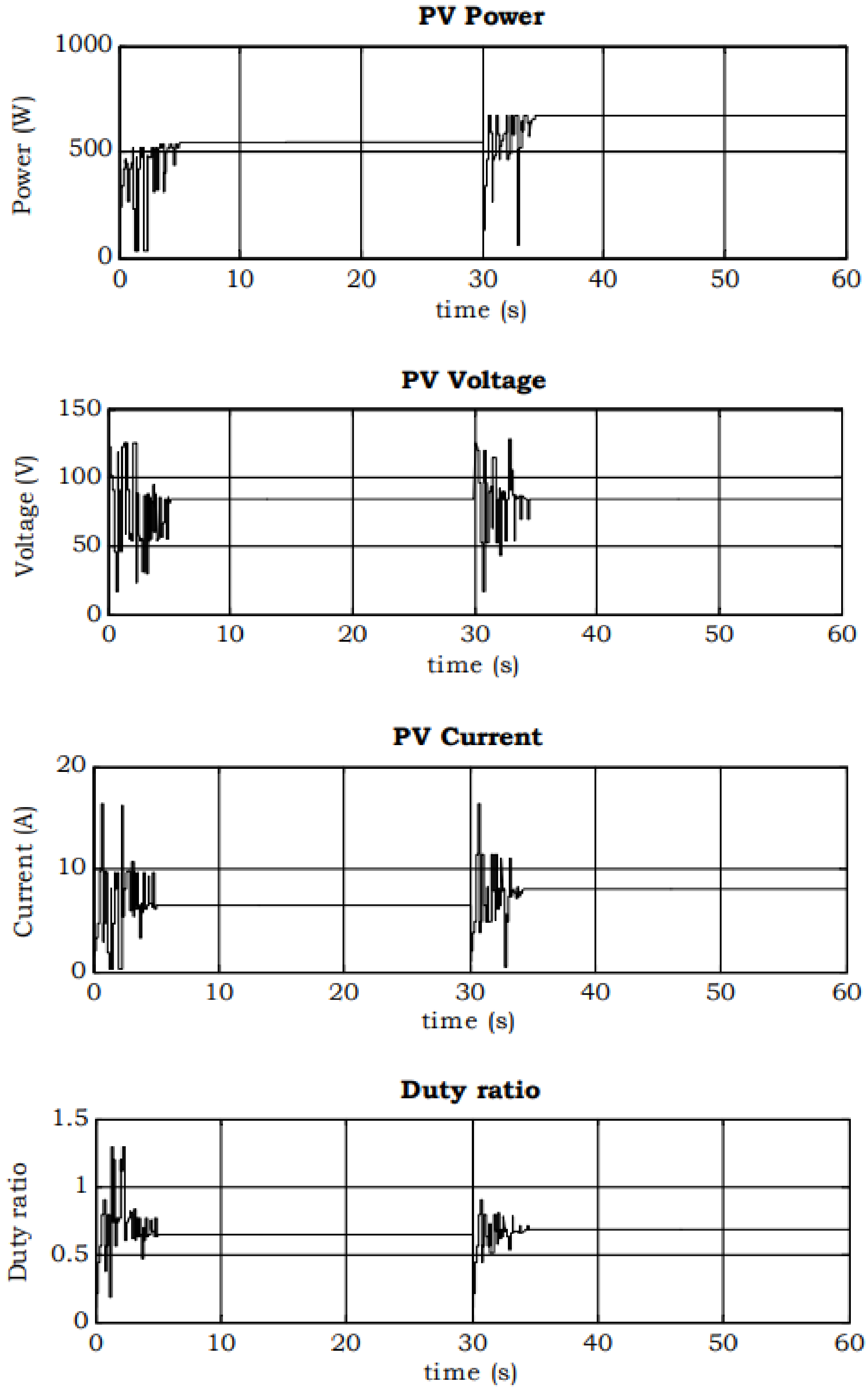


Figure 4.19. Tracking Curves of EGWO MPPT Algorithm for 4S2P PV configuration

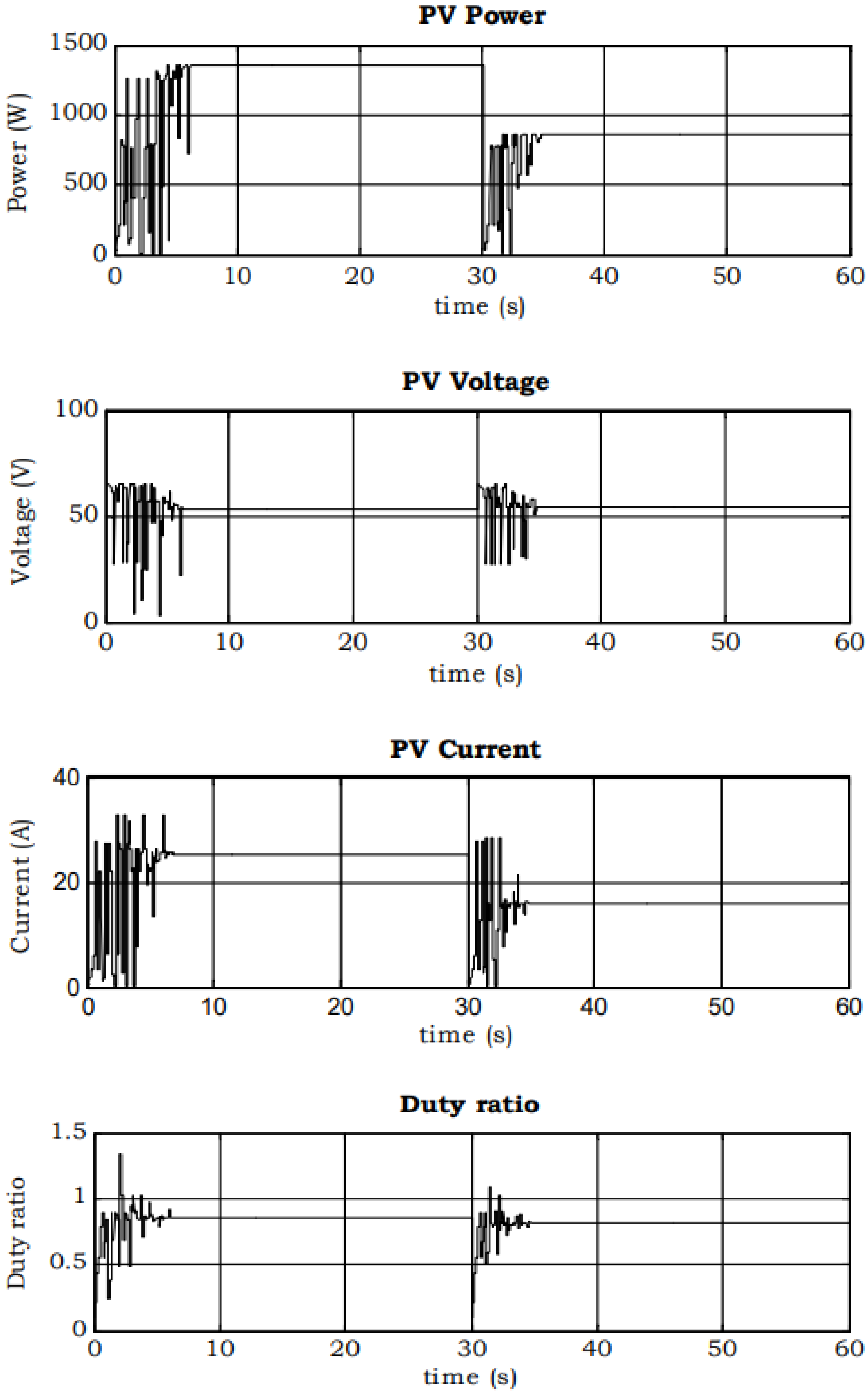


Figure 4.20. Tracking Curves of EGWO MPPT Algorithm for 2S4P PV configuration

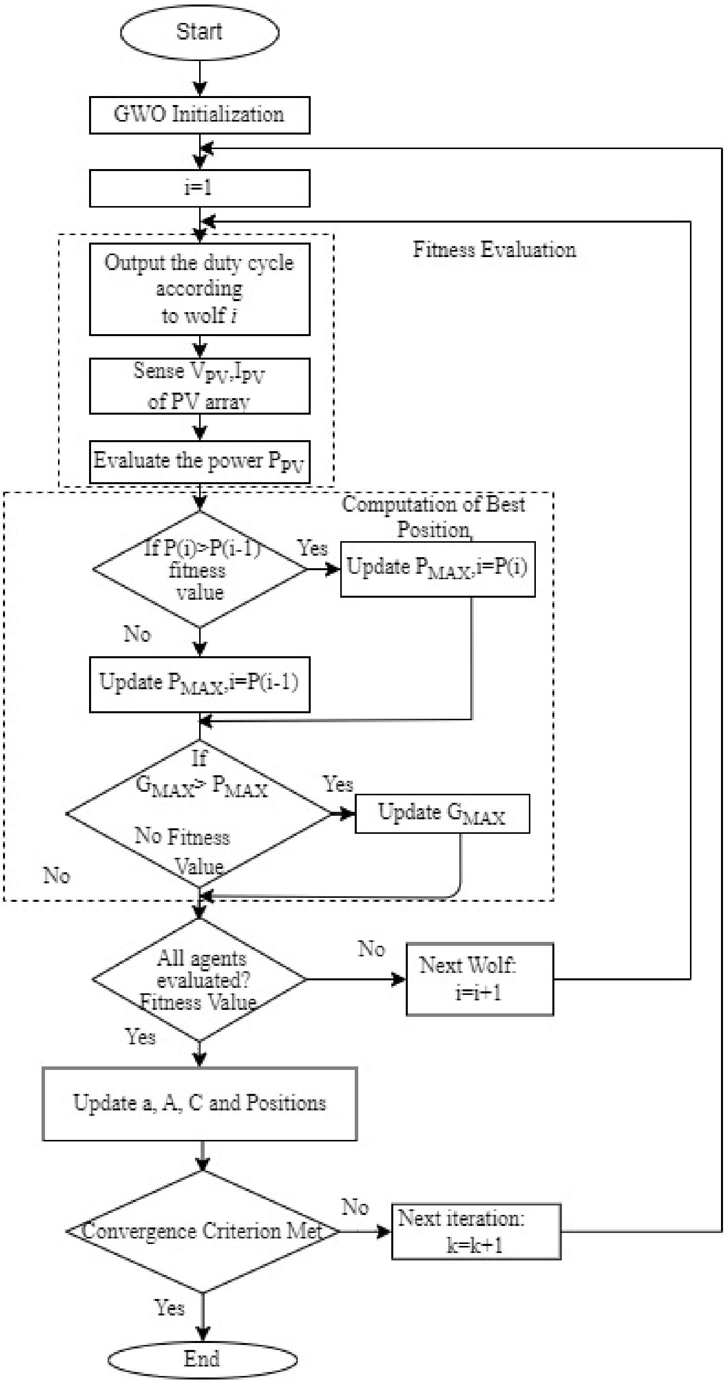


Figure 4.21. Flowchart of the GWO algorithm

4.5.1 Tracking curves of EGWO MPPT Algorithm for 8S PV Configuration

The proposed EGWO MPPT algorithm dynamic performance is observed by 8S PV system operating at different dynamically changing shading conditions Figure 4.18 shows the EGWO MPPT algorithms' tracking curves for PV power, voltage, current, and duty ratio for 8S PV system. From this, it is noticed that proposed EGWO algorithm extracts the maximum power of 540.24 W and 573.8 W in 5.4 sec and 4.3 sec for pattern 1 and pattern 2.

4.5.2 Tracking curves of EGWO MPPT Algorithm for 4S2P PV Configuration

By running a 4S2P PV system under various dynamically varying shading patterns, the suggested EGWO MPPT algorithm's dynamic performance is evaluated. Figure 4.19 shows the EGWO MPPT algorithms' tracking curves for PV power, voltage, current, and duty ratio for a 4S2P PV system. Below Figures show that suggested EGWO algorithm extracts the maximum power of 541.01 W and 670.35 W for patterns 3 and 4 in 5.1 sec and 4.4 sec, respectively.

4.5.3 Tracking curves of EGWO MPPT Algorithm for 2S4P PV Configuration

The suggested EGWO MPPT algorithm's dynamic performance is evaluated by running a 2S4P PV system under various dynamically changing shading patterns. Figure 4.20 shows the EGWO MPPT algorithms' tracking curves for PV power, voltage, current, and duty ratio for a 2S4P PV system. Figure shows that for patterns 5 and 6, the proposed EGWO algorithm extracts the maximum power of 1360.8 W and 864.8 W in 6.8 sec and 4.8 sec [141].

4.6 MFO algorithm

A special navigation method at night which is called transverse orientation is followed by Moths. In this mechanism, maintaining a fixed approach with respect to the moon and flying traveling in a straight line for long distances. Moths fly around spirally when light source close by than with few corrections they finally converge towards it. New algorithm related to optimization based on moth’s flight characteristics proposed by Mirjalili known as MFO algorithm. In this MFO algorithm, each moth is forced to circle a different related flame, which enhances the search space's exploration and local optima stagnation with low probability. Therefore, taking moth positions into consideration set of flame locations are represented with same dimensions in the matrix [138].

It is also mentioned that both the flames and the moths are solutions. The way they are handled and updated in each iteration makes a distinction between them. In fact, moths act as search agents in the search area. Currently flames are the best option that moths have found. Here, flames may be thought of as flags or pins left by moths as they search an area. Each moth circles a flame and upgrades it if a better option is discovered. A moth hasn't ever lost its optimal solution with this process. The following equation is used to update each moth's location with relation to a flame in order to quantitatively simulate this behavior.

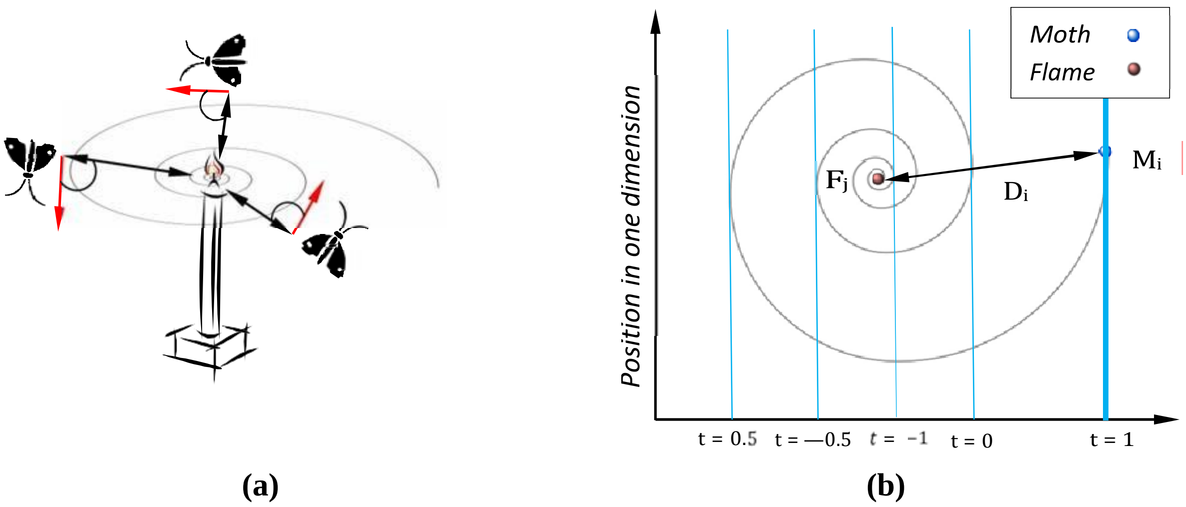


Figure 4.22. (a)Spiral flying path around close light sources (b)Logarithmic spiral, space around a flame, and the position with respect to t

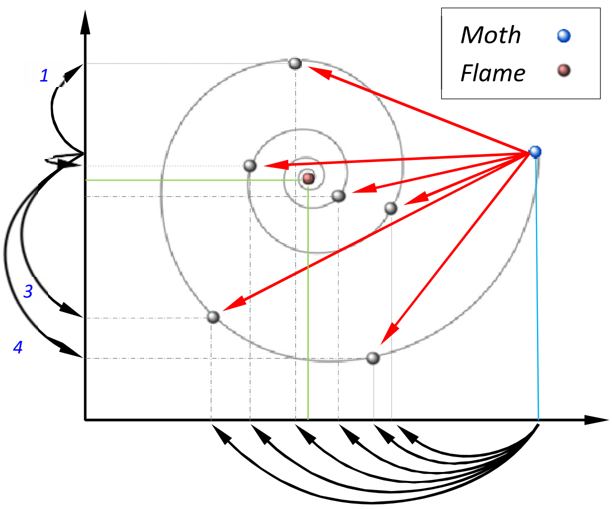


Figure 4.23. Some of the possible positions that can be reached by a moth with respect to a flame using the logarithmic spiral

$$\mathrm{Mi} = \mathrm{S}(\mathrm{M_i}, \mathrm{F_i}) \tag{4.16}$$

M_i represents i_{th} moth, Fj represents j_{th} flame, and spiral function represented by S. The spiral function categorized into subsequent conditions.

a) In spiral moth position is initial.
b) In spiral flame location is final.
c) The search space is the limit for the fluctuation range.

Taking these into consideration, the spiral function is represented as follows:

$$\mathrm{S}(\mathrm{M_i}, \mathrm{F_i}) = \mathrm{D_i}.\, \mathrm{e^{bt}}.\cos(2\pi \mathrm{t}) + \mathrm{F_j} \tag{4.17}$$

$$D_i = \left|F_j - M_i\right| \tag{4.18}$$

Distance connecting the moth i_{th} and the flame j_{th} is indicated by D_i. Spiral shape constant is represented by b, and random number in [r, 1] is t. To accelerate the convergence around a flame over the course of iterations, there is linear decrease in the adaptive convergence constant r from -1 to -2 i_{th} moth and j_{th} flame distance closer when the t value is lower. Moths spiral flight and its corresponding flame is indicated by Figure.4.22. and Figure.4.23. This issue is addressed by adaptively reducing the number of flames across the iterations as Eq (4.19). Each generation's related moth modifies its location in accordance with the worst flame position when the number of flames is reduced.

$$flame\ number = round\left(N - l * \frac{N-1}{T}\right) \tag{4.19}$$

Where the current iteration is represented by I, N denotes maximum number of flames, and maximum number of iterations is denoted by T. In a solution space, the established balance between the exploration and exploitation is provided by adaptive mechanism of flame number

4.6.1 MFO MPPT Application

This study solves numerous peaks and tracks the GMPP of a PV system under PSCs [138], taking into account the better capability of the MFO algorithm with respect to local optima avoidance and convergence. Power–duty curve based direct MPPT control is done in this technique. Every responsibility is viewed as a moth, and each moth's ideal position is viewed as a flame, in order to execute the MFO-based MPPT. During optimization, in relation to their associated flames, moths must change their places and based on updated best fitness values in each iteration the sequence of the flames is dynamically adjusted. If a moth position's revised fitness value is higher than the associated flame, it’s in the next iteration updated location is selected as the flame location.

During MPPT the best solution to the organization problem between global and local searching is provided by the adaptive mechanism for the flame number.

If some external factors seriously affect the PV system, to track a GMPP newly, the MFO algorithm would be implemented again. The restart condition can be described as follow:

$$\left|\frac{P_i - P_o}{P_o}\right| > P_o \tag{4.20}$$

Where steady state power is P_0, next sampling period is P_1, and restart tolerance. MFO algorithm flow chart is presented in Figure.4.24

4.6.2 Simulation results and analysis

Many simulations are implemented using the MATLAB/Simulink program. PV system MPPT simulation model is composed of five components: 1) PV array, 2) MPPT control module, 3) Boost convertor, 4) Gate Drive, 5) Resistive load in figure 4.2.

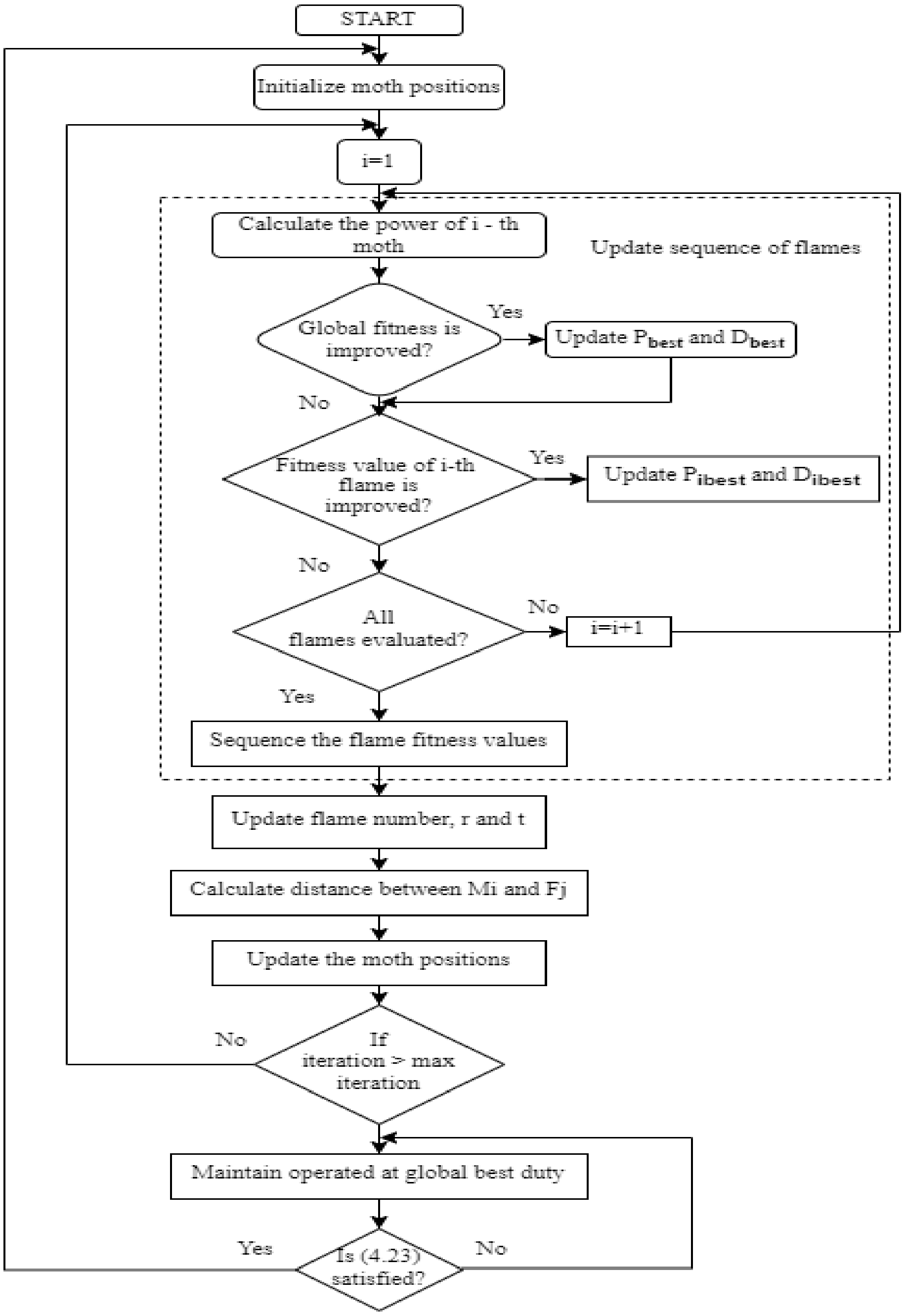


Figure 4.24. MFO algorithm Flowchart

MOSFET Frequency f = 50 kHz, R Load = 40Ω, C_1 = 100 F, C_2 = 100 F, and L = 0.5 mH for MPPT system. To run the simulation, a replacement model [27] is used. The model's primary simulation parameters are P_{MAX} = 100 W, V_{MP} = 18.48 V, and I_{MP} = 5.41.

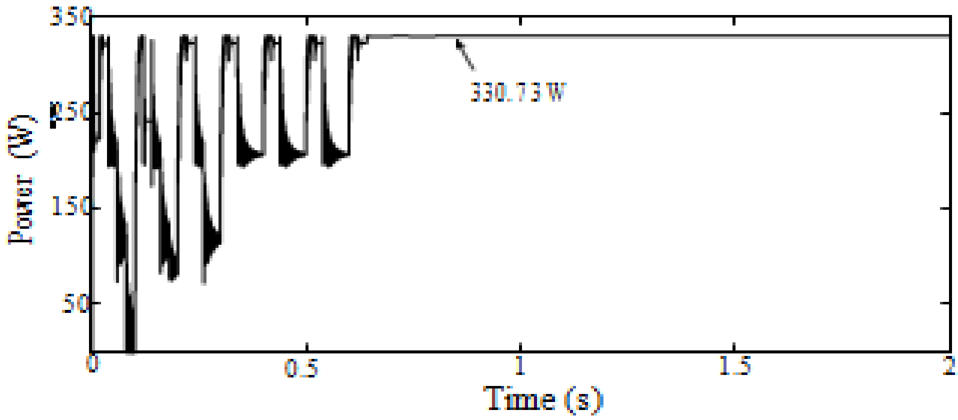


Figure 4.25.PV array Graphs under PSC-Tracking traces of MFO

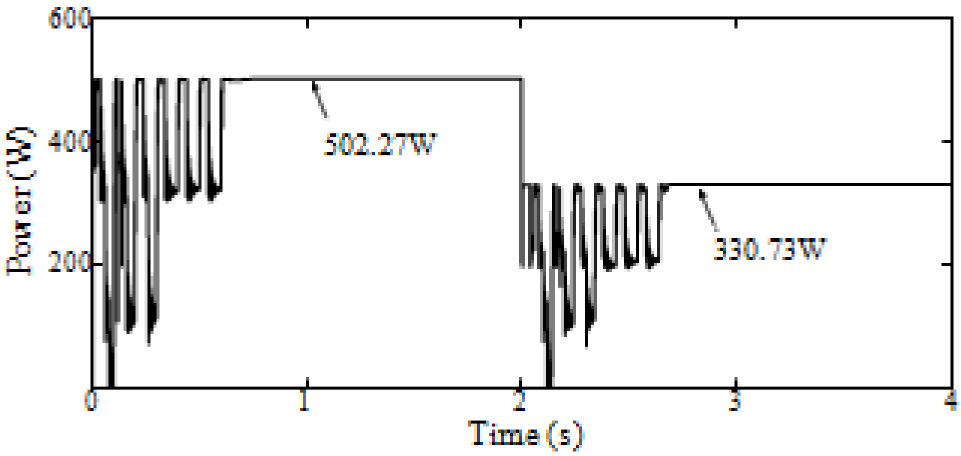


Figure 4.26.PV array Graphs under rapidly changing condition tracking traces of MFO

In comparison between PSO and WOA, tracking time is reduced to 76.47% by the MFO algorithm because the coordination issue between global and local searches can be effectively solved by the adaptive flame number approach as shown in Figure 4.25 and Figure 4.26. Therefore, in contrast to P&O, INC, PSO, and WOA, the obtained results experimentally shows greater tracking accuracy and tracking speed of MFO algorithm as shown in Figure 4.27 and Figure 4.28. When comparison is made with the four MPPTs, it is seen that the suggested MPPT algorithm performs better, i.e. P&O, INC, PSO and WOA under different circumstances including the PSC. In contrast to previous algorithms, the suggested method takes longer to respond. Future investigations will focus on this drawback of the MFO algorithm.

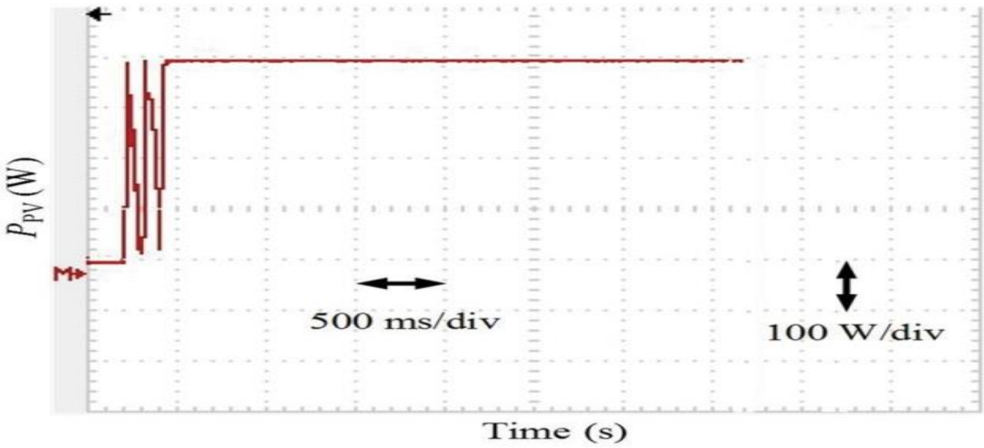


Figure 4.27. Experimental system under the uniform illumination condition tracking trajectories of MFO

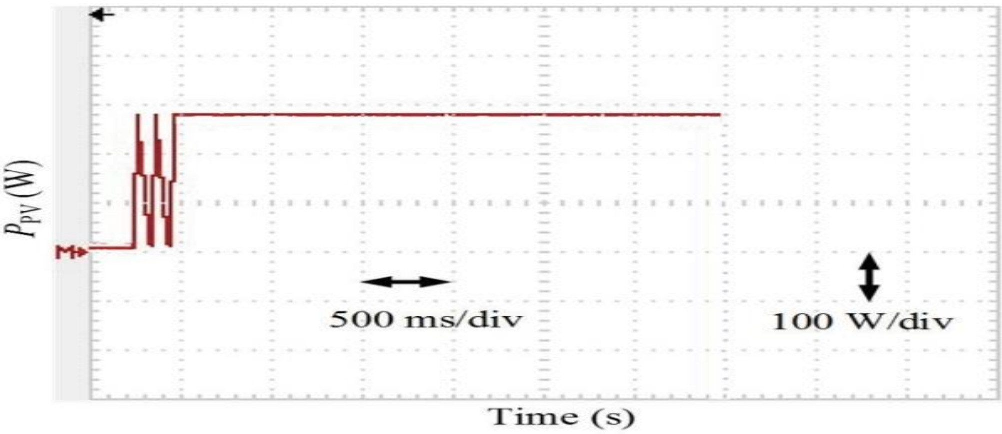


Figure 4.28. Experimental system under the PSC

4.7 Solar PV systems MPA MPPT technique under PSC

PSCs are the most important parameters impacting a PV system's characteristics, even though PV systems inevitably confront obstacles in a variety of environmental settings [69]. MPPT methods, like traditional and soft computing techniques are discussed in articles [88] [128] can be utilized to mitigate the effects of PSCs.

The aforementioned algorithm-based methodologies may simply and accurately determine the GMPP out of a variety of LMPPs and can discover the MPP under steady state settings without any oscillations.In the same topic of study, just a few additional modern literary works were examined [120], [112].

On the other hand, monitoring time, efficiency, and accuracy during emergency conditions is a challenge for these bio-inspired systems as well. In this work a bio-inspired novel MPA for GMPPT application under PSC, to eliminate the above challenges. In MPA by changing the derivative order we can change the speed position by taking an advantage of additional degree of freedom which further helpful for parameters identification of Solar PV.

4.7.1 MPA

The MPA is a meta-heuristic optimization method [77] that which is used to solve a number of optimization issues. A few of MPA's uses include determining solar PV cell parameter estimation [72], COVID-19 image categorization [71], and many others. In this work, the MPA is Optimizely implemented in MPPT to the best possible predicted outcome.

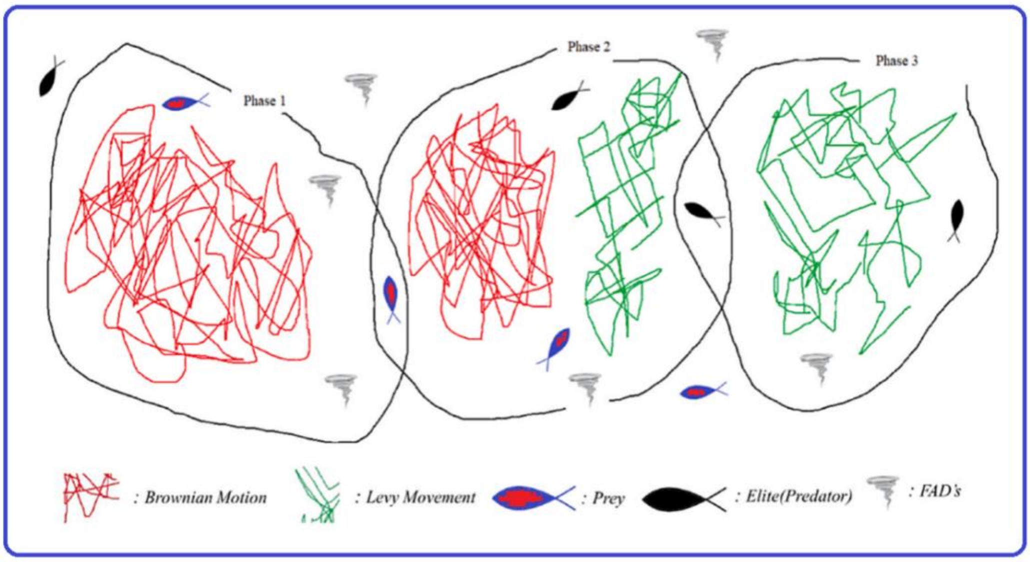


Figure 4.29. MPA optimization in three phases

The main three components of MPA are (i) Low concentration Levy-motion for prey environment (ii) High concentration Brownian-motion for prey environment, and (iii) Extremely good memory for partners and the site of successful hunting (see Figure 4.29).When compared to other bio-inspired systems, these characteristics make the MPA more sophisticated.

4.7.2 Levy flight

Equation describes the Levy flight, which consists solely of random integers with step sizes determined by the Levy distribution (4.21).

$$\text{Lévy}\ (\alpha) = 0.05\ \times \frac{x}{|y|^{\frac{1}{\alpha}}} \tag{4.21}$$

4.7.3 Brownian motion

Standard Brownian motion is the probability function derived from a stochastic process with a step size of 1 and a Normal Gaussian distribution with mean equal to 0 and 2 variance equal to 1. The probability density function (PDF) for this motion at position x gives in equation (4.22).

$$f(x;\ \mu, \sigma)\ =\ \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \tag{4.22}$$

4.7.4 Formulation of MPA

In MPA, one of the population-based techniques, the preliminary solution is uniformly distributed as the initial trial over the search space like other metaheuristic; the population can be started by equation (4.23). Lower limit for the variable is D_{MIN} and upper limit for the variable is D_{MAX} and the random number is denoted by rand.

$$D_0 =\ D_{min} + rand(D_{max} - D_{min}) \tag{4.23}$$

As per the "survival of the fittest" hypothesis, marine predators that are the fittest to establish an elite matrix. The top predators (denoted by de) are obviously excellent hunters, as seen in equation (4.24).

$$Elite = \begin{bmatrix} de_{1,1} & \cdots & de_{1,n} \\ \vdots & \ddots & \vdots \\ de_{m,1} & \cdots & de_{m,n} \end{bmatrix}_{m\times n} \tag{4.24}$$

Because they are both looking for food, search agents are both a predator and a victim. A new matrix with size designated as the prey is created by considering top predator is substituted by stronger predator, updating equation (4.24) in the process.

As a result, the predator's location is periodically updated. The Prey matrix is created, and equation states that $d_{i,j}$ represents the Prey's j_{th} location (4.25).

$$Prey = \begin{bmatrix} d_{1,1} & \cdots & d_{1,n} \\ \vdots & \ddots & \vdots \\ d_{m,1} & \cdots & d_{m,n} \end{bmatrix}_{m\times n} \tag{4.25}$$

4.7.5 Optimization process of MPA

Figure 4.29 depicts the three stages of optimization. The stages are categorized based on time and velocity ratio.

- *Phase 1:* In comparison to the predator, the prey is moving faster. (Velocity High Ratio)
- *Phase 2:*Both the predator and the prey travel at a similar speed. (Unity Velocity Ratio)
- *Phase 3:*In comparison to the prey, the predator is moving faster. (Velocity Low Ratio)

Phase 1: Velocity High Ratio

In comparison to the predator, the prey is moving faster. This is the phase of exploration, which occurs only in the initial algorithm iterations given by equations (4.26) and (4.27).

- In this case R is a rand [0, 1]. Till first third of iterations this phase lasts in order to establish a high exploration phase.

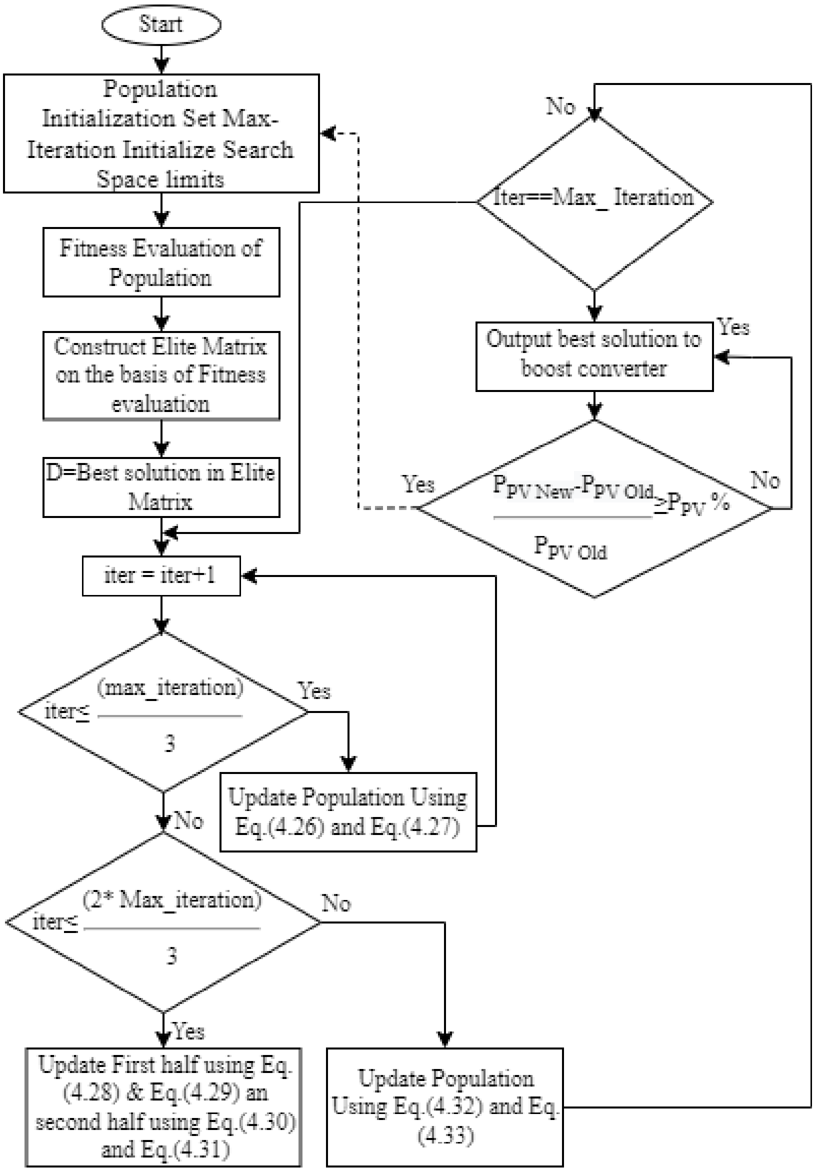


Figure 4.30. Flowchart for MPA based MPPT

$$\overrightarrow{Stepsize_a} = \overrightarrow{R_B} \times (\overrightarrow{Elite_a} - \overrightarrow{R_B} \times \overrightarrow{Prey_a}); \quad a = i \dots n \tag{4.26}$$

$$\overrightarrow{Prey_a} = \overrightarrow{Prey_a} + P\vec{R} \times \overrightarrow{Stepsize_a} \tag{4.27}$$

Phase 2: Unity velocity ratio

To set phases of exploitative and explorative, in the center of the number of iterations lies this phase. This phase indicating that both prey and predator are moving in the same pace. As exploring and exploitation goes simultaneously, exploring part represents one part of the population, and exploiting is the other part which indirectly shows that predator is responsible for the exploitation whereas prey is responsible for the exploration and it is given by the equations (4.28) to (4.31).

For predator population,

$$\overrightarrow{Stepsize_a} = \overrightarrow{R_L} \times (\overrightarrow{Elite_a} - \overrightarrow{R_L} \times \overrightarrow{Prey_a});\ a = i..\frac{n}{2} \tag{4.28}$$

$$\overrightarrow{Prey_a} = \overrightarrow{Prey_a} + P\vec{R} \times \overrightarrow{Stepsize_a} \tag{4.29}$$

For prey population,

$$\overrightarrow{Stepsize_a} = \overrightarrow{R_B} \times (\overrightarrow{R_B} \times \overrightarrow{Elite_a} - \overrightarrow{Prey_a});\ a = \frac{n}{2} \dots n \tag{4.30}$$

$$\overrightarrow{Prey_a} = \overrightarrow{Elite_a} + P\overrightarrow{CF} \times \overrightarrow{Stepsize_a} \tag{4.31}$$

CF is a regulating factor for predator's step size.

Phase 3: Low velocity ratio

Compared to the predator, the prey moves more slowly. Levy base is the random number that is supplied in equations (4.32) and (4.33) to set high exploitation phase (4.33).

$$\overrightarrow{Stepsize_a} = \overrightarrow{R_L} \times (\overrightarrow{R_L} \times \overrightarrow{Elite_a} - \overrightarrow{Prey_a});\ a = 1 \dots n \tag{4.32}$$

$$\overrightarrow{Prey_a} = \overrightarrow{Elite_a} + P\,\overrightarrow{CF} \times \overrightarrow{Stepsize_a} \tag{4.33}$$

The marine predators will be impacted by factors that affect the marine eco-system. Sometimes, fish aggregation devices (FADs) or eddy creation might alter the behavior of marine predators. Predators in the ocean may make large leaps to avoid FADs, as seen in the equation (4.34).

$$\overrightarrow{Prey_a} = \begin{cases} \overrightarrow{Prey_a} + CF\left(\overrightarrow{D_{min}} + \vec{R} \times \left(\overrightarrow{D_{max}} - \overrightarrow{D_{min}}\right) \times \vec{U}\right) if\, r \le FAD_1 \\ \overrightarrow{Prey_a} + (FAD_s \times (1 - r) + r)\left(\overrightarrow{Prey_{r1}} - \overrightarrow{Prey_{r2}}\right) if\, r \le FAD_s \end{cases} \tag{4.34}$$

4.7.6 MPA MPPT Implementation during PSCs

The MPA optimization strategy should be used to initialize the particles with a population size of 4 in the search space between D_{MIN} and D_{MAX} [0 to 1] since the task employs four panels in the array. The approach recommended will be used to revise each and every particle's location after it has been initialized. The conditional equation determines that when the power changes because of an irradiance change, the code will automatically restart or reinitialize (4.35).

$$if\ \frac{|P_{PV_{new}}-P_{PV_{old}}|}{P_{PV_{old}}} \geq P_{PV}(\%) \tag{4.35}$$

Suggested MPA which is bio-inspired MPPT flow chart is shown in Figure 4.30 and the pseudo-code for the equivalent is provided below.

Algorithm: MPA based MPPT Pseudo-code

```
initialize the particles Di (i = 1, 2,.. n)
while (iteration<max_iteration)
        evaluate fitness and make Elite matrix
if (iteration <max_iteration/3)
                update particles using equation (4.26) & (4.27)
else if ((max_iteration/3) < iteration < (max_iteration/(3/2)))
        first half of particles updated using (4.28) & (4.29)
        second half of particles updated using (4.30) & (4.31)
else if
        update particles using equations (4.32) and (4.33)
end if
        update Elite matrix
        apply FADs effect and update using equation (4.34)
end while
return dbest.
```

4.7.7 Experimental validation

For the four distinct PSC scenarios listed in Table 4.4, the performance of the suggested MPA approach for MPPT is empirically confirmed in 2*2 PV array each

250W and illustrated in figure 4.31. The ratings for the PV solar modules Kyocera KC 250GT that are utilized in this project are shown in Table 4.5. Transparent covers of different colors are used for creating various PSCs. In a boost converter application, the MOSFET IRFP450 is employed with a 500 V rating of drain-to-source voltage and 14 A of drain current capacity. To monitor the PV system's voltage and current, two sensors, specifically the LV-25P for voltage and the LA-25NP for current, are utilized. These sensor readings are then fed to controller an Arduino MEGA-2560, which generates drive circuit PWM signals.

Table 4.4. Four different cases of PSCs for experimental testing

Cases	**Irradiance in W/m2**			
	P11	**P12**	**P21**	**P22**
Case 1	1000	1000	1000	1000
Case 2	400	400	1000	1000
Case 3	500	800	700	1000
Case 4	200	300	700	1000

Table 4.5. PV module ratings at STC

Parameter	**Rating**
MPP Power (P_{MPP})	250 W
OC Voltage (V_{OC})	36.9 V
SC current (I_{SC})	8.81 A
MPP Voltage (V_{MPP})	30.3 V
MPP Current (I_{MPP})	8.11 A

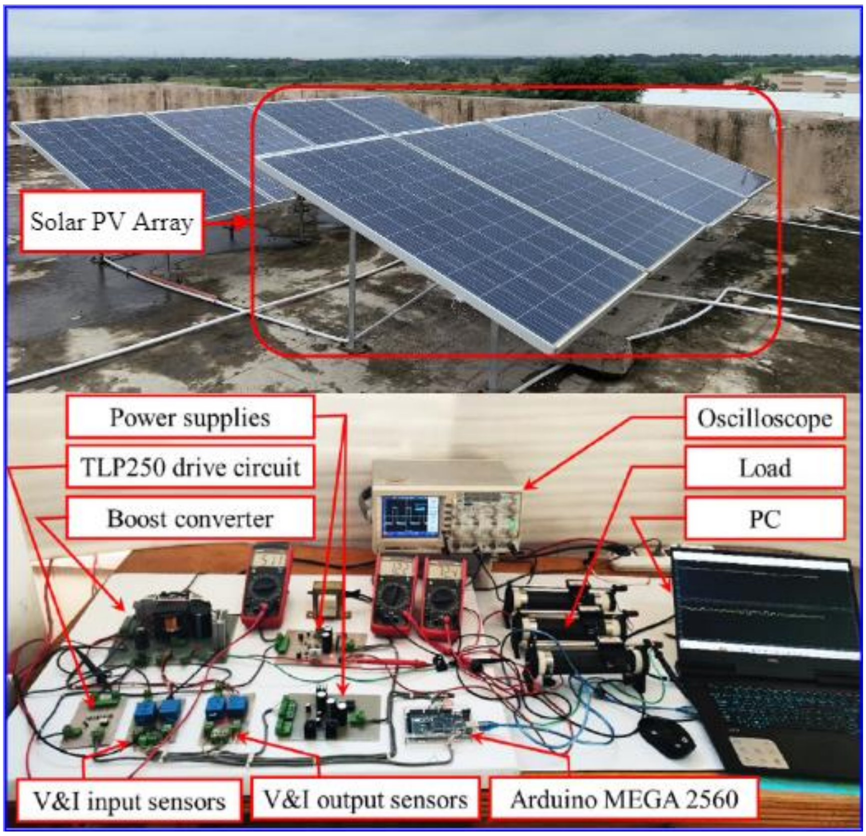


Figure 4.31. Hardware setup of the proposed system

A switching frequency of approximately 31.372 kHz has been selected for the operation. To manage the MOSFET's ON/OFF switching in the system, a TLP250 driver circuit serves as an intermediary component, bridging the control circuitry with the power circuitry. Furthermore, a data logger has been integrated into the setup to capture data related to the solar radiation and the temperature of the PV modules. This recorded data is then supplied as input to a MATLAB/simulation model. The purpose of this model is to forecast the PV characteristics under different PSC. The findings are displayed in the subsections below, and it is clear from them that MPA performs significantly superior than other strategies.

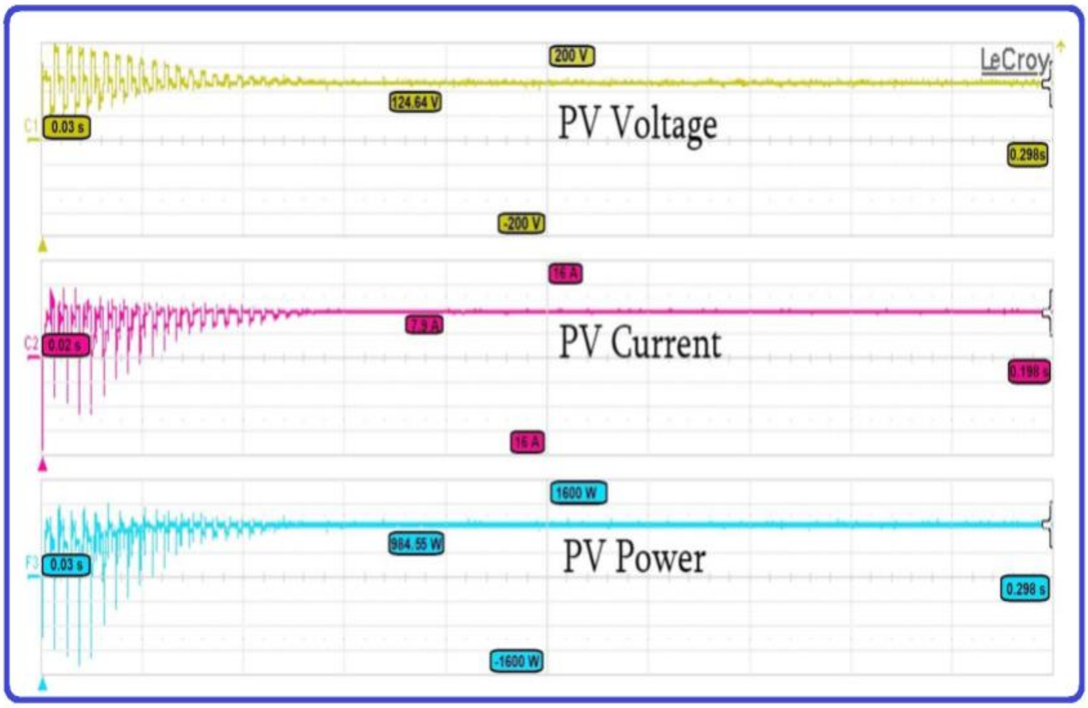


Figure 4.32. MPA Experimental results for case 1

Case 1:

In case1, the PV array received unique irradiation, and the time required for GMPP extraction is recorded. Figure 4.32 makes it abundantly evident that the simulation results are closer to experimental findings that is indicated by the simulation's time requirement of 0.08 seconds and 984.55 W to accomplish the GMPP.

Case 2:

In case2, the PV array received varying amounts of irradiation, and the time required for GMPP extraction was subsequently recorded. With 630.39 W at 121.23 V and 5.2 A, Figure 4.33 clearly demonstrates that for Case 2, to reach the GMPP the time taken is 0.03 seconds.

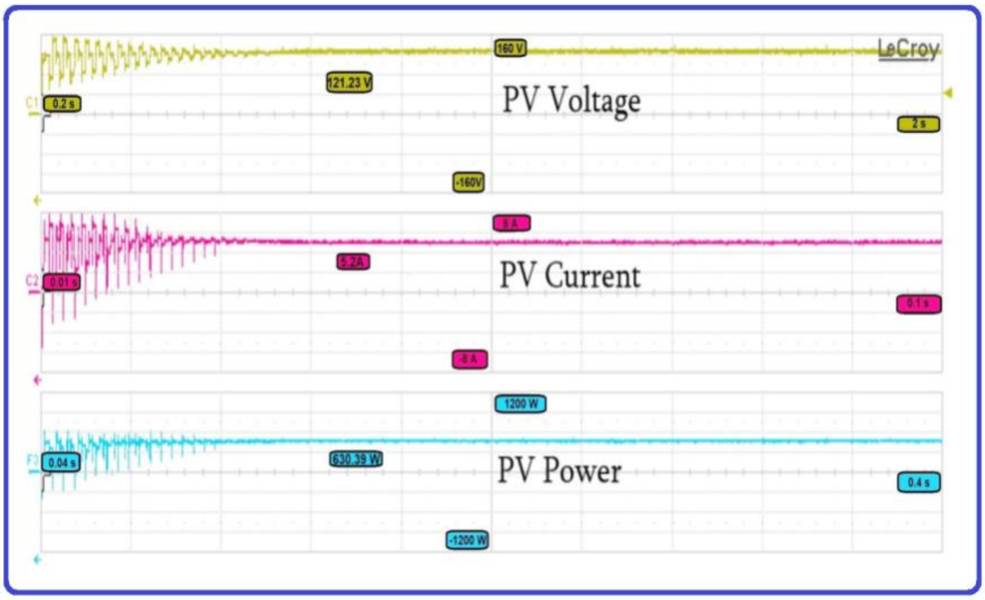


Figure 4.33. MPA Experimental results for case 2

Case 3:

In case 3, the PV array received varying amounts of irradiation, and the time required for GMPP extraction was subsequently recorded. According to Figure 4.34, it takes 0.03 seconds and 603.66 W to reach the GMPP, which is as same as the simulation result for the identical instance.

Case 4:

In scenario 4, the PV array received uneven irradiations across all of its panels, and the duration of the GMPP extraction process is documented. Figure 4.35 displays the findings for Case 4, where the GMPP is achieved in 0.05 seconds with a corresponding power of 350W, which is similar with the simulation results.

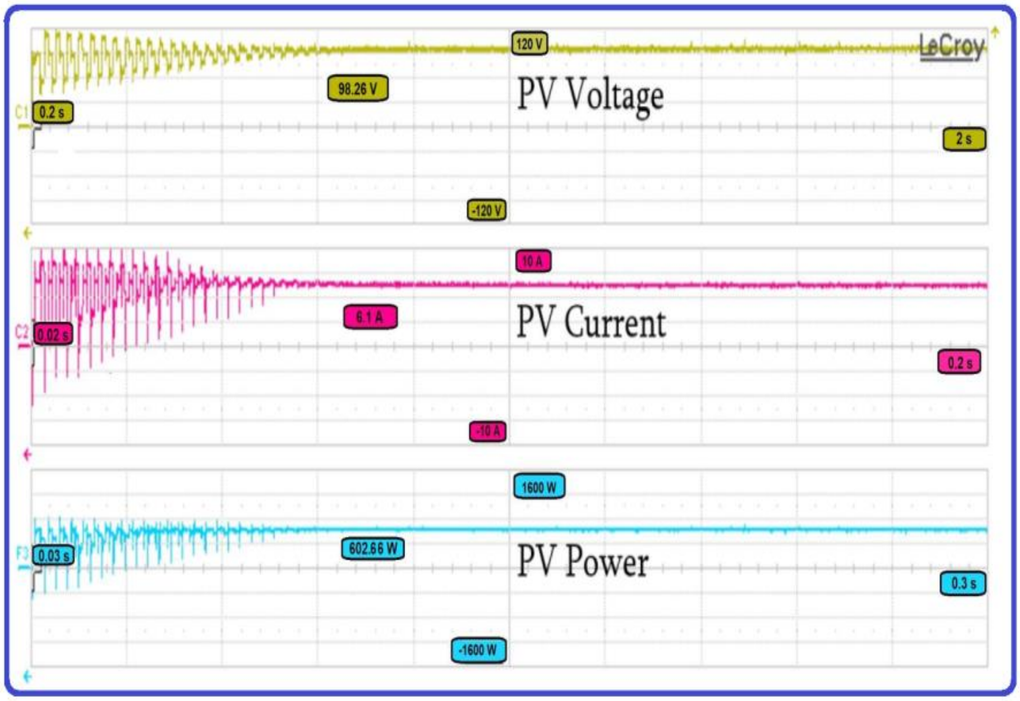


Figure 4.34. MPA Experimental results for case 3

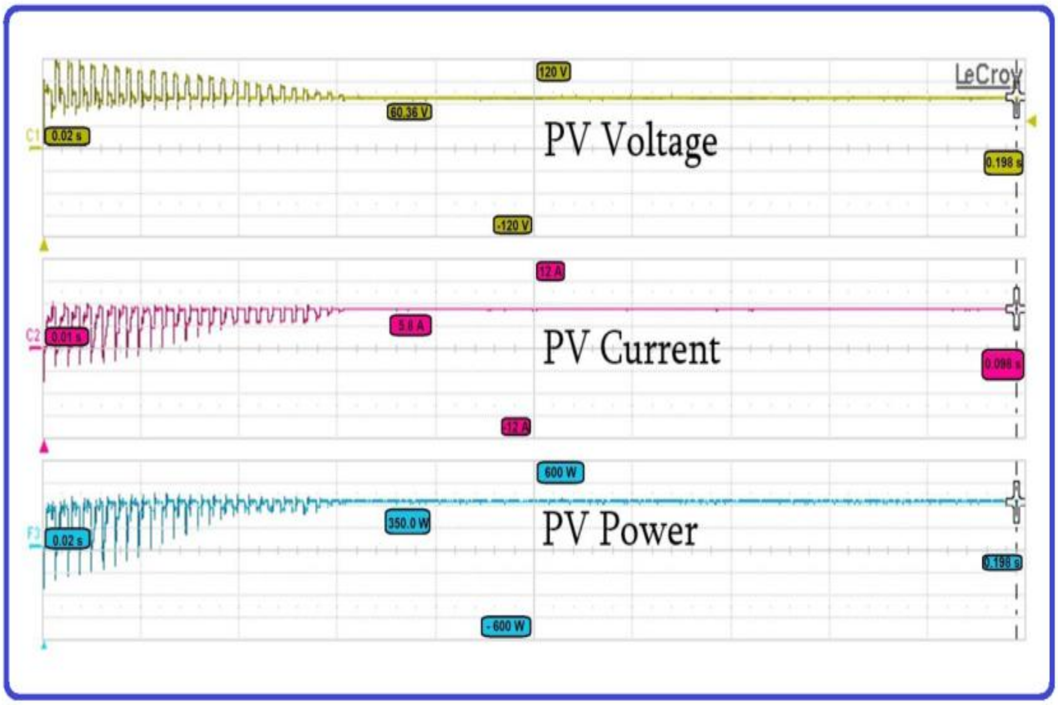


Figure 4.35. MPA Experimental results for case 4

4.7.8 Summary

In this chapter Dual-Stage PSO, Forward Backward PSO, Enhanced GWO, MFO algorithms are studied and novel MPA MPPT proposed. Detailed explanation of these algorithm's applications for MPPT is done. To evaluate the effectiveness of the current algorithms, comprehensive simulations have been conducted. These simulations involve various PV array configurations, namely 8S, 4S2P, and 2S4P, and they are exposed to dynamically changing PSC. The proposed MPPT algorithm MPA is realized experimentally and the tracking results are shown. Efficiency, power at MPP, and time to track MPP for different PSCs were all calculated to demonstrate the potential of the MPA approach. Tracking curves for PV power, voltage, current and duty ratio of these MPPT algorithms is presented. The detailed explanation of maximum power extracted and tracking time for algorithms is made in this chapter.

5

Comparative Analysis

5.1 Introduction

This chapter presents a comparison of the traditional PSO, GWO, MFO, and proposed MPA approaches in terms of tracking speed and efficiency. Because of the stochastic character of optimization methods, 100 trial runs were performed for the indicated MPPT methodologies, and statistically similar results are reported in this chapter. Arduino MEGA-2560 controller is used for implementing the various MPPT techniques. This chapter also includes graphical representations of the presented approaches' maximum power extracted and tracking speed.

5.2 Statistical Performance Analysis

The ratio of the maximum power acquired using the MPPT technique to the maximum power gained from the PV curve is the tracking efficiency in this scenario. The typical PSO MPPT approach takes the longest of all MPPT strategies to monitor the GMPP, whereas MPA takes the quickest.

Utilizing MATLAB/Simulink, evaluation of the suggested MPA based MPPT for PV systems was conducted. The methodology was compared to MPPT methods based on MFO [138], GWO [105], and PSO [83] in order to validate the findings in four distinct partial shading instances. Under STC the rating of the panels is shown in Table 4.5 for the four 250 W solar PV panels that were employed in this experiment and coupled in a series-parallel arrangement and validation of PSCs used in this work are listed in Table 5.1 [140].

Table 5.1 Four different cases of PSCs for testing

Irradiance (W/m^2)	Cases			
	Case 1	**Case 2**	**Case 3**	**Case 4**
P11	1000	400	500	200
P12	1000	400	800	300
P21	1000	1000	700	700
P22	1000	1000	1000	1000

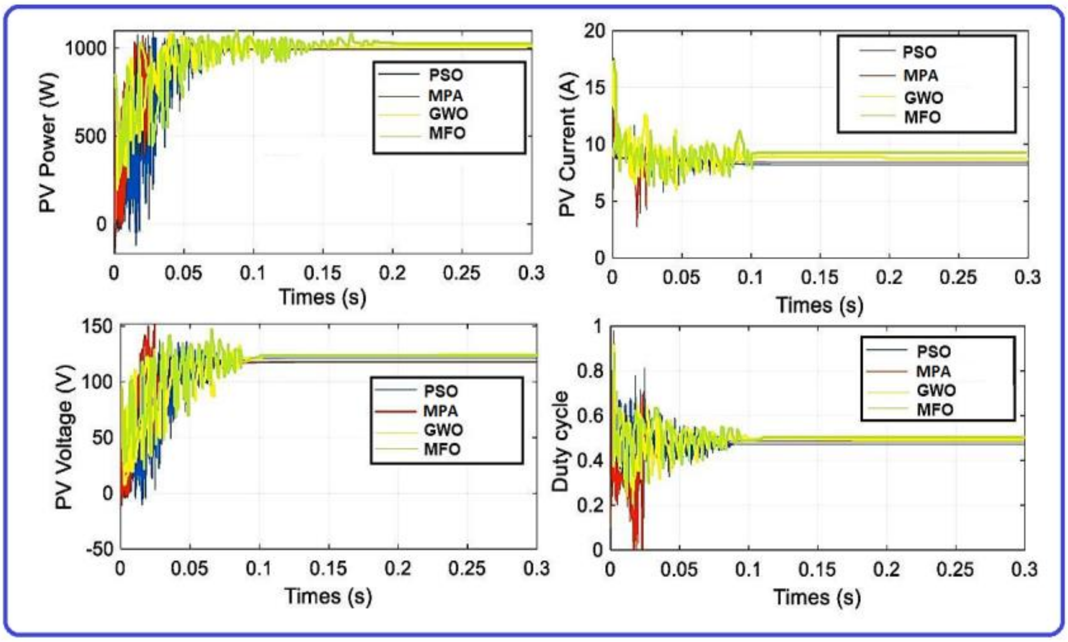


Figure 5.1. PV Power, Current, Voltage, and Duty Cycle for MPA [Proposed], PSO [83], GWO [105], and MFO [138] at case 1

Case 1:

All 4 modules in this scenario 1, received an identical amount of illumination, or 1000 W/m^2. Voltage, current, power, and duty cycle measurements may be used to assess the performance characteristics of the array. All of the data are shown in relation to time is shown in Figure 5.1. Three more MPPT techniques along with the suggested MPA algorithm are PSO, MFO, and GWO algorithms were added to the system for comparison. Figure 5.1 shows that the suggested MPA approach has 99.82%

efficiency and that it takes 0.07 seconds to achieve the MPP. Furthermore, it is obvious that the performance of the suggested MPA approach is superior to that of the other strategies.

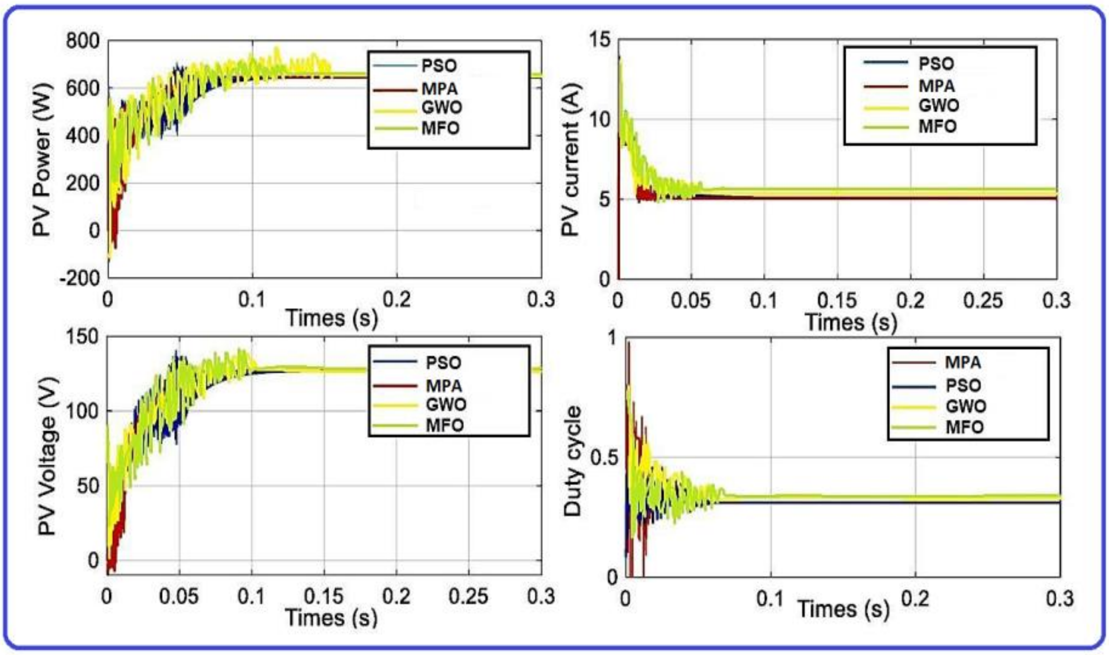


Figure 5.2. PV Power, Current, Voltage, and Duty Cycle for MPA [Proposed], PSO [83], GWO [105], and MFO [138] at case 2 [138]

Case 2:

All 4 modules in this instance, received varied irradiance according to table 5.1 voltage, current, power, and duty cycle measurements may be used to assess the performance characteristics of the array. All of the data are shown in relation to time is shown in Figure 5.2 which shows that the suggested MPA approach is 99.86% efficient and takes 0.06 seconds to achieve the MPP, faster than remaining strategies in instance 2.

Case 3:

All four modules in case 3 received varied irradiance as shown in table 5.1, Figure 5.3 shows all the data for power, voltage, current, and duty cycle with respect to time. From this, it can be observed that the proposed MPA method takes 0.04 seconds to achieve the MPP and efficiency of 98.84%, which is superior than remaining techniques in case 3.

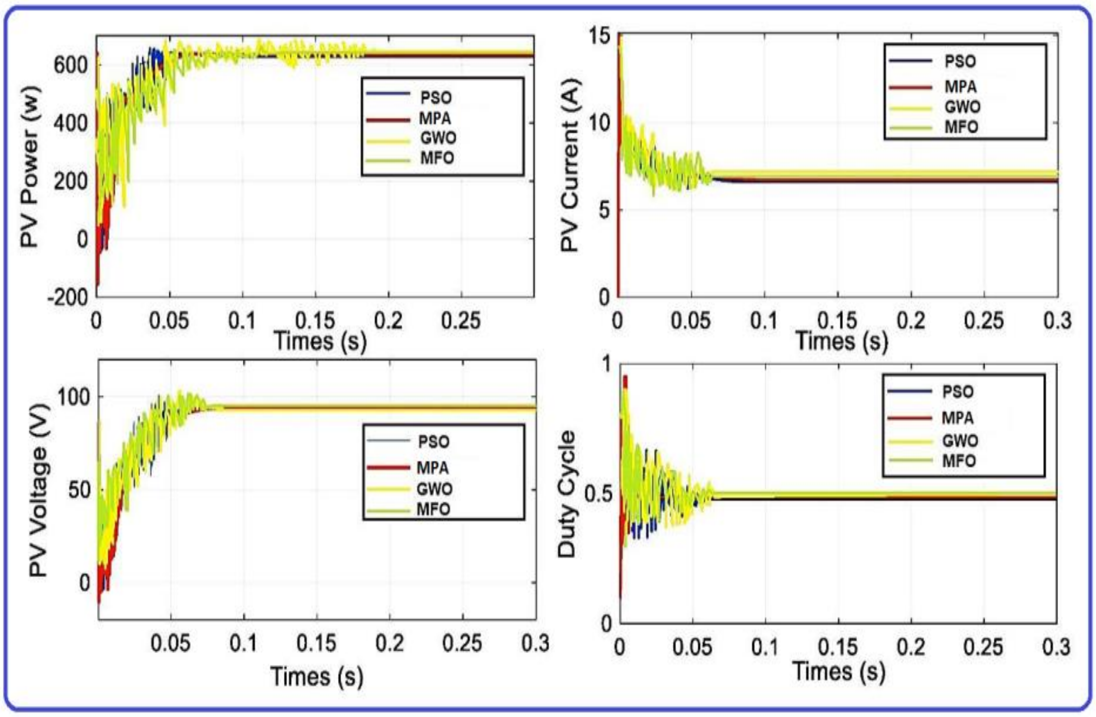


Figure 5.3. PV Power, Current, Voltage, and Duty Cycle for MPA [Proposed], PSO [83], GWO [105], and MFO [138] at case 3

Case 4:

Analogous to the previous 2 situations, all four modules in case 4 received varied irradiance as seen in table 5.1. MPP reaches in 0.04 seconds, and the MPA MPPT efficiency is 98.84%. In case 4 MPA outperforms the other three techniques. Figure 5.4 shows all the data of voltage, current, power, and duty cycle with respect to time.

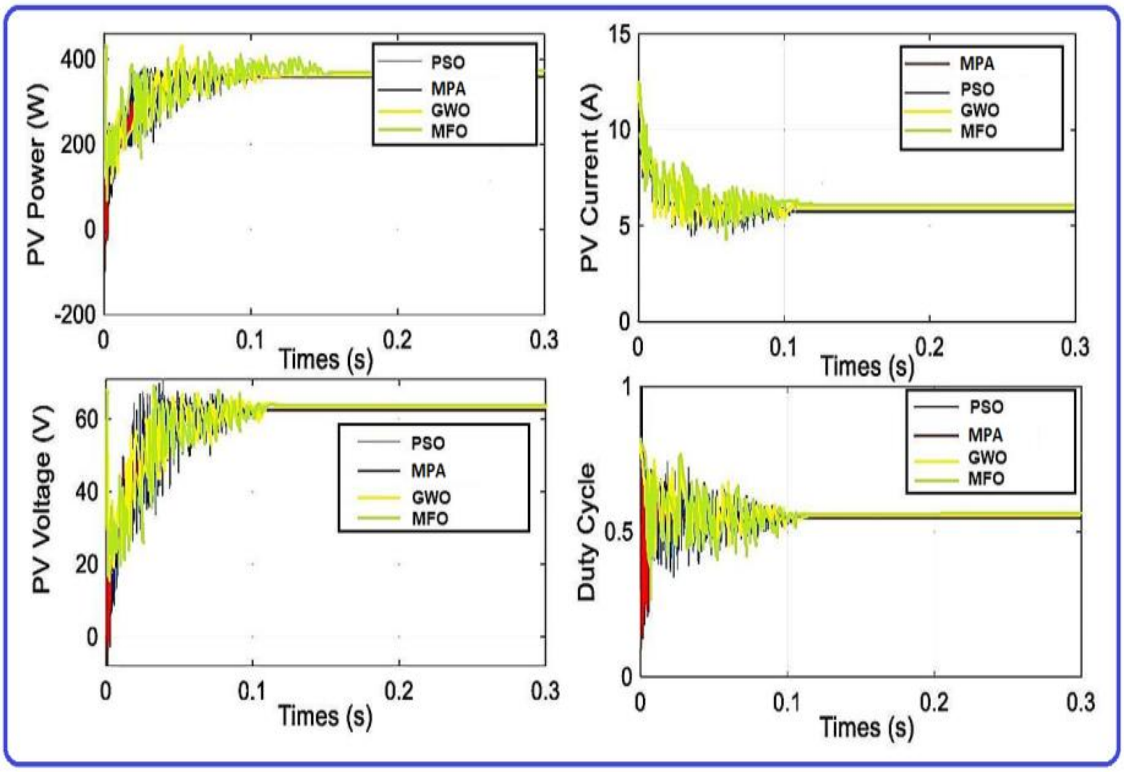


Figure 5.4. PV Power, Current, Voltage, and Duty Cycle for MPA [Proposed], PSO [83], GWO [105], and MFO [138] at case 4

Table 5.2. Comparative analysis of MPA [Proposed], PSO [83], GWO [105], and MFO [138] methodologies for various test scenarios

Performance Parameters	Case1				Case2				Case3				Case4			
	Various MPPT Techniques															
	MPA	PSO	GWO	MFO	MPA	PSO	GWO	MFO	MPA	PSO	GWO	MFO	MPA	PSO	GWO	MFO
Power extracted at MPP (Watts)	995.0	992.9	995.0	995.2	674.5	672.3	674.6	674.6	654.1	653.8	654.5	654.5	364.2	358.5	364.5	364.7
Time to attain MPP (seconds)	0.07	0.09	0.12	0.20	0.06	0.10	0.16	0.12	0.04	0.10	0.18	0.12	0.04	0.10	0.12	0.16
Efficiency (%)	99.84	99.76	99.93	100	99.86	99.82	100	100	98.85	98.83	99.99	99.99	99.85	99.45	99.98	100

Table 5.2 compares MPA PSO, GWO, and MFO approaches in its whole while taking four separate test situations into account. Power at MPP, the amount of time

needed to reach MPP, and PV efficiency are all taken into account when comparing. The graph in figure 5.5 clearly demonstrates that MPA approach consistently outperforms other strategies in terms of convergence time for all four scenarios. Efficiency is also practically on par with top-tier technique. The suggested MPA approach can also be simply implemented in real-time hardware [140].

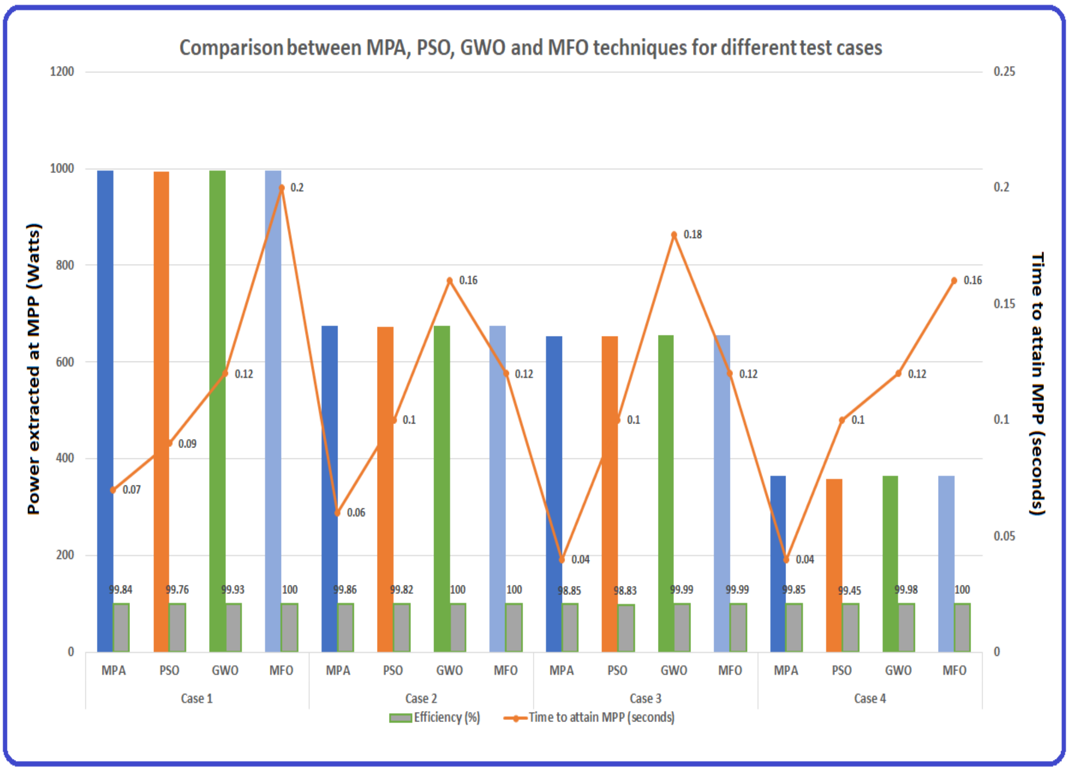


Figure 5.5 Comparison of four separate test scenarios using MPA [Proposed], PSO [83], GWO [105], and MFO [138] methodologies

5.3 Summary

This chapter compares the proposed MPA MPPT approach with standard PSO, GWO and MFO using statistical analysis and bar charts. Analytical comparison reveals that each of the techniques that have been suggested tracks the global MPP of various PV systems that are subject to dynamically changing shading patterns. Out of all techniques, the suggested MPA MPPT approach tracks GMPP in the shortest amount of time. Because of the stochastic character of optimization methods, 100 trial runs were performed for the indicated MPPT methodologies, and the results are provided.

Results show that owing to local MPP trapping, traditional PSO has a relatively significant standard deviation when compared to the suggested MPA approach. With a very low standard deviation and accurate tracking of the total MPP for the finished trail runs, the proposed MPA MPPT technique can be used extensively.

6

Conclusion

6.1 Concluding Remarks

An overview of different solar power generation techniques, solar scenario in the world and in India is presented. Different methods to reduce the effect of PSC on PV systems are discussed in chapter 1. The importance of MPPT and its implementation problems along with DC-DC boost converter is discussed in chapter 1. The research background of the work and research objectives motives are explained. Research objectives are framed and thesis organization are given in chapter 1.

An extensive literature for period of last fifteen years on different types of PV systems, different methods of modelling the PV systems under both uniform irradiation and PSC, different methods to extract PV parameters, different techniques to mitigate the effect of PSC, different MPPT techniques overview to extract maximum power from the PV System along with equations and diagrams is presented in chapter 2.

In this work PV system analytical modelling under PSC based on SDM by considering shunt and series resistance effect is developed. The electrical characteristics of PV module under varying temperature, irradiation conditions and internal parameters like shunt and series resistance effect are presented in chapter 3. The electrical characteristics of altered combinations of eight PV modules i.e. 8S, 4S2P and 2S4P PV configurations for different PSCs are presented in chapter 3.

Existing MPPT techniques fall short to track the GMPP under PSC and therefore useful PV power gets wasted. An alternative under such partial shaded condition is swarm intelligence based MPPT techniques. Larger exploration of search space and larger settling time are the disadvantages of most implemented PSO based MPPT algorithm which are due to random initialization and output power oscillations which decreases the efficiency of the PV system. To overcome these disadvantages, two new improved PSO algorithms i.e. DPSO and FBPSO techniques are studied in chapter 4. Also, MFO based MPPT and its characteristics are studied where the supremacy in terms of efficiency is proved. In this work an MPPT EGWO technique improved its performance by eliminating the unwanted phase in conventional GWO MPPT Technique which is discussed here. This research employed a comprehensive methodology that involved the implementation of the MPA algorithm for MPP tracking in a simulated environment. Subsequently, the simulated results were validated through rigorous experimental trials conducted on an actual solar PV system. The experiments covered varying environmental conditions, ensuring a holistic evaluation of the algorithm's performance presented in chapter4.

In this work, a pulse width modulation control boost converter is employed to track the MPP of the PV panel using the suggested bio-inspired MPA approach with great precision. The calculations of efficiency, power at MPP, and time to track the MPP for different PSCs were done in order to show the efficacy of the MPA approach. The outcome reveals a remarkable level of precision in tracking the MPP compared to PSO, GWO, and MFO algorithms in steady-state conditions. Experimentally from comparative analysis it is concluded that the proposed algorithm is effective in tracking GMPP of PV system under PSC in terms of accuracy and tracking speed.

The significance of research works done were added in the conclusion (Chapter 6). The trend of renewable energy is booming especially solar PV system must be operated efficiently and effectively even during PSCs. So, identification of parameters, finding the MPP called MPPT during PSCs using a simple and cost-efficient method called bio-inspired MPA along with comparison of other methods were done. These research woks are very much essential to run the solar PV system in an efficient and effective manner. The research work mentioned in the thesis are aimed to reach the above-mentioned target and achieved successfully. So, in future many people do not hesitate to install solar PV power plants due to the issue of PSCs.

Overall, the research demonstrates the efficacy of the Marine Predator Algorithm (MPA) as a superior MPPT technique for solar PV systems. MPA exhibited consistent and superior tracking efficiency, along with remarkable tracking speed, making it well-suited for dynamic and unpredictable environmental conditions. The findings of this research support the adoption of MPA as a reliable and efficient solution for optimizing solar PV system performance. Further studies could explore the adaptability of MPA in large-scale PV installations and its integration into smart grid systems for enhanced energy management.

6.2 Future Scope

The research MPPT algorithms for solar PV systems, with a focus on the Marine Predator Algorithm (MPA), opens up several future avenues for exploration and improvement. Here are potential future scopes for the above research:

- As a part of future work, the effect of PSC on PV arrays, comparison with more meta-heuristics algorithms and integrate them into the grid via an inverter will be analyzed along with the parameter estimation using MPA.
- Since it offers an extra degree of flexibility to adjust the position speed by altering the order of the derivative, this MPA can also be used to identify the parameters of solar PV models.
- New Bio-Inspired algorithms may be developed to get less time consuming, less cost and high accuracy for extracting GMPP from PV array.
- Optimization of MPA Parameters: Investigate the impact of different parameter settings within the MPA algorithm on tracking efficiency and speed. Fine-tune these parameters to enhance the algorithm's adaptability to various environmental conditions.
- Hybrid Algorithms: Explore the possibility of developing hybrid MPPT algorithms that combine the strengths of MPA with other optimization techniques.

Hybrid approaches may offer improved performance under specific conditions and contribute to the development of more versatile MPPT strategies.

- Machine Learning Integration: Investigate the integration of machine learning techniques to enhance the learning capabilities of MPPT algorithms. Machine learning models could adapt the algorithm's behavior based on historical data, leading to improved performance in predicting and responding to changing environmental conditions.
- Real-Time Implementation: Extend the research to real-time implementation and testing on larger-scale PV systems. Evaluate the scalability of the MPA algorithm and its efficiency in optimizing power production in practical scenarios.
- Hardware Implementation: Move beyond simulation and conduct hardware implementations of the MPPT algorithms, including MPA, on physical PV systems. Assess the feasibility of deploying these algorithms in real-world applications and consider any hardware-specific challenges or optimizations.
- Robustness Analysis: Conduct a thorough analysis of the robustness of the MPA algorithm by subjecting it to various challenging scenarios, such as rapid environmental changes, partial shading, and varying load conditions. Evaluate its ability to maintain stable and efficient operation under diverse circumstances.
- Adaptation to Emerging PV Technologies: Investigate how MPPT algorithms, particularly MPA, can adapt to emerging PV technologies, such as tandem solar cells, perovskite-based cells, and other advanced materials. Assess the algorithm's performance in optimizing power extraction from these evolving technologies.
- Implementation in Smart Grids: Explore the integration of MPPT algorithms, especially MPA, into smart grid systems. Investigate how these algorithms can contribute to improved energy management, grid stability, and the efficient integration of renewable energy sources within smart grid infrastructures.
- Energy Storage Integration: Evaluate the performance of MPPT algorithms, including MPA, in systems with energy storage components. Analyze their effectiveness in optimizing the charging and discharging cycles of batteries, contributing to enhanced energy storage efficiency.
- Environmental Impact Assessment: Assess the environmental impact of employing different MPPT algorithms, considering factors such as energy

production efficiency, system reliability, and overall sustainability.Compare the life cycle assessments of PV systems optimized with various MPPT techniques.

- Market Adoption and Industry Collaboration: Investigate the adoption of MPPT algorithms, particularly MPA, in the solar industry.Collaborate with industry stakeholders to understand practical challenges, obtain feedback on real-world implementations, and contribute to the integration of advanced MPPT techniques into commercial PV systems.

By exploring these future scopes, researchers can contribute to the ongoing development and optimization of MPPT algorithms, paving the way for more efficient and reliable solar PV systems in the evolving landscape of renewable energy technologies.

Appendix

A.1 PV module specifications

Kyocera KC a 250GT PV module specification which is used in modeling of PV system:

Table 6.1 Specifications of PV module

Maximum Power (P_{MP})	250W
Open Circuit Voltage (V_{OC})	36.9V
Short Circuit Current (I_{SC})	8.81A
Voltage Temperature Coefficient (k_V)	-1.23 x 10-1 V/ºC
Current temperature coefficient (k_I)	3.18 x 10-3 A/ºC
Maximum Power Voltage (V_{MP})	30.3V
Maximum Power Current (I_{MP})	8.11A

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List of Publications

International Journals

[1] **Vankadara, S.K.**; Chatterjee, S.; Balachandran, P.K.; Mihet-Popa, L. Marine Predator Algorithm (MPA)-Based MPPT Technique for Solar PV Systems under Partial Shading Conditions. Energies 2022**(SCIE Indexed)**, 15, 6172. https://doi.org/10.3390/en15176172.**(Impact Factor 3.2)**

[2] **Vankadara, S. K.**, Chatterjee, S., & Balachandran, P. K. (2022). An accurate analytical modeling of solar photovoltaic system considering Rs and Rsh under partial shaded condition. International Journal of System Assurance Engineering and Management **(Scopus)**, 1-10.https://doi.org/10.1007/s13198-022-01658-6 **(Impact Factor 2.0)**

International Conferences

[3] **Vankadara Sampath Kumar** of Lovely Professional University, Punjab has presented the paper titled “Comparative Analysis of Photovoltaic Module Electrical Characteristics using a Two-Diode Model with Single-Diode Model and its Application under Partial Shading Conditions” in the “4th International e-Conference on Intelligent Circuits and Systems (ICICS-2022)” held on April 8-9th, 2022, organized by School of Electronics and Electrical Engineering at Lovely Professional University, Punjab.

[4] **S. Kumar Vankadara**, S. Chatterjee and P. Kumar Balachandran, "Applications of Metaheuristic Algorithms for MPPT Under Partial Shaded Condition in PV System," 2023 4th International Conference for Emerging Technology (INCET)**(Scopus)**, Belgaum, India, 2023, pp. 1-5, doi: 10.1109/INCET57972.2023.10170183.

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