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Department of Electrical-Electronic Engineering

HYBRID MAXIMUM POWER POINT TRACKING TECHNIQUE BASED ON GWO-P&O FOR PHOTOVOLTAIC SYSTEM UNDER VARIOUS CONDITIONS

Master Thesis

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THESIS INTRODUCTION FORM

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Turkish Abstract **:**

Kısmi gölgeleme durumu, küresel maksimum power point'in kesin olmayan takibi nedeniyle fotovoltaik sistemlerin çıkış gücünü etkileyen ana zayıf noktalardır. Güç-Voltaj eğrisinde birçok maksimum power point'in olduğu kısmi gölgeleme koşullarında, perturb & gözlem, artımlı iletkenlik algoritmaları gibi geleneksel algoritmalar, global maksimum güç noktasını izleyemiyor, dolayısıyla genel PV sistem verimliliğini azaltıyor. Bu çalışma, hızlı güneş ışınımı ve kısmi gölgeleme koşullarına maruz kalan bir PV sisteminden maksimum gücü çıkarmak için gri kurt optimizasyon algoritmasını perturb & gözlem algoritmasıyla birleştiren hibrit bir GWO-P&O algoritması önermektedir. Gri kurt optimizasyon algoritması, küresel zirveye daha hızlı yakınsama sağlamak için ilk aşamaları, ardından Perturb & Observe algoritmasını son aşamada ele alır. Hibrit tekniği kullanmanın ardındaki fikir, küresel zirveye doğru yakınsamayı hızlandırmaya yardımcı olan GWO'nun arama alanını küçültmektir. Hibrit GWO-P&O algoritması önce MATLAB/SIMULINK kullanılarak gerçeklenir, ardından pratik uygulaması için deneysel bir kurulum tasarlanmıştır. Önerilen algoritmanın sonuçları, geleneksel P&O algoritması, geleneksel GWO algoritması ve PSO algoritması ile karşılaştırılmıştır. Sonuçlardan, önerilen algoritmanın diğer algoritmalara kıyasla yüksek izleme verimliliği, MPP etrafında düşük salınımlar, MPP'ye hızlı yakınsama, yüksek doğruluk ve MPP'ye ulaşmak için küçük zamana sahip olduğu kanıtlanmıştır.

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DECLARATION

I hereby declare that in the preparation of this thesis, scientific ethical rules have been followed, the works of other persons have been referenced in accordance with the scientific norms if used, there is no falsification in the used data, any part of the thesis has not been submitted to this university or any other university as another thesis.

Ameer Mahmood Rahman ALKHUZAIE

/ /2022

TO ISTANBUL GELISIM UNIVERSITY
THE DIRECTORATE OF INSTITUTE OF GRADUATE STUDIES

The thesis study of Ameer Mahmood Rahman titled as Hybrid Maximum Power Point Tracking Technique Based on GWO-P&O For Photovoltaic System Under Various Conditions has been accepted as MASTER THESIS in the department of ELECTRICAL-ELECTRONIC ENGINEERING by our jury.

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APPROVAL

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Director of the Institute

SUMMARY

The partial shading condition is the main weak point that affects the output power of photovoltaic systems, due to imprecise tracking of the global maximum power point. In partial shading conditions with many maximum power points on the Power–Voltage (P-V) curve, traditional algorithms such as perturb & observe, incremental conductance algorithms are failing to track the global maximum power point, thus reducing the overall PV system efficiency. This study proposes a hybrid GWO-P&O algorithm that combines the grey wolf optimization algorithm with the perturb & observe algorithm for extracting the maximum power from a PV system exposed to rapid variations of solar irradiation and partial shading conditions. The grey wolf optimization algorithm handles the initial phases followed by Perturb & Observe algorithm at the final phase to achieve faster convergence to the global peak. The idea behind using the hybrid technique is to scale down the search space of GWO which helps to speed up to achieve convergence towards the global peak. The hybrid GWO-P&O algorithm is first implemented using MATLAB/SIMULINK, then an experimental setup is designed for its practical implementation. The results of the proposed algorithm are compared with the traditional P&O algorithm, the traditional GWO algorithm, and the PSO algorithm. From the results, it has been proved that the proposed algorithm has high tracking efficiency, low oscillations around MPP, fast convergence toward MPP, high accuracy, and small-time to reach MPP compared to other algorithms.

ÖZET

Kısmi gölgeleme durumu, küresel maksimum power point'in kesin olmayan takibi nedeniyle fotovoltaik sistemlerin çıkış gücünü etkileyen ana zayıf noktalardır. Güç-Voltaj eğrisinde birçok maksimum power point'in olduğu kısmi gölgeleme koşullarında, perturb & gözlem, artımlı iletkenlik algoritmaları gibi geleneksel algoritmalar, global maksimum güç noktasını izleyemiyor, dolayısıyla genel PV sistem verimliliğini azaltıyor. Bu çalışma, hızlı güneş ışınımı ve kısmi gölgeleme koşullarına maruz kalan bir PV sisteminden maksimum gücü çıkarmak için gri kurt optimizasyon algoritmasını perturb & gözlem algoritmasıyla birleştiren hibrit bir GWO-P&O algoritması önermektedir. Gri kurt optimizasyon algoritması, küresel zirveye daha hızlı yakınsama sağlamak için ilk aşamaları, ardından Perturb & Observe algoritmasını son aşamada ele alır. Hibrit tekniği kullanmanın ardındaki fikir, küresel zirveye doğru yakınsamayı hızlandırmaya yardımcı olan GWO'nun arama alanını küçültmektir. Hibrit GWO-P&O algoritması önce MATLAB/SIMULINK kullanılarak gerçeklenir, ardından pratik uygulaması için deneysel bir kurulum tasarlanmıştır. Önerilen algoritmanın sonuçları, geleneksel P&O algoritması, geleneksel GWO algoritması ve PSO algoritması ile karşılaştırılmıştır. Sonuçlardan, önerilen algoritmanın diğer algoritmalara kıyasla yüksek izleme verimliliği, MPP etrafında düşük salınımlar, MPP'ye hızlı yakınsama, yüksek doğruluk ve MPP'ye ulaşmak için küçük zamana sahip olduğu kanıtlanmıştır.

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ABBREVIATIONS

GMPP	**:**	Global Maximum Power Point
P&O	**:**	Perturb and Observe
GWO	**:**	Grey Wolf Optimizer
PSO	**:**	Particle Swarm Optimization
STC	**:**	Standard Test Conditions
PSC	**:**	Partially Shaded Conditions
PV	**:**	Photovoltaic
MPPT	**:**	Maximum Power Point Tracking
MPP	**:**	Maximum Power Point
D	**:**	Represents the current grey wolf
L	**:**	Inductor
C	**:**	Capacitor
R	**:**	Resistance
AC	**:**	Alternating Current
DC	**:**	Direct Current
d	**:**	duty cycle

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INTRODUCTION

The global energy demand is significantly growing in parallel with the ever-expanding population. Due to the increase of greenhouse gas emissions from fossil fuels, global warming is intensifying (S. R. Chowdhury et al, 2010). Several studies recommended the adoption of renewable energies to tackle the issues of diminishing energy supplies while minimizing fossil fuel-related side effects in the future (A. Senthilvel et al, 2020). With regards to the aforementioned, the advancement of renewable energy sources has been made a worthwhile area of research in the past decade. Renewable energy resources including solar PV systems are often regarded as the most attractive renewable energy choices (G. E. Ahmad et al, 2006) and (Mingxuan et al, 2020).

The Current-Voltage (I-V) and Power- Voltage (P-V) characteristics of the PV panels are nonlinear and depend on many factors like applied load, radiation, and temperature. As shown in Fig 1, the cell is operating at maximum efficiency at one specific point on the P-V characteristic curve which is known as the maximum power point (MPP) (A. Jager-Waldau et al, 2017). Manipulating the maximum power point tracking (MPPT) technique appropriately can ensure more power output under a variety of weather situations (Kandemir et al, 2017) and (Altwallbah et al, 2020). MPPT technology is an electrical system that feeds a suitable duty cycle to a power conversion system to continuously provide maximum power. Cost, efficiency, and lost energy are all major factors to consider when determining the ideal MPPT for a PV system (Birane et al, 2017) and (R. Ahmad et al, 2019). PV modules are used to generate power as they are connected either by parallel or series combinations to meet the need for power (Ali M. Eltamaly et al, 2019). Even though PV panels are installed on rooftops, there is no guarantee that the modules are perfectly exposed to equal irradiance due to shadows, passing clouds, bird feces, and dust on the panels. These shortcomings cause the partially shaded condition (K. Ishaque et al, 2012) and (K. Chen et al, 2014). Regardless of being set in series or parallel, PV modules may have different voltages. When operating the PV system using PSC, numerous peaks may appear in the P-V characteristics (J. Prasanth Ram et al, 2020). The peak with the highest magnitude is denoted as a global maximum power point (GMPP), while the rest of the peaks are considered as local maximums. The controller's work is to keep track of GMPP during PSC (MANSI JOISHER et al, 2020). Traditional MPPT methods are known to frequently fail in achieving GMPP because it assumes the initial local peak as the ideal operating position. Due to this behavior of conventional trackers methodology, a novel MPPT scheme to optimize global MPP under the PSC of the PV system is proposed in this paper. The applications of Genetic Algorithm (GA) (M. Seyedmahmoudian et al, 2016), Gray Wolf Optimization (GWO) (S. Mohanty et al, 2016), Particle swarm optimization (PSO) (K. Ishaque et al, 2012), Fuzzy Logic (FL) (W. Na et al, 2017), Ant Colony Optimization (ACO) (K. Sundareswaran et al, 2016), and Neural network (NT) (M.A. Islam et al, 2011), have comparable performance to conventional approaches, but because of the random nature of the population, real implementation to track GMPP effectively is complicated.

Among optimization techniques, GWO can identify local and global peaks of the MPP under partial shading conditions more effectively (DALIA YOUSRI et al, 2020). It offers also many advantages such as low parameter requirements, few operators, and less steady-state oscillations (Abdulaziz Almutairi et al, 2020). But GWO affects the MPPT speed of the PV inverter due to the highly complex computing processes. The proposed method can significantly improve the MPP iterative calculation since the improved GWO algorithm requires less iterations. The main aim of this study is to propose a hybrid (GWO and P&O) algorithm to enhance the convergence speed and eliminate power oscillations. GWO-P&O-based MPPT algorithms are comparable to those of P&O, PSO, and GWO approaches. To achieve fast convergence, the existing algorithm is improved by following the social behavior of grey wolves and is known as the GWO strategy to extract the maximum power point. The proposed hybrid algorithm, which combines the GWO method with P&O-based MPPT, was able to achieve MPPT with much less power oscillations around the MPP in a short time, and higher accuracy. The results of the MPPT algorithms were taken under standard test conditions and partially shaded conditions (PSC).

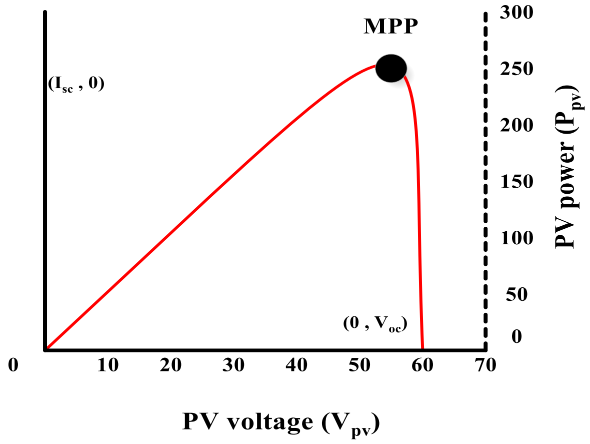


Figure.1: MPP characteristic

CHAPTER ONE

PURPOSE OF THE THESIS

1.1Literature Survey

Several studies have used a variety of algorithms to track the MPP under PSC, hence enhancing the efficiency of solar cells. Andrew Lewis (2014) proposed a new Swarm Intelligence (SI) technique based on grey wolves. Grey wolves' social structure and hunting behavior were modeled in the proposed method. Twenty-nine test functions were used to evaluate the proposed algorithm's performance. First, the findings on unimodal functions demonstrated the GWO algorithm's superior exploitation. Second, the results on multimodal functions supported GWO's exploration ability. Third, the composite function findings revealed a high level of local optima avoidance. Finally, GWO's convergence study validated the algorithm's convergence.

Hadeed Ahmed Sher (2015) proposed an improvement to the offline MPPT approach in this study. Either the Fractional Open Circuit Voltage (FOCV) or the Fractional Short Circuit Current (FSCC) can benefit from the proposed enhancement. For FSCC MPPT, simulation and experiments have been carried out. The proposed improvement intelligently calculates the appropriate time to isolate the PV panel, eliminating the necessity for time-based short circuit current measurement. The main disadvantage of this method is its field to track the maximum power point during PSC.

Under PSC, K. girinath (2018) proposed a novel evolutionary methodology termed Grey Wolf Optimization Differential Evolution (WODE) for MPPT. This WODE algorithm is a combination of Differential Evolution (DE) and Wolf Optimization (WO) evolutionary algorithms. DE lowers the action of random constants and metaheuristic nature, whereas WO has a great-searching ability in a wide area. As a result, the algorithm performs well but with large oscillations around MPP and with low tracking accuracy compared to other algorithms.

T.R. Premila (2018) proposed gray wolf optimization as a new evolutionary computing methodology for designing an algorithm for PV systems operating under PSC. The total performance of this novel MPPT was compared to that of present MPPTs to determine its effectiveness. The proposed GWO-PO hybrid-MPPT is known for its greater performance but with large oscillations around MPP compared and low accuracy to other algorithms.

M. V. Rocha (2018) revealed the creation of GWO-Beta-MPPT, a hybrid MPPT algorithm that can effectively extract the MPP from a PV array even when it is partially shaded. Simulation results were used to assess the efficacy of the proposed GWO-Beta-based MPPT, and the proposed hybrid MPPT approach was compared to three other MPPT strategies.

Dmitry Baimel et al. (2019) proposed using a semi-pilot cell instead of a pilot cell to reduce the power loss during open-circuit voltage measurements. The semi-pilot cell is part of the PV array and contributes to the total generated power when it is in regular functioning. When the semi-pilot cell is detached from the array, an open-circuit voltage is measured. As a result, the semi-pilot cell's power is only lost when it is unplugged, not regularly but it still works with low accuracy compared to other algorithms.

Kashif Javed (2019) developed a Modified Perturb and Observation (MP&O) algorithm that can successfully monitor MPP and discover PSC or Fast Transient Conditions (FTC). The energy loss during PSC is estimated to be 0.0834 percent of the daily generation, which is not substantial. When compared to P&O and other Evolutionary Algorithm (EA) approaches, the algorithm's tracking speed is substantially faster, and it integrates all of the benefits and features of more complicated algorithms that require a high-cost controller. Because of the algorithm's simplicity, it is simple to implement with a low-cost microcontroller, making it inexpensive and accessible.

Dilip Kumar1 (2019) proposed a detailed analytical model of a PV system in partial shadow. By eliminating the ω and δ phase of the traditional GWO algorithm, an enhanced GWO MPPT algorithm is presented to track the MPP of PV systems under PSC but with high oscillations around MPP.

Shailendra Suthar developed a new methodology dubbed gray wolf optimization for designing a maximum power extraction method for solar systems operating with PSC conditions (2019). In this presentation of the effectiveness of this novel MPPT (MPPT based on gray wolves), the performance was compared to two MPPT, namely the MPP techniques based on PSO and P&O, and the results revealed that the MPPT based on GWO outperformed the other two MPPT.

Rubi Debbarma, proposed a grey wolf methodology for PV systems with rapidly changing irradiance in the year (2020). The system outputs a constant power with no oscillations. Accuracy and efficiency have both improved. Meta-heuristics or artificial intelligence-based algorithms can track global MPP much more accurately than traditional MPPT techniques.

In (2020), Neda Altwallbah introduced a new hybrid method based on Extremum Seeking Control (ESC) and P&O approach. Under PSC, the suggested algorithm can track the maximum achievable power. The standard P&O and IC algorithms were compared to the hybrid MPPT method. The proposed method can improve convergence time, remove oscillations around power but operates with low tracking accuracy.

J. Prasanth discussed the creation of a new bioinspired-based hybrid Flower Pollination Algorithm and P&O (FPA-P&O) in (2020). Furthermore, it has been discovered in the literature that the hybridization of the bio-inspired techniques with the P&O method has been done superficially, and the switch from FPA to P&O has also not been adequately confirmed. As a result, a new mathematical verification is performed in this paper, and the transfer from bio-inspired to P&O is judicially certified.

In the year (2020), A. Senthilvel introduced a Periodic Power Hunt (PPH) MPPT algorithm to reach MPP from PV systems under partial shade conditions. To assess the overall performance of the proposed PPH approach, simulation experiments are carried out. MPPT's overall performance was evaluated and compared to the present MPPT P&O algorithm approach. As a consequence of the simulation findings and many experimental studies, the proposed PPH MPPT technique is capable of efficiently tracking global peaks under partial shade conditions but it takes more time to reach MPP.

Abdulaziz Almutairi implemented in 2020 using the Opposition-based learning with the GWO (OGWO) technique to maximize the extraction of power available in photovoltaic arrangements. An equivalent circuit that performs similarly to a PV panel was employed to gain a better understanding of how it works. The full conversion system is documented and studied, from the PV panel through the grid connection. As a result, an MPPT controller based on the GWO optimization approach has been created so that the PV system may effectively reach GMPP. By directing the search for the optimal solution, the Opposition-Based Learning (OBL) algorithm is introduced to the GWO to speed up the reach of MPP. To best explain the functionality of the OGWO-MPPT approach, experimental trials of many states of the system were done. The algorithms also show that they can converge to the GMPP in the shortest time possible for rapid changes in solar irradiation when the PV panel is partially shaded but with high oscillations around the MPP.

Mansi Joisher (2020) presents a hybrid algorithm based on a sequential mathematical analysis of Differential Evaluation (DE) and Particle Swarm Optimization (PSO) algorithms. To overcome their flaws, the major features of DE and PSO are integrated. To avoid all local peaks, the proposed hybrid MPPT employs a random mutation cycle. The maximum number of iterations determines when this loop is triggered. Both simulation and hardware setup are used to verify the hybrid MPPT's performance. Three different PSCs are used to test the proposed methodology. This algorithm can track the global MPP under the PSC but also produces high oscillations around the MPP which leads to the loss of more power.

In (2020), Sampurna Panda stated that the fundamental P&O algorithm is simple to implement but difficult to obtain MPP owing to swaying. Because classical P&O has many of the drawbacks outlined in this study, researchers have demonstrated promising results by making minor changes or adding auxiliary algorithms to it. As a result, adjustments or the addition of new elements to the core algorithm are required. Several studies have demonstrated that tweaking the core algorithm improves performance. Every changed algorithm, whether it is artificial intelligence-based or adaptive perturbation, has produced remarkable output in PV power production and also can track global MPP but it takes more time to reach MPP compared to other algorithms.

In 2020, Mingxuan Mao analyzed and summarized the main MPPT approaches for PV systems, categorizing them into three classes based on control theoretic and optimization concepts. The benefits and drawbacks of the MPPT approach for PV systems under PSC are compared and studied in particular.

1.2Problem Statement

Due to imprecise tracking of the GMPP, partial shadowing is one of the negative phenomena that affect the power output of PV systems. Under uniform insolation conditions, there is only one peak which is the global peak, traditional MPPT approaches such as P&O, Incremental Conductance, and Hill Climbing can effectively track the MPP, but they fail under PSC because there are many peaks, one of them is global and the remains are local. The meta-heuristic algorithms to work at the global peak is an appealing solution under partial shading conditions.

1.3 Thesis objectives

The main objectives of this study are

- To track the maximum power point under STC and PSC.
- To design and simulate of maximum power point tracking system on a PV system.
- To implementation practical experiments to track the maximum energy point under various conditions
- To compare the hybrid algorithm with the other algorithm and under various condition

1.4 Thesis Organization

The thesis consists of five chapters

- **Chapter One** Provides general information about the thesis, including the literature survey, the problem statement, and the objective of the thesis.
- **Chapter Two** Explanation of the general structure of photovoltaic systems, which consists of solar panels, boost converter, and MPPT systems, where each of them is briefly explained.
- **Chapter Three** Explains the methodology for the proposed hybrid algorithm in detail.
- **Chapter Four** Presents the results of the proposed hybrid GWO-P&O algorithm using MATLAB simulation and shows a comparison between the proposed hybrid method and other MPPT methods.
- **Chapter Five** This chapter explains the practical implementation of the system with convenient hardware. Also shows the performance of the proposed algorithm in practical experimentation.
- **Chapter Six** Discusses the conclusions and future benefits of the proposed algorithm.

CHAPTER TWO

THEORETICAL BACKGROUND

Several studies recommended the adoption of renewable energies to tackle the issues of diminishing energy supplies while minimizing fossil fuel-related side effects in the future. The advancement of renewable energy sources has been made a worthwhile area of research in the past decade. A renewable energy technology that turns sunlight into electricity using photovoltaics is known as a photovoltaic system. Solar PV systems are often regarded as the most attractive renewable energy choices. Solar panels do not require much maintenance and it is the best choice for a clean environment without any pollution, as it produces no pollution or emissions and offers a variety of benefits.

2.1 PV system modeling

A PV system is made up of four separate components; a solar PV array, a boost DC-DC converter, MPPT controller, and a load as presented in figure 2.

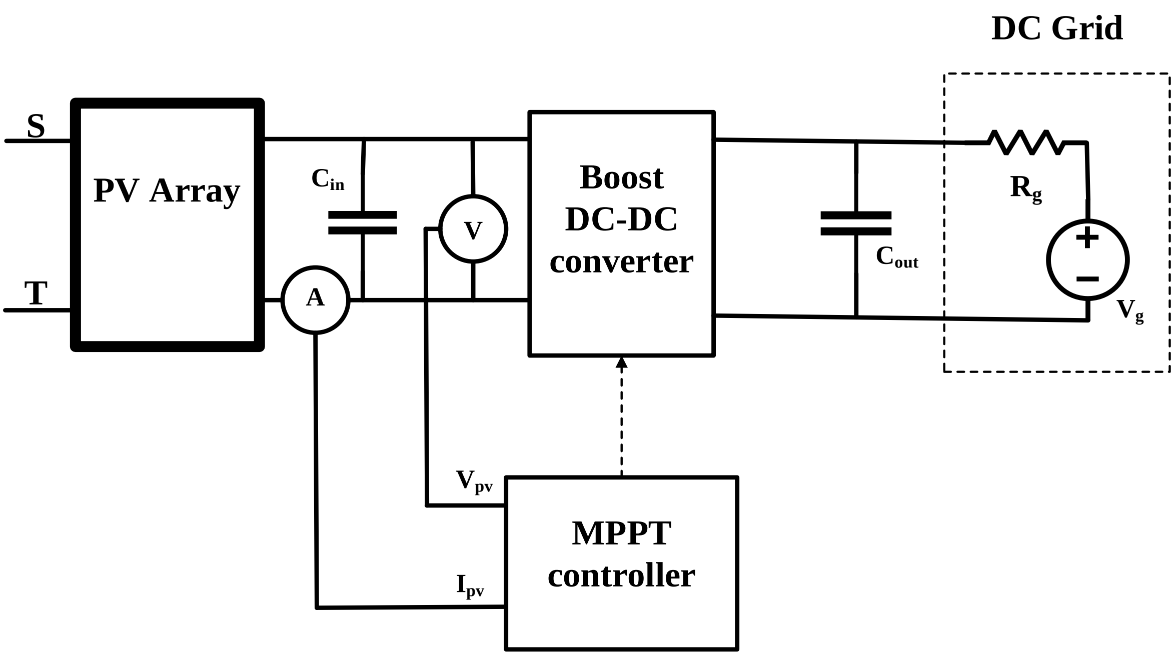


Figure.2: The photovoltaic system

The MPPT controller receives input from the PV module voltage and current values, which are sensed from the solar cells. The controller of MPPT is made up of circuitry that tracks the MPP. The MPPT algorithms use direct duty ratio control, so the duty ratio is modified in response to changing irradiance levels and fed into the boost converter as an input. The boost converter is responsible for impedance matching between the source and the load, allowing it to retain the maximum operating voltage and extract maximum power regardless of changing meteorological circumstances.

PV systems have many advantages over other forms of energy generation. Below is a list of the most important ones.

- Solar PV systems can be adapted to fit a set of uses and operational requirements, allowing them to be tailored to your exact requirements. Solar panels are available in both home and commercial sizes.
- After the solar PV system is installed properly, it will only need minor maintenance. Thus, it will provide you with electricity all the time with high efficiency and reliability.
- Solar PV systems emit no noise or pollution and rely on a natural resource which is sunlight to supply long-term energy generation.
- Though solar panel installation prices are significant, it's crucial to remember that a solar PV system will keep your money in the long term because it's free to run.

2.2 Solar PV module

PV panels generate DC-current by utilizing sunlight as a source. A PV Panel is a grouping of PV units, while an array is a collection of panels. Solar electricity is supplied to electrical devices through PV arrays. Modules generate electricity via the PV-effect, which uses light energy (photons) from the Sun. The majority of modules rely on thin-film or wafer-based crystalline silicon cells. The top layer or the back layer can be the structural (load-bearing) part of a module. Mechanical and moisture damage must be avoided by cells. The majority of modules are rigid; however, some are semi-flexible and based on thin-film cells. A solar panel is made up of several solar cells (X. Weidong et al, 2004). These characteristics allow the cell to catch sunlight and turn it into useable electricity. In this study, a single diode model is used to model a solar cell as shown in the figure. 3

The solar array current is represented in the equations below (Latefa A. El-sharawy et al, 2019)

$$I = (I_{Pv} \times N_p) - (I_o \times N_p) \times \left[exp \left\{ \frac{V + R_S \left(\frac{N_s}{N_p}\right) I}{V_t \, \alpha \, N_s} \right\} - 1 \right] - \frac{V + R_S \left(\frac{N_s}{N_p}\right) I}{R_{sh}\left(\frac{N_s}{N_p}\right)} \quad (1)$$

Where:

I_{Pv}: Currents of the PV array.

N_p: Number of parallel cells.

N_s: Number of series cells.

α: Ideal factor.

R_S : Series resistance.

R_{sh}: Shunt resistance.

V_t: Thermal voltage at nominal temperature.

I_o : Reverse saturation current.

The array thermal voltage can be obtained by:

$$V_t = N_s K \frac{T}{q} \quad (2)$$

Where:

K: Boltzmann's constant =1.38×10^{-23} J/K.

q: Electron charge =1.6×10^{-19} C.

T: Temperature of the p-n junction in K.

In addition, the photovoltaic current I_{pv} can calculate as follow:

$$I_{Pv} = \{ I_{pv,m} + k_c \, \Delta T \} \times \frac{G_p}{G_n} \quad (3)$$

$$\Delta T = T_p - T_n$$

Where:

ΔT **:** Temperature difference

$I_{pv,m}$: PV current at nominal conditions (1000W/m^2,25°C).

k_c : Cells temperature coefficient under short circuit current condition.

G_p : Irradiance on PV module Surface.

G_n : Nominal conditions irradiance.
T_p : Module temperature (K).
T_n : Module nominal temperature (K).

The saturation current of the diode can be calculated by:

$$I_o = I_{o,m} \left(\frac{T_n}{T_p}\right)^3 exp\left[\frac{q\,E_g}{\alpha\,K}\left(\frac{1}{T_n} - \frac{1}{T_p}\right)\right] \quad (4)$$

Where:
I_o : Current of the diode
$I_{o,m}$: Reverse saturation current under nominal conditions.
E_g : The semiconductor's band gap energy of polycrystalline silicon.

The nominal reverse saturation current can be given by:

$$I_{o,m} = \frac{I_{sc,m}}{exp\left(\frac{V_{oc,m}}{\alpha\,V_{t,m}}\right) - 1} \quad (5)$$

Where:
$I_{sc,m}$: Nominal conditions short circuit current.
$V_{oc,m}$: Nominal conditions open-circuit voltage.
$V_{t,m}$: Nominal Temperature thermal voltage of the array.

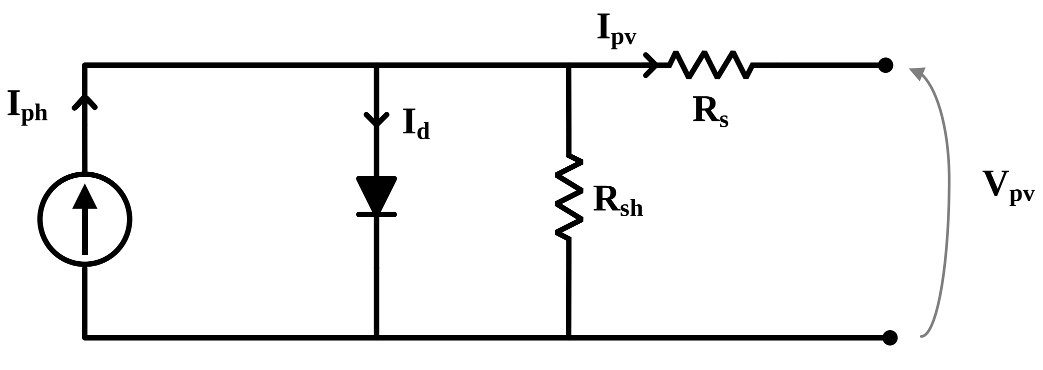


Figure.3: Equivalent circuit of a PV module

As appear in figure 4, there is a single point on the "P-V" curve of PV cells called the maximum power point, which is dependent on temperature and irradiance (N. A. Kamarzaman et al, 2014) and (E.V. Paraskevadaki et al, 2011). The voltage functioning of PV cells is also dependent on the load's impedance. When PV cells are connected to a load it drops to the different operating points. To overcome these issues, the MPPT approach and power conversion between the load and solar cells are linked, as shown in figure 2

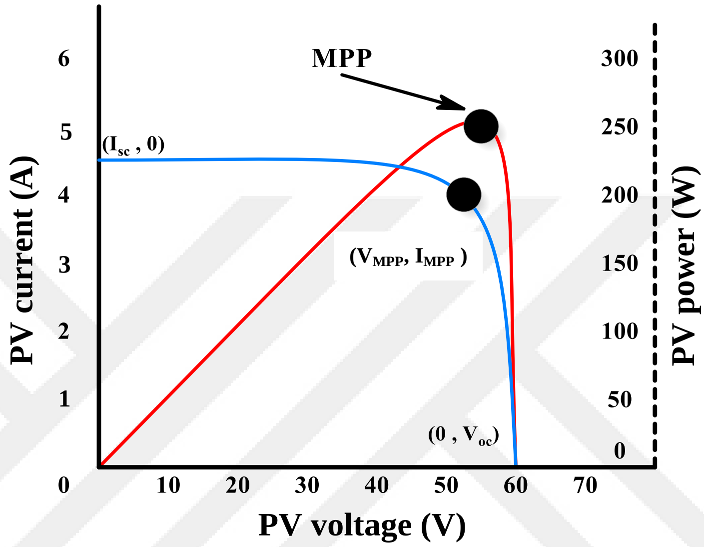


Figure.4: Solar module characteristic

The solar cell I-V characteristics span from zero output volts at I_{sc}, to zero current at V_{oc}. At I_{mp} and V_{mp}, there is one specific set of V and I for which the power achieves its maximum value. As a result, the MPP is defined as the ideal running of a PV panel. A solar cell's MPP is located at the curvature in the I-V characteristics curve.

As shown in figure.5. The voltage increases when connecting arrays in a series combination, while the current increases when connecting arrays in parallel. The PV panels are linked together, which results in the upper-right-hand corner being the MPP of the array.

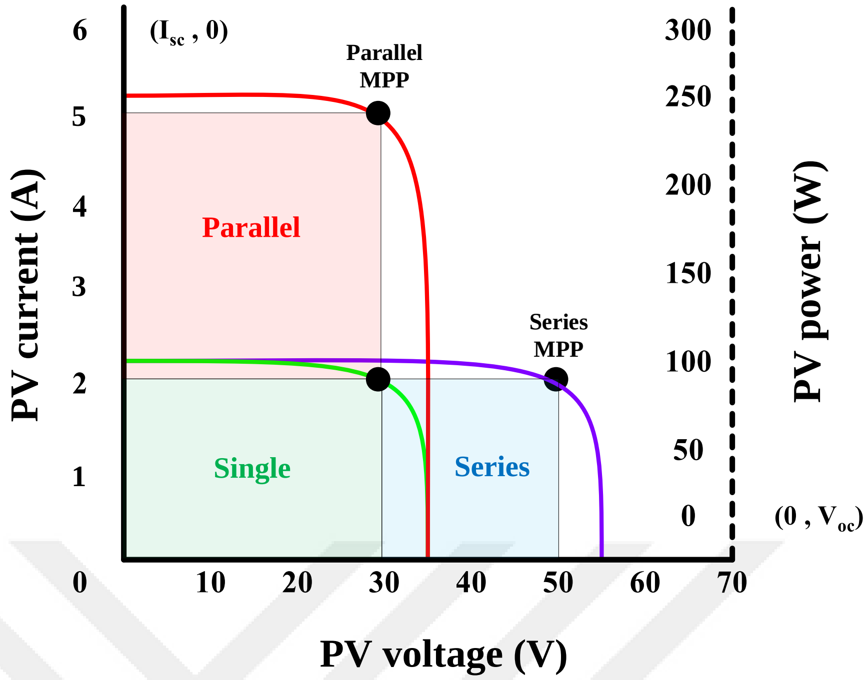


Figure.5: Connectivity of solar panels

The characteristic curves of a solar panel are the voltage and current graphs under different radiation and temperatures, which can reveal the ability of the panel to convert sunlight into energy. As illustrated in figure.6, the intensity and amount of solar radiation determine the amount of current. As shown in figure.7, the temperature of the solar panels influences the output voltage of the PV panel.

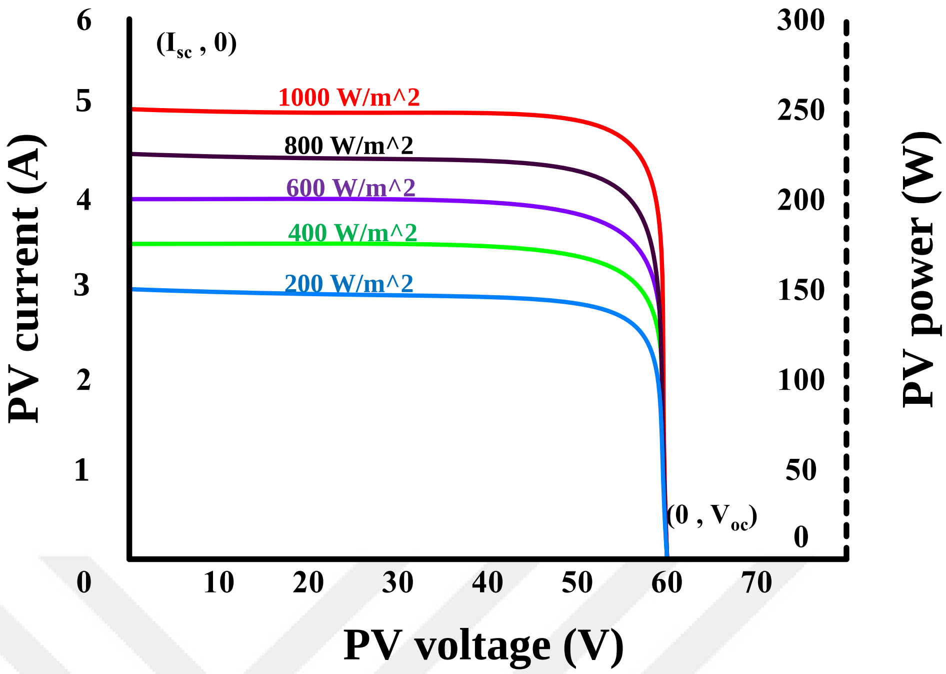


Figure.6: Variation of I-V with the amount of solar radiation

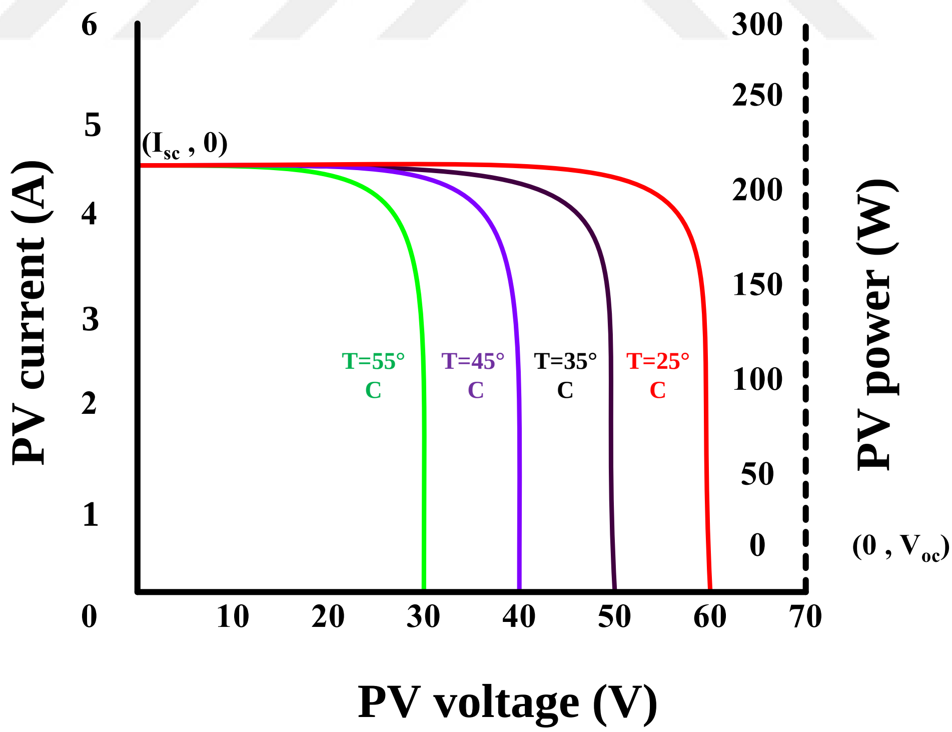


Figure.7: Variation of I-V with the amount of temperature

2.3Boost Converter Modeling

In photovoltaic systems, various types of converters are used as an interface between the load and the source, most notably the buck-boost converter and the boost converter depending on the solar system and the loads.

A boost converter has high efficiency across a wide power range in systems that only need to raise the voltage. In this study, only need to increase the voltage and compare it with the variation in power to determine the amount of duty cycle. That is why it is commonly used as an input voltage boosting stage in PV systems (Tejan L et al, 2015).

The aim is to extract the maximum power from the PV panel, and for this reason, need to ensure the maximum power point t to extract the maximum power under certain conditions. And then if you take look over the working principle of the boost converter it is a converted where the PV input voltage is lower than the battery voltage of the system, so usually to control the PV power output or control the charge of storage you need to use this boost converter used for MPPT Tacking.

The output of the converter is altered according to the duty cycle of the pulse train, which is known as pulse width modulation (PWM). Pulse train requires extremely little power and can be overlooked. The pulse train is simple to construct by evaluating and designing the variables which are the duty cycle, inductor, and capacitor. As shown in figure 8, the boost converter consists of L, C, R, Diode, S, and a Voltage Source (VS). The switch could be open or closed depending on the output requirement.

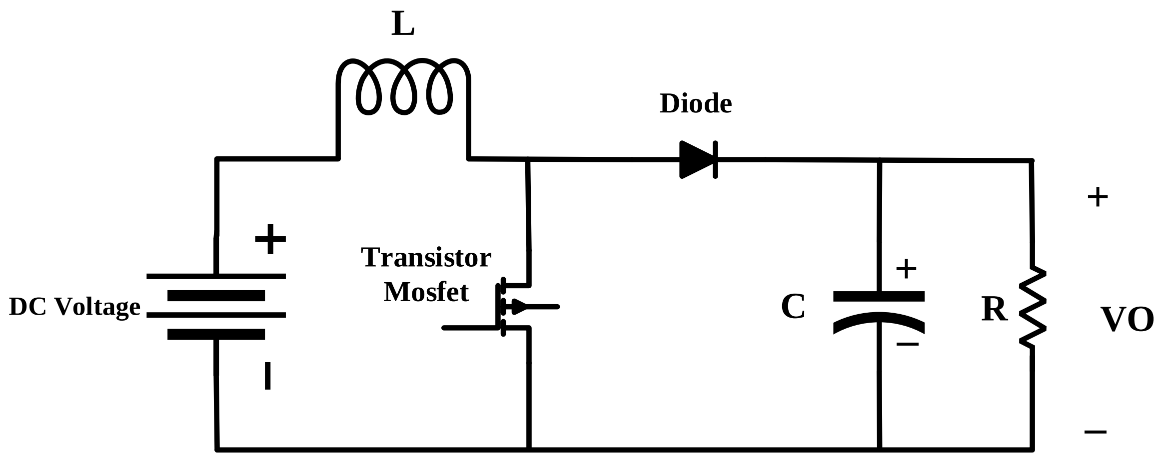


Figure. 8: Boost converter

2.3.1 Operating principle of the boost converter

Because of switches, the boost converter can operate in two processes. The inductor stores energy and the capacitor release it when the switch is closed. The inductor releases energy and the capacitor store it when the switch is turned on. Because the L, C, S, and diode do not expend energy in ideal conditions, there must be two main conservation laws between the input and the output, as shown in the circuit of a DC/DC boost converter in figure 9. The first law is the energy balance states that the input and output energy must be equal as:

$$P_{in} = P_{out} \rightarrow I_s \times V_s = I_{out} \times V_{out} \quad (6)$$

The charge balance (7) is the second law, which states that the input charge equals the output charge

$$Q_{in} = Q_{out} \rightarrow I_s (1 - d) \times T = I_{out} \times T \quad (7)$$

Where:

Q_{in} : is the input charge,

Q_{out} : is the output charge,

I_s: is the source current,

I_{out} is the output current,

d: is the duty cycle,

T: temperature

By deriving the two equations above, the relationship between the input and output voltage can be given by:

$$V_o = \frac{V_s}{1-d} \quad (8)$$

Where:

d is the duty cycle,

Vs is the source voltage,

V_o is the output voltage.

2.3.2 DC-DC boost converter design

For the boost converter, the minimum value of inductance and the minimum value of the filter capacitor resulting in ripple voltage is given by equations 9 and 10. Where Continuous Conduction Mode (CCM) is used in this study as shown in figure 9. Boost converter when operated in CCM provides continuous output current with the least ripple in voltage and current at the output. Low ripple value at output enables boost converter to produce best results for PV-MPPT application. (Amit Patel et al, 2017)

$$L_{min} = \frac{(1-d^2) \times d \times R}{2f} \quad (9)$$

$$C = \frac{d}{R \times \frac{\Delta V_O}{V_O} \times f} \quad (10)$$

Where:

f is the switching frequency.

d is the duty cycle.

R is the load

V_o is the output voltage

ΔV_o is the ripple in output voltage

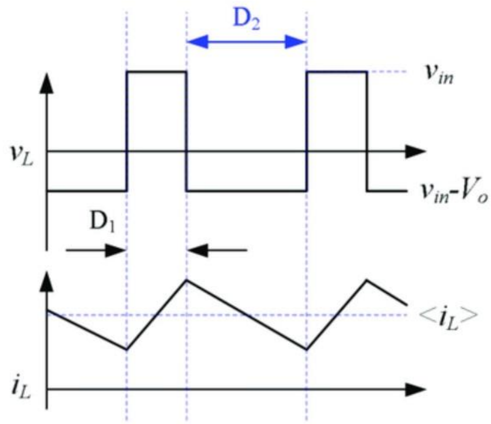


Figure. 9: Operating waveforms of the boost converter

2.4 Maximum Power Point Tracking

The MPP is at a unique point on the PV array's P-V curve, which shifts according to weather conditions. Power conversion is used with the MPPT methodology to track and monitor the MPP. The fundamental principle of this system is to supply a proper duty cycle for power conversion for the output of the PV panel in the form of voltage and current, as well as temperature and irradiance inputs. To regulate the operation of the power conversion system, a gate driver circuit transforms the duty cycle into a signal. Many MPPT approaches have been presented in recent years; each with its own set of benefits and drawbacks such as:

P&O algorithm (K. Sundareswaran et al. 2016), which contains a major drawback, which is the inability to track the global MPP under PSC.

Fractional Open Circuit Voltage algorithm (FOCV) (Dmitry Baimel et al. 2019) and Fractional Short Circuit Current algorithm (FSCC) (Hadeed Ahmed Sher et al. 2015) where the samples are taken from the open-circuit voltage and the closed-circuit current continuously and periodically. The frequency and duration of the sampling process directly affect the accuracy and the output power, as result, the output power is greatly reduced, which leads to a decrease in the tracking efficiency of these algorithms.

GWO algorithm (S. Mohanty et al, 2016), This algorithm can work under PSC, but the search space of this algorithm is relatively large, so it takes more time to reach the MPP, and the tracking accuracy is relatively low.

PSO algorithm (K. Ishaque et al, 2012) can track the global MPP under PSC, but it takes a long time to reach the global point, and also the fluctuations around the MPP are relatively large.

Since the MPP of a PV panel is vital, a slew of MPP tracking techniques has been developed and deployed. The strategies differ in terms of convergence speed, complexity, necessary sensors, effectiveness domain, cost, implementation hardware, and other factors. The varieties have made determining which method, new or old, is best for a particular PV system, become challenging. The characteristic curve for a PV panel is shown in figure 4. MPPT approaches attempt to automatically determine the I_{MPP} or V_{MPP} at which a PV panel should run to achieve the maximum power at given irradiation and temperature. Although it is feasible to have numerous local maxima under partial shade conditions in some situations, there is only one real MPP overall. Most approaches react to variations in both temperature and irradiation, but some are more advantageous than others when the temperature remains relatively constant. Most strategies automatically respond to variations in the solar array caused by aging, while some require periodic fine-tuning due to the open loop.

When looking for the optimum methodology, numerous factors must be considered, including efficiency, lost energy, cost, and type of execution.

The tracker should be capable of tracking the real MPP in the shortest time possible and must not need periodic tuning. In partial shading conditions with many maximum power points inside the P–V curve, traditional algorithms such as perturb & observe, incremental conductance algorithms (K.S. Teyet al. 2014) are failing to track the global MPP, thus reducing the overall PV system efficiency. To overcome this problem, meta-heuristic algorithms were used to operate at the global maximum power point under partial shading conditions.

The hybrid GWO-P&O algorithm that combines the grey wolf optimization algorithm with the perturb & observe algorithm is suitable for extracting the maximum power from the PV system exposed to rapid variations of solar irradiation and partial shading conditions.

The grey wolf optimization algorithm handles the initial phases followed by Perturb & Observe algorithm at the final phase to achieve faster convergence to the global peak. The idea behind using the hybrid technique is to scale down the search space of GWO which helps to speed up for achieving convergence towards the global peak.

CHAPTER THREE

METHODOLOGY

3.1 Perturb and Observe algorithm

The P&O approach is common in tracking MPP (Sampurna Panda et al, 2020). A slight perturbation is introduced in this technique to cause a change in the power of the PV module (Abdelsalam et al, 2011). As shown in figure 10, PV output power is monitored regularly, and compared to the prior power. The same process is repeated if the output power increases; otherwise, the perturbation is reversed. To see if the power has grown or reduced, the PV voltage is increased or decreased. The operational point is on the left of the MPP when an increase in voltage translates to an increase in power. As a result, more disturbance to the right is required to approach MPP. If an increase in voltage causes a loss in power, the PV module's operating point is to the right of the MPP, requiring further perturbation to the left to reach MPP (M.A. Elgendy et al, 2012). The microcontroller will then use voltage and current measurements to calculate the P_{new}, which is then compared to the P_{old}. If P_{new} is greater than P_{old}, the PWM duty cycle is increased to get the most power from the panel. If P_{new} is smaller than P_{old}, the duty cycle is shortened to ensure that the system returns to its MPP, as shown in figure11. This MPPT method is simple, straightforward to implement, and minimal in cost while providing great accuracy. The duty cycle of the dc chopper is adjusted, and the operation is repeated until reaching the MPP. The MPP is the center of the system's oscillation. By reducing the step size, the oscillation can be decreased. Short step sizes, on the other hand, slow down the MPPT.

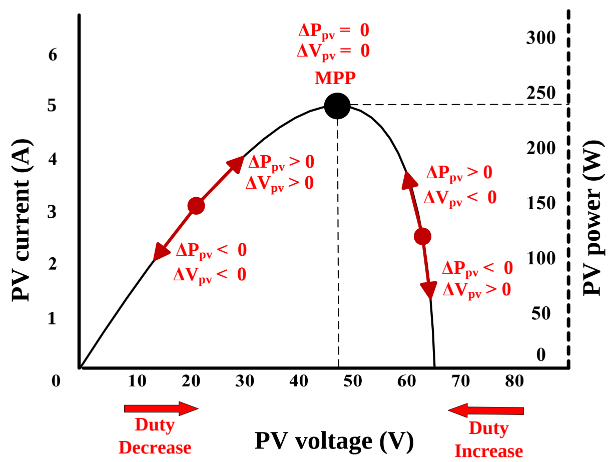


Figure.10: P&O MPPT technique

The P&O MPPT algorithm has been widely employed in a variety of PV systems (Manickam et al, 2016). This is due to the P&O algorithm's basic control structure and the fact that power track only requires a few monitored parameters. Furthermore, because the MPPT technique does not rely on PV module properties, it may be used for any PV panel. The conclusion of the PV power comparison, as well as the PV voltage situation, decide the direction of the following disturbance. As presented in figure 11, the bigger the step size, the faster the operating point can be driven to the MPP for a given perturbation interval. The oscillations around the MPP in steady-state increase as the perturbation step-size increases, these oscillations would diminish the performance of the PV power conversion. A smaller step minimizes the number of oscillations around the MPP and optimizes energy conversion efficiency after the MPP is reached as shown in figure 12. However, under rapidly changing environmental conditions. Variable step sizes may help to reduce the disadvantages of fixed step sizes.

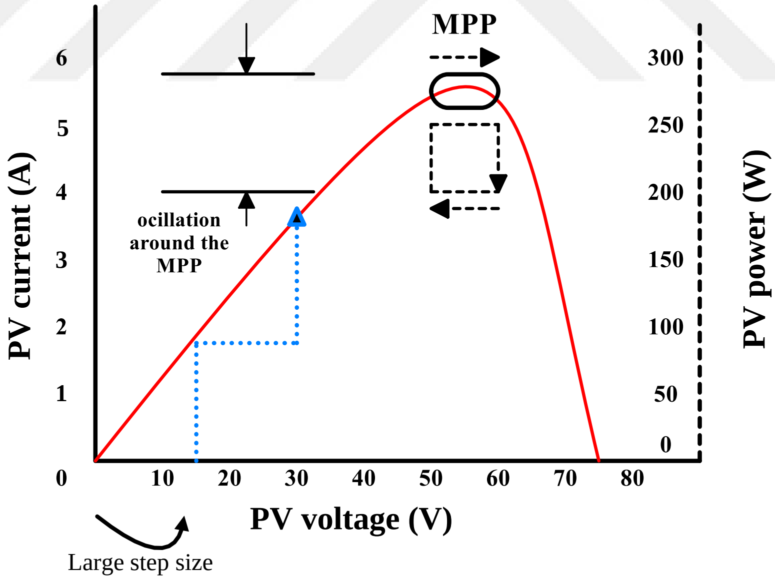


Figure.11: Large fixed step size

The main disadvantage of the traditional P&O MPPT method is its inability to extract MPP under PSC. The PV curve in figure 13 shows the characteristics of the solar PV during PSC, in which cells get low levels of irradiance. On the PV curve, there are two peak points: local and global MPP. The exact point reached by the MPPT method is the global MPP, whereas the local MPP is another point that appeared due to the PSC. The locations of local peaks confused the P&O MPPT because the PV characteristic appears to be nonlinear. The tracking operations will be repeated and the algorithm will oscillate and get stuck at the local point, which is not the real MPP. Therefore, the power output of the PV system will be lower because it presents the power deduced from the local, and not the global MPP.

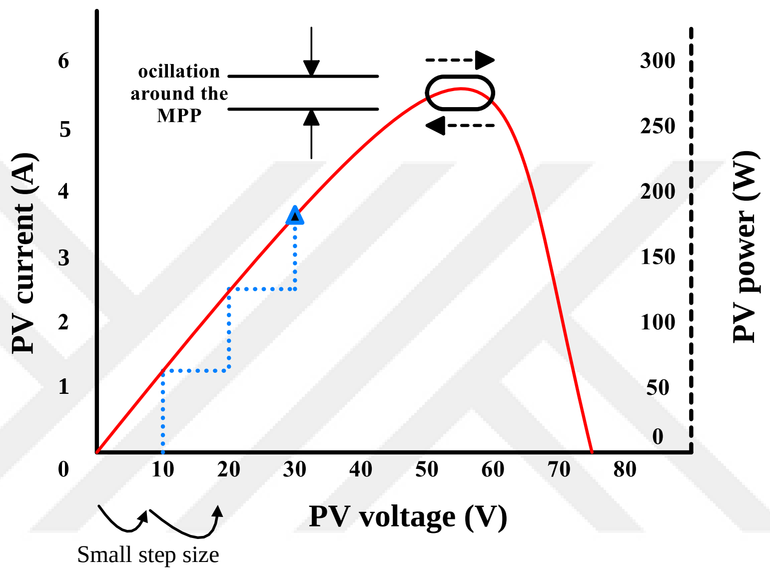


Figure.12: Small fixed step size

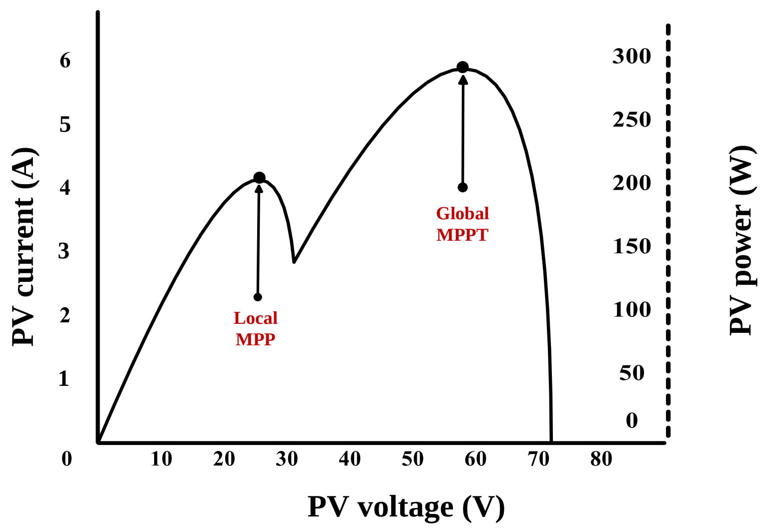


Figure.13: Power-V curve of P&O MPPT under PSC.

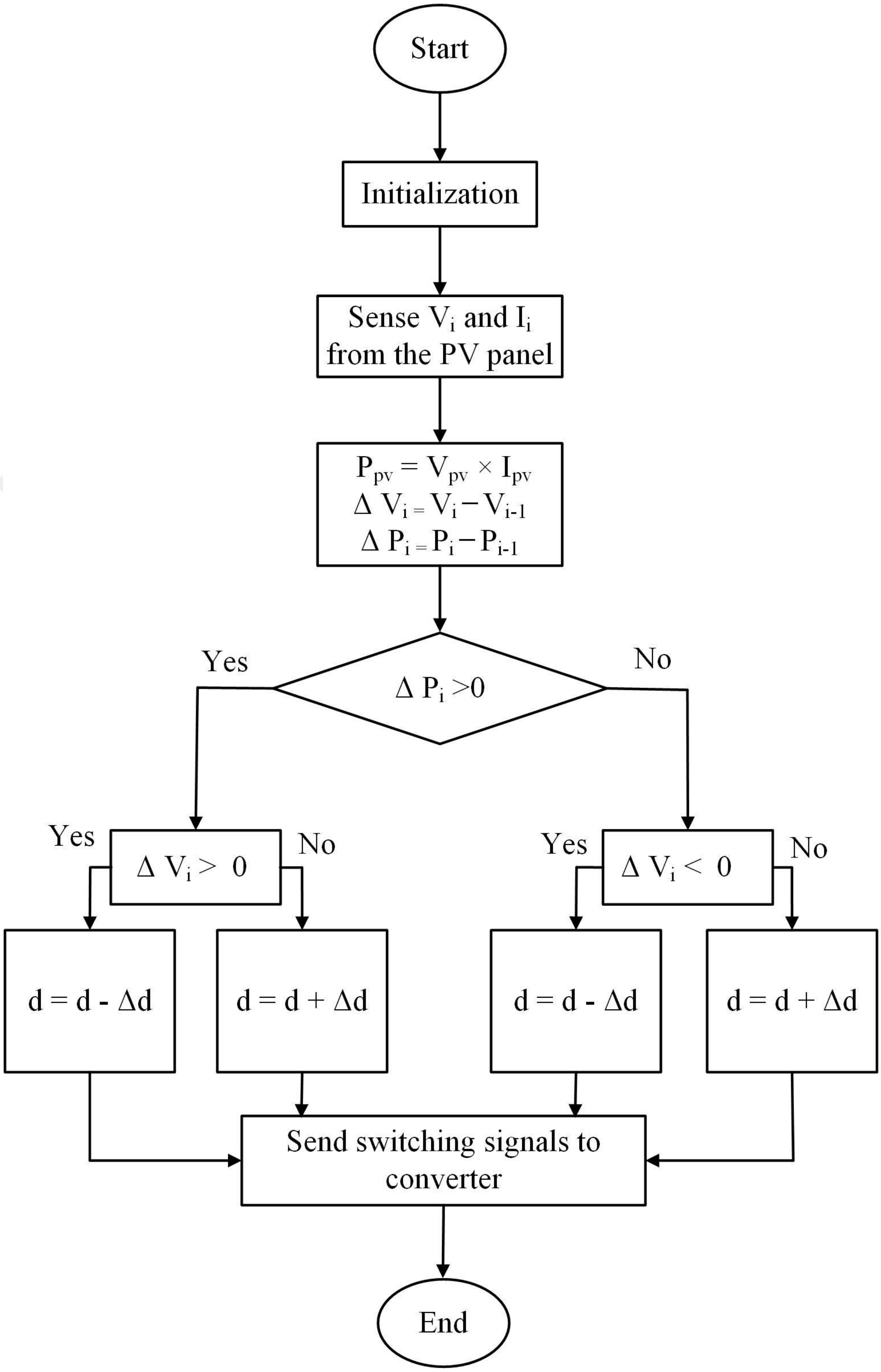


Figure.14: P&O algorithm (M. V. Rocha et al, 2018)

3.2 Grey Wolf Optimization algorithm

Meta-heuristic optimization techniques have become increasingly popular due to their simplicity, adaptability, derivation-free, and avoidance of local minima (Mirjalili et al, 2014). Techniques based on swarm intelligence behavior are categorized as population-based meta-heuristics. Swarm intelligence approaches are known for their exploration and exploitation phases. To solve non-linear problems, an effective optimization strategy is required (Mohanty et al, 2016). GWO mimics the grey wolves in nature. According to the leadership hierarchy, the wolf swarm is classified into four types which are alpha, beta, delta, and omega (Andrew Lewis et al, 2014). Grey Wolf (GW) are apex predators, which means they are the top predators in the food series. GW prefers to be with other wolves in a pack and to be part of a pack. The typical size of a group is 5-12 members. As shown in figure 15, they have a tight public dominant hierarchy and this is of great interest (C.H.S Kumar et al, 2017).

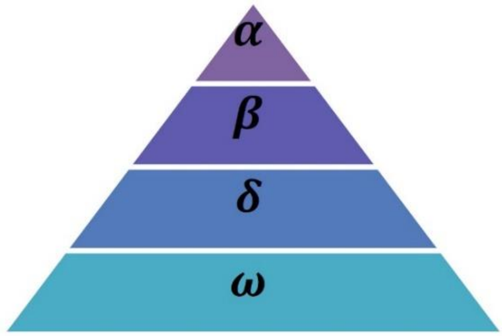


Figure.15: Hierarchy of grey wolf

The leaders, known as alphas (α), are a female and a male. When hunting, the alpha is generally responsible for deciding where to hunt, when to go to sleep, and when to wake up. In addition, packs have shown instances of democratic behavior, in which an α wolf follows the other pack members. While pack leaders do not necessarily have to be the strongest members of the set but the superior in terms of set management. This proves that the power of a set is not nearly as significant as its structure and discipline.

Beta (β) is the second degree in the grey wolf hierarchy. The β are the wolves who help the alpha in making decisions and other duties. The β wolf is the most likely contender to become the alpha wolf if one of the α wolves becomes too old or dies. Omega (ω) is the lowest-ranking grey wolf. The ω is used as a scapegoat. Although the omega may appear to be an unimportant member of the set, it has been noted that if the omega is missing, the pack faces internal strife and problems. This is due to the omega's venting of all wolves' rage and anger. The omega can also be the pack's babysitters. A wolf is referred to as delta if it is not an alpha or beta, or omega. Despite delta having to be subject to alphas and betas, delta wolves have the upper hand over the omegas. Scouts, sentinels, elders, hunters, and caretakers make up this group. Scouts are in charge of monitoring the territory's boundaries and informing the pack if there is any threat. Sentinels protect the pack. Elders are wolves who have previously served as α or β. Hunters serve the α and β by hunting animals and providing food for the pack. Finally, the caretakers are taking care of the weak, ailing, and injured wolves (Mirjalili et al, 2014).

Grey wolves share in group hunting as shown in figure 16, which is a good social characteristic in addition to their social hierarchy. The primary phases of grey wolf hunting, according to (Muro et al, 2011), are as follows:

1- Following the prey, chasing it down, and approaching it

2- Pursue, encircle, and annoy the prey until it comes to a halt.

3- Attack the prey

Figure.16: Grey wolf hunting behavior: (A) pursuing, approaching, and tracking prey (B-D) pestering, surrounding, and chasing (E) stationary position and attack.

3.2.1 Mathematical model and algorithm

- **3.2.1.1 Social hierarchy:**

Generally, consider the fittest solution as alpha (α) to mathematically model the social structure of wolves when constructing GWO. As a result, the second and third-best solutions are known as beta (β) and delta (δ). Omega (ω) is assumed for the rest possible solutions.

- **3.2.1.2 Encircling the prey:**

Encircling prey during the hunt is done according to the following equations (11):

$$\vec{D} = [\vec{C} \times \overrightarrow{X_{P(t)}} - \overrightarrow{X_{P(t)}}] \qquad (11)$$

$$\overrightarrow{X_{(t+1)}} = [\overrightarrow{X_{P(t)}} - \vec{A} \times \vec{D}] \qquad (12)$$

Where *t* is the current iteration, $\vec{A}$ and $\vec{D}$ denote coefficient vectors, $\overrightarrow{X_{P(t)}}$ indicates the position vector of the prey, and $\vec{X}$ denotes the position vector of a grey wolf.

Vectors $\vec{A}$ and $\vec{C}$ are calculated as in:

$$\vec{A} = 2a \times \vec{r_1} - \vec{a} \qquad (13)$$

$$\vec{C} = 2 \times \vec{r_2} \qquad (14)$$

Where $\vec{a}$ is always linearly decreased from 2 to 0 throughout iterations, and $\vec{r_1}$ and $\vec{r_2}$, are random vectors in [0,1].

- **3.2.1.3 Hunting:**

The hunt is always led by the α, whereas β and δ may participate on occasion. α, β, and δ are supposed to have the best information of the likely place of prey to mathematically mimic the hunting behavior. As a result, save the best three solutions found and force the omegas and other search factors to update their locations to match the location of the best search agent as shown by the following equations:

$$\overrightarrow{D_\alpha} = [\vec{c_1} \times \overrightarrow{X_\alpha} - \vec{X}] = [\overrightarrow{C_2} \times \overrightarrow{X_\beta} - \vec{X}] = [\overrightarrow{C_3} \times \overrightarrow{X_\delta} - \vec{X}] \qquad (15)$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1} \times \overrightarrow{D_\alpha} \qquad (16)$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2} \times \overrightarrow{D_\beta} \qquad (17)$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3} \times \overrightarrow{D_\delta} \tag{18}$$

$$\overrightarrow{X_{(t+1)}} = \frac{X_1+X_2+X_3}{3} \tag{19}$$

- **3.2.1.4 Search for prey (exploration):**

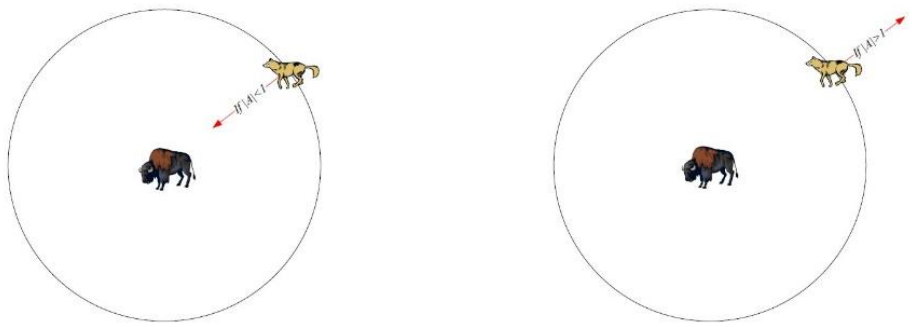
Grey wolves generally use α, β, and δ locations when searching. They split apart to hunt for prey before reuniting for the attack. To mathematically imitate divergence, $\vec{A}$ is used with stochastic values more than 1 or less than -1 to drive the search agent to diverge from the prey. Figure 18 (b) further illustrates that $|A|>1$ causes grey wolves to separate from their prey to find better suitable prey. To summarize, the GWO algorithm creates a random population of grey wolves at the start of the search process. During the iteration period, α, β, and δ wolves assess the likely position of the prey. The distances of the candidate solutions from the prey are always updated. The value of an is lowered from 2 to 0 to emphasize exploration and exploitation. When $|A|$ is greater than 1, the solutions deviate from the prey. When $|A|$ is less than 1, all of the solutions converge on the prey. When an end criterion is met, the GWO algorithm is terminated. Table 1 shows **α**, **β**, **δ**, and **ω** in the proposed hybrid GWO-P&O algorithm.

Table 1: The variables in the hybrid GWO-P&O

The General Social variables in GWO	In Our approach
α	Global peak
β	First local peak
δ	Second local peak
ω	Rest of the local peak

- **3.2.1.5 Attacking prey (exploitation):**

The GW ends the hunt by attacking the prey, as previously stated. The value of $\vec{a}$ is reduced to a mathematically model approaching the prey. It's noted that $\vec{A}$ The fluctuation zone is also reduced. When $\vec{A}$ has random values between [-1,1], a search agent's future position can be anywhere between its current location and the location of the prey. |A|<1 forces the wolves to assault the prey, as shown in figure 17(a).



(a) If |A|<1, Attack prey /solution   (b) If A| >1 , Search of better prey/solution

Figure.17: Search and Attack the prey

3.2.2 GWO Algorithm Applications

GWO is a new optimization strategy that addresses the shortcomings of P&O and improved PSO (IPSO) strategies (T. H. Kwan et al, 2017), such as steady-state oscillations, reduced tracking efficiency, and transients. Over 50 separate runs, statistical measurements such as mean, standard deviation, iteration, best, worst, and epsilon are taken to validate the performance of the GWO as shown in figure 19. Compared to other well-known optimizers, GWO can provide efficient results with its main merits are its simplicity, flexibility, robustness, and ease of implementation. There are also fewer control settings to fine-tune (Eltamaly et al, 2020). Experiments reveal that the proposed algorithm outperforms others in terms of exploiting the optimum and offers advantages in terms of exploration (N. S. D'Souza et al, 2017). Some of the important applications of GWO are:

- The multi-layer perception training algorithm
- Issues with economic dispatch (Sultana et al, 2016).
- Selection of Feature Subsets.
- Grid of the power system.
- Population dynamics in evolution (de Moura Oliveira, 2016).
- Improving important values.

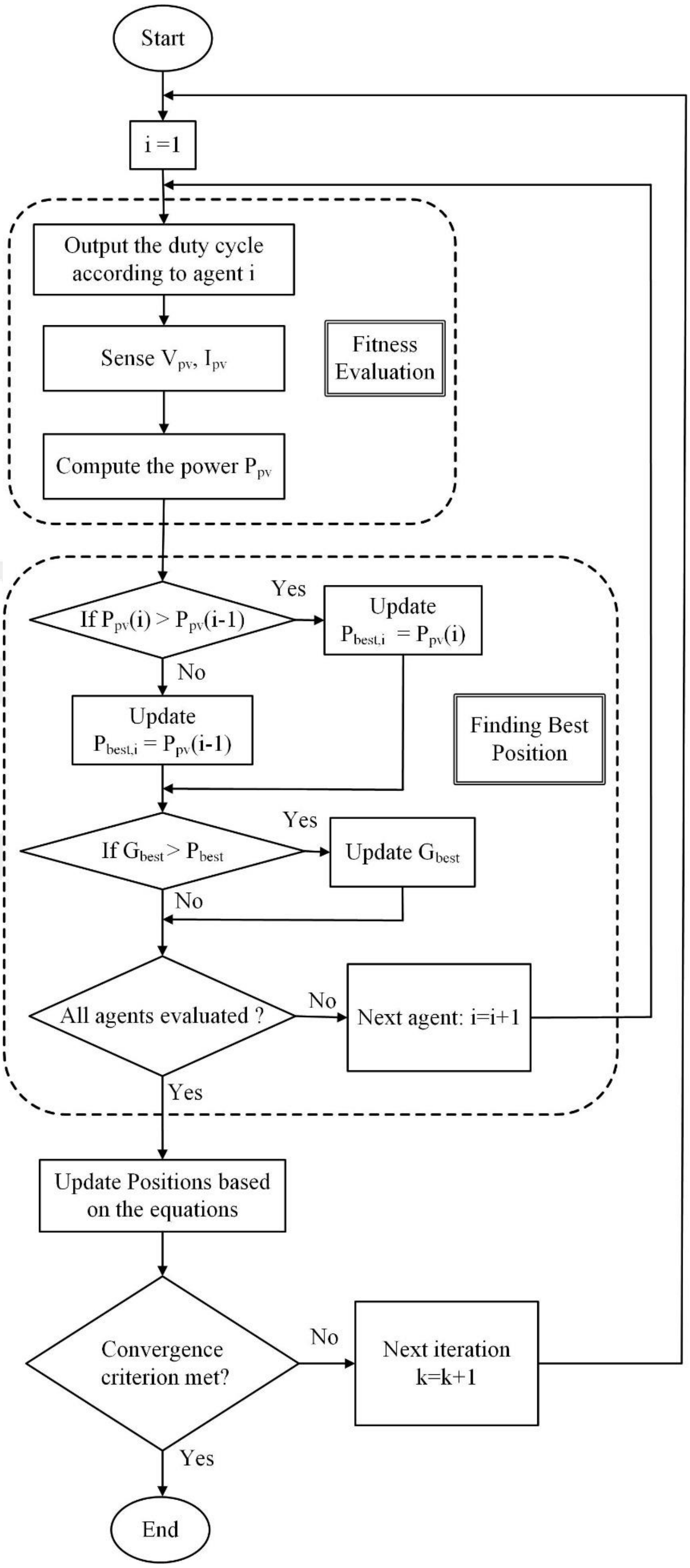


Figure. 18: GWO algorithm (S. Mohanty et al, 2016)

3.3 Hybrid GWO-P&O Algorithm

The proposed hybrid GWO-P&O technique combines GWO and P&O-based MPPT techniques in a smart computational algorithm that averts the disruption that may arise during the conversion of homogeneous to non-homogeneous, and vice versa. For example, during uniform radiation, P&O MPPT tracks the MPP, while during non-uniform radiation, the hybrid GWO-P&O technique tracks and captures the global MPP, with initialization of the GWO technique first, followed by the P&O technique. The P&O MPPT gets started at the position of the better wolf in the GWO operation when the grey wolves reach each other. The position of a wolf in the hybrid GWO-P&O algorithm refers to the duty ratio of the dc-dc converter used to application MPPT. This simplifies the controller and lowers the calculations load of fine-tuning the controller gain. The accuracy of the MPP improves as the number of wolves increases, but the computing burden increases as well. As a result, the number of grey wolves may be reduced to three to save computing time. The hybrid GWO-P&O technique's flowchart is shown in Figure 19. The proposed algorithm is executed as:

- Step **1**: Place the wolves in fixed positions with equal space, somewhere between 10% and 90% of the duty ratio.
- Step **2**: Activate the converter and analyze output power ($P_{pv} = I_{pv} \times V_{pv}$) to maximize PV array output power at each wolf position.
- Step **3**: Adjust the grey wolf's position as (20):

$$D_i(k+1) = D_i(k) - a \times e \qquad (20)$$

where D represents the current grey wolf, k represents the number of iterations, **i** represents the number of current grey wolves, and a, e represents the coefficient vectors.

- Step **4**: Repeat steps **3** until all of the wolves have converged on the MPP.
- Step **5**: Once you've found the MPP, start the P&O loop to track the GMPP. To reduce oscillations in PV output power and increase tracking efficiency, choose a small step size.

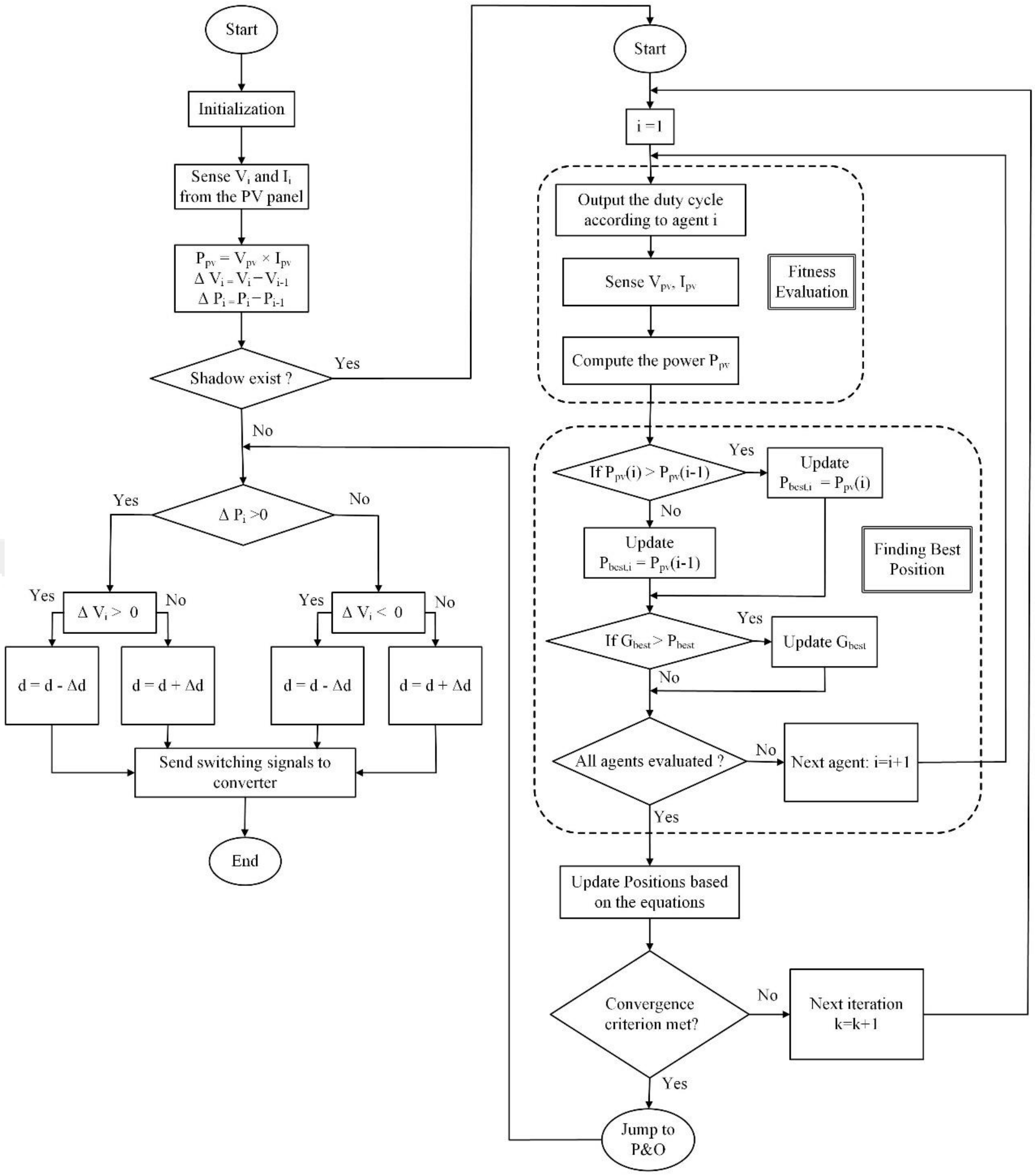


Figure.19: Hybrid GWO-P&O technique.

CHAPTER FOUR

SYSTEM SIMULATION

4.1 Simulation setting

Data for the solar module is obtained from the MATLAB/Simulink model library for the solar device. To test the solar module under partial shadowing, three different irradiance levels (1000 W/m^2, 800 W/m^2, and 500 W/m^2) are applied to it at different times. For uniform irradiation, the solar panels are exposed to constant 1000 W/m^2. MPPT mechanisms are designed as MATLAB code, where four different MPPT approaches are used. The hybrid's ability to track the GMPP under PSC is tested. The traditional GWO, PSO, and P&O together are offered for this comparative study. Figure 20 depicts the simulation model utilized in this comparison.

Table 2 lists the parameters of the boost converter that used in this simulation under STC. While the parameters of the boost converter under PSC are listed in Table 3.

Table 2: Parameters of Boost Converter Under STC

Boost Converter Parameters Under STC	
Switching Frequency	Fs = 50kHz
Resistive Load	R= 20 Ω
Inductance	L_b = 2.4998e-4 H
PV Input Capacitance	C_{pv} = 0.494 μF
Boost Converter Output Capacitance	C_O = 0.00046 μF

Table 3: Parameters of Boost Converter Under PSC

Parameters of Boost Converter Under PSC	
Switching Frequency	Fs = 40kHz
Resistive Load	R= 40 Ω
Inductance	L_b = 6.32217e-4 H
PV Input Capacitance	C_{pv} = 0.3089 µF
Boost Converter Output Capacitance	C_O = 0.00046 µF

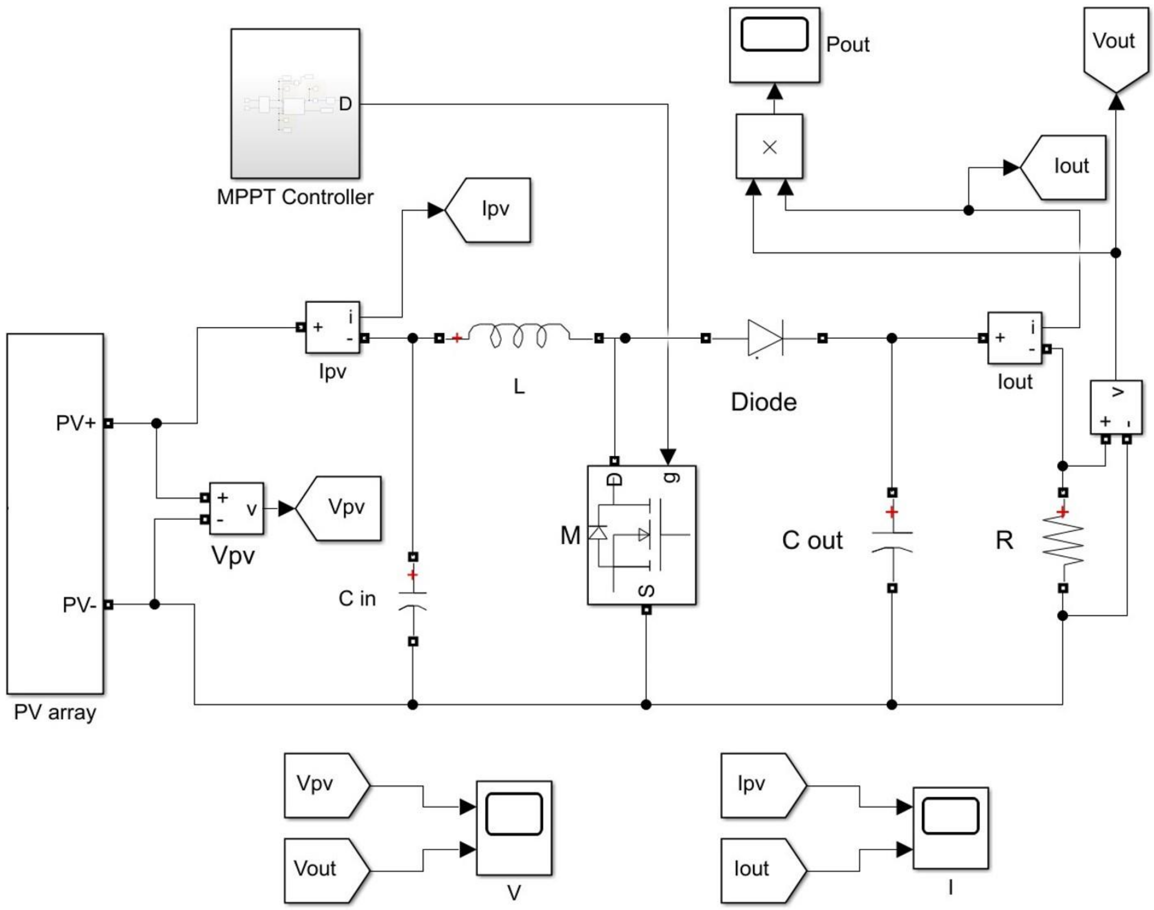


Figure. 20: The simulation model of Hybrid GWO-P&O

The used parameters for all MPPT algorithms are: sampling time Ts = 0.2s, population count = 7, search space limits ub = >1 and lb = <0, and the remaining parameters are listed in Table 4. The Voc, Isc, and P for each panel for these simulations was 7.2 V, 3.92 A, and 22.02 W, with 60 cells per module (N cell). The characteristics of the PV panel employed are listed in Table 5. Three panels were connected in series. The first PV panel in this string is unshaded and has a 100% irradiation, allowing it to produce its rated currents. Partially darkening the irradiance of the second and third PV panels was done on purpose to create partial shading.

Table 4: The parameters of the Hybrid GWO-P&O, P&O, PSO, and GWO algorithms

The parameters of the algorithms used in this study	
Algorithms	**Parameters**
Hybrid GWO-P&O	maximum iteration = <40, delta D = 0.001, number of your variables = 1, population size = 7, initial duty = 0.4, upper bound = i>1, lower bound = i<0,
P&O	initial duty = 0.2 or 0.5, minimum duty =0, maximum duty =0.85, delta D = 0.003
PSO	initial duty = 0.5, variable (W) = 0.4, variable (C1) = 1.2, variable (C2) = 2, global best = 0.5, phi1=2.05, phi2=2.05,
GWO	maximum iteration = <100, delta D= 0.001, number of your variables = 1, population size = 5, d = 0.5, upper bound = i>1, lower bound = i<0,

Table 5: The specifications of the PV panel

Specification of photovoltaic solar panels used in the practical part (Jiangmen JingPin NE Module JP-22-18/Bb)	
Maximum PV Power	Pmax = 22.02 W
MPP Voltage	Vmpp = 6 V
MPP Current	Impp = 3.67 A
Open-Circuit Voltage	Voc = 7.2 V
Short-Circuit Current	Isc = 3.92 A
Power Tolerance	± 5%
Number of panels	3
Cells per module (N cell)	60

4.2. The simulation results of the hybrid GWO-P&O

The first GMPP may be easily tracked using heuristic techniques such as PSO or GWO. GMPP's value and location change when the PSC changes and the searching agents may not be able to track the new GMPP. So, the heuristic strategies are re-initialized to make it track and capture the new MPP by scattering the search agents through the search space again. Furthermore, GWO, PSO, and other heuristic approaches may have oscillations around the GMPP. As a result, as illustrated later in the simulation of the next methodology, employing the hybrid GWO-P&O to fine-tune the produced power at GMPP.

The goal of utilizing the hybrid methodology is to minimize the GWO search space, which helps to increase the convergence towards the global peak, reduce oscillations around the GMPP, and improve accuracy. To achieve faster convergence to GMPP, GWO handles the initial phases of MPPT, followed by the implementation of the P&O method at the final phase. As a result, this MPPT avoids the computational cost.

4.2.1. Hybrid GWO-P&O under STC simulation

Figure 21 shows the electrical properties of the PV system under STC. Because there is no partial shading on the boards, characteristics exhibit one global MPP without any local points. To extract the maximum available power, the solar system will be run at global MPP.

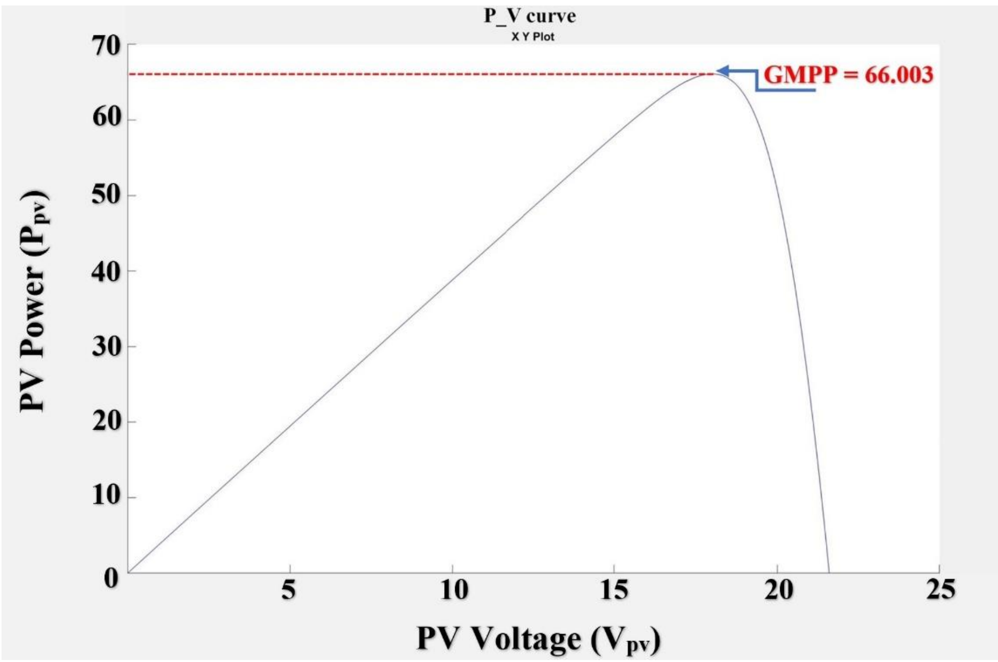


Figure. 21: Characteristics of PV system under STC

Hybrid GWO-P&O's performance is evaluated under uniform irradiance conditions. Figure 22 depicts the tracking of PV array power, voltage, and current for hybrid GWO-P&O MPPT algorithms of 3S PV (three solar panels in a series) configurations subjected to uniform irradiation circumstances. As can be seen in the figure, the proposed method is capable of tracking global MPP with high efficiency. For uniform irradiance conditions, the maximum power tracked by the proposed hybrid GWO-P&O algorithm is 66.003 W with a tracking time of 0.064 sec, the maximum voltage tracked by the hybrid GWO-P&O algorithm is 36.3253V with a tracking time of 0.055 sec, the maximum current is 1.817A, with an efficiency of 99.91%. The tracking efficiency of the hybrid GWO-P&O method is compared, and it is clear that the recommended method performs well during STC.

Figure 22 depicts the power, voltage, and current curves for the hybrid GWO-P&O under STC. figure 22-A depicts the output power of the hybrid GWO-P&O. The hybrid GWO-P&O approach has a high tracking efficiency, high precision, a short time to reach MPP, and low oscillations, as shown by the power curve. The input and output voltages of the hybrid GWO-P&O are obtained in figure 22-B, demonstrating the tracking efficiency, accuracy, and short time to approach MPP. Also, figure 22-C shows the input and output current of the hybrid GWO-P&O under STC. Finally, the proposed hybrid GWO-P&O algorithm successfully tracks the GMPP in a very short time and with excellent accuracy under STC.

The equation (21) can be used to calculate the tracking efficiency of hybrid GWO-P&O:

$$\eta_{\text{efficiency}} = \frac{P_{\text{average}}}{P_{\text{available}}} \times 100\% \qquad (21)$$

Where:

$P_{available}$ is the output power of a solar PV system

$P_{average}$ is the output power gained via simulation.

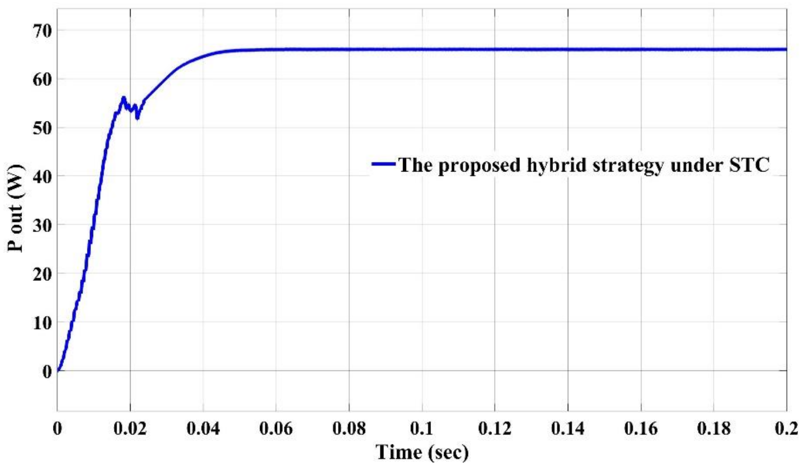


Figure 22A: Output power

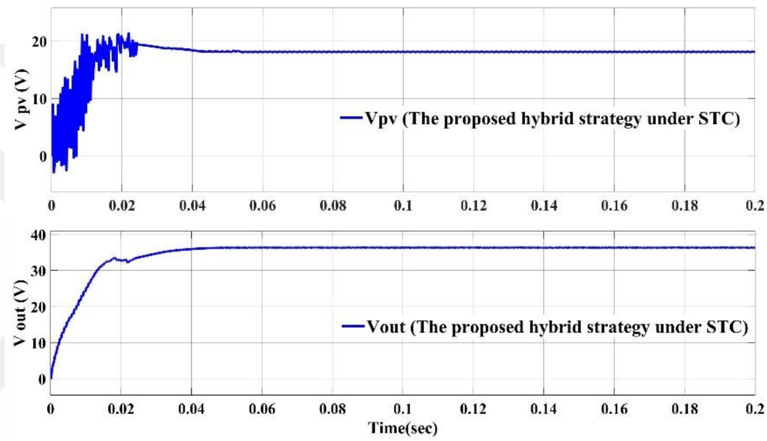


Figure 22B: Output voltage and PV voltage

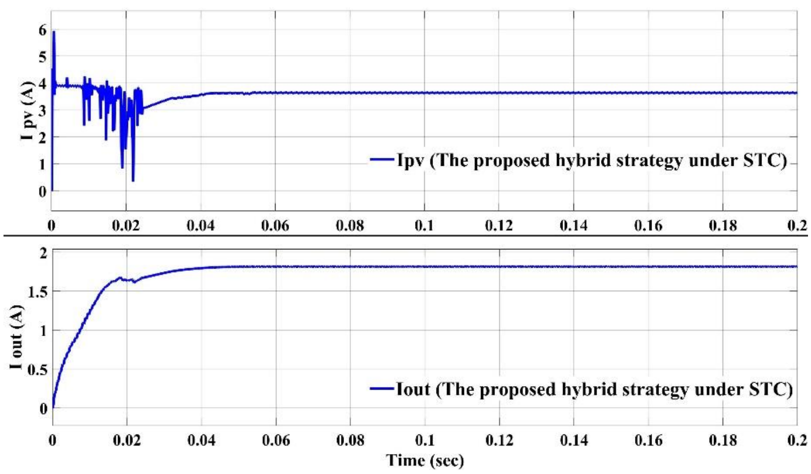


Figure 22C: Output current and PV current

Figure 22: Power, voltage, and current of the hybrid GWO-P&O under STC

Table. 6 Shows the tracking results using the hybrid GWO-P&O. The table shows that the hybrid GWO-P&O has high efficiency of 99.91% and no large oscillations around the GMPP. Furthermore, under uniform irradiation conditions, hybrid GWO-P&O successfully tracks the global MPP in a small time with great precision.

Table 6: The tracking results of the Hybrid GWO-P&O under STC

PV System Operating Under Stander Test Condition	
MPPT techniques	**Hybrid GWO-P&O**
Time to reach MPP	0.064
Ideal Power of Solar Panels (W)	66.06
Power extracted at MPP (W)	66.003
Output Current (I)	1.817
Output Voltage (V)	36.3253
Tracking efficiency (%)	99.91%

4.2.2. Hybrid GWO-P&O under PSC simulation

The distinct P–V curve of a PV system under PSC, with the maximum output dropping from 66 to 36 W is presented in figure 23. The hybrid GWO-P&O scheme is utilized to track the GMPP under PSC. Multiple local and one global peak can be seen due to shade. To use the most available power, the PV system must be operated at global MPP.

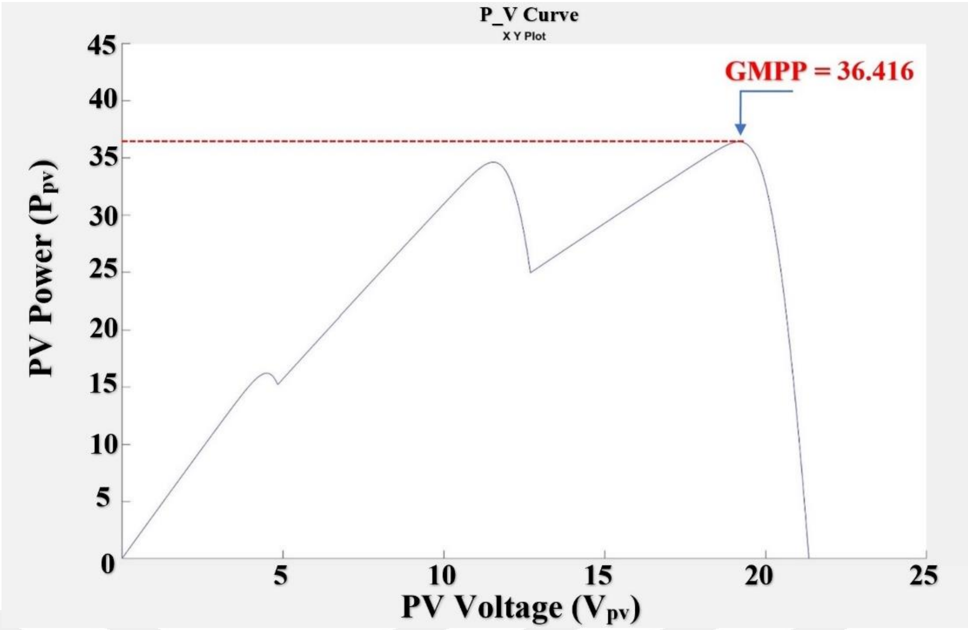


Figure. 23: characteristics of PV system under PSC

figure 24 shows the tracking curves of P, V, and I for hybrid GWO-P&O under PSC. The maximum power tracked by the proposed hybrid GWO-P&O algorithm under PSC is 36.416 W with a tracking time of 0.085 sec, the maximum voltage is 38.141 V with a tracking time of 0.05 sec., the maximum current is 0.954A, with a tracking time of 0.06 sec, and with an efficiency of 99.91%. figure 24-A shows the output power of the hybrid GWO-P&O. Through the power curve, it can be seen that the hybrid GWO-P&O technique has efficient tracking, high accuracy, and minimal time to approach MPP. The input and output voltages of the hybrid GWO-P&O are shown in figure 24-B, where the tracking efficiency, accuracy, and little time to reach MPP are visible. Also, figure 24-C shows the input and output current of the hybrid GWO-P&O under PSC.

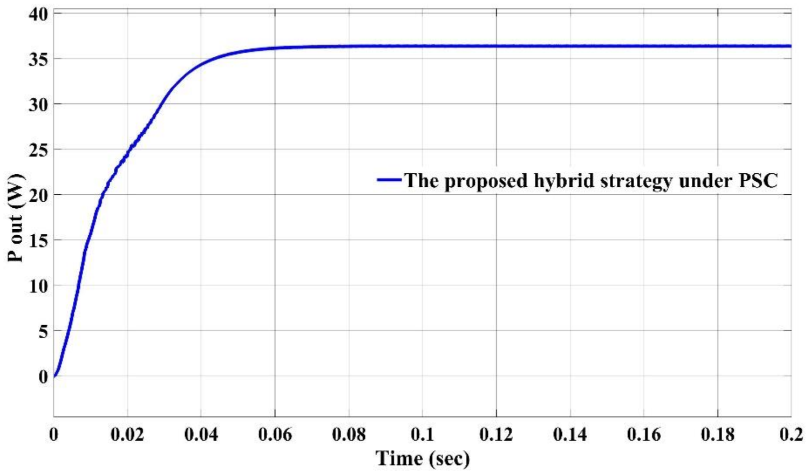


Figure 24A: Output power

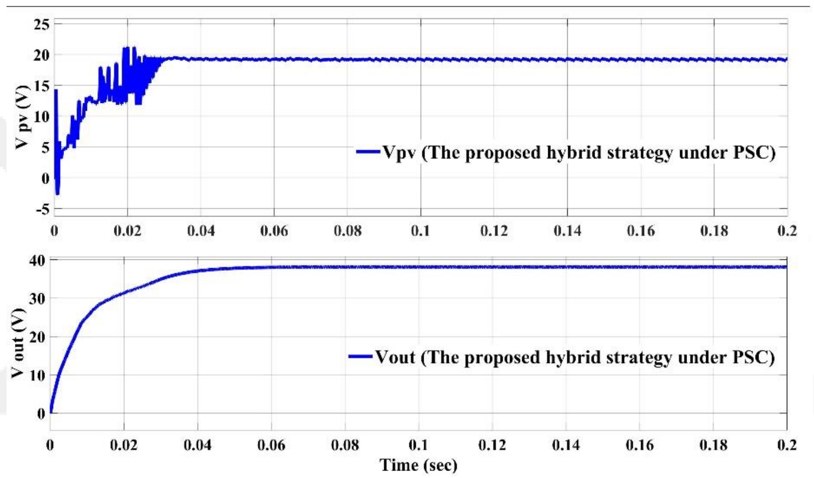


Figure 24B: Output voltage and PV voltage

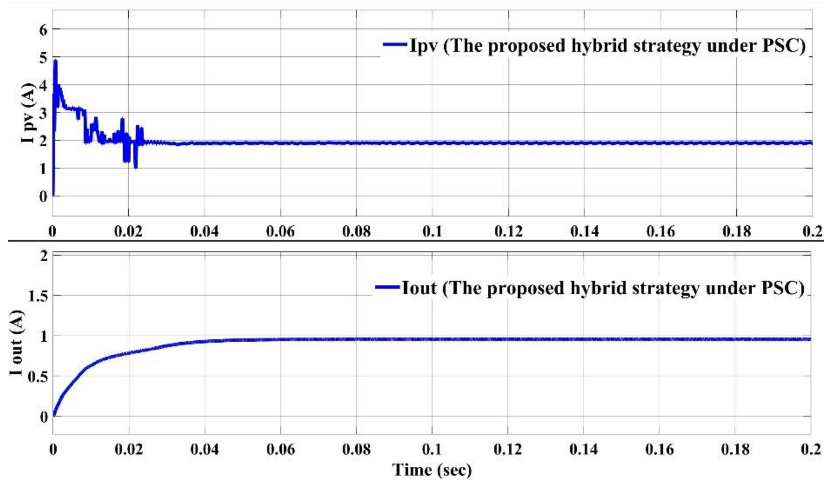


Figure 24C: Output current and PV current

Figure 24: Power, voltage, and current of the hybrid GWO-P&O algorithm under PSC

Under partial shading conditions, table 7 shows the tracking results using the hybrid GWO-P&O algorithm. The table shows that the proposed algorithm has high efficiency of 99.91% with small oscillations around the MPP and takes a small time to reach MPP. The tracking efficiency of the hybrid algorithm is calculated by dividing the power extracted at MPP by the ideal power of solar panels multiplied by 100%. This percentage represents the efficiency of the hybrid algorithm only, not the whole system.

Table 7: The tracking result of the Hybrid GWO and P&O under PSC

PV System Operating Under PSC	
MPPT techniques	**Hybrid GWO-P&O**
Time to reach MPP	0.085
Ideal Power of Solar Panels (W)	36.416
Power extracted at MPP (W)	36.386
Output Current (I)	0.954
Output Voltage (V)	38.141
Tracking efficiency (%)	99.91 %

4.3. Comparative Analysis

Under similar conditions, the proposed hybrid GWO-P&O algorithm is compared with the traditional GWO MPPT algorithms, PSO MPPT algorithms, and traditional P&O MPPT algorithms. Tables (5 to 9) show the results of the hybrid GWO-P&O, PSO, GWO, and P&O MPPT algorithms in terms of accuracy and speed for tracking global MPP. According to the table, the hybrid GWO-P&O outperforms traditional GWO and PSO, as well as traditional P&O algorithms. The ability of the proposed hybrid GWO-P&O algorithm to track GMPP has been proved with greater accuracy than the GWO algorithm, in less time than the PSO MPPT method, and with greater efficiency than traditional P&O because of the traditional P&O track the local MPP.

4.3.1. Comparing the Hybrid GWO-P&O algorithm with other algorithms under STC

Under uniform irradiation, the characteristic of a solar PV module has only one peak which it's global MPP. With uniform irradiation, finding the maximum power is an easy task for the all algorithms (hybrid GWO-P&O, P&O, GWO, and PSO). According to the simulation results, the maximum power that a solar PV module can produce is 66.06 W. Table 8 shows the results. When it comes to tracking efficiency, all technologies perform well due to the presence of one MPP. The radiation of 1000 W/m^2 and temperature of 25 C is used to replicate the PV system under STC.

Table 8: Comparisons of the MPPT methods under STC

PV system operation	**PV System Operating Under STC**			
MPPT techniques	**P&O**	**GWO**	**PSO**	**Hybrid GWO-P&O**
Time to reach MPP	0.052s	0.09s	1.79s	0.064s
Ideal Power of Solar Panels (W)	66.06	66.06	66.06	66.06
Power extracted at MPP (W)	65.98	65.79	66.041	66.003
Output Current (I)	1.817	1.815	1.817	1.817
Output Voltage (V)	36.313	36.2504	36.3463	36.3253
Tracking efficiency (%)	99.87	99.59	99.97	99.91

The comparison of power, voltage, and current between the P&O algorithm and the hybrid GWO-P&O under STC is shown in the figure. 25. As shown in figure 25 A, the output power of the P&O algorithm and the hybrid GWO-P&O are exhibited and compared. Under the conditions of uniform irradiation, there is no significant difference between the performance of the hybrid algorithm and the P&O algorithm, where both algorithms provide high tracking efficiency, low oscillations around MPP, fast convergence toward MPP, high accuracy, and small-time to reach MPP. In figure. 25. B, the input and output voltages of the two algorithms are compared. Also, figure. 25. C compares the input and output currents of the two algorithms. Under STC, there is only one MPP which is the global MPP, so both approaches can easily reach the MPP. The P&O method reaches MPP with a time of 0.052s and a tracking efficiency of 99.87 with low power oscillation, whereas the hybrid GWO-P&O achieves MPP with a time of 0.064s and a tracking efficiency of 99.91 with low power oscillation.

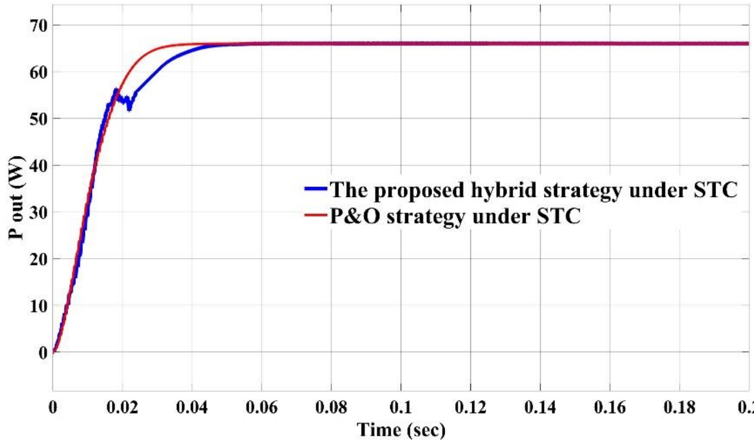


Figure 25. A: Output power

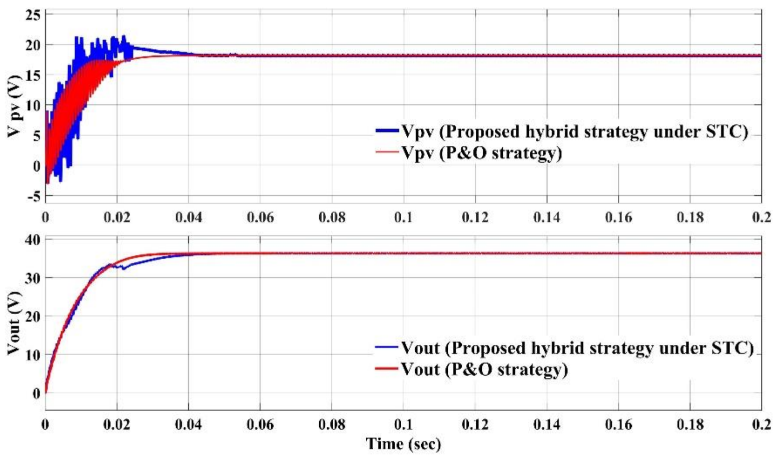


Figure 25. B: Output voltage and PV voltage

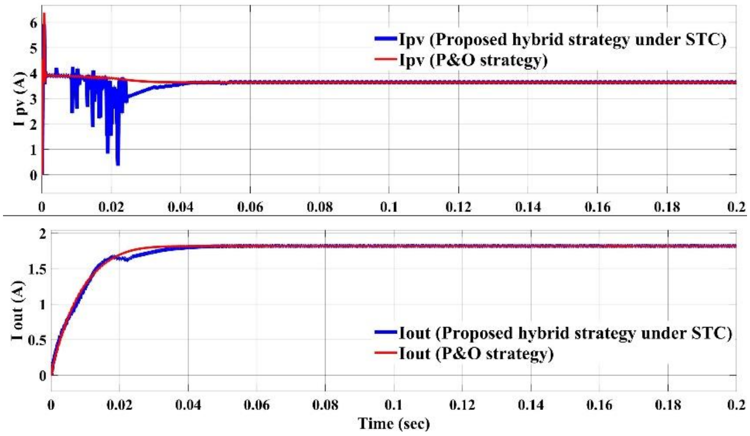


Figure 25. C: Output current and PV current

Figure 25: Comparing the hybrid algorithm with the P&O algorithm under STC.

Figure 26 clarifies the MPPT results obtained using the PSO Method. The PSO algorithm can extract the global MPP but it takes a long time. Also, this approach shows steady-state oscillations. figure. 26 A, illustrates the output power of the PSO algorithm and hybrid GWO-P&O. A difference in tracking efficiency can be deduced where the hybrid GWO-P&O performs significantly better in delay compared to the PSO. The input and output voltage of the two algorithms are also compared in figure 26. B. Also, figure.26 C compares the input and output currents of the two algorithms. Both strategies are successful in obtaining MPP. However, the PSO approach takes a long time to reach MPP, where takes 1.79s with a tracking efficiency of 99.97, whereas the hybrid GWO-P&O takes only 0.064s and has a tracking efficiency of 99.91. In other words, both methods work well under STC, however, hybrid GWO-P&O has a higher tracking efficiency.

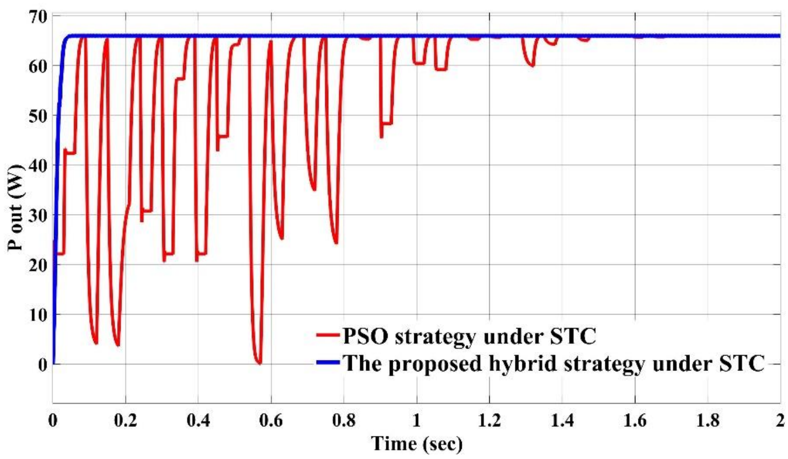


Figure 26A: Output power

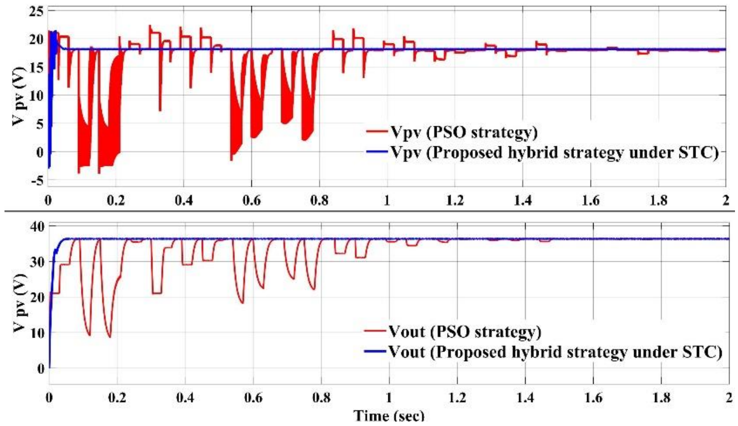


Figure 26. B: Output voltage and PV voltage

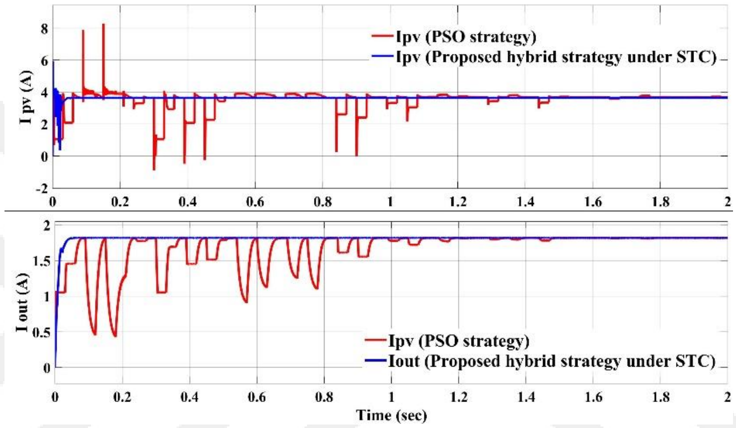


Figure 26. C: Output current and PV current

Figure 26: Comparing the hybrid algorithm with the PSO algorithm under STC.

figure. 27 shows the results of the GWO-based MPPT algorithm under STC. MPP is obtained but with oscillations in the steady-state. In figure. 27 A, the output power of the GWO algorithm and the hybrid GWO-P&O are exhibited and compared. The hybrid GWO-P&O outperforms the GWO algorithm in terms of tracking efficiency since it tracks the global MPP more effectively and accurately than the GWO algorithm and takes less time to reach MPP. In figure 27. B, the input and output voltages of the two algorithms are compared. Also, figure. 27. C compares the input and output currents of the two algorithms. The GWO technique reaches the MPP but with a lower tracking accuracy than the hybrid GWO-P&O. It takes 0.142s to attain MPP with a tracking efficiency of 99.59, whereas the hybrid GWO-P&O takes 0.064s and has a tracking efficiency of 99.91. In another word, both methods work well in the absence of shadows, but the hybrid GWO-P&O has a higher tracking efficiency and accuracy. The simulation results of the four MPPT algorithms are summarized in table 9 where results show that under STC, all algorithms provided great performance due to the presence of one MPP, which was the global point. Nonetheless, there were some differences between the algorithms in terms of accuracy, speed, and efficiency.

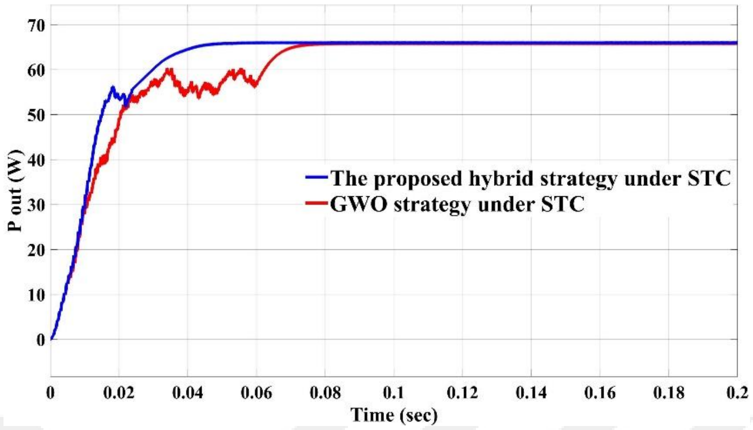


Figure 27. A: Output power

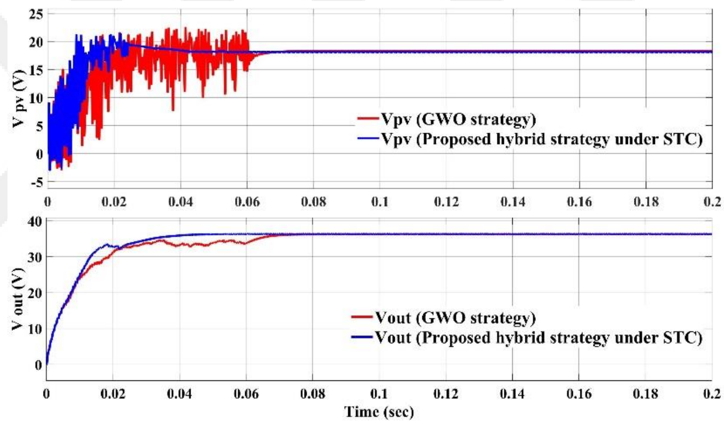


Figure 27. B: Output voltage and PV voltage

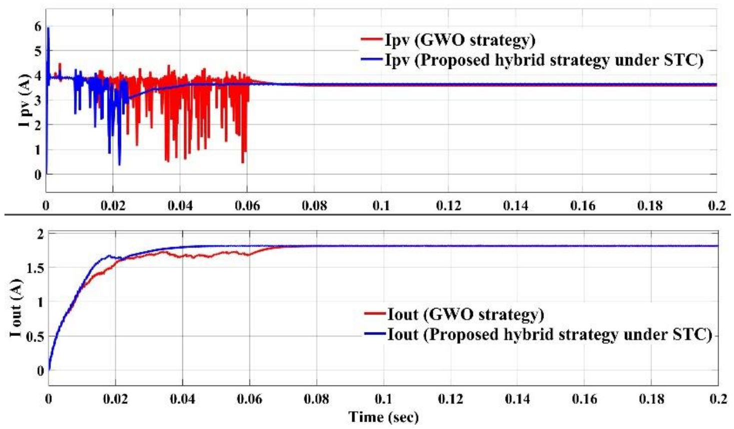


Figure 27. C: Output current and PV current

Figure 27: Comparing the hybrid algorithm with the GWO algorithm under STC.

Table 9: The simulation results of the four MPPT algorithms under STC

PV system operation	PV System Operating Under STC			
MPPT techniques	**P&O**	**GWO**	**PSO**	**Hybrid GWO-P&O**
Tracking Speed	Fast	Medium	Slow	Fast
Tracking accuracy	Accurate	Accurate	Highly Accurate	Highly Accurate
Convergence to GP	Yes	Yes	Yes	Yes
Steady-state oscillations	Medium	Medium	Medium	Medium
Power efficiency	High	High	Very high	Very High
Algorithm Complexity	Low	Medium	Medium	High
Implementation complexity	Low	Medium	Medium	Medium
Dynamic response	Poor	Good	Good	Good

4.3.2. Comparing the Hybrid GWO-P&O algorithm with other algorithms under PSC

The insolation of the PV panel changes abruptly from 1000 W/m^2 to 800 W/m^2 to 500 W/m^2 to simulate varied shading situations for the PV array. Figure 23 depicts the distinct P–V curve of a PV system under unequal radiation circumstances, with the maximum output dropping from 66 to 36 W. The hybrid GWO-P&O is utilized to track the PV system's global MPP under PSC, and the global tracking performance is then compared to that of other MPPT approaches. Two local peaks in P-V characteristics can be seen due to shade. Under uniform irradiance, a PV system can deliver a maximum power of 66 Watt but due to PSC, the output power will reduce to 37 Watt. As a result, the MPPT controller's work is to extract the most quantities of power. Table 10 compares the hybrid GWO-P&O with the other MPPT methods, showing tracking efficiency, steady-state oscillation, time to achieve MPP, and power extracted at MPP for each methodology. The comparison in the table below indicates that the hybrid GWO-P&O performs well under PSC. The hybrid GWO-P&O has an efficiency of 99.91 % and a time to reach MPP of 0.085. This percentage represents the efficiency of the hybrid algorithm only, not the whole system. The PV system is simulated under PSC, in which solar irradiance (G) changes abruptly from 1000 W/m^2 to 800 W/m^2 to 500 W/m^2 while temperature (T) is kept constant at 25 C.

Table 10: Comparison among the MPPT techniques under PSC

PV system operation	PV System Operating Under PSC			
MPPT techniques	**P&O**	**GWO**	**PSO**	**Hybrid GWO-P&O**
Time to reach MPP	0.018s	0.144s	1.89s	0.085s
Ideal Power of Solar Panels (W)	36.416	36.416	36.416	36.416
Power extracted at MPP (W)	16.91	36.379	36.378	36.386
Output Current (I)	0.954	0.954	0.954	0.954
Output Voltage (V)	17.73	38.134	38.133	38.141
Tracking efficiency (%)	46.43	99.89	99.89	99.91

The output power of the hybrid GWO-P&O algorithm and the P&O method under PSC is shown in the figure. 28. Two local peaks and one global peak are obtained as a result of PSC, with magnitudes of 34 Watt and 17 Watt for local peaks and 36 Watt for the global peak. As a result, P&O has stayed to the first 17Watt local peak while the hybrid GWO-P&O reaches the global MPP. The P&O approach fails to track global MPP and stay operate at the first local peak, causing a huge waste of power. Because the hybrid GWO-P&O can reach global MPP, the PV system can extract the maximum amount of energy. Under PSC, figure 28 shows a comparison of (P, V, I) between the P&O algorithm and the hybrid GWO-P&O approach.

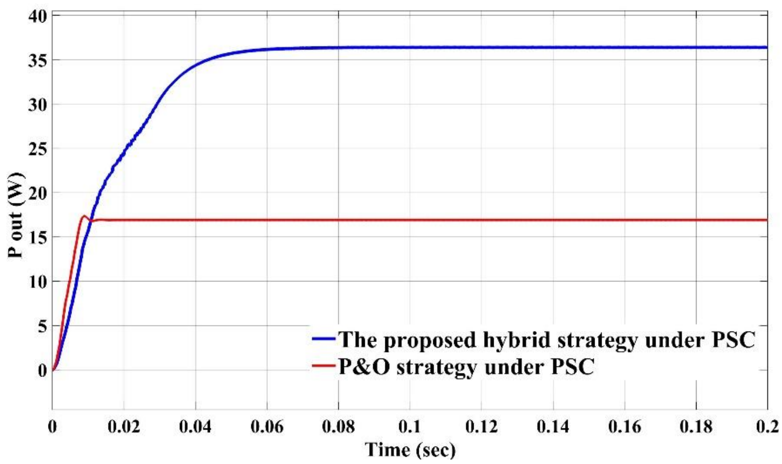


Figure 28. A: Output power

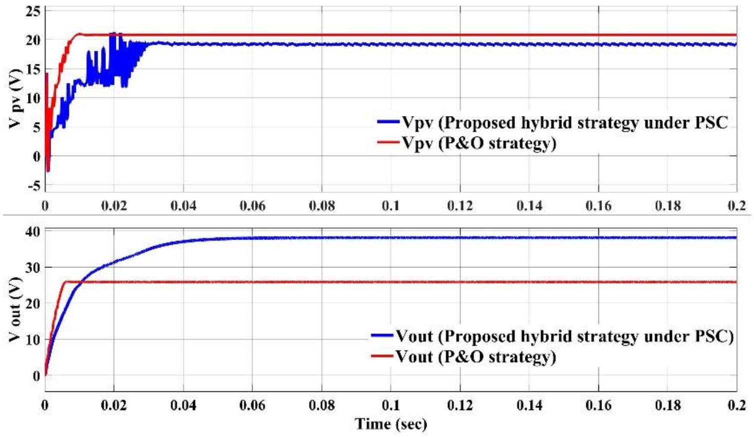


Figure 28. B: Output voltage and PV voltage

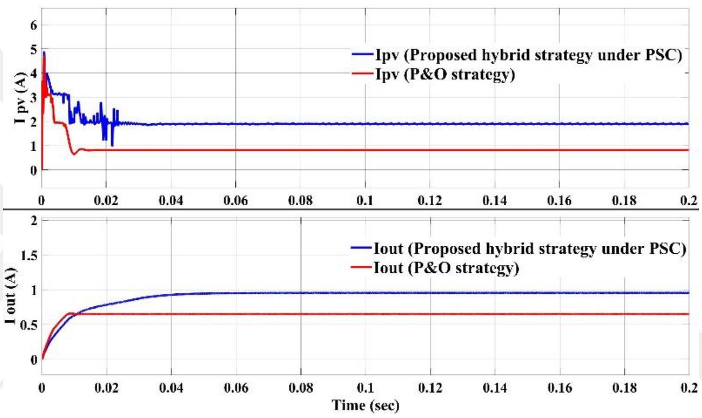


Figure 28. C: Output current and PV current

Figure 28: Comparing the hybrid algorithm with the P&O algorithm under PSC.

In figure. 28-A, the output power of the P&O algorithm and the hybrid GWO-P&O are exhibited and compared. It is deduced that the hybrid GWO-P&O performs much better than the P&O algorithm under PSC because the hybrid GWO-P&O can track the global MPP while the P&O algorithm tracks the local MPP. The input and output voltage of the two algorithms are compared in figure 28 B. Also, figure 28 C compares the input and output currents of the two algorithms.

The hybrid GWO-P&O is compared to the PSO approach under various irradiance conditions. The PSO algorithm is capable of extracting the most quantities of power attainable in a PV array under PSC, but it takes a long time, this approach also shows steady-state oscillations. The comparison of power, voltage, and current between the PSO method and the hybrid GWO-P&O under PSC is shown in the figure. 29. In figure 29 A, the output power of the PSO algorithm and the hybrid GWO-P&O are exhibited and compared. The hybrid GWO-P&O performs better than the PSO algorithm because it takes less time to reach the global MPP. The input and output voltage of the two algorithms are also compared in figure 29 B. Also, figure 29 C compares the input and output currents of the two algorithms. Finally, both strategies are successful in obtaining MPP. However, the PSO approach takes a long time to reach MPP, where takes 1.89s with a tracking efficiency of 99.89, whereas the hybrid GWO-P&O takes only 0.085s and has a tracking efficiency of 99.91. In other words, both methods work well under PSC, however, the hybrid GWO-P&O has a higher tracking efficiency because the PSO method takes a long time to reach MPP.

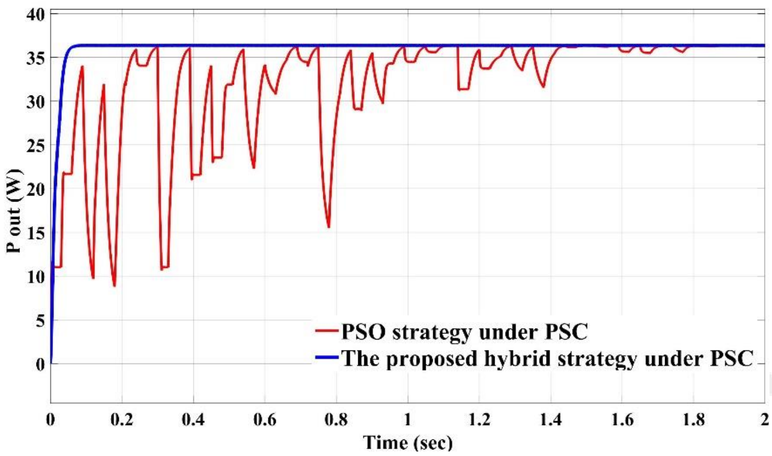


Figure 29. A: Output power

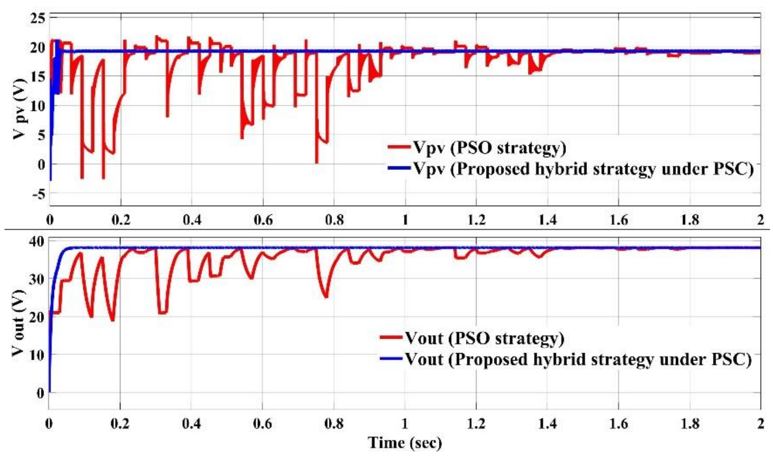


Figure 29. B: Output voltage and PV voltage

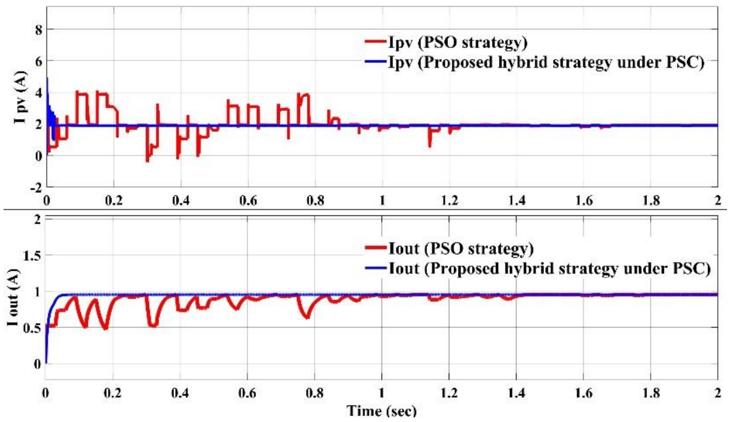


Figure 29. C: Output current and PV current

Figure 29: Comparing the hybrid algorithm with the PSO algorithm under PSC.

The comparison of power, voltage, and current between the GWO method and the hybrid GWO-P&O under PSC is shown in figure 30. As shown in figure 30 A, the output power of the GWO method and the hybrid GWO-P&O are exhibited and compared. The hybrid GWO-P&O outperforms the GWO algorithm in terms of tracking efficiency and accuracy. The hybrid GWO-P&O tracks the global MPP more efficiently than the GWO algorithm and with high accuracy. The input and output voltage of the two algorithms are compared in figure 30 B. Also, figure 30 C, compares the input and output currents of the two algorithms. The GWO reaches the MPP but with a lower tracking accuracy than the hybrid GWO-P&O, it takes 0.144s to reach MPP with a tracking efficiency of 99.89%, whereas the hybrid GWO-P&O takes 0.085s and has a tracking efficiency of 99.91%.

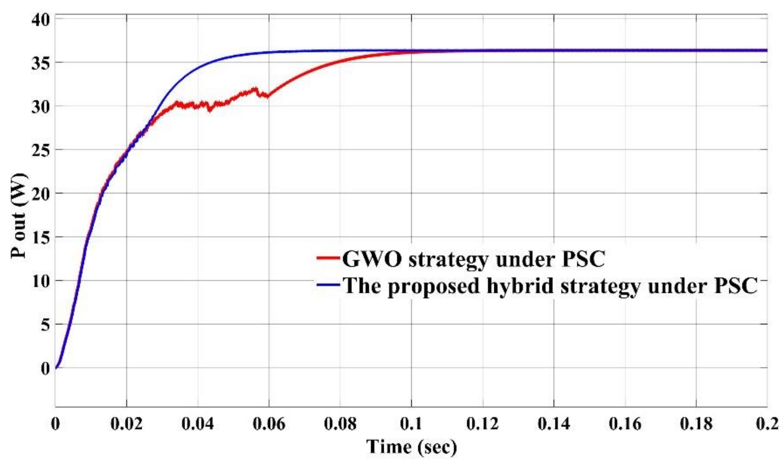


Figure 30. A: Output power

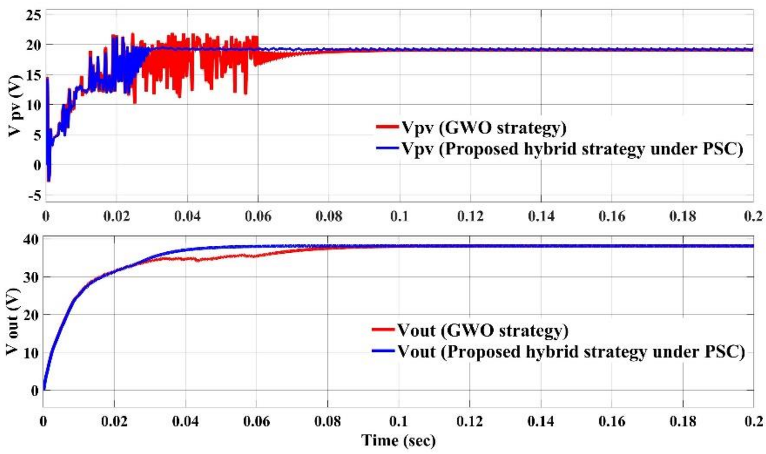


Figure 30. B: Output voltage and PV voltage

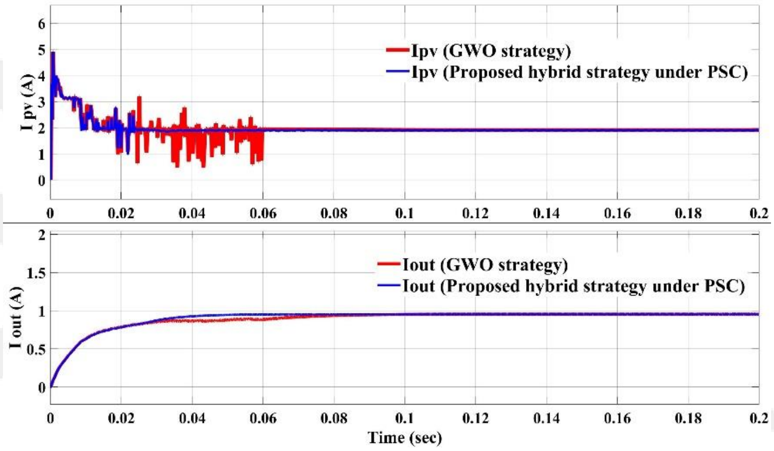


Figure 30. C Output current and PV current

Figure 30: Comparing the hybrid algorithm with the GWO algorithm under PSC.

The simulation results of the four MPPT algorithms are summarized in Table 11. When the PV system worked under PSC, the proposed hybrid GWO-P&O algorithm could converge immediately to the GMPP with a time of 0.085s. Compared to previous MPPT methods, the proposed MPPT algorithm produced low power oscillations in the steady-state and had a high tracking efficiency.

Table 11: The simulation results of the four MPPT algorithms under PSC

PV system operation	PV System Operating Under PSC			
MPPT techniques	**P&O**	**GWO**	**PSO**	**Hybrid GWO-P&O**
Tracking Speed	Slow	Medium	Slow	Fast
Tracking accuracy	Low	Accurate	Accurate	Accurate
Convergence to GP	No	Yes	Yes	Yes
Steady-state oscillations	Medium	Medium	Medium	Medium
Power efficiency	Low	High	High	Very High
Algorithm Complexity	Low	Medium	Medium	High
Implementation complexity	Low	Medium	Medium	Medium
Dynamic response	Poor	Good	Good	Good

CHAPTER FIVE

HARDWARE IMPLEMENTATION

5.1 Hardware Implementation and Experimental Results

The Hybrid GWO-P&O algorithm efficiently tracks the global MPP under both uniform and PSC and can distinguish easily between these two situations. Experiments on a selected PV array are conducted to validate the efficiency of the hybrid GWO-P&O algorithm as shown in figure 31 and figure 32. In this experiment, three 66 W solar modules (Jiangmen Jing Pin NE Module Type: JP-22-18/Bb) are utilized. Table 12 lists the specifications of solar panels used. Pieces of cardboard of various forms are used on PV modules to generate partial shading. The PWM signals are generated using an Arduino MEGA controller with many ADC and DAC channels. The CPU is responsible for executing MPPT algorithms as well as generating PWM signals for the boost converter's power switch.

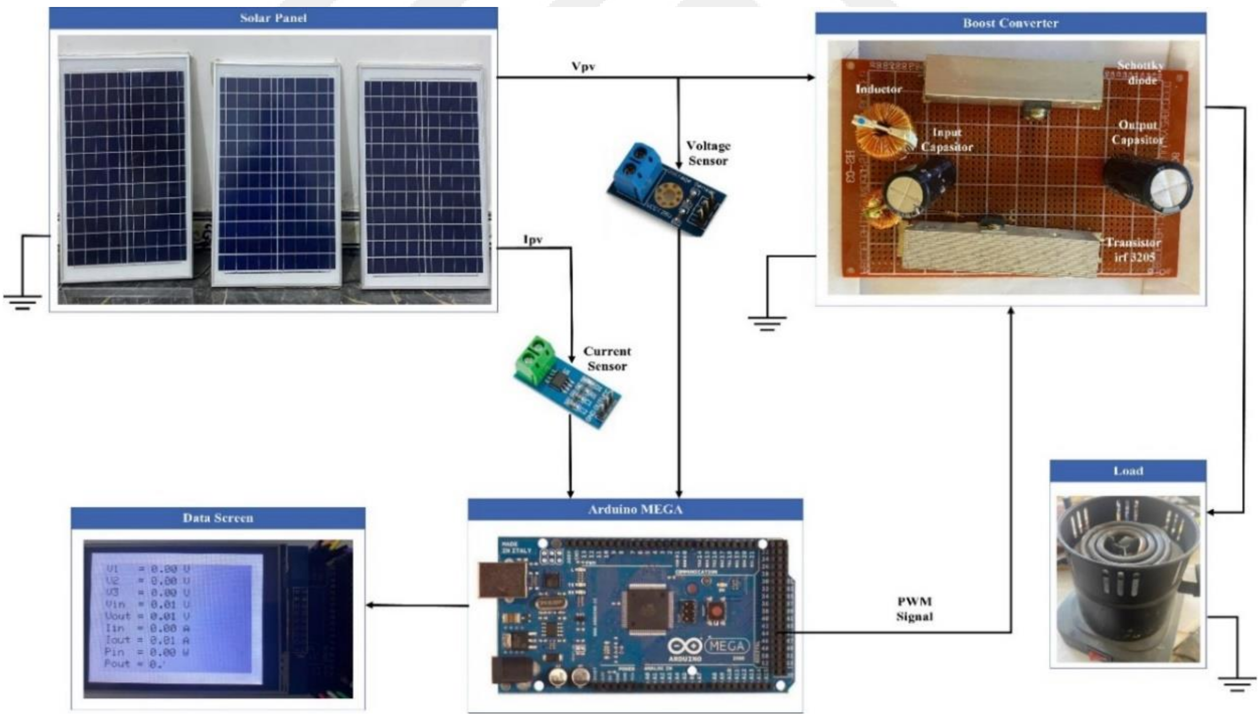


Figure 31: The experimental setup of the proposed system

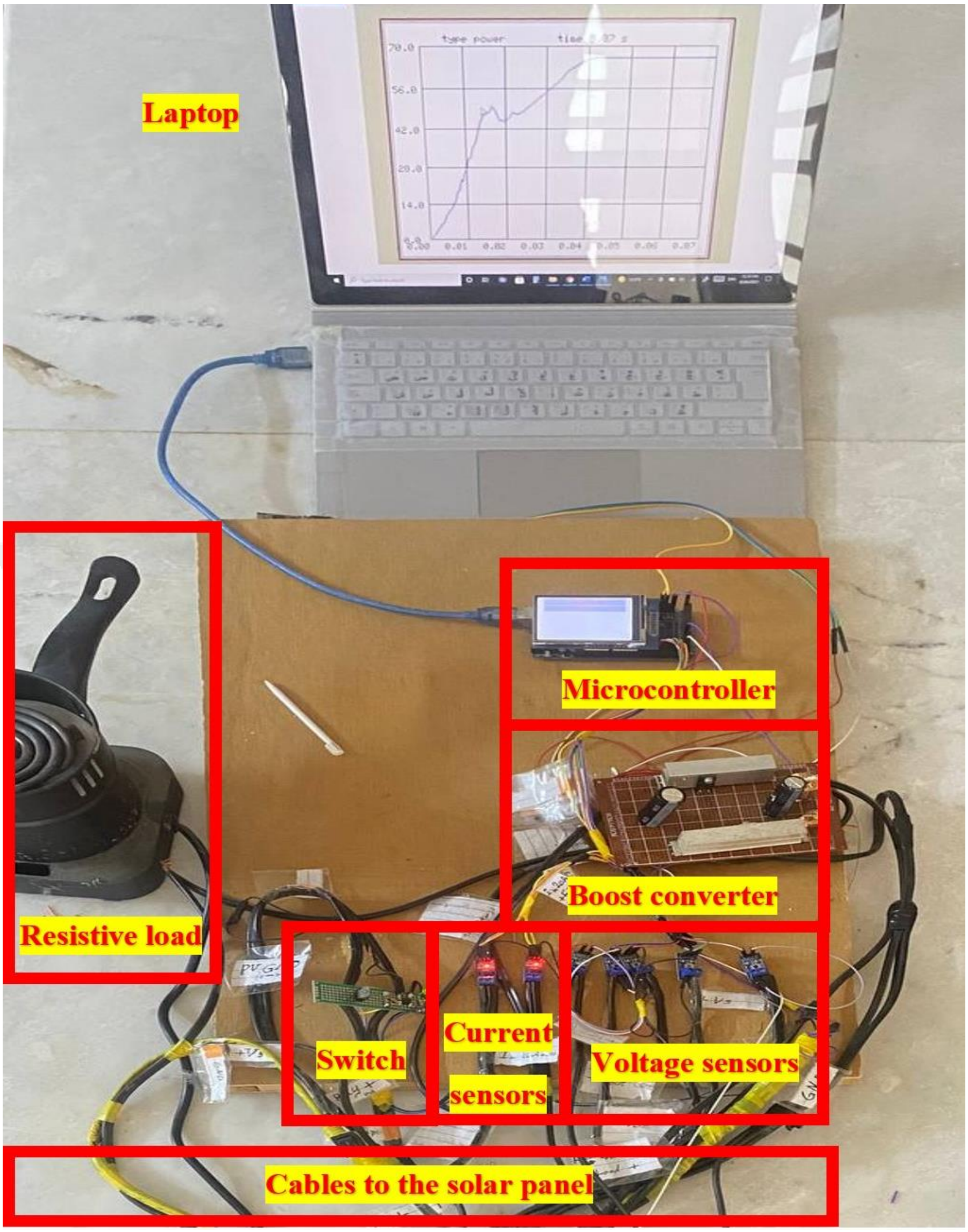


Figure 32: Practical part contents

Table 12: Specifications of solar panels used

Specifications of solar panels used	
Maximum PV Power	Pmax = 22.02 W
MPP Voltage	Vmpp = 6 V
MPP Current	Impp = 3.67 A
Open-Circuit Voltage	Voc = 7.2 V
Short-Circuit Current	Isc = 3.92 A
Power Tolerance	± 5%
Number of panels	3
Cells per module (N cell)	60

To sense the current and voltage of the solar panels, a DC voltage sensor (0-25 V) and a DC sensor (ACS712-5A and 20A) are utilized. Table 13 lists the parameters of the boost converter that used in this experience.

Table 13 :Parameters of Boost Converter

Parameters of Boost Converter	
Switching Frequency	Fs = 30kHz
Resistive Load	R_O= 16 Ω
Inductance	L_b = 0.45857 mH
PV Input Capacitance	C_{pv} = 120 µF
Boost Converter Output Capacitance	C_O = 2200 µF

5.2 Practical results of the hybrid GWO-P&O

A low-cost microcontroller can be used to accomplish this strategy and does not require more sensors. The hybrid GWO-P&O has been tested in the lab, Through the collected results, the ability of the hybrid algorithm to track the global MPP under STC and PSC has been proved with high tracking efficiency, few oscillations, and a small-time to reach MPP.

5.2.1 Implementation of the hybrid GWO-P&O under STC

Figure 21 shows the electrical properties of the PV system under STC. To extract the most quantities of available power, the solar system will be run at global MPP. The proposed algorithm's performance is evaluated under STC as depicted in Figure 33 by the tracking curves of power, voltage, and current of 3S PV configurations subjected to uniform irradiation circumstances. As can be seen in figure 33, the hybrid GWO-P&O is capable of tracking global MPP with high efficiency. The maximum power tracked by the proposed hybrid GWO-P&O algorithm is 65.68 W with a tracking time of 0.052 sec, the maximum voltage tracked by the hybrid GWO-P&O algorithm is 34 V with a tracking time of 0.051 sec, the maximum current is 1.932 A with a tracking time of 0.049 sec, and an efficiency of 99.43% under STC. The hybrid GWO-P&O has a high tracking efficiency, high precision, a short time to reach MPP, and low oscillations, as shown by the power curve. The output voltage and output current of the hybrid GWO-P&O is shown in figures 33. B and C.

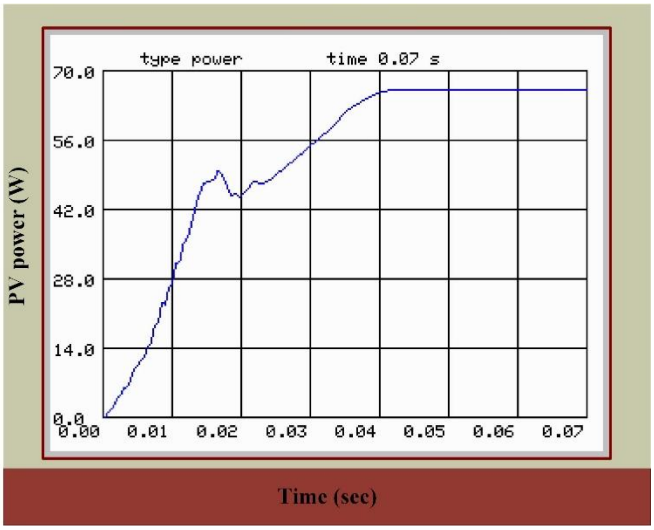


Figure 33. A: Output power

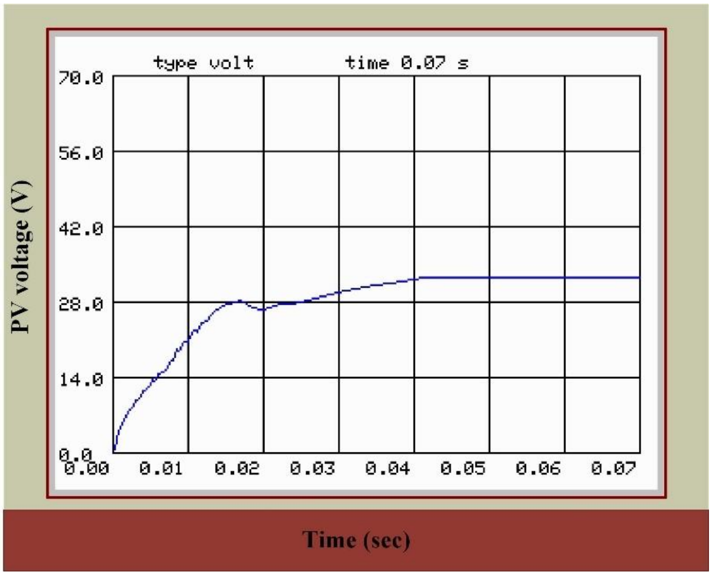


Figure 33. B: Output voltage

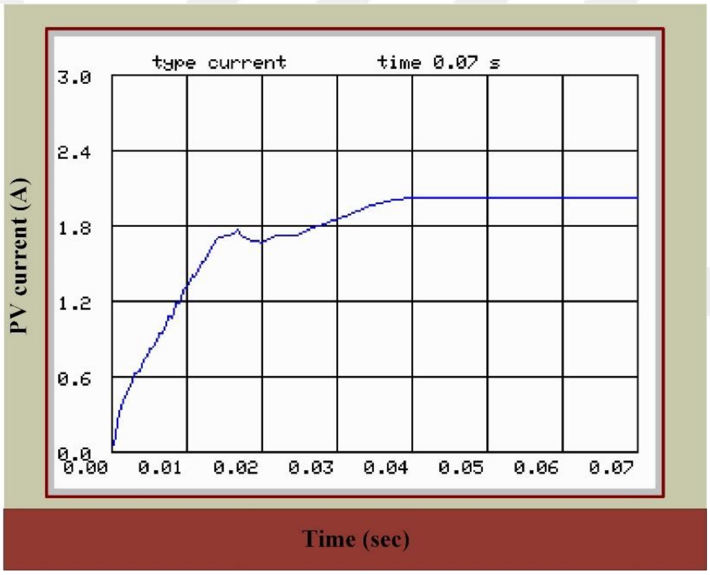


Figure 33. C: Output current

Figure 33: Power, voltage, and current of the hybrid GWO-P&O algorithm under STC

Table 14 shows the tracking results using the hybrid GWO-P&O. The table shows that the hybrid GWO-P&O has high efficiency of 99.43% and no major oscillations around the GMPP. Furthermore, under STC, hybrid GWO-P&O successfully tracks the global MPP in a small time with great precision.

Table 14: Hybrid GWO-P&O method under STC

PV System Operating Under STC	
MPPT techniques	**Hybrid GWO-P&O**
Time to reach MPP	0.052
Ideal Power of Solar Panels (W)	66.06
The power extracted at MPP (W)	65.68
Output Current (I)	1.932
Output Voltage (V)	34
Tracking efficiency (%)	99.43

5.2.2 Implementation of the hybrid GWO-P&O under PSC

The hybrid GWO-P&O is utilized to track the global MPP under PSC. Multiple peaks can be seen due to shade. To use the most available power, the PV system must be operated at GMPP. Figure 34 depicts the distinct P–V curve of a PV system under PSC, with the maximum output dropping from 66 to 41 W. PV power variation is estimated with the duty ratio of the DC-DC converter when the PV is exposed to different shadings. Partial shading is generated using pieces of cardboard of varied thicknesses which are then stacked over the PV modules. The GMPP has a total of 41.58 W with one local peak in the P-V curve.

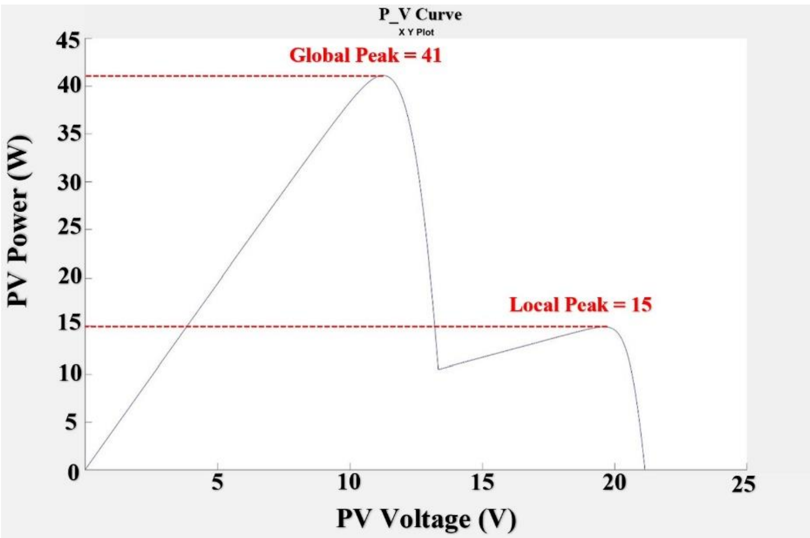


Figure 34. : Practical characteristics of the PV configuration under PSC

Figure 35 shows the tracking curves of power, voltage, and current for hybrid GWO-P&O algorithms under PSC. Under PSC, the maximum power tracked by the proposed hybrid GWO-P&O algorithm is 41.47 W with a tracking time of 0.031 sec, the maximum voltage is 25.6 V with a tracking time of 0.028 sec, the maximum current is 1.62 A with a tracking time of 0.03 sec, and with an efficiency of 99.74 %. Figure 35-A shows the output power of the hybrid GWO-P&O. Through the power curve, it can be seen that the hybrid GWO-P&O has efficient tracking, high accuracy, and minimal time to approach MPP. Also, the tracking efficiency, accuracy, and time to MPP are shown in terms of the input voltage and current of the hybrid algorithm in figure 35. B and C. Under PSC, the proposed hybrid GWO-P&O algorithm successfully tracks the global MPP with high accuracy and in small time.

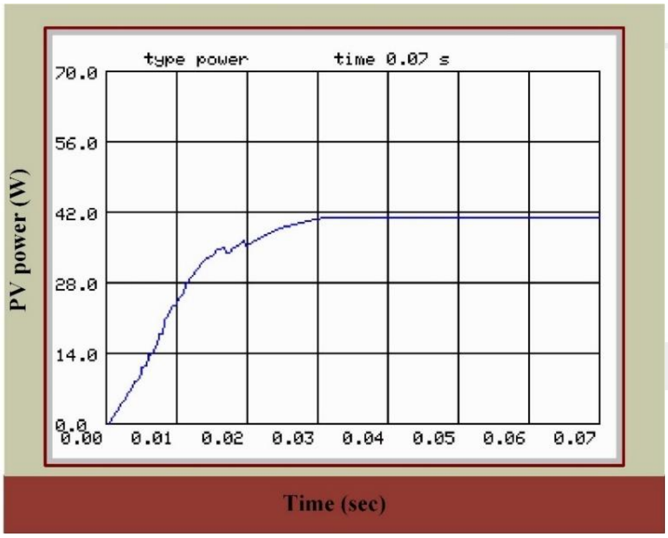


Figure 35. A: Output power

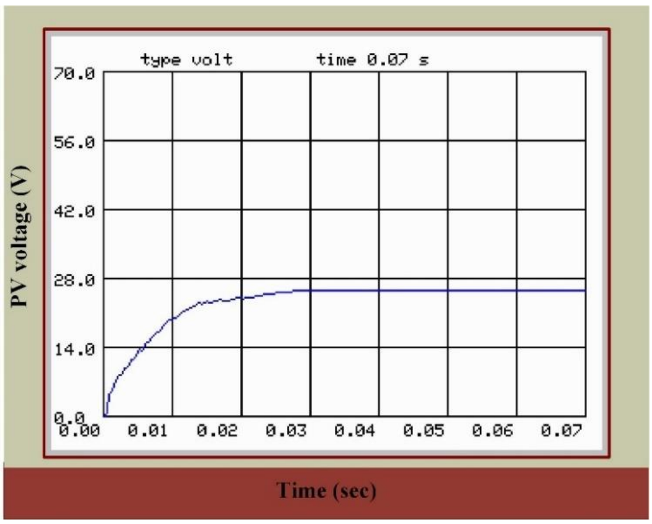


Figure 35. B: Output voltage

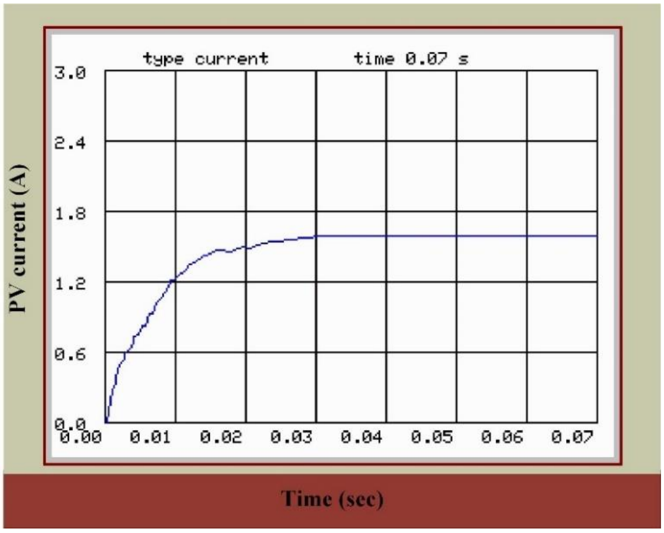


Figure 35. C: Output current

Figure 35: Power, voltage, and current of the hybrid GWO-P&O algorithm under PSC

Table 15 shows the tracking results using the hybrid GWO-P&O under PSC. The table shows that the hybrid GWO-P&O has high efficiency of 99.74% with small oscillations around the MPP and takes a small time to reach MPP.

Table 15: The tracking results of the Hybrid GWO -P&O under PSC

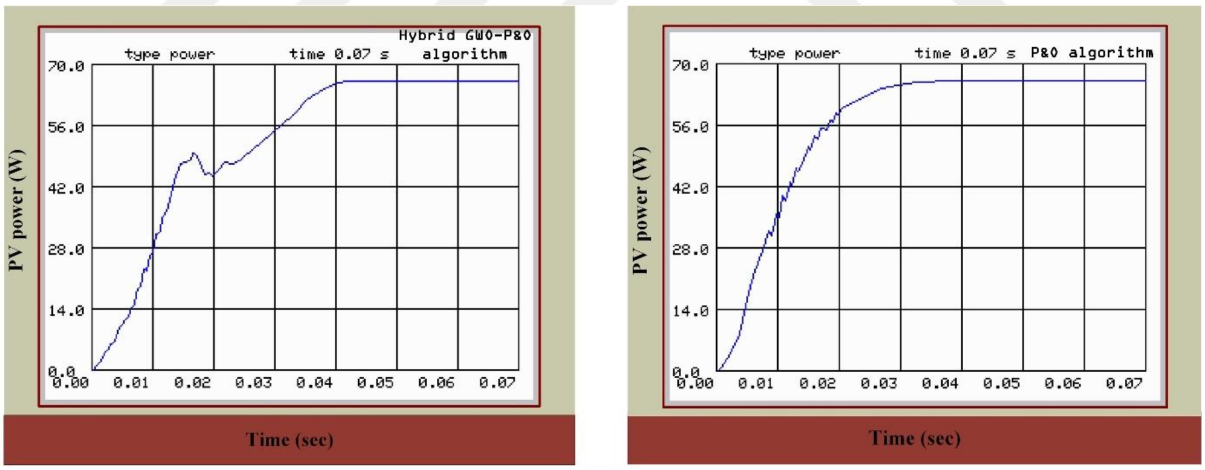
PV System Operating Under PSC	
MPPT techniques	**Hybrid GWO-P&O**
Time to reach MPP	0.031
Ideal Power of Solar Panels (W)	41.58
Power extracted at MPP (W)	41.47
Output Current (I)	1.62
Output Voltage (V)	25.6
Tracking efficiency (%)	99.74

5.3 Comparative Analysis

The hybrid GWO-P&O is compared with traditional GWO MPPT algorithms and traditional P&O MPPT algorithms under similar conditions. According to the collected results, the hybrid GWO-P&O outperforms traditional GWO and traditional P&O algorithms. It has been proved that the hybrid GWO-P&O can track GMPP with greater accuracy than the GWO algorithm, and with greater efficiency than traditional P&O because the traditional P&O tracks the local MPP.

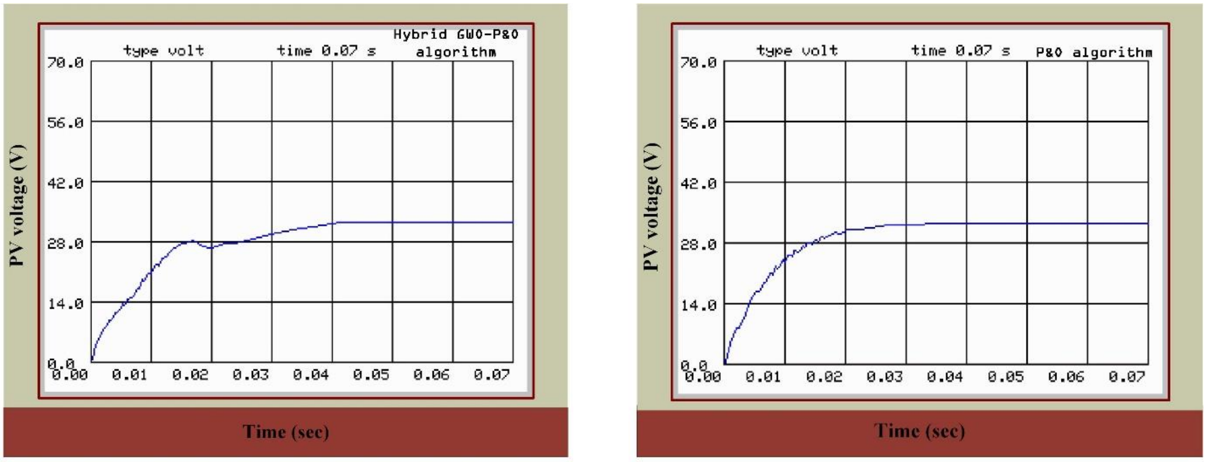
5.3.1 Comparing of GWO-P&O hybrid algorithm with other algorithms under STC

According to the practical results, the maximum power that a solar PV module can produce is 66.06 W. The comparison of power, voltage, and current between the P&O algorithm and the hybrid GWO-P&O under STC is shown in figure 36. The output power of the P&O algorithm and the hybrid GWO-P&O are compared.



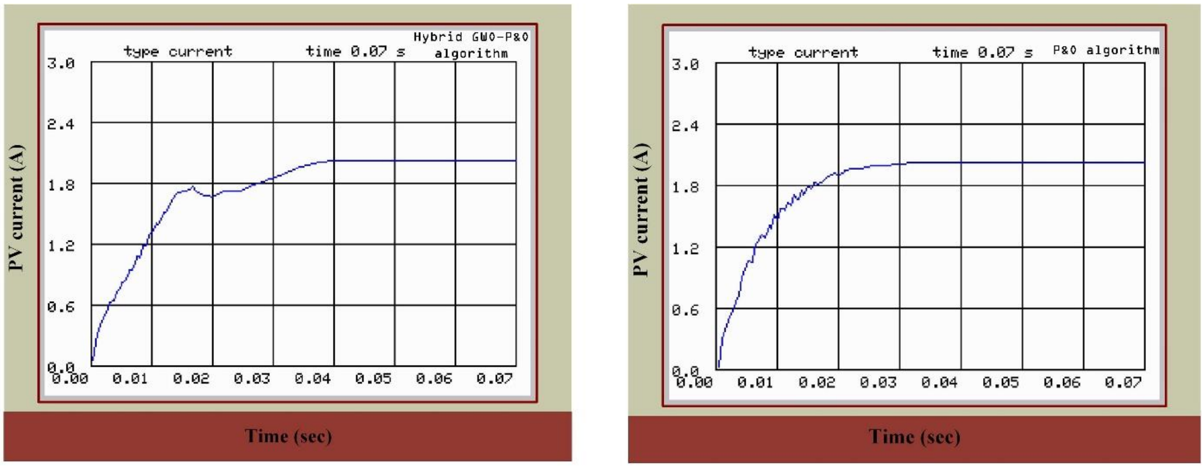
Pout of the proposed hybrid algorithm | **Pout of the P&O algorithm**

Figure 36. A: Output power



Vout of the proposed hybrid algorithm **Vout of the P&O algorithm**

Figure 36. B: Output voltage



Iout of the proposed hybrid algorithm **Iout of the P&O algorithm**

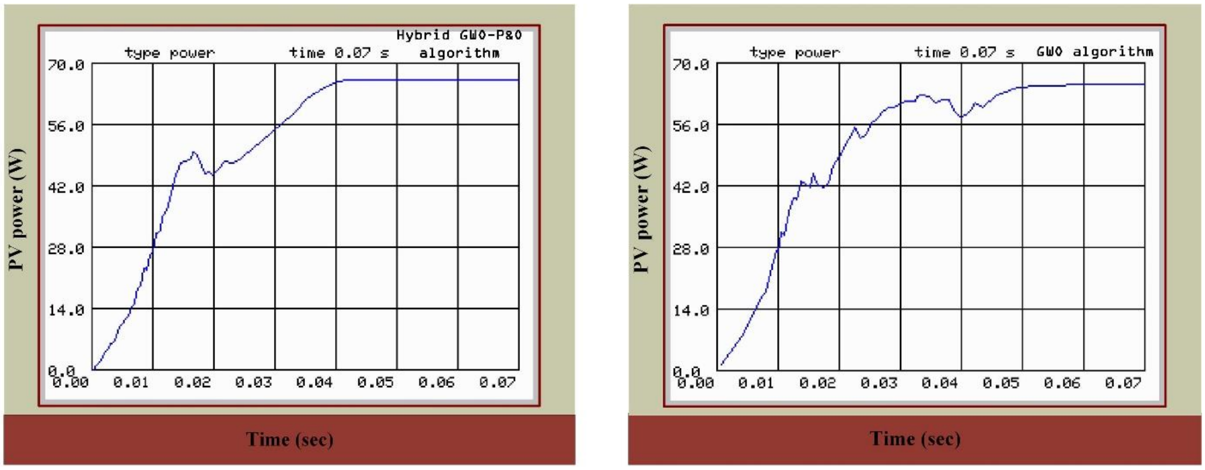
Figure 36. C: Output current

Figure 36: Comparing the hybrid GWO-P&O algorithm with the P&O algorithm under STC

In figure 36. B, the input and output voltages of the two algorithms are compared. Also, figure. 36. C compares the input and output currents of the two algorithms. Under STC, there is only one MPP which is the GMPP, so both approaches can easily reach the MPP. The P&O method reaches MPP with a time of 0.035s and a tracking efficiency of 99.59% with low power oscillation, whereas the hybrid GWO-P&O achieves MPP with a time of 0.042s and a tracking efficiency of 99.43% with low power oscillation.

Figure 37 also illustrates the comparison of power, voltage, and current between the GWO algorithm and the hybrid GWO-P&O under STC. The output power of the GWO algorithm and the hybrid GWO-P&O are compared. The hybrid GWO-P&O algorithm outperforms the GWO algorithm in terms of tracking efficiency since it tracks the global

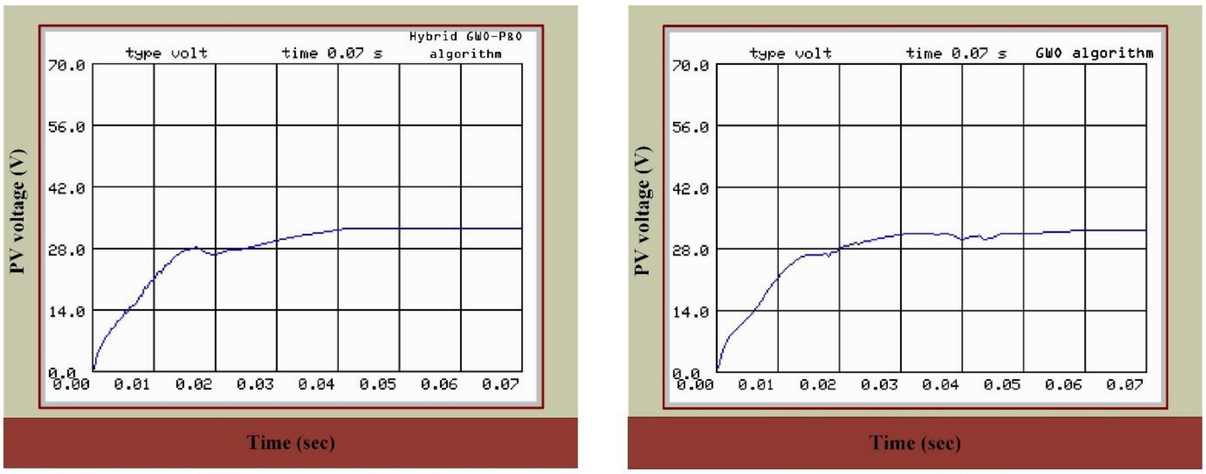
MPP more effectively and accurately than the GWO algorithm and takes less time to reach MPP. In figure 37. B, the input and output voltages of the two algorithms are compared. Also, figure. 37. C compares the input and output currents of the two algorithms. Finally, the GWO technique reaches the MPP but with a lower tracking accuracy than the hybrid GWO-P&O. It takes 0.059 seconds to attain MPP with a tracking efficiency of 98.81%, whereas the hybrid GWO-P&O approach takes 0.042 seconds and has a tracking efficiency of 99.43 %.



Pout of the proposed hybrid algorithm

Pout of the GWO algorithm

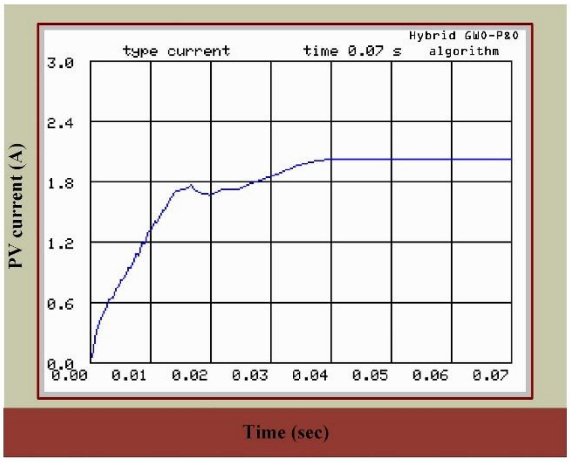
Figure 37. A: Output power



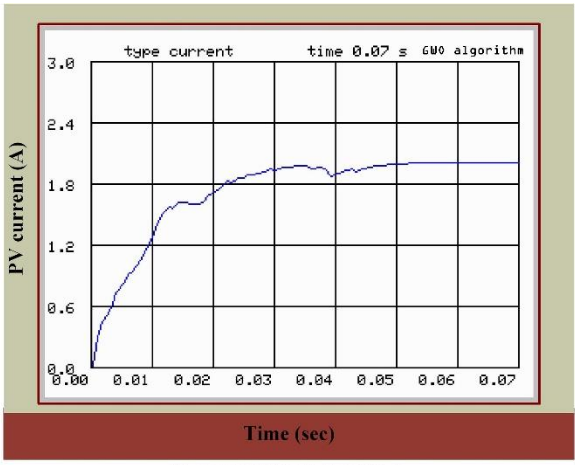
Vout of the proposed hybrid algorithm

Vout of the GWO algorithm

Figure 37. B: Output voltage



Iout of the proposed hybrid algorithm



Iout of the GWO algorithm

Figure 37. C: Output current

Figure 37: Comparing the hybrid GWO-P&O algorithm with the GWO algorithm under STC

The practical results of the three MPPT algorithms are summarized in tables 16 and 17. The obtained results showed that under STC, all algorithms provided great performance, due to the presence of one MPP which was the global point. Nonetheless, there were some differences between the algorithms in terms of accuracy, speed, and efficiency.

Table 16: The practical results of the three MPPT algorithms under STC

PV system operation	**PV System Operating Under STC**		
MPPT techniques	**P&O**	**GWO**	**Hybrid GWO-P&O**
Ideal Power of Solar Panels (W)	66.06	66.06	66.06
Actual Output Power (W)	65.79	65.28	65.68
Output Current (I)	1.935	1.92	1.932
Output Voltage (V)	34	34	34
Time to reach MPP	0.035s	0.059s	0.042s
Tracking efficiency (%)	99.59 %	98.81 %	99.43 %

Table 17: The practical results of the three MPPT algorithms under STC

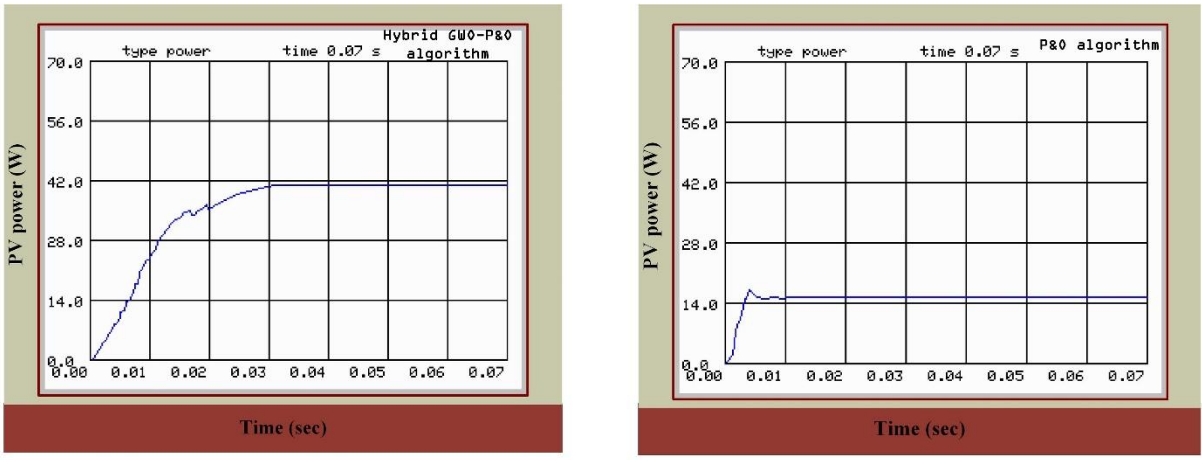
PV system operation	PV System Operating Under STC		
MPPT techniques	**P&O**	**GWO**	**Hybrid GWO-P&O**
Tracking Speed	Fast	Medium	Fast
Tracking accuracy	Accurate	Accurate	Highly Accurate
Convergence to GP	Yes	Yes	Yes
Steady-state oscillations	Medium	Medium	Medium
Power efficiency	Very High	High	Very High
Algorithm Complexity	Low	Medium	High
Implementation complexity	Low	Medium	Medium
Dynamic response	Poor	Good	Good

5.4 Comparing of GWO-P&O hybrid algorithm with other algorithms under PSC

To make partial shading, a piece of cardboard is placed on one of the solar panels. The insolation of the PV panel changes abruptly. Figure 34 depicts the distinct P–V curve of a PV system under PSC with the maximum output dropping from 66 to 41 W. The hybrid GWO-P&O is utilized to track the GMPP under PSC, and the global tracking performance is then compared to that of other MPPT approaches. One local peak and one global peak in P-V characteristics can be seen due to shade. Under uniform irradiance, the PV system can deliver a maximum power of 66 Watt but due to PSC, its ability is restricted to 41 Watt. As a result, the MPPT controller's job is to extract the most quantities of available power.

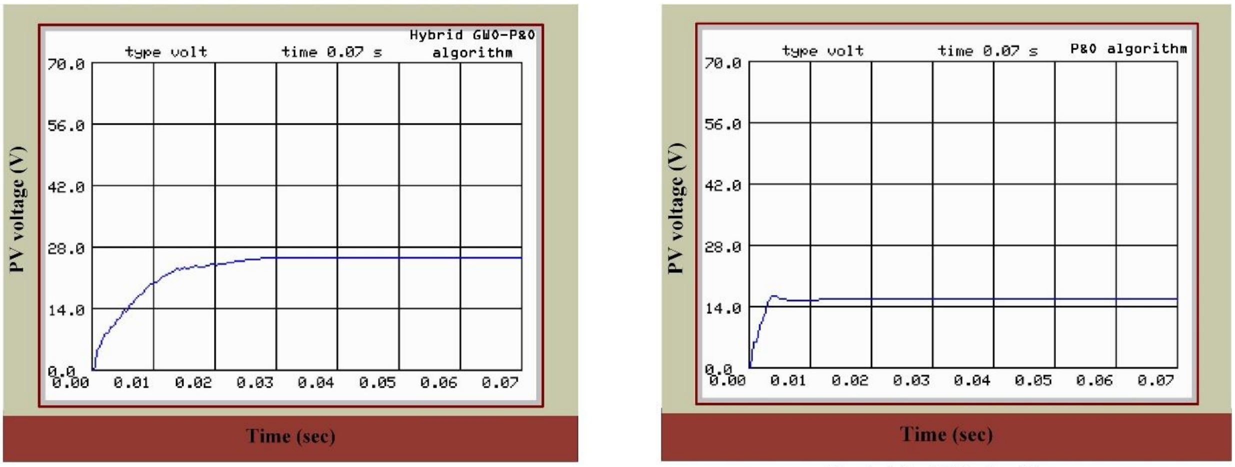
The comparison indicates that the hybrid GWO-P&O performs well under PSC. The proposed hybrid algorithm has an efficiency of 99.74 % and a time to reach MPP of 0.03.

Figure 38 shows a comparison of power, voltage, and current between the P&O algorithm and the hybrid GWO-P&O under PSC. As shown in figure 38. A, the output power of the P&O algorithm and the hybrid GWO-P&O are exhibited and compared. One local peak and one global peak are obtained as a result of PSC, with magnitudes of 15 Watt for the local peak and 41 Watt for the global peak. The hybrid GWO-P&O reaches the GMPP. The P&O approach fails to track global MPP and instead operates at the first locally obtained peak, resulting in significant power waste. The hybrid GWO-P&O performs much better than the P&O algorithm under PSC because the hybrid GWO-P&O can track the global MPP while the P&O algorithm tracks the local MPP. The input and output voltage of the two algorithms are compared in figure 38. B. Also, figure 38. C compares the input and output currents of the two algorithms.



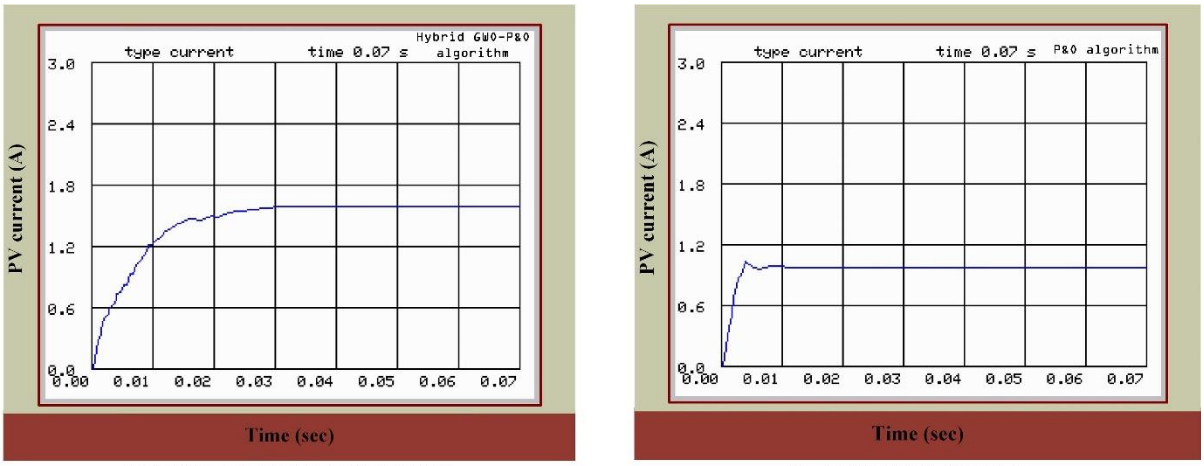
Pout of the proposed hybrid algorithm **Pout of the P&O algorithm**

Figure 38. A: Output power



Vout of the proposed hybrid algorithm **Vout of the P&O algorithm**

Figure 38. B: Output voltage



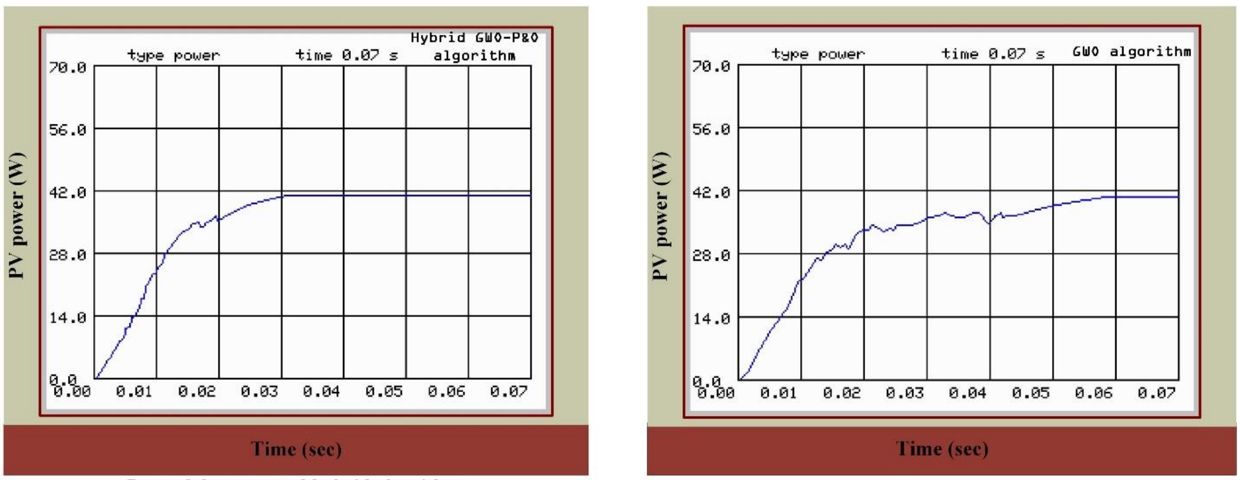
Iout of the proposed hybrid algorithm

Iout of the P&O algorithm

Figure 38. C: Output current

Figure 38: Comparing the hybrid GWO-P&O algorithm with the P&O algorithm under PSC

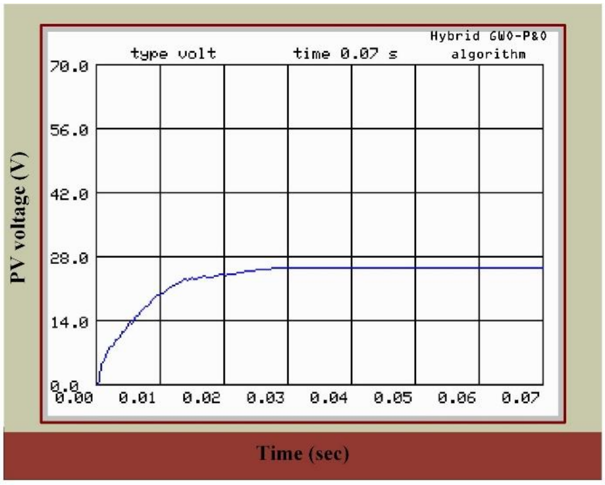
The GWO algorithm is capable of extracting the MPPT under PSC. Figure 39 shows the comparison of power, voltage, and current between the GWO algorithm and the hybrid GWO-P&O under PSC. As shown in figure 39 A, the output power of the GWO method and the hybrid GWO-P&O are exhibited and compared. The hybrid GWO-P&O outperforms the GWO algorithm in terms of tracking efficiency and accuracy. The hybrid GWO-P&O tracks the global MPP more efficiently than the GWO algorithm and with high accuracy. The input and output voltage of the two algorithms are compared in figure 39. B. Also, figure 39. C compares the input and output currents of the two algorithms. The GWO technique reaches the MPP but with a lower tracking accuracy than the hybrid GWO-P&O. It takes 0.069s to reach MPP with a tracking efficiency of 98.50%, whereas the hybrid GWO-P&O takes 0.03 s and has a tracking efficiency of 99.74%.



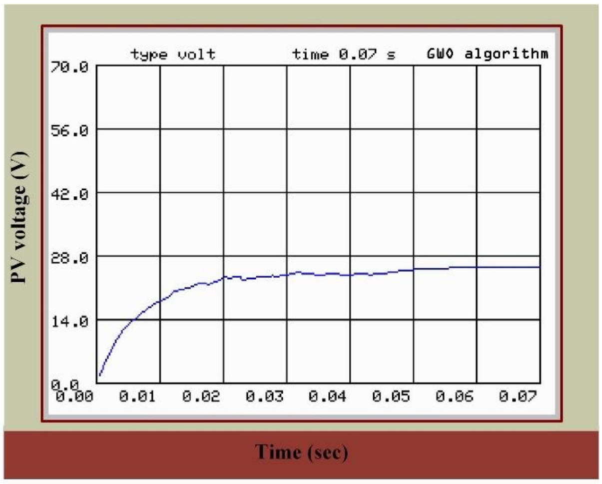
Pout of the proposed hybrid algorithm

Pout of the GWO algorithm

Figure 39. A: Output power

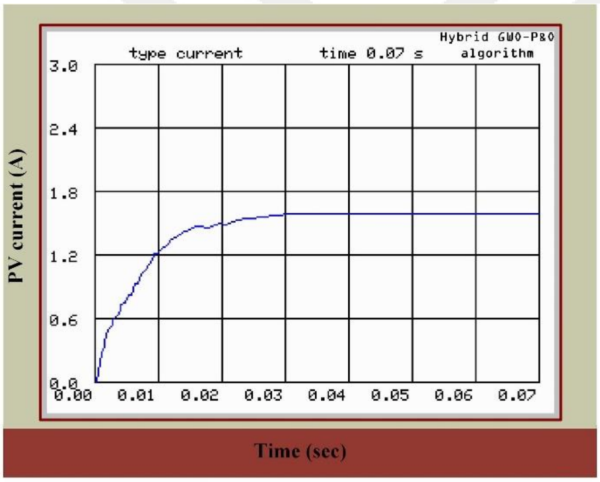


Vout of the proposed hybrid algorithm

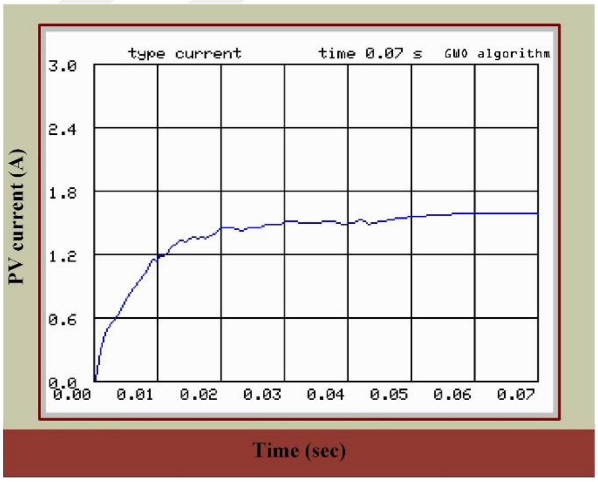


Vout of the GWO algorithm

Figure 39. B: Output voltage



Iout of the proposed hybrid algorithm



Iout of the GWO algorithm

Figure 39. C: Output current

Figure 39: Comparing the hybrid GWO-P&O algorithm with the GWO algorithm under PSC

The practical results of the three MPPT algorithms are summarized in tables 18 and 19. When the PV arrangement functioned under PSC, the simulation results proved that the hybrid GWO-P&O could immediately converge to the GMPP. Furthermore, compared to previous MPPT methods, the hybrid GWO-P&O produced minimal power oscillations in the steady-state and had a greater tracking efficiency.

Table 18: The simulation results of the three MPPT algorithms under PSC

PV system operation	**PV System Operating Under PSC**		
MPPT techniques	P&O	GWO	Hybrid GWO-P&O
Ideal Power of Solar Panels (W)	41.58	41.58	41.58
Actual Output Power (W)	15.41	40.96	41.47
Output Current (I)	0.94	1.6	1.62
Output Voltage (V)	16.4	25.6	25.6
Time to reach MPP	0.01	0.069	0.03
Tracking efficiency (%)	37 %	98.50 %	99.74 %

Table 19: The simulation results of the three MPPT algorithms under PSC

PV system operation	**PV System Operating Under PSC**		
MPPT techniques	**P&O**	**GWO**	**Hybrid GWO-P&O**
Tracking Speed	Slow	Medium	Fast
Tracking accuracy	Low	Accurate	Accurate
Convergence to GP	No	Yes	Yes
Steady-state oscillations	Medium	Medium	Medium
Power efficiency	Low	High	Very High
Algorithm Complexity	Low	Medium	High
Implementation complexity	Low	Medium	Medium
Dynamic response	Poor	Good	Good

CHAPTER SIX

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

In partial shading conditions with many maximum Power Points on the P-V curve, traditional algorithms such as P&O, and incremental conductance fail to track the global MPP, thus reducing the overall PV system efficiency. This study proposes a hybrid GWO-P&O algorithm that combines the GWO algorithm with the P&O algorithm for extracting the maximum power from a PV system exposed to rapid variations of solar irradiation and partial shading conditions. The proposed hybrid algorithm GWO-P&O has a high tracking efficiency, a short time to reach the MPP, high accuracy, less oscillations around MPP, and a faster convergence towards the MPP compared to the other tested algorithm.

To prove the efficiency of the hybrid GWO-P&O, MATLAB/SIMULINK is used to mimic the PV system. Different shading patterns are used. The simulation results show that hybrid GWO-P&O outperformed other algorithms such as traditional P&O, PSO, and traditional GWO. Through simulation results, the maximum power tracked by the proposed hybrid GWO-P&O algorithm is 66.003 W with a tracking time of 0.064 sec, the maximum voltage tracked by the hybrid GWO-P&O algorithm is 36.3253V with a tracking time of 0.055 sec, the maximum current is 1.817A with a tracking time of 0.045 sec, and an efficiency of 99.91% under STC.

Under PSC, the maximum power tracked by the proposed hybrid GWO-P&O algorithm is 36.416 W with a tracking time of 0.085 sec, the maximum voltage is 38.141 V with a tracking time of 0.05 sec, the maximum current is 0.954A with a tracking time of 0.045 sec, and with an efficiency of 99.91%.

To test the system in practice, a hardware prototype is created and tested. Solar panels with a boost DC-DC converter and microcontroller board are used to build the hardware prototype. The practical experiment results show that hybrid GWO-P&O outperformed other algorithms. Through practical results, the maximum power tracked by the proposed hybrid GWO-P&O algorithm is 65.68 W with a tracking time of 0.052 sec, the maximum voltage tracked by the hybrid GWO-P&O algorithm is 34 V with a tracking time of 0.051 sec, the maximum current is 1.932 A with a tracking time of 0.049 sec, and an efficiency of 99.43% under STC.

Under PSC, the maximum power tracked by the proposed hybrid GWO-P&O algorithm is 41.47 W with a tracking time of 0.031 sec, the maximum voltage is 25.6 V with a tracking time of 0.028 sec, the maximum current is 1.62 A with a tracking time of 0.03 sec, and with an efficiency of 99.74 %.

6.2 Future work

The following suggestion can be taken into consideration to develop the work presented in this study.

1- Another optimization technique can be proposed to improve the tracking efficiency, accuracy, time required to reach the MPP, and reduce the oscillations around the MPP.

2- A buck-boost converter for the photovoltaic system can be used to increase the efficiency of tracking of the hybrid GWO-P&O algorithm.

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ANNEXES

Matlab code for the proposed hybrid (GWO-P&O) algorithm

```
%% AMEER MAHMOOD RAHMAN
%% Hybrid solar PV MPPT
%% With Grey Wolf optimization and Perturb and observer
method For mutiple shadding patterns

function [D,iteration1] = GWO(Vpv,Ipv) %%fnctiuon [output]
= name[input]

dim = 1; % dim = number of your variables
m = 7;    % population size
persistent dc Dprev Ppv Vprev Pprev
persistent fitness
persistent D_new;
persistent alpha;
persistent alpha_pos Beta_pos;
persistent iteration Beta_score Delta_score Delta_pos;
persistent Gmax;
persistent i
persistent to1

if(isempty(iteration))
    iteration=0;
    to1=90;
end

if(isempty(D_new))
    D_new = 0.4;
end

if(isempty(Gmax))
     Gmax=0;
end

if(isempty(alpha))
    alpha=0;
end

if(isempty (Beta_pos))
    alpha_pos=zeros(1,dim);
    Beta_pos=zeros(1,dim);
    Delta_pos=zeros(1,dim);
    Beta_score=0;
    Delta_score=0;
end
```

```
if(isempty(alpha))
    alpha=0;
end

% Initialize the internal values for the voltage and power
on the first pass
if isempty(Dprev)
    Dprev = 0.3;
    Vprev = 70;
    Pprev = 300;
end

if (isempty(alpha_pos))
    alpha_pos=zeros(1,dim);
end

if(isempty(dc))
    dc=zeros(5,1);

    dc(1)=0.1;
    dc(2)=0.2;
    dc(3)=0.3;
    dc(4)=0.4;
    dc(5)=0.5;
%   dc(6)=0.6;
%   dc(7)=0,7;
%   dc(8)=0.8;
%   dc(9) =0.9;
%   dc(10)=1;
end

    if (isempty(i))
    i=0;
    D = 1;
    end
% D = 0.4;
iteration1 = 0;
if (iteration <40 )
        iteration1=iteration;
```

```
    if i<5  % where i represents the wolf number
        i = i+1;
        % Return back the search agents that go beyond the
boundaries of the search space
        Flag4ub=dc(i,:)>1;  %  ub=[ub1,ub2,...,ubn]  where
ubn is the upper bound of variable n
        Flag4lb=dc(i,:)<0;  %  lb=[lb1,lb2,...,lbn]  where
lbn is the lower bound of variable n
        dc(i)=(dc(i).*(~(Flag4ub+Flag4lb)))+1.*Flag4ub;

        %  Calculate  objective  function  for  each  search
agent
        fitness=Vpv*Ipv;
        tol = abs(alpha-fitness);
        if fitness>alpha
    alpha=fitness; % Update alpha
    alpha_pos=dc(i);
end
if fitness<alpha && fitness>Beta_score
    Beta_score=fitness; % Update beta
    Beta_pos=dc(i);
end

if      fitness<alpha     &&     fitness<Beta_score     &&
fitness>Delta_score
    Delta_score=fitness; % Update delta
    Delta_pos=dc(i);
end

D_new =dc(i);
Dprev = dc(i);
Vprev = Vpv;
Pprev = fitness;
D = dc(i);
       return;
    end

    iteration = iteration+1;
    i = 0;
    dc1                      =                     pos_up
(iteration,alpha_pos,dc,Beta_pos,Delta_pos);
    dc = dc1;
end
```

```
% Initialize algorithm parameters
deltaD = 0.001;
% Pprev=alpha;
% Dprev=D;
% Calculate measured array power
Ppv = Vpv*Ipv;

% Increase or decrease duty cycle based on conditions
if (Ppv-Pprev) ~= 0
    if (Ppv-Pprev) > 0
        if (Vpv-Vprev) > 0
            D = Dprev - deltaD;
       else
           D  =  Dprev  +  deltaD;
       end
    else
        if  (Vpv-Vprev)  >  0
             D = Dprev + deltaD;
        else
             D = Dprev - deltaD;
        end
    end
else
    D = Dprev;
end
% Update internal values
Dprev = D;
Vprev = Vpv;
Pprev = Ppv;

end
function             D1              =             pos_up
(l,alpha_pos,D_cur,Beta_pos,Delta_pos)
a=0.4-1*((0.4)/90);  %  a  decreases linearly fron 2 to 0
D1=zeros(5,1);
for kk=1:5     % Update the Position of search agents
    r1=rand(); % r1 is a random number in [0,1]
    r2=rand(); % r2 is a random number in [0,1]
    A1=2*a*r1-a; % Equation (3.3)
    C1=2*r2; % Equation (3.4)
    D_alpha=abs(C1*alpha_pos-D_cur(kk));    %    Equation
(3.5)-part 1
    X1=alpha_pos-A1*D_alpha; % Equation (3.6)-part 1
```

```
r1=rand(); % r1 is a random number in [0,1]
    r2=rand(); % r2 is a random number in [0,1]
    A2=2*a*r1-a; % Equation (3.3)
    C2=2*r2; % Equation (3.4)
    D_beta=abs(C2*Beta_pos-D_cur(kk)); % Equation (3.5)-
part 2
    X2=Beta_pos-A2*D_beta; % Equation (3.6)-part 2

    r1=rand(); % r1 is a random number in [0,1]
    r2=rand(); % r2 is a random number in [0,1]
    A3=2*a*r1-a; % Equation (3.3)
    C3=2*r2; % Equation (3.4)
    D_delta=abs(C3*Delta_pos-D_cur(kk));    %    Equation
(3.5)-part 3
    X3=Delta_pos-A3*D_delta; % Equation (3.5)-part 3

           X=(X1+0.4*X2+0.1*X3)/1.5; % Equation (3.7)

    D1(kk)=X1; % Equation (3.7)
%      if D1(kk)>1
%          D1(kk)= 1;
%      end
%      if D1(kk)<0
%          D1(kk)=0;
%      end
end
end
```