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Title

PERFORMANECE IMPROVEMENT OF SOLAR PV ARRAY TOPOLOGY DURING PARTIAL SHADING CONDITIONS

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الإهداء

مرت قاطرة البحث بكثير من العوائق، ومع ذلك حاولت أن أتخطاها بثبات بفضل من الله ومنه

إلى أبوي وأخوتي وأصدقائي، فقلد كانوا بمثابة العضد والسند في سبيل استكمال البحث

ولا ينبغي أن أنسى أساتذتي ممن كان لهم الدور الأكبر في مساندتي ومدي بالمعلومات القيمة

أهدي لكم بحث تخرجي

داعياً المولى عز وجل أن يطيل في أعماركم ويرزقكم بالخيرات

التشكرات

نشكر الله تعالى بشكل خاص على الإرادة والصحة والصبر التي قدمها لنا خلال كل هذه السنوات الطويلة.

نعرب عن عميق امتناننا لوالدينا الأعزاء على تشجيعهم ودعمهم والتضحيات التي تحملوها.

نود أيضًا أن نعرب عن خالص شكرنا لمشرفنا بوجلال بلال أولاً وقبل كل شيء على الذي لم يتوقف عن تقديم نصائح وملاحظات قيمة لنا.

شكرًا أيضًا لجميع الاساتذة الذين رافقونا طوال السنوات الماضية ولجميع أولئك الذين ساهموا بشكل مباشر أو غير مباشر في تحقيق هذه الأطروحة.

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Glossary

IGBT	Insulated Gate Bipolar Transistor
MCC	Continuous Conduction Mode
PWM	Pulse Width Modulation
MPPT	Maximum Power Point Tracking
PV	Photovoltaic
P&O	Perturbation and observation
PSO	Particle Swarm Optimization
MPP	Maximum power pointe

Nomenclature

C_{dc}	Boost converter output capacitor
C_{pv}	Boost Converter Integer Capacitor
f_s	PV System Frequency
i_{cell}	The current supplied by the photovoltaic cell
i_{ph}	Photonic current, from the model of a photovoltaic cell
i_{pv}	Photovoltaic system current
I_{sat}	The saturation current
I_{rr}	The saturation current of the diode
I_{sc}	The short-circuit current
V_{oc}	Open-circuit voltage
V_{cell}	The voltage across the cell
G	Sunshine
q	Charge of the electron
α	Temperature coefficient of Iph.
K	Boltzmann's Constant
E_g	The energy of the band gap
n	Factor of ideality of the junction
Ns	Number of cells connected in series
Np	Number of cells connected in parallel
L_{Gpv}	Inductance of the photovoltaic system converter
Ppv	Power delivered by the photovoltaic solar source

General Introduction

General Introduction

The need for renewable energy sources is growing day by day because of the severe energy crisis in the world today. Renewable energy sources play a significant role in electricity generation. Several renewable energy sources (like solar, wind, geothermal, and biomass) can be used for generation of electricity and for meeting our daily energy demands. Solar energy is the most viable option for electricity generation because it is available everywhere and is free to utilize [1][2].

Solar Photovoltaic (PV) arrays convert the solar energy into electrical energy. With the current concentration on greener and cleaner sources of power, PV arrays are being used as an important source of power in many applications [3-13].

One of the main causes for the reduced energy yield of many PV systems is a partial shading of PV arrays. The phenomenon of partially shaded conditions is widespread in all kinds of photovoltaic systems. This thesis proposes a performance improvement of solar PV array topology during partial shading conditions [14-20].

Partial shading represents one of the most significant technical challenges in photovoltaic (PV) system operation, causing substantial reductions in power output, the formation of potentially damaging hotspots, and overall system efficiency degradation. These effects stem primarily from current-voltage mismatch losses when different sections of a PV array experience non-uniform irradiance conditions [14-20].

This study begins by presenting an overview of photovoltaic solar energy systems, highlighting their structure, working principles, and the main parameters that define their electrical behavior. It also discusses the influence of external factors like solar irradiance and temperature on the performance of PV panels, laying the groundwork for understanding the system's limitations.

To address the efficiency issues, the second part of the study focuses on efficiency improvement in PV systems using Maximum Power Point Tracking (MPPT) techniques, with an emphasis on the Perturb and Observe (P&O) algorithm. This algorithm, widely used in commercial systems, is known for its simplicity and low implementation cost. While effective under uniform conditions, its performance declines under partial shading or rapidly changing irradiance, due to its tendency to oscillate near the maximum power point.

To overcome these limitations, the third part explores the application of Particle Swarm Optimization (PSO) in PV systems. PSO is a bio-inspired optimization technique that uses a population-based search mechanism to locate the global maximum power point with higher precision, especially under non-uniform irradiance conditions. Its superior adaptability and noise resistance make it a promising alternative to traditional MPPT methods.

This study offers some solutions for partial shading conditions and provides a comparative analysis of P&O and PSO algorithms in the context of solar PV systems, particularly under partial shading scenarios. The results demonstrate that while P&O is well-suited for simpler conditions, PSO offers enhanced efficiency and robustness, making it a more effective solution for optimizing energy harvest in real-world PV installations.

In summation, this thesis represents a comprehensive endeavor to advance our understanding of photovoltaic technology and its implications for sustainable energy generation. By examining the intricacies of PV system construction, modeling, and control, this research seeks to contribute to the ongoing discourse on renewable energy innovation and pave the way for a more sustainable energy future.

Chapter I. Overview of Photovoltaic Solar Energy Systems

Chapter I. Overview of Photovoltaic Solar Energy Systems

I.1 Introduction

Solar energy is at the forefront of clean energy, and it is an obvious example of renewable energy that comes purely from a natural source and harnessing energy from the sun.
Solar energy is predominant all over the globe and all the time. It is the most direct way to convert solar radiation into electricity based on the photovoltaic cell effect; 120,000 TW is the radiation level that is deposited from the sun onto the surface of the Earth, which far exceeds human needs [1].

Solar energy can be exploited in three major ways, namely the captured heat, which can be utilized as solar thermal energy; the conversion of incident solar radiation into electrical energy, which can be achieved with the assistance of solar photovoltaic cells, and the storage of solar energy as heat.

I.2 Type of Solar Panels

I.2.1 Monocrystalline Solar Panels

Monocrystalline panels are made from a single silicon crystal structure, resulting in a uniform appearance and high efficiency. They are typically more expensive but offer better performance in limited space and higher temperature conditions.

I.2.2 Polycrystalline Solar Panels

Polycrystalline panels are composed of multiple silicon crystals, resulting in a fragmented appearance. They are less expensive to manufacture but have slightly lower efficiency compared to monocrystalline panels. However, they perform better in low-light conditions.

I.2.3 Thin-Film Solar Panels

Thin-film panels are characterized by their thin and flexible design. They are typically less efficient than crystalline panels but offer advantages such as better performance in low-light conditions, reduced weight, and the ability to be integrated into various surfaces.

I.2.4 Concentrated Solar Panels

Concentrated solar panels use lenses or mirrors to concentrate sunlight onto a smaller area, increasing the intensity of light and improving efficiency. This technology is often used in large-scale solar power plants and requires precise tracking systems to follow the sun's movement.

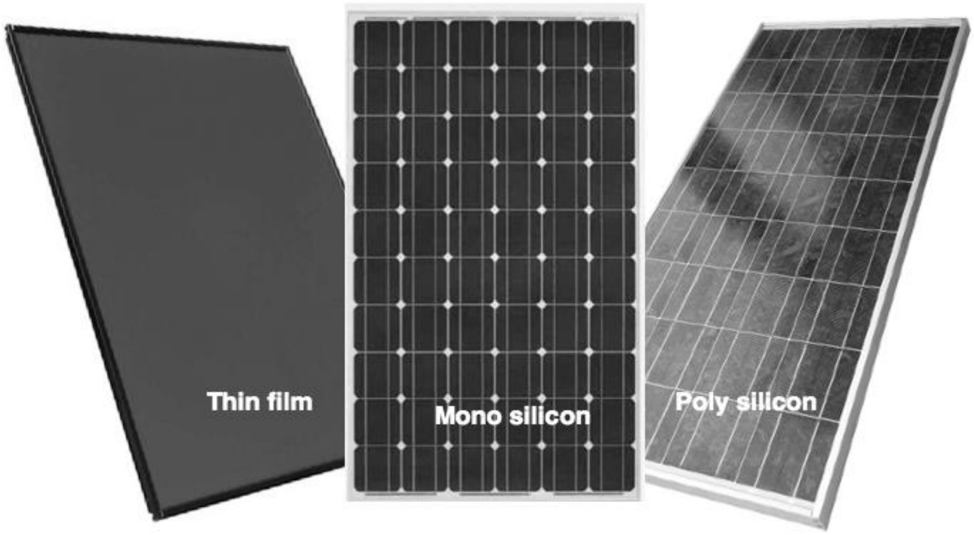


Figure I.1– Types of Solar Panels

I.3 Operational Principles of Solar Panels

Solar panel’s function based on the photovoltaic effect, which is the ability of certain materials to generate an electric current when exposed to sunlight. This effect occurs within the solar cells present in the panels.

I.3.1 Photovoltaic Effect

The photovoltaic effect is primarily driven by the interaction of photons (light particles) with the semiconductor material in the solar cells. When photons strike the cells, they excite electrons, causing them to break free from their atoms and create a flow of electric current.

I.3.2 Working Mechanism

Solar panels consist of multiple interconnected solar cells, typically made of silicon. These cells are sandwiched between protective layers and wired together to form a module. When sunlight hits the solar panel, the photons are absorbed by the semiconductor material, generating an electric charge. This charge is then collected by metal contacts on the cells, creating direct current (DC) electricity.

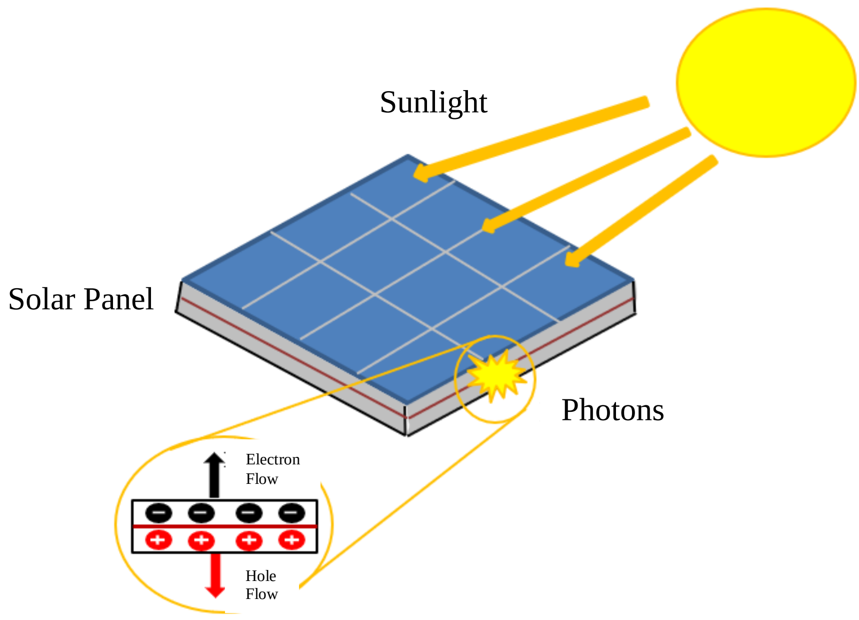


Figure I.2– Principles Of Solar Panels

I.4 Limitations of Solar Energy

The efficiency levels to convert from light to electricity are in the range of 15 to 22% [2] relying on the technology used as the technology is in an evolving stage. The initial exploitation cost of this technology is very high. These days, the technology is surviving because of subsidy schemes available by the government. As a matter of fact, solar energy is available only during the daytime.

On the other hand, load profiles indicate peak load in the evening. This necessitates expensive storage devices as a battery, which requires more maintenance and replacement every three to five years.

Solar energy heavily relies on atmospheric conditions. Solar insolation is different from location to location. Therefore, there are certain geographic limitations for generating solar power

I.5 Types of Solar Systems

Solar energy systems can be categorized into three main types: On-grid, Off-grid, and Hybrid solar systems. Each system operates differently and serves specific energy needs. Here is a brief overview of these systems

I.5.1 ON-Grid Solar System

Grid-tied systems are solar panel installations that are connected to the utility power grid. With a grid-connected system, a home can use the solar energy produced by its solar panels and electricity that comes from the utility grid.

If the solar panels generate more electricity than a home needs, the excess is sent to the grid. In some places, a utility will purchase the solar energy sent to the grid in the form of a bill credit to offset future electricity costs thanks to a billing structure called net metering.

Grid-tied solar panel systems are so popular because they provide the best value for how much they cost, especially in areas with full-retail net metering. Their cost is low because they require less equipment than other solar system types. However, this also means grid-tied systems can’t keep your lights on when the power is out.

I.5.2 OFF-Grid Solar System

An off-grid solar system is a solar panel system that has no connection to the utility grid at all. To keep a house running off-grid, you need solar panels, a significant amount of battery storage, and usually another backup power source, like a gas-powered generator.

Sometimes called standalone systems, they’re common among homeowners who don’t have access to the grid, like in rural areas or remote cabins. There are plenty of places throughout the country that the utility grid doesn’t service. Off-grid systems give these remote areas access to electricity. Being off-grid also makes you more self-reliant; you’re not beholden to a utility company, and the power is in your hands.

But, off-grid systems are very expensive. You need a lot of battery storage to power an entire home without help from the grid, and the cost adds up. Going off-grid also requires certain lifestyle changes. You have to be very energy-conscious when you don’t have a grid with unlimited supply. Off-grid homeowners need to monitor their consumption and solar production to ensure they have the electricity needed.

I.5.3 Hybrid Solar System

Hybrid solar systems combine the best of grid-tied and off-grid solar systems; the solar panels are attached to batteries and the utility grid. You’ll commonly see hybrid solar systems referred to as “solar-plus-storage” systems.

Solar-plus-storage systems are popular in areas that experience frequent grid failures or in places that don’t have full-retail net metering. Without a battery, solar panels can't run your home when the power goes out. Batteries also allow you to rely less on the grid by using stored energy when your solar panels aren’t producing electricity. This also maximizes the amount of clean energy your home uses

Plus, batteries can even save a bit more money if you don't have access full retail net metering. However, the high upfront cost of batteries means they often don't pencil out financially.

I.6 Relationship among PV Cell, Module and Array

Photovoltaic cells are the basic building blocks for construction of PV power systems. Typically, the amount of power delivered by a PV cell is limited to a few watts because of the surface area limitations.

This low power is not enough to reach hundreds of watts. Thus, PV cells are connected in series or parallel to form a PV module. In a similar way, it is possible to link a group of PV modules (series, parallel or both) to produce desired current ad voltage, called PV arrays, whose power range is established from kilowatts to megawatts

I.6.1 Photovoltaic Cell

A PV cell is a p-n semiconductor junction, and the most common type of cell is made from silicon. A thin semiconductor layer is specially treated to form an electric field, positive on one side and negative on the other. When the light energy of the sun hits the solar cell, this electrical field performing in a flow of current while the solar cell is linked to an electrical load.

This conversion from solar radiation into electricity occurs by a photoelectric effect. Because of the low voltage that is generated in a PV cell, which is around 0.5V, numerous PV cells are connected electrically in parallel for high current and series for high voltage [3]

I.6.2 Photovoltaic Module

The combination of PV cells sealed in an environmentally protective laminate-called PV module will produce an appreciable amount of electrical power. A PV module, which is known as a panel, is a grouping of cells. The main advantage of PV modules is that there is no moving parts, so there is no noise or emissions. Basically, PV cells are connected in parallel or series to shape a PV module for the desired output.

In fact, the power output of one module is not sufficient to achieve the demand for power in a home or business. There are two methods of connecting the modules in a PV array: in series to obtain the desired voltages or in parallel to allow the system to produce more current

I.6.3 Photovoltaic Array

A photovoltaic array is a correlation of modules, made up of many PV cells in either series or parallel. The single PV module is seldom enough for commercial use. Consequently, the PV array consists of many modules in a system. Additionally, these modules can be connected in series to increase voltage or in parallel to increase current on a single rack or multiple racks. Therefore, the PV array fulfills the requirement of power load

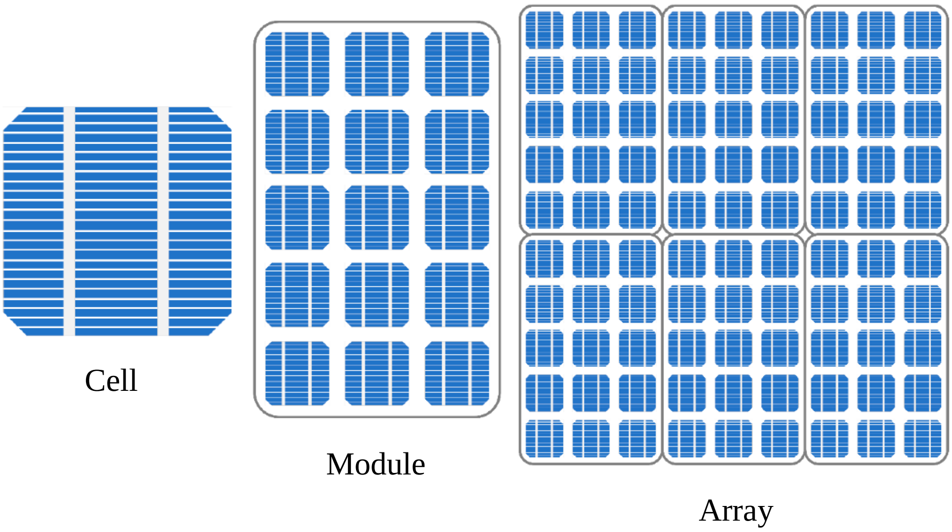


Figure I.3– Different Type of Solar Panels

I.7 Photovoltaic System

Photovoltaic (PV) cells provide an environmentally friendly a source of electricity as renewable energy.

A photovoltaic solar system consists of solar modules or arrays to absorb and convert sunlight into electricity. Grid-connected PV system applications mainly composed of five components: a PV (module or array) that converts solar energy into electric energy, a DC-DC converter that converts low dc voltages generated by the PV arrays into a high dc voltage, an inverter that converts the high DC voltage to an AC voltage, an MPPT digital controller that controls the converter operation, an AC filter that absorbs voltage, and current harmonics generated by the inverter

I.7.1 Characteristics of PV Cell

A single PV cell is a photodiode. Typically, the single cell equivalent circuit can be modeled by a current source dependent on irradiation and temperature in parallel with an inverted diode that conducts reverse saturation current.

However, no solar cell is ideal, and that means shunt and series resistances are added to the model as shown in Figure I.4. Series resistance (R) is due to hindrance in the path of flow of electrons from the n top junction, and it has intrinsic series resistance whose value is small. Shunt resistance (R) is due to the leakage current, which has a very high value

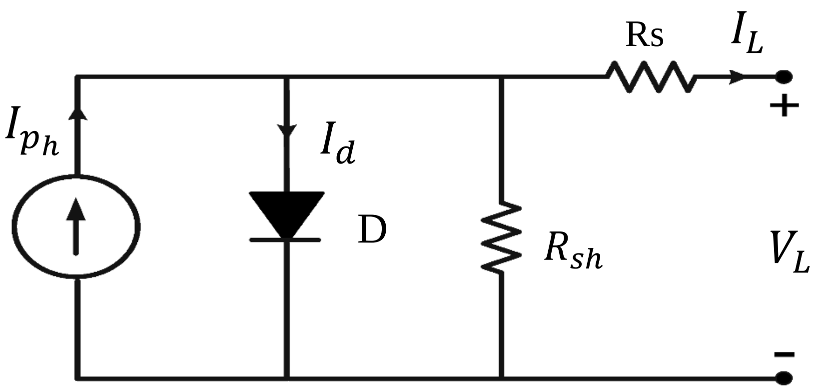


Figure I.4– Equivalent Circuit Model of a Solar Cell

The electrical equivalent circuit of solar cells is as seen in Figure I.4. The current equation in its simplest form for the equivalent circuit can be written as $I_{Pv} = I_P - I_D - I_{SH}$
Where, I_{pv} is the photocurrent generated in the cell and I_D is the current through the diode (D). I_D can be substituted with the diode equation as:

$$I_d = I_0 I_0 \left[e^{\frac{q(V_{pv}+R_S I_{pv})}{NKT}} \right] - 1 \quad \text{(I.1)}$$

Therefore, current from the solar cell can be written as:

$$I_{PV} = I_P - I_0 \left[e^{\frac{q(V_{pv}+R_S I_{pv})}{NKT}} - 1 \right] - \frac{V_{pv}+R_S I_{pv}}{R_{SH}} \quad \text{(I.2)}$$

The above equation represents ideal current from the solar cell excluding the parasitic effects. In a real solar cell, there will be a certain amount of leakage of currents through shunt resistance R_{SH} [4].

Where Ipv is photocurrent, Io is initial current, Rs is series resistance of solar cell, R_{SH} is shunt resistance of solar cell, q is the electric charge (1.602 × 10^-19 C), N is diode ideality factor, k is Boltzmann constant (1.38 × 10-23 J/K), T is temperature (in Kelvin).

When it comes to PV energy generation, PV array characteristics play a major role. These characteristics vary from one model to another. A PV characteristic has three essential points, namely open circuit voltage (Voc), short circuit current (Isc) and maximum power point (Vmpp, Impp) [17] as seen in Figure I.5, respectively.

The I_{PV}-V_{PV} operating characteristic of a solar cell can be seen above in Figure I.5. The PV array is composed of some individual PV cells that are connected together to gain a suitable power rating. The characteristic of the PV array can be determined by multiplying the current by the number of cells connected in parallel and multiplying voltage of an individual cell by the number of cells connected in series.

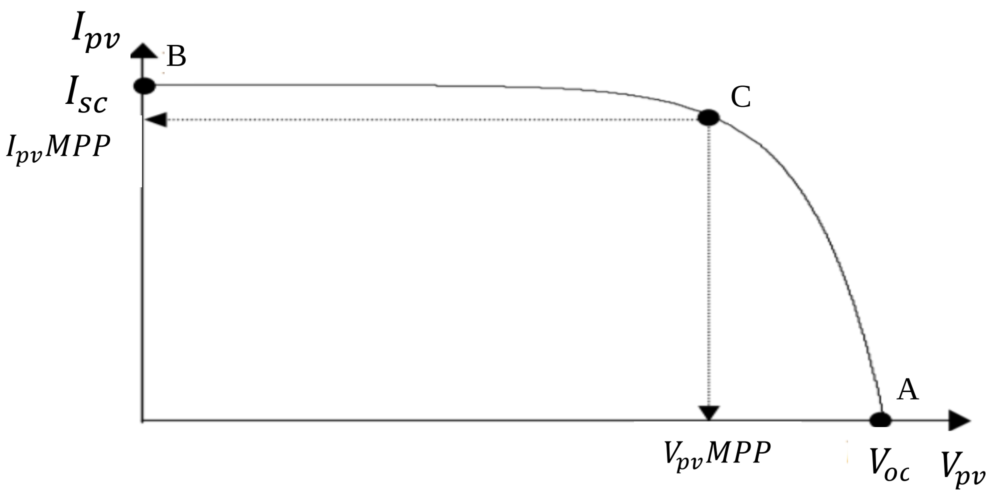


Figure I.5– PV Cell Has Three Important Operating Points

I.7.1.1 Open Circuit Voltage

The open circuit voltage (V_{oc}) has occurred when there is no current passing through the cell (At current I_{pv} = 0 and Voltage = V_{oc}).

VOC is the maximum voltage difference across the cell for a forward-bias sweep in the power quadrant. For forward-bias power quadrant, $V_{oc} = V_{max}$ Point An on-Figure I.6 illustrates the open circuit voltage. An open circuit voltage with a neglected shunt current [5][6] represents in Figure I.6

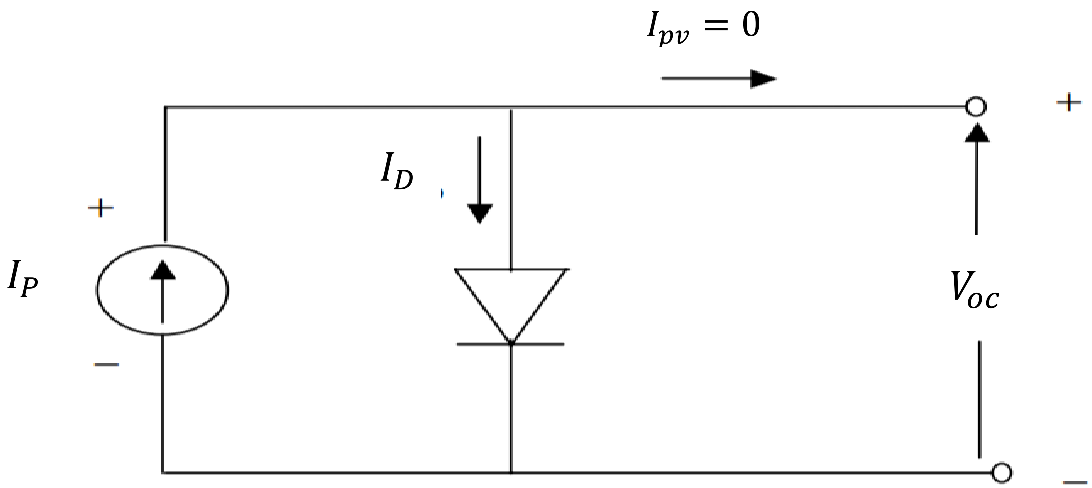


Figure I.6– Open Circuit Voltage

$$I_P - I_0 \left[\frac{qV_{oc}}{e^{nKT} - 1} \right] = 0$$

$$V_{oc} = \frac{nKT}{q} \ln \left[\frac{I_P + I_0}{I_0} \right] \qquad (I.3)$$

I.7.1.2 Short Circuit Current

The short circuit current (Isc) has occurred when the voltage equals zero. At *Vpv=0*, *Ipv=Isc*. Isc happens at the beginning of the forward-bias sweep and is the maximum current value in the power quadrant. For forward-bias power quadrant,
Point B on Figure I.5 illustrates the short circuit current. A short circuit current with the series resistance Rs neglected [6] [5] is represented in Figure I.7.

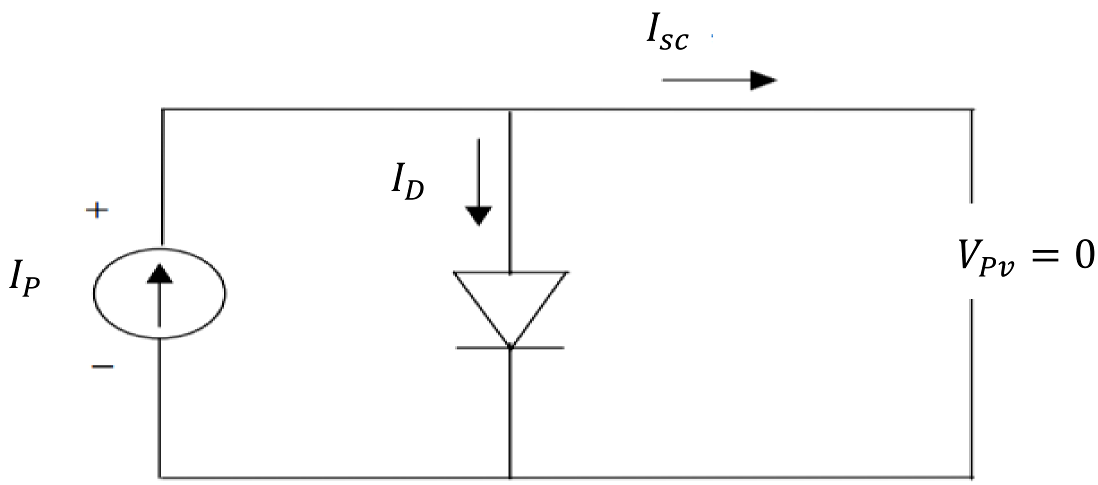


Figure I.7– Open Circuit Voltage

I.8 Non-Uniform Irradiance of Solar PV Array

The operation of PV solar panels is strongly affected by environmental conditions such as irradiance and the temperature of the PV cells. Under uniform conditions, the nonlinear electrical characteristics of PV panels have only one point at which the maximum power can be obtained. Non-uniform irradiance can have a significant effect on the operation and energy yield of the PV panels [18].

In the case of non-uniform irradiance of solar PV array, the power loss will increase proportionally to the number of shaded cells. As a consequence of a non-uniform irradiance, overheating of shaded cells will appear. In addition, the overall PV system efficiency becomes degraded due to the power loss that leads to reducing the energy yield as well. If the system is not suitably protected, a hot-spot problem can emerge, and in several cases, the system can be irreversibly destroyed. To overcome those problems, a DC-DC converter is connected to a PV array output to behave as a constant input power load [7], as shown in Figure I.8.

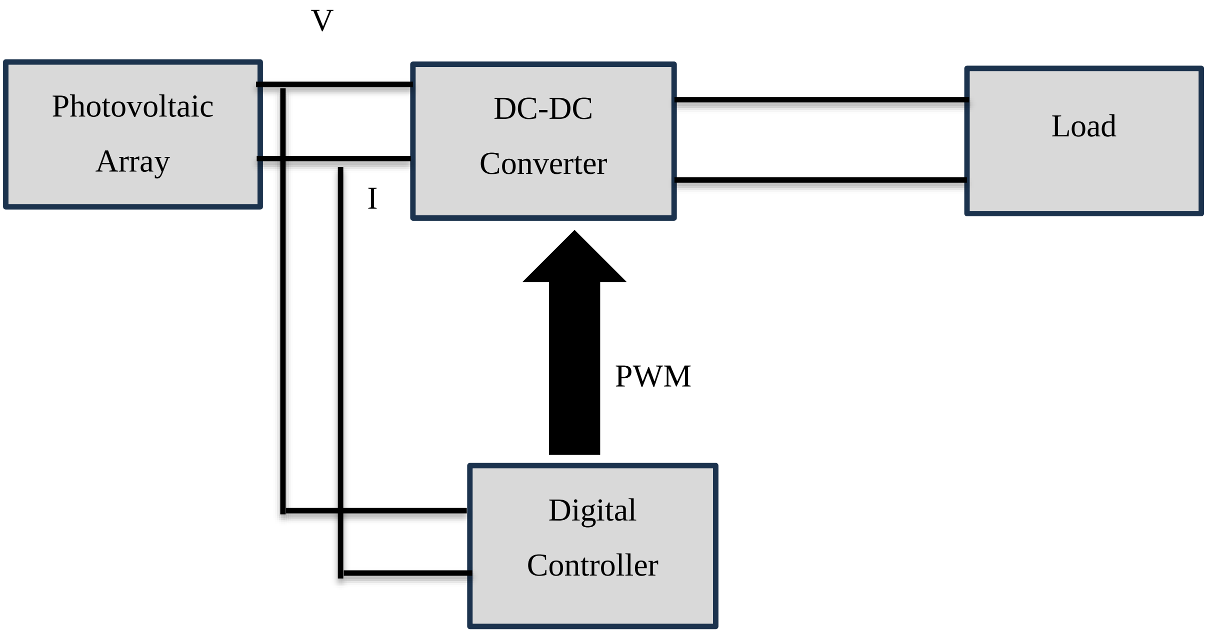


Figure I.8– General Block Diagram of an MPPT System

I.9 PV Generator (GPV)

The PV generator model is designed by MATLAB /Simulink software, MATLAB-Simulink tools were used to simulate the PV generator I-V and P-V curve under irradiance 1000W/m2 and temperature 25° C.

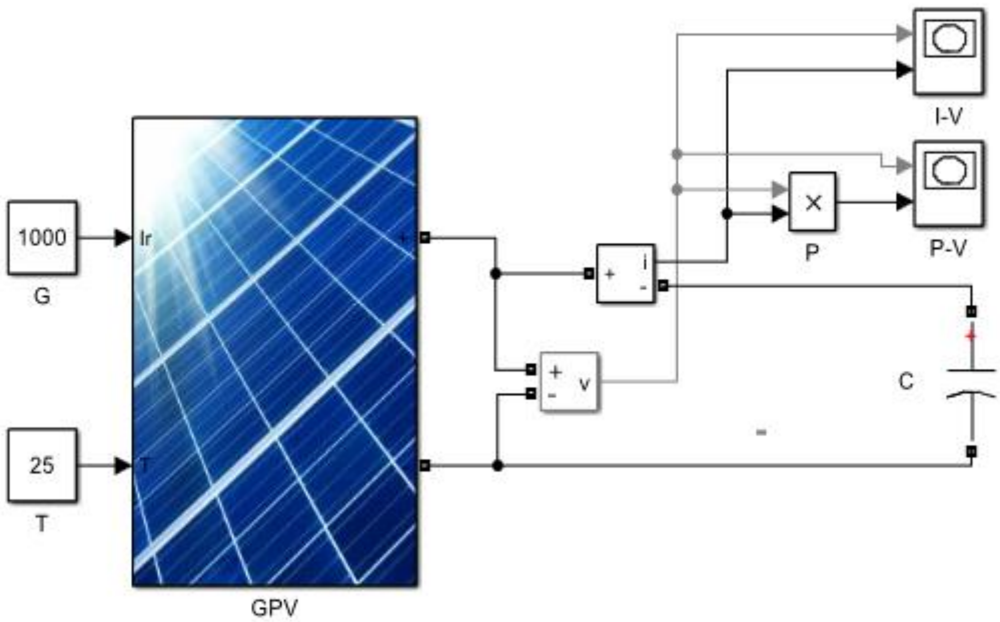


Figure I.9– PV Generator Model In MATLAB/Simulink.

Figure. I.10 and I.11 gives the electrical characteristics I (V) and P (V) of a PV generator. These curves were plotted at constant solar irradiation level of 1000W/m² and a constant temperature of 25°C. And as presented, the model data are in accordance with the experimental data both in the current and power curves as presented in Table I.1

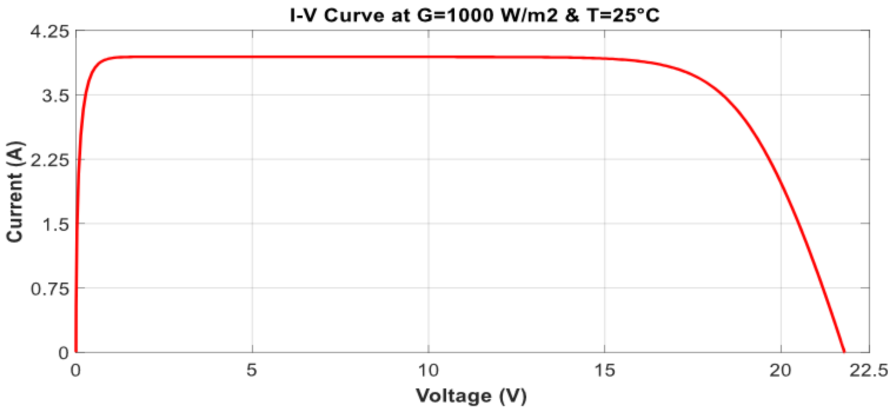


Figure I.10– PV Current-Versus-Voltage Characteristic

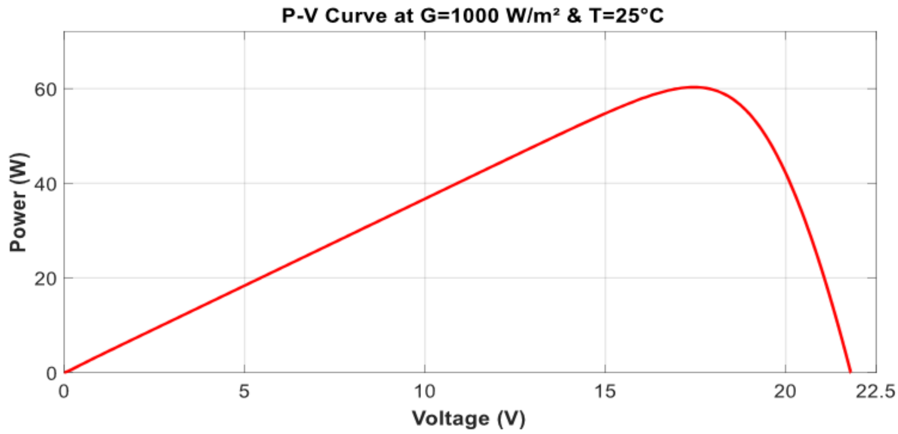


Figure I.11– PV Power-Versus-Voltage Characteristic

The influence of illumination and sunshine on the operation of the PV generator, Simulation of PV generator was performed under different irradiation and operating temperatures conditions.

The I-V & P-V curves planned through simulation are presented below in Figures I.12, I.13, I.14, and I.15.

The V-I & P-V characteristics are plotted for different irradiation levels are as follows: 1000, 800 and 600 W/m2 and a constant temperature of 25°C, and they are also plotted for different temperatures are as follows: 50, 35 and 25°C and a constant irradiation of 1000 W/m2.

The results show that the power increases with the increase in radiation level or with decreases in temperature and vice-versa. The I(V) and P(V) curves has a maximum power point; this point is associated with both current and voltage ($Impp$ and $Vmpp$). They are also not linear. The corresponding optimum voltage and current are MPPI and MPPV shown in Figure I.16.

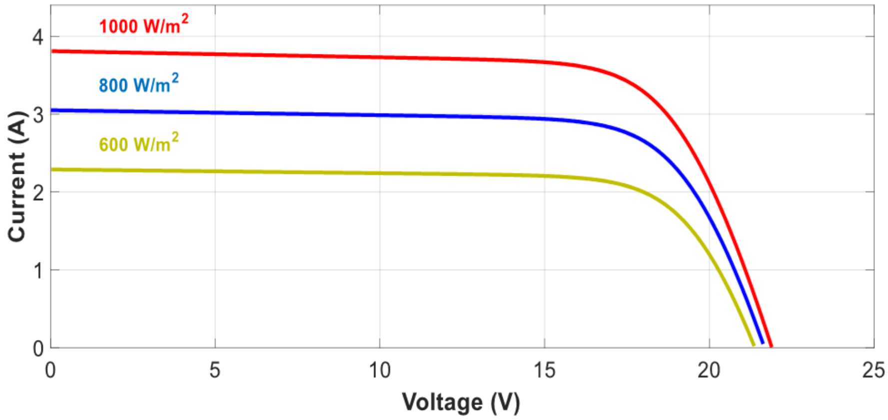


Figure I.12– I-V Curve for Different Solar Irradiance

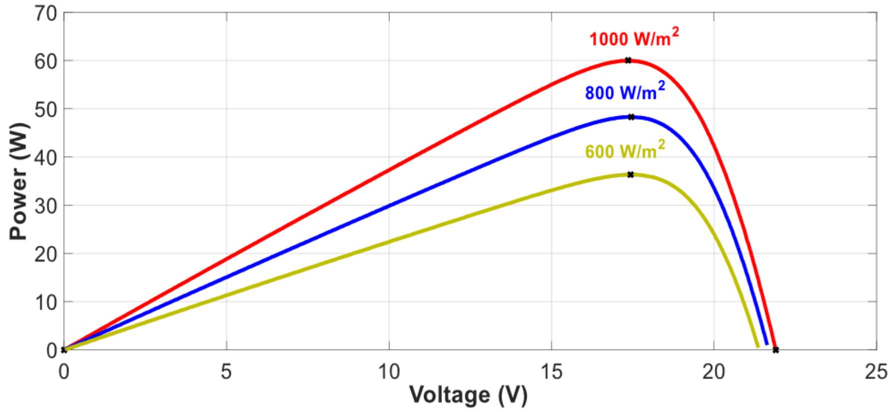


Figure I.13– P-V Curve for Different Solar Irradiance

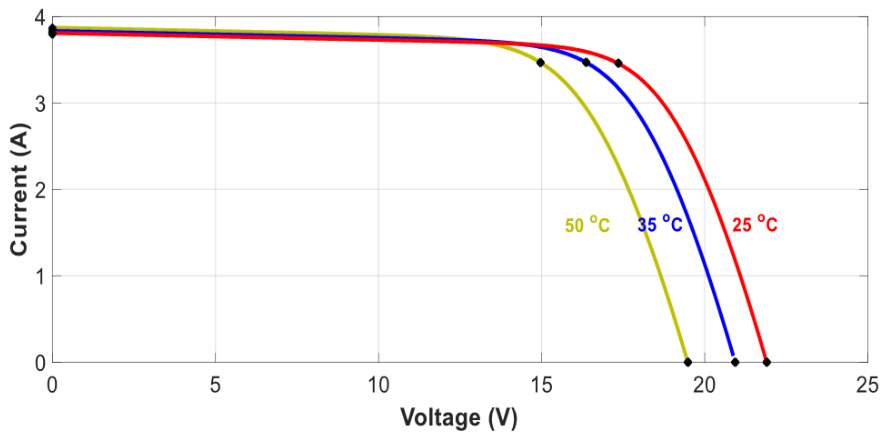


Figure I.14– I-V Curve for Different Solar Temperature

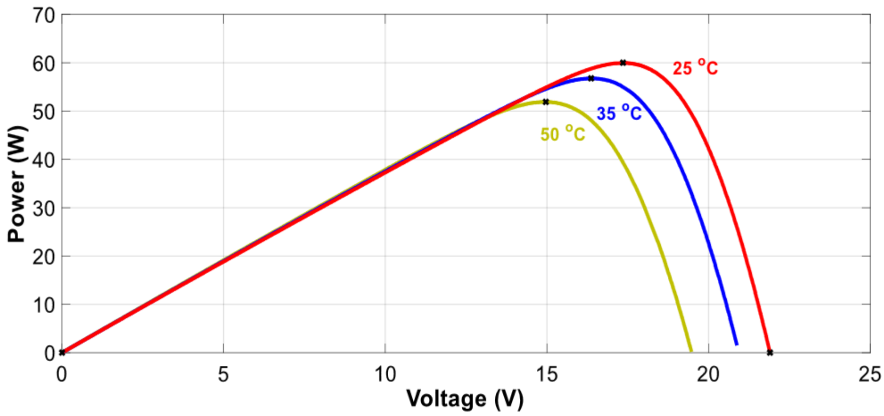


Figure I.15– P-V Curve for Different Solar Temperature

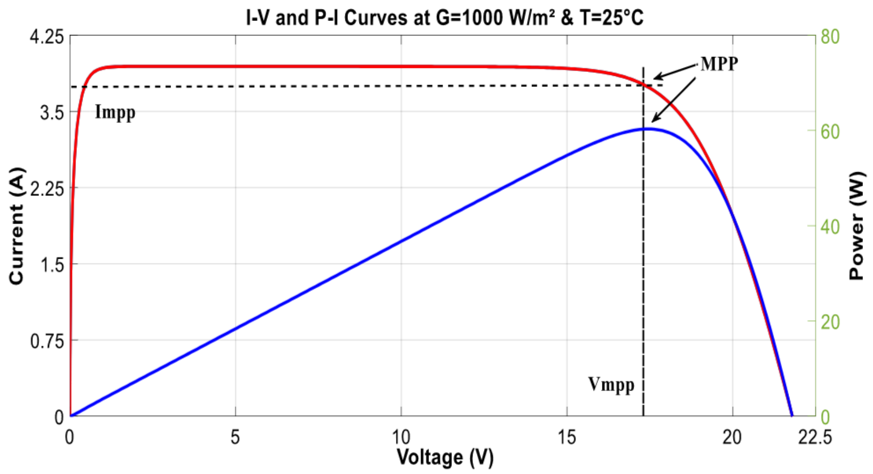


Figure I.16– I-V and P-V Characteristics under 25°C and 1000 Watts/M²

Table I.1 – Electrical Parameters of the PV Model

Parameters Of the Pv Model	
Maximum Power	60.03W
Voltage MPP	17.35V
Current MPP	3.46A
Open Circuit Voltage	21.3V
Short Circuit Current	3.8A

I.10 Solar PV Array under Partial Shading Condition

It is a well-documented fact that the output power capacity will be reduced by a partial shading of a photovoltaic array; however, the reduction in energy production cannot be determined in a direct method, as it is frequently not proportional to the shaded area.

Some of the previous studies supposed that the decrease in power production is proportional to the shaded area and reduction in solar irradiance as well [19]. In actuality, this concept is valid for just a single cell. The power reduction at the array level is predominantly far away from linearity with the shaded portion.

Numerous factors can influence the performance of a photovoltaic (PV) system. One of the most significant factors is shading. Shading indicates a shadow on the PV modules on the outer surface that will decrease the system energy yield. As a consequence, the three fundamental PV module characteristics of power, voltage, and current will be affected. With changing irradiation during the day, the array output varies in a wide range. This variation of array output is expected [20].

However, uniform lighting concentration in a panel is not roughly satisfied due to unexpected shading effects caused by dust, clouds, trees, buildings, atmosphere fluctuation, an existence of clouds, and daily sun angle changes causing shading on cells or side of modules as shown in Figure I.17

Shade impact depends on module type, fill factor, bypass diode placement gravity of shade, and string configuration. Power loss happens from the shade as well as current mismatch within a PV string and voltage mismatch between parallel strings [8].

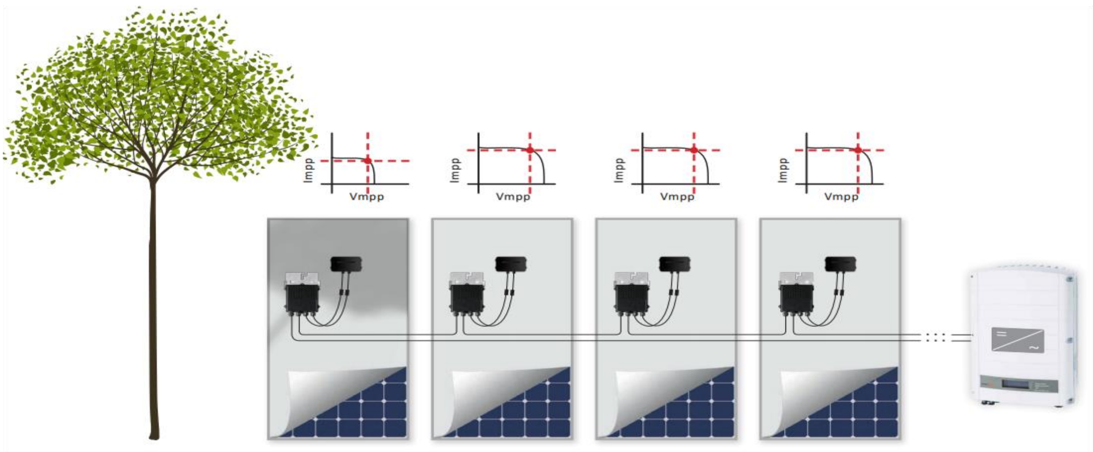


Figure I.17– Partial Shaded Of Module

PV solar panels are very sensitive to shading. In PV systems, it is virtually impossible to utterly avoid shading [16]. Looking at the electrical characteristics of PV solar panels, partial shading effect results in a distortion of the overall I-V and P-V curves of the PV solar panels. As a result, the I-V and P-V characteristics of the solar panels become more complex with existing multiple maximum power points (MPP) under the non-uniform irradiance conditions. This effect can be considerably different in shape compared to a normal unshaded curve as seen in Figure I.18 and I.19 respectively.

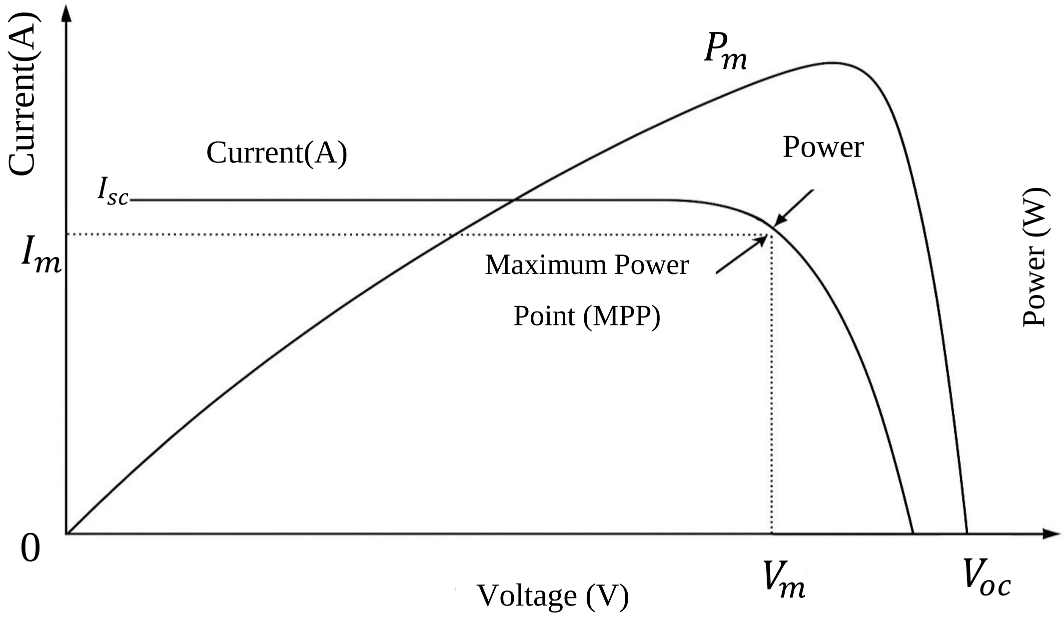


Figure I.18– I-V and P-V Characteristic of the Solar Array

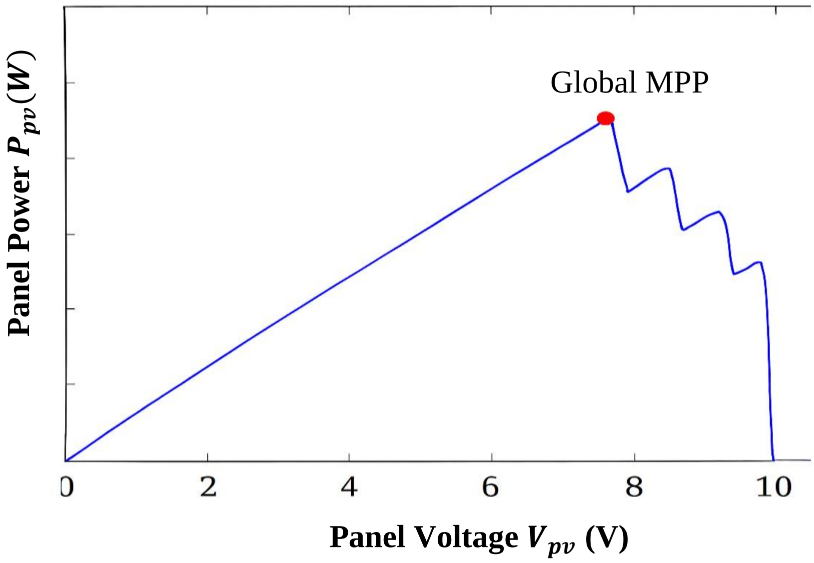


Figure I.19– P-V Curves of PV Array under Partial Shading Condition

The total output power of a PV module will be reduced by a shadow falling on it from two mechanisms, which are reducing the energy input and increasing energy losses. Even though only one cell is shaded in the PV module, around 30% power loss will happen. The power losses will increase proportionally to the number of shaded cells.

A partial shading problem results in a deformity of the overall I-V curve, and this impact can be illustrated by the mismatch between the individual modules' I-V curves [9].

I.11 Importance of MPPT for Photovoltaic Systems

Solar radiation that hits the photovoltaic modules has a variable character depending on the position, the direction of the solar field, the season, and the hour of the day. During the line of a day, a shadow may be decanted on the cell, which may be contemplated, as in the case of a structure near the solar field, or unforeseeable as those created by clouds. The advance of PV systems as distributed power generation systems has increased drastically in the last many times. Because of this Maximum Power Point Tracking (MPPT) is getting more and more substantial as the amount of energy generated by PV systems is adding [12].

An MPPT technique must be used to track the maximum power point since the MPP depends on solar irradiation and cell temperature. In general, when the impedances of the load and source are matched, the maximum power is transferred to the load from the source only. The generated energy from PV systems must be maximized, as the effectiveness of solar panels is low [21].

For that reason, to get the maximum power, a PV system is constantly equipped with an MPP tracker. Several MPP pursuit techniques have been proposed and enforced in recent times

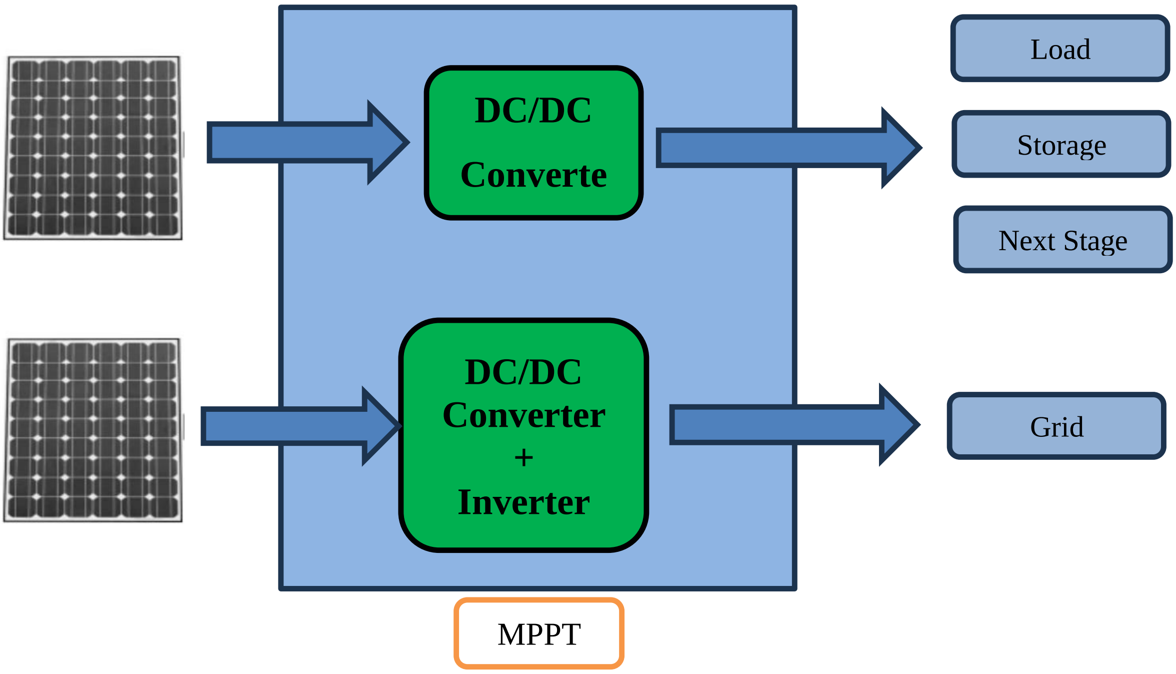


Figure I.20– Need for MPPT

The use of the recently developed power control mechanisms, called Maximum Power Point Tracking (MPPT) algorithms, has led to increasing the efficiency of the operation of the solar modules. Therefore, MPPT is efficient in the field of exploitation of renewable sources of energy [MPPT technics]. Maximum power point tracking is a DC-to-DC converter that optimizes the match between the solar array (PV modules) and the battery bank or utility grid. It converts a higher voltage DC output from solar PV arrays or modules down to the lower voltage needed to charge batteries and vice versa. Maximum Power Point Tracking is an electronic arrangement that routinely finds the voltage (VMPP) or current (IMPP) at which PV modules should operate to achieve maximum power output (PMPP) under partial shading conditions. It runs the PV modules in a way that allows the modules to generate all the power they are capable of producing [10].

MPPT is an electronic tracking system, whether digital or analog. There are many approaches to finding and tracking the maximum power point for PV cells. For instance, neural network, open circuit voltage, short circuit current, fuzzy logic control, perturb and observe, and incremental conductance are the most popular methods to track the maximum power point tracking. As a matter of fact, many systems have combined methods, for example, using the open circuit voltage (OV) to find the starting point for the iterative methods such as Perturbation and Observation or Incremental. The levels of irradiance play an important part in changing from one scheme to another. For example, at low levels of irradiance, methods like open circuit voltage and short circuit current could be more suitable as they can be more noise-immune. When the cells are connected in a series, the iterative methods can be a preferable solution. When a portion of the string is in partial shade, search algorithms are needed [11].

In general, the accurate method is better than the fast method because fast methods tend to bounce around the maximum power point due to noise present in the power conversion system. Of course, an accurate and fast method would be preferred, but the cost of implementation needs to be considered.

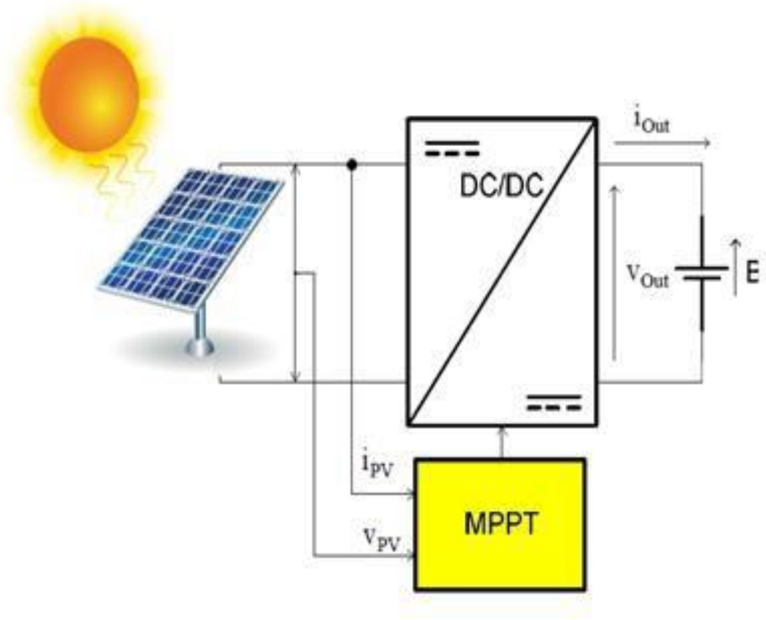


Figure I.21– MPPT Technique with Solar Cell

I.12 DC-DC Converter

A DC-DC converter is a vital part of alternative and renewable energy conversion, portable devices, and many industrial processes. It is essentially used to achieve a regulated DC voltage from an unregulated DC source, which may be the output of a rectifier or a battery or a solar cell, etc. Nevertheless, the variation in the source is significant, mainly because of the variation in the line voltage, running out of a battery, etc., but within a specified limit. DC-DC converters are one of the important electronic circuits that are widely used in power electronics.

The main problem with the operation of DC-DC converters is unregulated power supply, which leads to improper function of DC –DC converters. There are various analogue and digital control methods used for DC-DC converters, and some have been adopted by the industry, including voltage- and current-mode control techniques. The DC-DC converter inputs are generally unregulated DC voltage inputs, and the required outputs should be a constant or fixed voltage [22].

The application of a voltage regulator is that it should maintain a constant or fixed output voltage irrespective of variation in load current or input voltage.

Various kinds of voltage regulators with a variety of control schemes are used to enhance the efficiency of DC-DC converters. Today due to the advancement in power electronics and improved technology a more severe requirement for accurate and reliable regulation is desired. This has led to need for more advanced and reliable design of controller for dc-dc converters.

Basically, two inductors are used for feeding the load by two independents switches. One inductor charges up by load voltages and another inductor discharges its energy into load during this time. The output power is almost doubled, where the ripple voltage is reduced by a factor of two when compared to the conventional DC to DC converter [13].

I.12.1 Buck Converter

Figure I.22 shows a simplified electric schematic of a basic buck converter. When the switch is on, the power supply is connected to the inductor and the diode is reverse polarized. A current flows in the inductor L, which results in accumulating energy in the inductor. When the transistor turns off, the energy stored in the inductor is output through the diode D. DC-DC buck converter operates as a step-down system that will step down the high input voltage to the low output voltage which the magnitude of output voltage is always lower than the input voltage. The objective of this circuit is to produce a purely DC output by adding the LC low pass filter to the basic circuit of this converter. This DC-DC buck converter can be connected to low voltage DC load or battery bank from a high PV array voltage [14].

The dynamics of the converter in one switching period is represented by the following system:

$$\begin{cases} C_1 \frac{dv_{in}(t)}{dt} = i_{in}(t) - di_L(t) \\ C_2 \frac{dv_{out}(t)}{dt} = i_L(t) - i_{out}(t) \\ L \frac{di_L(t)}{dt} = dv_{in}(t) - v_{out}(t) - R_L i_L(t) \end{cases} \quad \text{(I.4)}$$

Where $i_{in}(t)$, $i_{out}(t)$ and $i_L(t)$ are the input, the output and the inductor current, respectively. $v_{in}(t)$, $v_{out}(t)$ and $v_L(t)$ are the input, the output and the inductor voltgae, respectively.

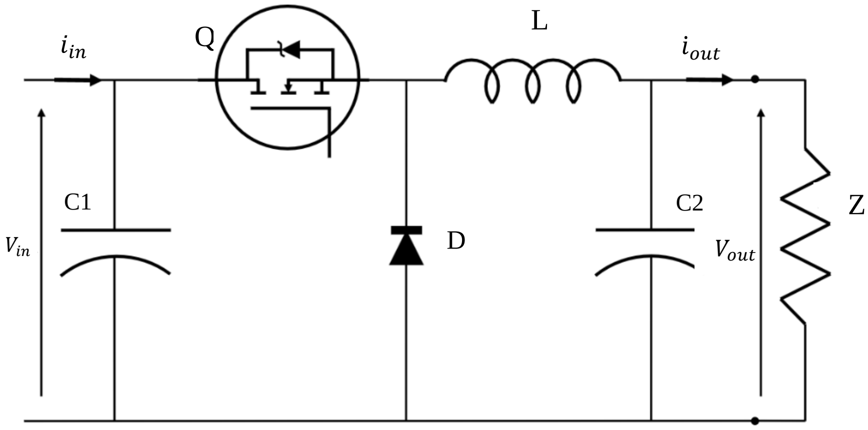


Figure I.22– Electrical Circuit of a Buck Converter

I.12.2 Boost Converter

Another basic switched-mode converter is the boost converter shown in Figure I.23. This converter converts an input voltage to a higher output voltage. It is also named the step-up converter. The transistor works as a switch which is turned on and off by a pulse-width modulated control voltage. During the on-time of the transistor, the voltage across L is equal to Vin and the inductor current increases linearly. When the transistor is turned off, the inductor current flows through the diode and charges the output capacitor. The function of the boost converter can also be described in terms of energy balance: During the on-phase of the transistor, energy is loaded into the inductor.

This energy is then transferred to the output capacitor during the blocking phase of the transistor. The output voltage is always larger than the input voltage. Even if the transistor is not switched on and off the output capacitor charges via the diode until $v_{out}(t)$=$v_{in}(t)$. When the transistor is switched the output voltage will increase to higher levels than the input voltage [14].

The dynamics of the converter in one switching period is represented by the following system:

$$\begin{cases} C_1 \frac{dv_{in}(t)}{dt} = i_{in}(t) - i_L(t) \\ C_2 \frac{dv_{out}(t)}{dt} = (1-d)i_L(t) - i_{out}(t) \\ L \frac{di_L(t)}{dt} = v_{in}(t) - (1-d)v_{out}(t) - R_L i_L(t) \end{cases} \quad (I.5)$$

Where $i_{in}(t)$, $i_{out}(t)$ and $i\ (t)$ are the input, the output and the inductor current, respectively. v_{i} i_{in} $_{out}(t)$ and L(t) are the input, the output and the inductor voltage, respectively.

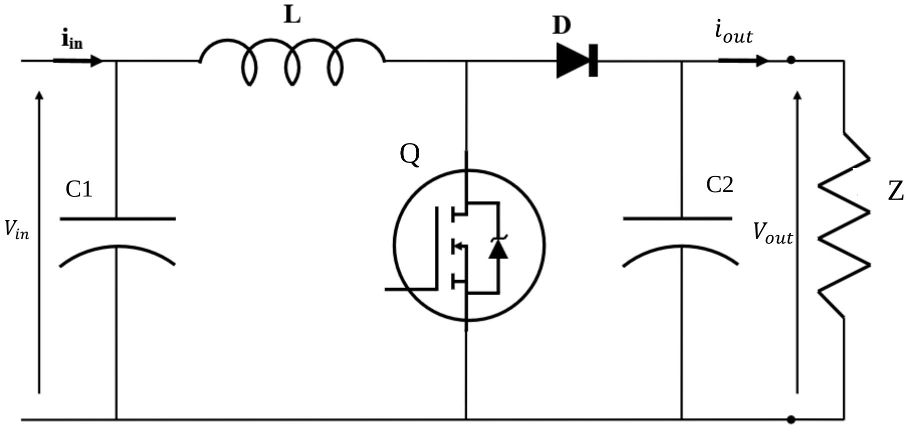


Figure I.23– Electrical Circuit of a Boost Converter

I.12.3 Buck Boost Converter

Figure I.24 shows a simplified electric schematic of a basic inverting buck-boost converter. During the closing time dT_s of the transistor, the source voltage v_{in} is applied across the inductor L, which results in accumulating energy in the inductor. During the opening period (1 − d) T_s, the diode D is forward-biased and the voltage of the inductance is applied to the load Z. The current flows anticlockwise through the diode D. Thus, the output voltage will be negative [14]

The dynamics of the converter in one switching period is represented by the following system:

$$\begin{cases} C_1 \frac{dv_{in}(t)}{dt} = i_{in}(t) - di_L(t) \\ C_2 \frac{dv_{out}(t)}{dt} = -(1-d)i_L(t) - i_{out}(t) \\ L \frac{di_L(t)}{dt} = dv_{in}(t) + (1-d)v_{out}(t) - R_L i_L(t) \end{cases} \quad (I.6)$$

Where $i_{in}(t)$, $i_{out}(t)$ and $i_L(t)$ are the input, the output and the inductor current, respectively. $v_{in}(t)$, $v_{out}(t)$ and $v_L(t)$ are the input, the output and the inductor voltgae, respectively.

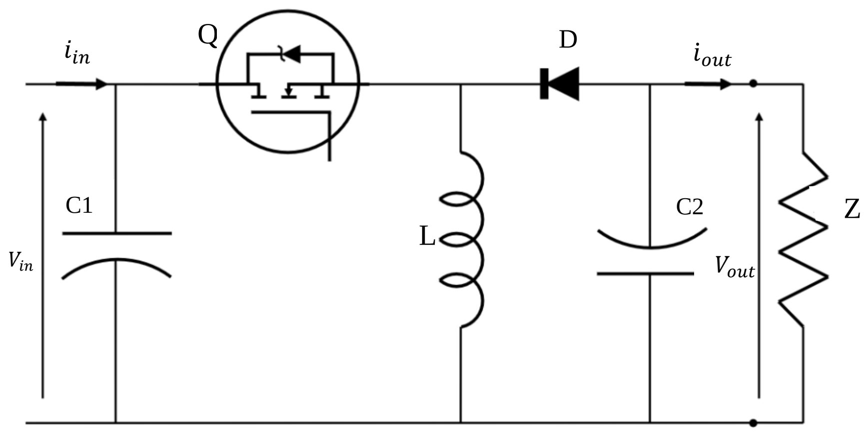


Figure I.24– Electrical Circuit of a Buck-Boost Converter

I.13 Conclusion

Photovoltaic (PV) solar systems are a clean and renewable energy solution that converts sunlight directly into electricity through the photovoltaic effect, where solar radiation excites electrons within semiconductor materials, generating direct current (DC). These systems are categorized into three main types: grid-tied systems, which are connected to the public electricity grid and typically do not use batteries; off-grid systems, which operate independently and rely on battery storage; and hybrid systems, which combine grid connection and battery storage for greater reliability. Key characteristics of PV cells include the open-circuit voltage (Voc), which is the maximum voltage when the cell is not connected to a load, and the short-circuit current (Isc), the maximum current when the cell's terminals are directly connected with no resistance. Both parameters are essential in analyzing the performance of a solar panel under standard test conditions.

However, PV systems can experience reduced efficiency under partial shading, where even a small shadow on part of a solar array can drastically lower output due to the series configuration of cells, causing mismatch losses and potential hot spots. To counter these issues and maximize energy extraction, Maximum Power Point Tracking (MPPT) is implemented. MPPT algorithms continuously track and adjust the operating point of the PV system to ensure it always works at its optimal power output despite changes in sunlight or temperature. This is done in conjunction with a DC-DC converter, which regulates the output voltage and current to match the load or battery requirements, ensuring stable and efficient power delivery.

Overall, the integration of MPPT and DC-DC converters significantly enhances the performance of PV systems, making them more effective even under variable environmental conditions. Understanding the types, characteristics, and critical components of solar PV systems is essential for designing reliable, high-efficiency renewable energy solutions.

Chapter II. Efficiency Improvement in Solar Panels Using MPPT Technology

Chapter II. Efficiency Improvement in Solar Panels Using MPPT Technology

II.1 Introduction

Our ever-depleting conventional energy resources call for immediate measures and a switch to greener energy. Presently, we are entirely dependent on non-renewable Energy resources pose a serious threat to a sustainable future. Thus, the present scenario demands a clean and green energy

The most widely popular renewable energy resources include a photovoltaic system, wind turbines, and an energy storage system used for the generation of electricity. Among them, Solar cells are most viable owing to their use in various fields of application, both residential and industrial. D.C power is more preferred than A.C because of lower losses. Photovoltaic systems are thus more useful as they provide a D.C output. Modeling of photovoltaic devices and simulating their behavior represents a significant portion of today's research in the field of solar energy.

The photovoltaic systems, although being environmentally friendly, suffer from a few major flaws. The most notable being their efficiency of conversion of solar energy to electrical energy. This drawback has been considered, and an improved approach for utilizing solar power has been developed in this paper.

Perturb and observe algorithm has been implemented to obtain a more optimized system. The developed model works at a higher efficiency. The other benefit of this model is that it can serve as the base model for the implementation of other MPPT techniques. And the equivalent circuit is used for modelling because it allows performing a joint simulation of the photoelectric device with power electronics interfaces. Such Simulations aid us in optimizing the system before practical application, thus being cost-effective. The yardstick of a good Photovoltaic Generator is its efficiency, which can be carried out if it is constantly converts the maximum of the available solar power to all the time. Thus, we can state the maximum power delivered, should always be in harmony with the prevailing conditions, i.e., irradiance, temperature, wind speed (in the case of windmills) for keeping the MPP [maximum power point] at its global maximum.

Maximum power production is performed by a voltage converter associated with an electronic maximum power point tracking (MPPT) system. The influences of irradiance and temperature on the power output of the PV modules are also taken into account. The most commonly used MPPT technique, which is based on the Perturb and Observe (P&O), is tested under MATLAB/Simulink environment.

II.2 The Proposed Method

The desired power output is obtained by joining several PV cells together. The block diagram of the proposed model is given in Figure II.1 shows a PV system where a PV array feeds a DC-DC converter. The output of the converter is represented by a constant DC voltage source. This kind of converter with constant output voltage may be used in battery charging systems or in systems with a second cascaded conversion stage (e.g. DC-AC). The output power of the PV array is regulated by the converter. In this example the MPPT block observes the power at the terminals of the array and controls the input voltage or the input current of the converter, forcing the PV array to operate at the maximum power point. Depending on the converter topology one may choose the voltage or current as the control variable. Because the input current of the buck converter is discontinuous and the capacitor provides a low voltage ripple, the MPPT algorithm can be used to control the output voltage of the PV array. The output capacitor C is necessary to keep the array output voltage constant and to filter the discontinuity of the buck input current.

Of course, one can chose to measure the output current of the PV array before the capacitor and use the current as the control variable. Yet another possibility is to control the output current of the buck converter and observe the output power of the converter instead of observing the output power of the PV array. If a boost converter is employed, the output current of the PV array and the converter inductor current are the same, so the MPPT algorithm can observe the array output power and optionally use the converter inductor current as the control variable.

Many configurations and control schemes are possible and each one presents pros and cons. If the MPPT algorithm observes the converter output power the global efficiency of the system (including the PV array and the converter) is considered and the system output power is optimized. If the MPPT observes the array output power only the PV array power is optimized and the converter efficiency is not taken into account. Because converter efficiencies for PV applications are generally very high, in practice there is little or no difference on the system performance depending on the MPPT configuration employed [23].

II.3 Perturbation and Observation

The turbulence stages size is lowered to prevent oscillation, yet the process of getting to the MPP point is slowed significantly by this. This approach creates a basic closed-loop regulator with only a few controllable parameters. By regularly adjusting the solar panel voltage by means of a miniscule incremental stage to lessen the fluctuation round an MPP or

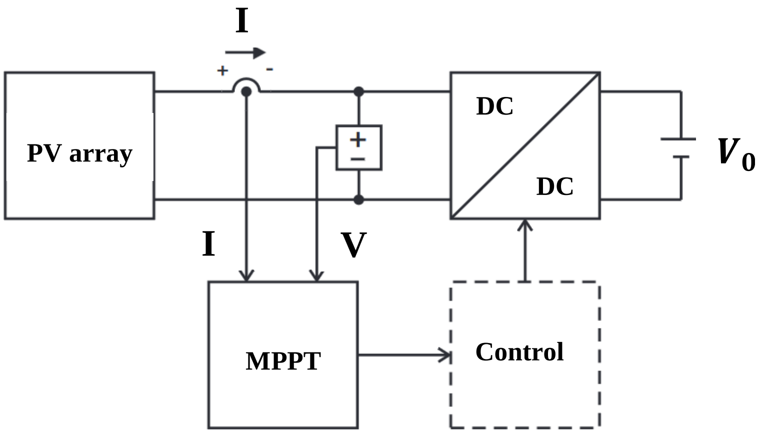
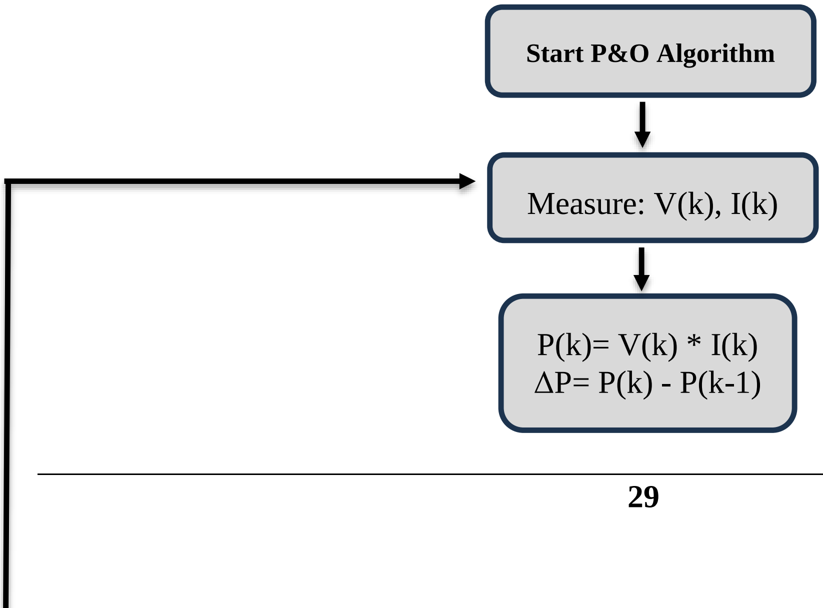


Figure II.1– PV Array Feeding A DC-DC Converter With Constant Output Voltage

any intended stage, the P&O algorithm made a comparison of the power that was previously given with the one following a disruption. Because of its simplicity and the fact that it only involves a few measured parameters, such algorithm was commonly used commercially Figure II.2 depicts the P&O algorithm flowchart [15].

The P&O approach regularly changes the PV output voltage through the terminals then compares a former cycle strength with present one. Whether voltage and power are straight connected, so that when one rises, the second rises besides, an equipment for regulating position adapts accordingly; an operating point then exchanges to the other direction. The existing changes at a steady pace after the current shift position is detected [24]. This level is a variable that may be changed to apportion stability among quick feedbacks by reducing state variance.



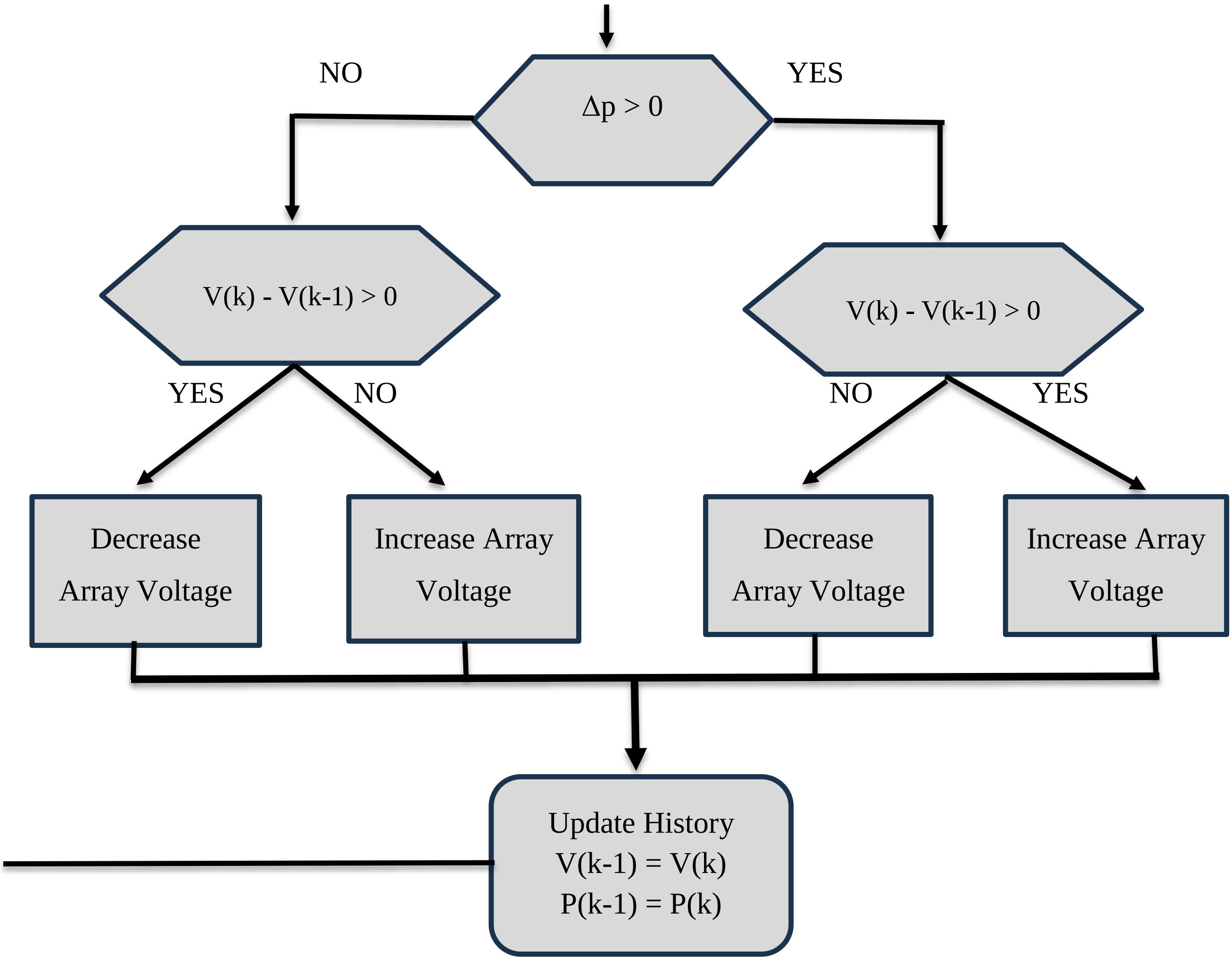


Figure II.2– Flowchart Of Perturb & Observe Algorithm

The Perturb & Observe algorithm states that when the operating voltage of the PV panel is perturbed by a small increment, if the resulting change in power ΔP is positive, then we are going in the direction of MPP and we keep on perturbing in the same direction. If ΔP is negative, we are going away from the direction of MPP and the sign of perturbation supplied has to be changed.

Figure II.3 shows the plot of module output power versus module voltage for a solar panel at a given irradiation. The point marked as MPP is the Maximum Power Point, the theoretical maximum output obtainable from the PV panel. Consider A and B as two operating points. As shown in the figure above, the point A is on the left-hand side of the MPP. Therefore, we can move towards the MPP by providing a positive perturbation to the voltage. On the other hand, point B is on the right-hand side of the MPP. When we give a positive perturbation, the

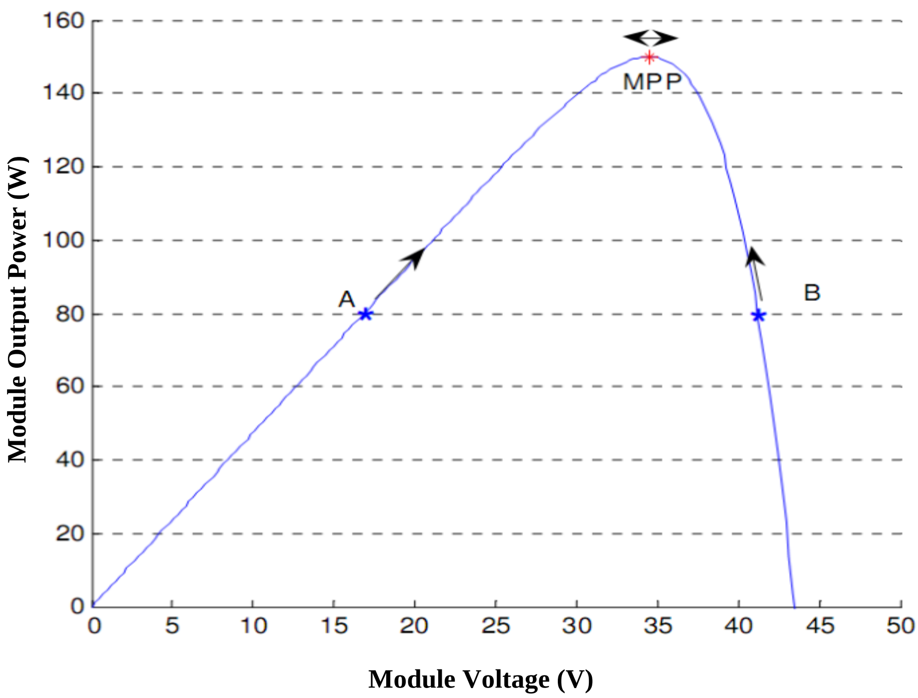


Figure II.3– Solar Panel Characteristics Showing MPP And Operating Points A And B

value of ΔP becomes negative, thus it is imperative to change the direction of perturbation to achieve MPP. The flowchart for the P&O algorithm is shown in Figure II.2

II.3.1 Limitations Of Perturb & Observe Algorithm

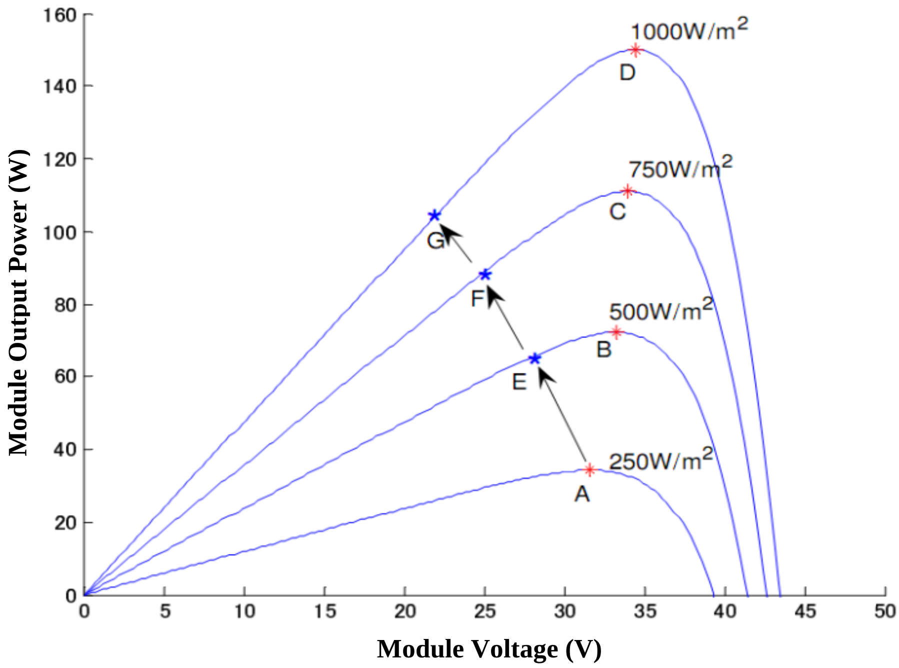


Figure II.4– Curve Showing Wrong Tracking Of MPP By P&O Algorithm Under Rapidly Varying Irradiance

In a situation where the irradiance changes rapidly, the MPP also moves on the right-hand side of the curve. The algorithm takes it as a change due to perturbation and in the next iteration it changes the direction of perturbation and hence goes away from the MPP as shown in the figure II.4.

However, in this algorithm we use only one sensor, that is the voltage sensor, to sense the PV array voltage and so the cost of implementation is less and hence easy to implement. The time complexity of this algorithm is very less but on reaching very close to the MPP it doesn't stop at the MPP and keeps on perturbing in both the directions. When this happens the algorithm has reached very close to the MPP and we can set an appropriate error limit or can use a wait function which ends up increasing the time complexity of the algorithm [25].

II.3.2 Positives and Negatives Of the Perturb and Observe (P&O)

Here's a clear and structured summary of the positives and negatives of the Perturb and Observe (P&O) algorithm used in MPPT (Maximum Power Point Tracking) [26] for photovoltaic (PV) systems:

The Positives (advantages) of the P&O Algorithm are given below:

- Simplicity: Easy to understand and implement on microcontrollers;
- No prior knowledge required: Does not require the PV module's characteristics (like I-V curves);
- Cost-effective: Requires minimal hardware and computational power;
- Real-time response: Can operate in real time and track MPP under slowly changing irradiance and temperature [30];
- Wide adoption: Well-tested and supported in literature and industry, making troubleshooting easier [30];
- Suitable for small to medium PV systems: Effective in low-cost or standalone applications where performance trade-offs are acceptable [30].

The Negatives (Disadvantages) of the P&O Algorithm are given below:

- Oscillations around MPP: Keeps perturbing even after reaching MPP, causing power losses;
- Slow dynamic response: Not efficient under rapidly changing irradiance (e.g., passing clouds) [30];
- Drift problem: May lose track of MPP during fast environmental changes (irradiance or load) [30];

- Fixed step size issue : A small step slows response, while a large step causes more oscillation — trade-off is unavoidable [30];
- Suboptimal in shaded conditions : Performs poorly in partial shading, as it can get stuck in local maxima instead of the global MPP [30];
- Lacks intelligence: No adaptive or predictive control — reacts only to immediate changes in power [30].

II.4 Modeling Of the Perturb and Observe (P&O)

The total MATLAB/Simulink execution may be seen at Figure II.5, that involves PV generator represented by a group of panels connected in series and parallel, where a solar panel an of BP Solar SX3200W is utilized, DC-DC buck converter, and MPPT algorithm which is based on the P&O algorithm for controlling the converter's duty cycle, in addition to resistive load. Table II.1 shows specifications of the PV panels and buck converters which were in employment. Double scenarios of changing solar irradiation are run in this section of the simulation in parallel to examine the effectiveness and precision of the suggested MPPT tactic for tracking accessible power in various insolation situations and conversion points.

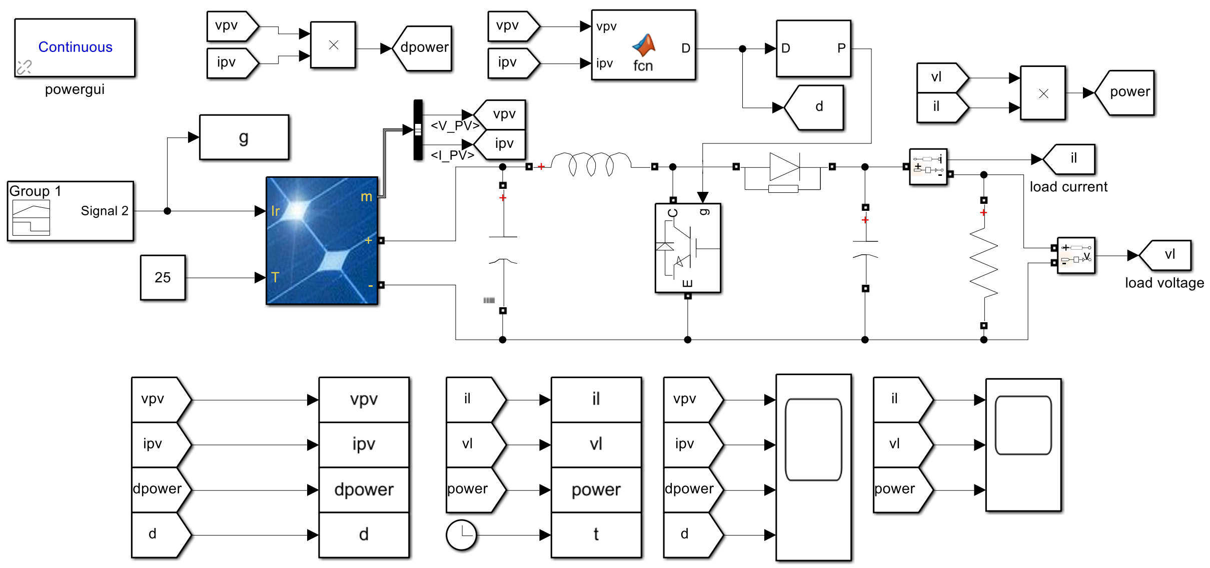


Figure II.5– SIMULINK Model of MPPT System Using P&O Algorithm

To evaluate the performance of the MPPT-P&O control under different environmental conditions, the following test is performed:

II.4.1 Irradiation Signal

Variable irradiance and constant temperature to observe the effect of solar irradiance G on power, the temperature is maintained at a constant value (T = 25°C) while the solar irradiance changes rapidly. Figure II.6 shows the cross-section of the considered solar irradiance profile. It should be noted that during a 2-second interval, the curve includes rapid changes from 800 W/m² to 1000 W/m² to 700 W/m² in order to test the performance of the P&O-type MPPT algorithm.

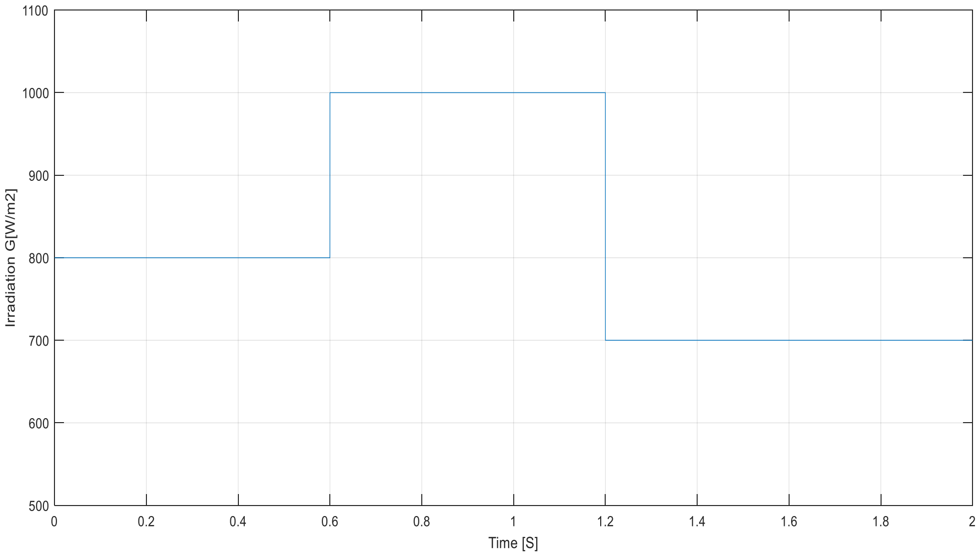


Figure II.6– Irradiation Signal

Table II.1 – Parameters of the adjusted model of the BP Solar SX3200W solar array at nominal operating conditions

Parameter	Typical Value
Maximum Power (Pmax)	*199.92 W*
Open Circuit Voltage (Voc)	*30.8 V*
Voltage at MPP (Vmp)	*24.5 V*
Temperature Coefficient of Voc (%/deg.C)	*-0.33*
Cells per module (Ncell)	*50*
Short Circuit Current (Isc)	*8.7 A*
Current at MPP (Imp)	*8.16 A*
Temperature Coefficient of Isc (%/deg.C)	*0.1*

II.4.2 MPPT Interfacing

The controlled voltage source and the current source inverter have been used to interface the modeled panel with the rest of the system and the boost converter which are built using the

SIMULINK MATLAB. The block diagram for the model shown in Figure II.5 is a simulation for the case where we obtain a varying voltage output. This model is used to highlight the difference between the power obtained on using an MPPT algorithm and the power obtained without using an MPPT algorithm.

II.4.3 Boost Converter

A boost converter has been used in our simulation. It finds applications in various real-life scenarios like charging of battery bank, running of DC motors, solar water pumping etc. The simulation.

Table II.2 – Different Parameters of the Standalone PV System

Parameter	Value taken for simulation
No of solar cells in series (NS)	*12*
No of rows of solar cells in parallel	*17*
Resistance of load (R)	*20*Ω
Capacitance of boost converter (C)	*40µF / 300µF*
Inductance of boost converter (L)	*0.8 mH*
Switching frequency of PWM	*50KHz*

II.5 Results and Discussions

The variations of voltage GPV voltage, current, and power for variable sunlight with time are shown in the various graphs. The irradiance is varied and the characteristics curves of voltage, current, and power are plotted with respect to time. From the graphs, the outputs as obtained are shown in Figure II.7 to II.18

Figure II.7 to II.18 presents the simulation results obtained for the P&O-type MPPT control applied to the GPV. For a solar irradiance of 1000 W/m² during the time interval t = [0.6s; 1.2s], the optimal operating point of the photovoltaic array corresponds to a power of 40.644 kW, the voltage varies around its optimal value Vmpp of 299 V, and the current varies around its optimal value Impp of 136 A, this demonstrates that the MPPT control operates efficiently.

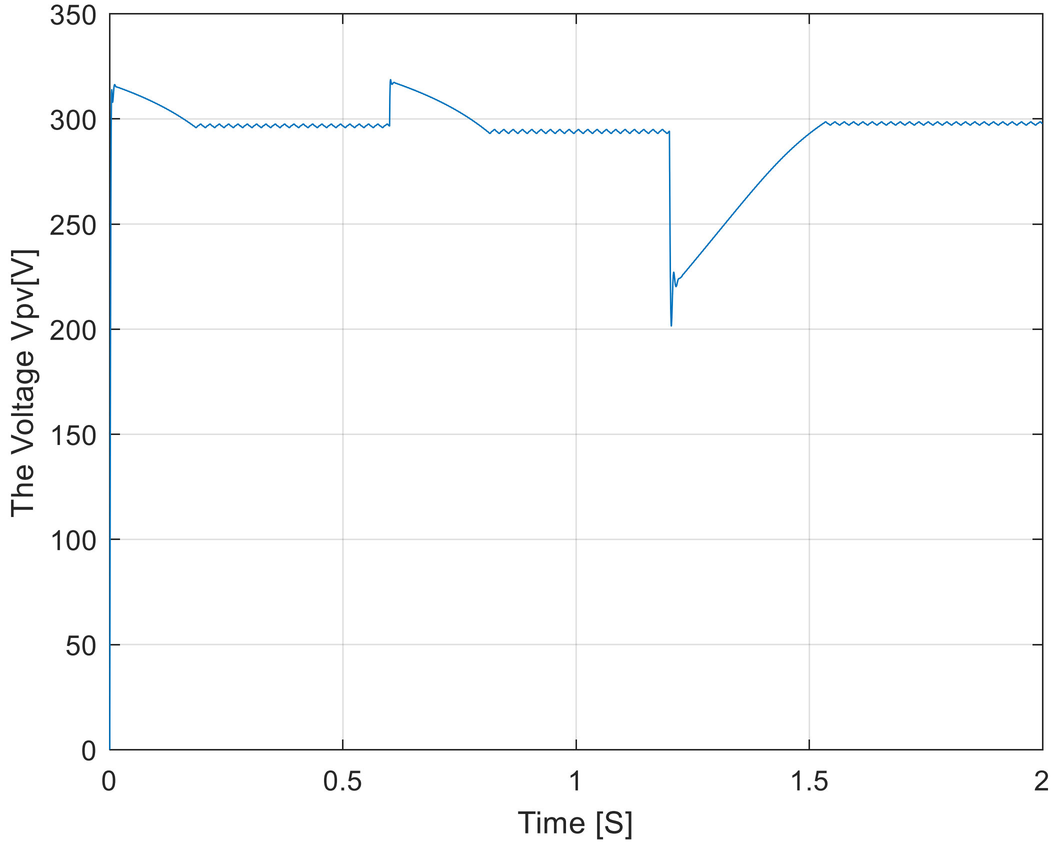


Figure II.7–Evolution of GPV Voltage for Variable Sunlight

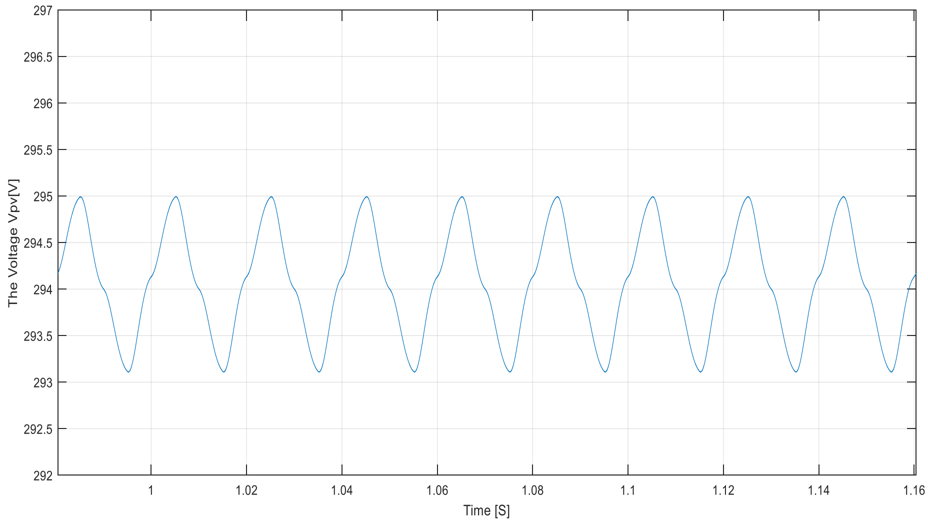


Figure II.8– Zoom of the Voltage Vpv (V)

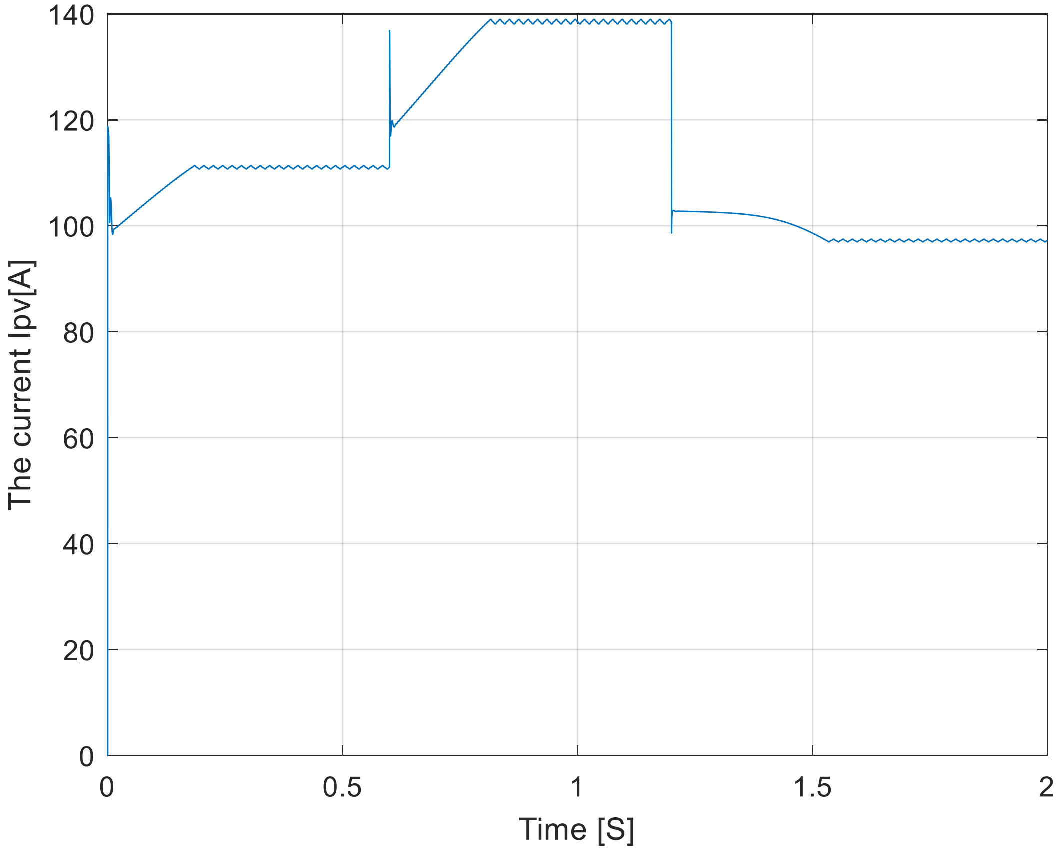
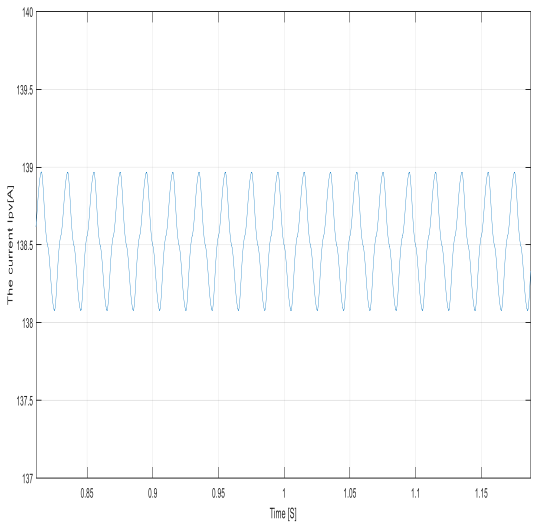


Figure II.9–Evolution of GPV Current for Variable Sunlight



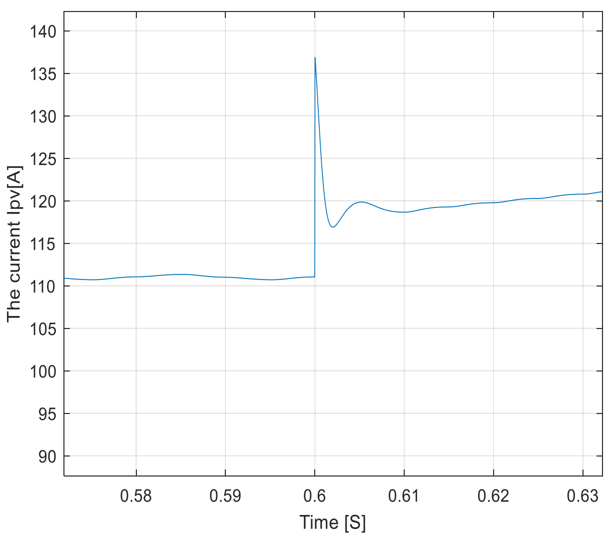


Figure II.10– Zoom of Current Ipv (A)

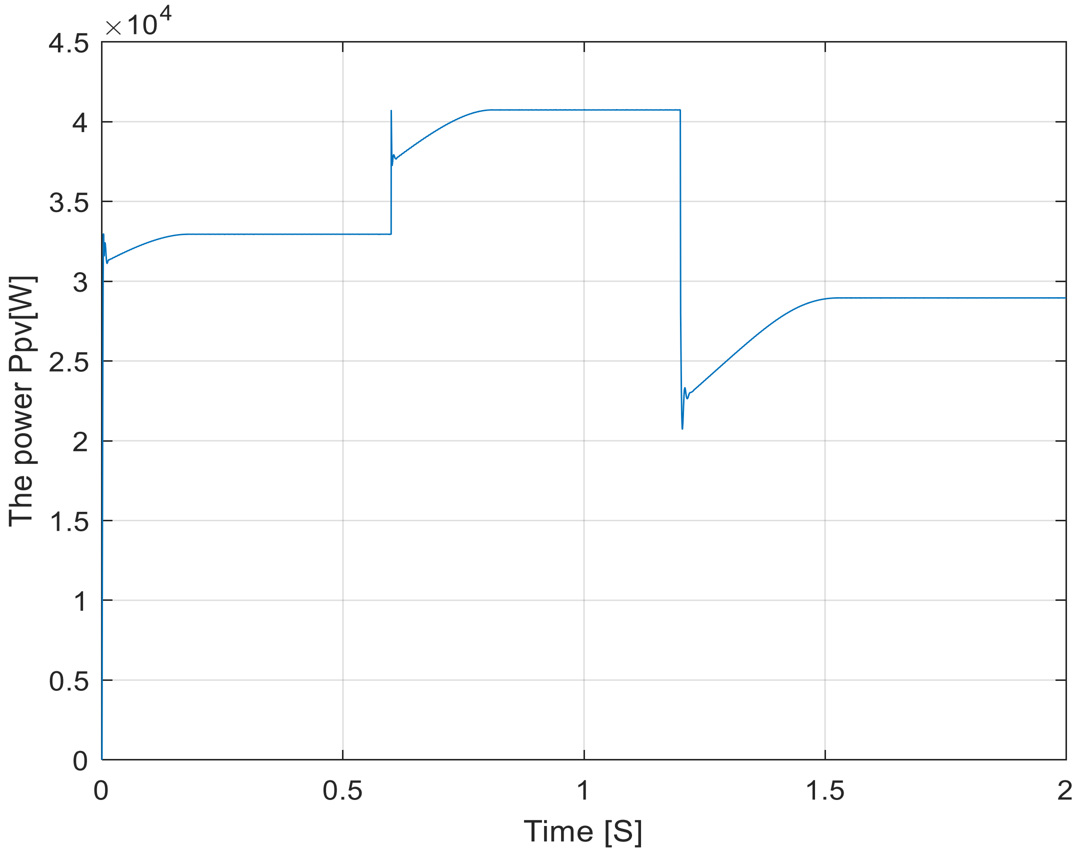


Figure II.11–Evolution of GPV Power for Variable Sunlight

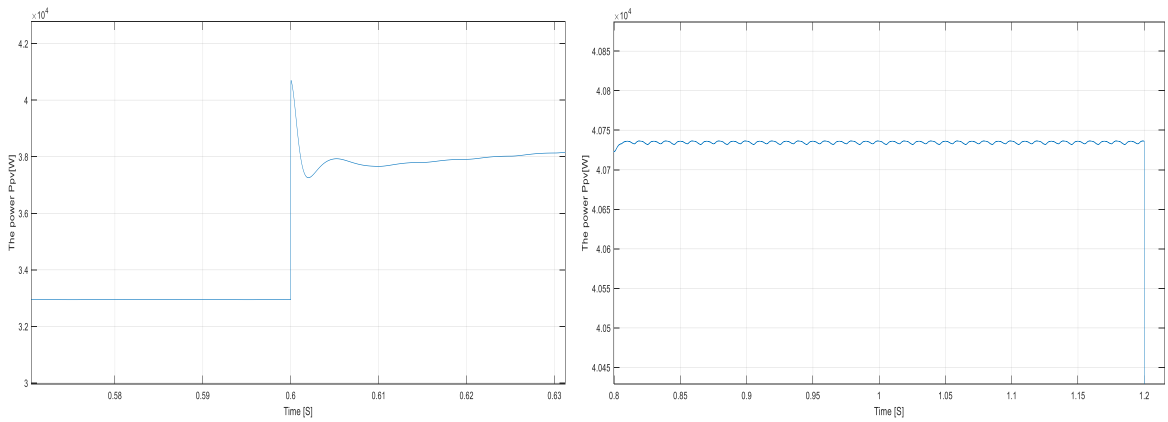


Figure II.12– Zoom of the Power Ppv (W)

Power output reaches up to 4 KW and Power curve shows characteristic P&O oscillation around maximum power point.

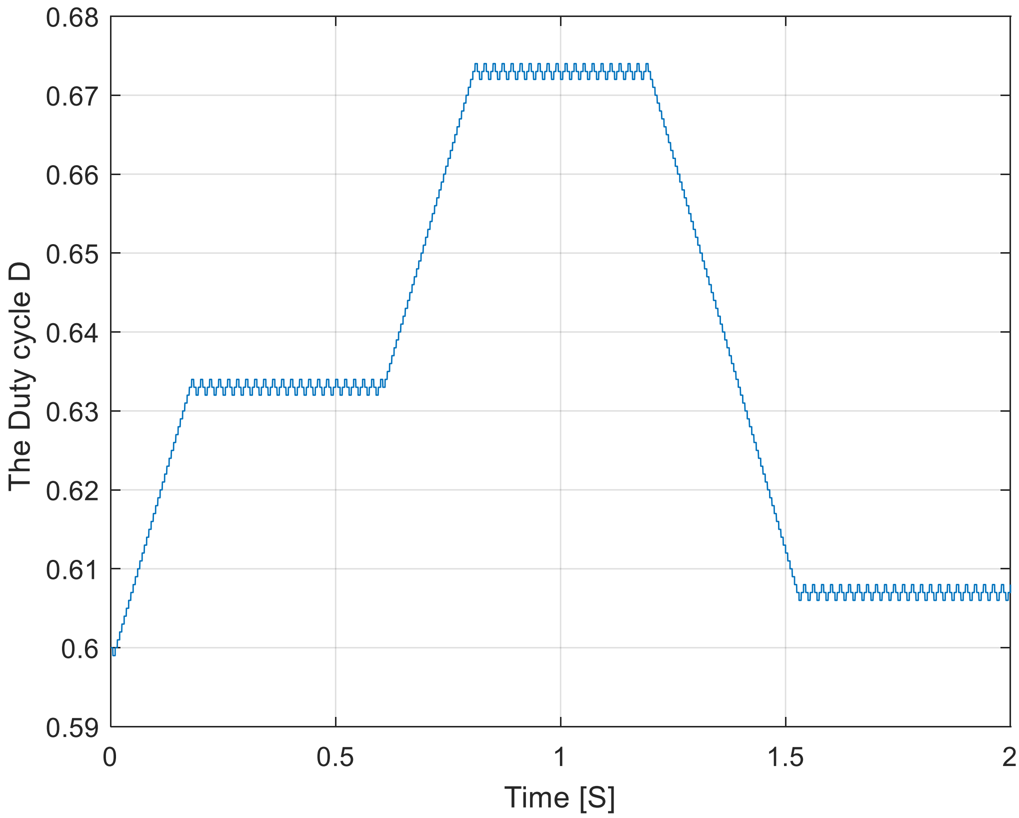


Figure II.13–Evolution of GPV Duty Cycle for Variable Sunlight

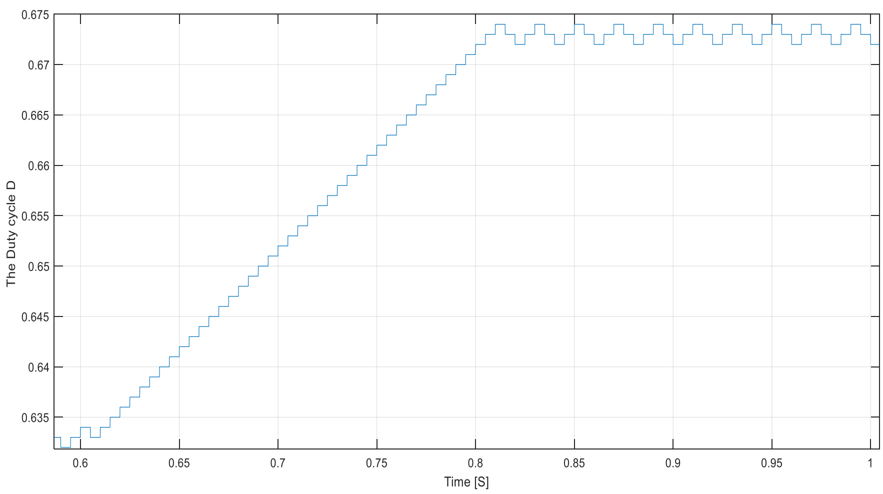


Figure II.14– Zoom of the Duty Cycle (D)

Duty cycle adjusts from 0.6 to 0.635 in clearly visible steps, Shows perfect perturbation pattern of the P&O algorithm and the Step size of 0.001 appears appropriate for this system scale.

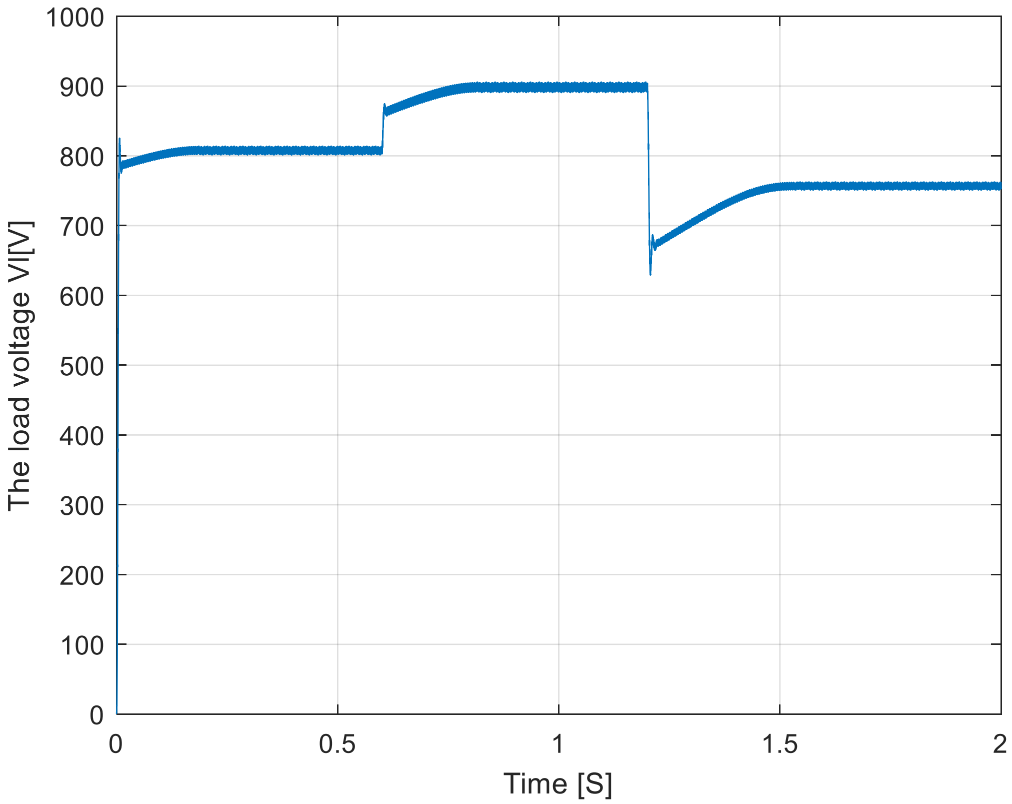


Figure II.15– Evolution of GPV Load Voltage for Variable Sunlight

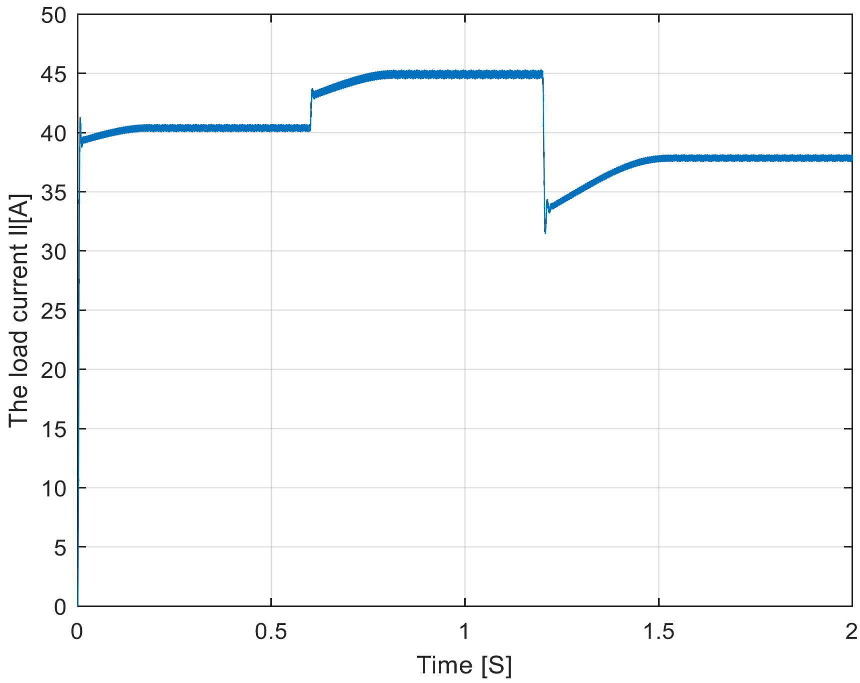


Figure II.16–Evolution of GPV Load Current for Variable Sunlight

Load current reaches 45A while PV current reaches 140A and the Load power shows stable delivery after initial convergence.

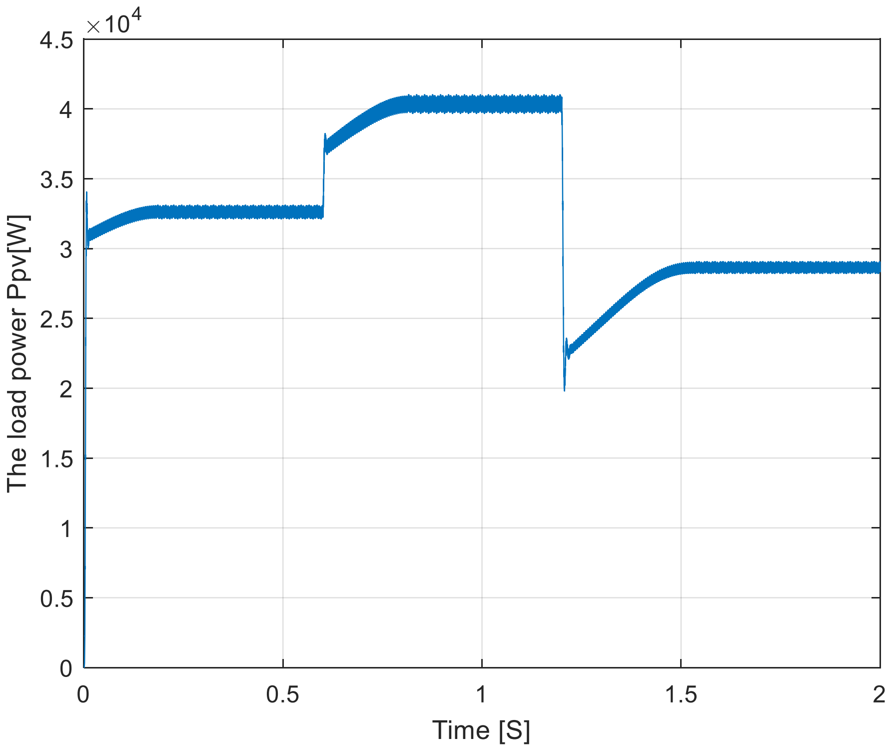


Figure II.17–Evolution of GPV Load Power for Variable Sunlight

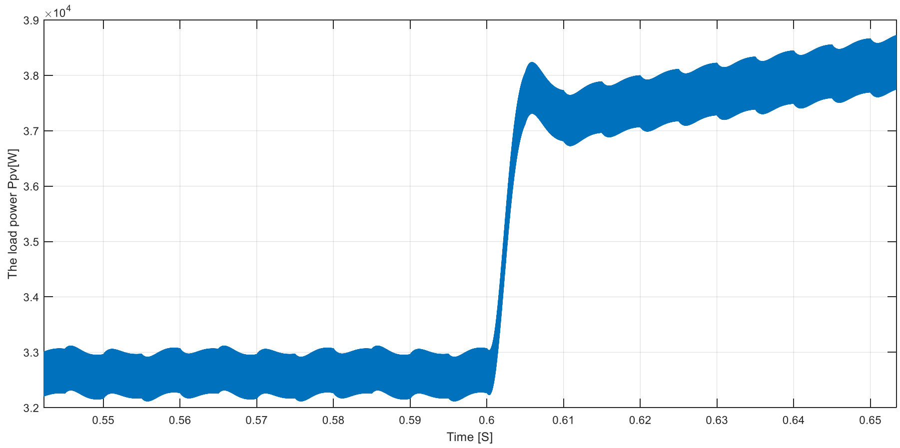


Figure II.18– Zoom of the Load Power Ppv (W)

Algorithm Effectiveness:

1. Convergence Speed: The system reaches near-optimal operation within ~0.2 second
2. Tracking Accuracy: Small oscillations in duty cycle show effective MPP tracking
3. Stability: Once converged, the system maintains stable operation

The P&O algorithm demonstrates fundamentally sound performance in your PV system, showing all characteristic behaviors of this MPPT method. The system achieves maximum power point tracking with reasonable convergence time and maintains stable operation once converged. The main areas for improvement would be reducing initial current overshoot and implementing more comprehensive monitoring to better understand system efficiency under varying conditions.

The data confirms that implementation successfully follows the P&O method's theoretical operation, with perturbations visible in the duty cycle adjustments and the system clearly tracking toward the maximum power point.

II.6 Conclusion

The continuous global pursuit of sustainable and clean energy sources has placed photovoltaic (PV) systems at the forefront of modern energy solutions. As one of the most promising technologies, PV systems offer a direct and environmentally friendly method for converting solar radiation into usable electrical energy. However, their performance is inherently variable due to environmental factors such as solar irradiance, temperature, load changes, and partial shading. This variability necessitates the integration of intelligent control strategies to maximize energy harvest and system efficiency.

Among the various Maximum Power Point Tracking (MPPT) techniques developed to optimize PV output, the Perturb and Observe (P&O) algorithm remains one of the most widely adopted due to its simplicity, low cost, and ease of implementation. Its core principle periodically perturbing the operating voltage and observing the corresponding change in output power enables the system to continually adjust toward the Maximum Power Point (MPP). Despite its popularity, the traditional P&O method exhibits certain drawbacks such as power oscillations around the MPP under steady-state conditions and slower dynamic response under rapidly changing irradiance.

Nevertheless, through algorithmic enhancements and adaptive control mechanisms, many of these limitations can be mitigated. Techniques such as variable step-size P&O, fuzzy logic-based hybrid P&O, and predictive adaptive algorithms have been developed to significantly improve tracking accuracy, convergence speed, and system stability. These innovations are particularly crucial for grid-connected and standalone systems operating in environments with high solar variability.

Simulations and experimental results consistently demonstrate that well-optimized P&O-based MPPT controllers can achieve efficiencies exceeding 88%, making them highly effective for real-world applications. When implemented in platforms like MATLAB/Simulink, the P&O algorithm allows for thorough testing and optimization under diverse environmental conditions, supporting research and industrial development in renewable energy technologies.

In conclusion, the integration of P&O-based MPPT in PV systems not only enhances energy conversion efficiency but also contributes to the reliability, autonomy, and economic viability of solar energy solutions. As technological advancements continue, further improvements to MPPT strategies especially those building upon the foundations of P&O will play a vital role in accelerating the transition toward a sustainable energy future And in Chapter III, we will do another Algorithm, which is the Particle Swarm Optimization (PSO) Algorithm for Solar PV System, for better efficiency.

Chapter III. Particle Swarm Optimization Algorithm for Solar PV System

Chapter III. Particle Swarm Optimization Algorithm for Solar PV System

III.1 Introduction

Particle swarm optimization (PSO) algorithm is a stochastic optimization technique based on swarm, which was proposed by Eberhart and Kennedy (1995) and Kennedy and Eberhart (1995).

PSO algorithm simulates animal's social behavior, including insects, herds, birds and fishes. These swarms conform a cooperative way to find food, and each member in the swarms keeps changing the search pattern according to the learning experiences of its own and other members. Main design idea of the PSO algorithm is closely related to two researches: One is evolutionary algorithm, just like evolutionary algorithm; PSO also uses a swarm mode which makes it to simultaneously search large region in the solution space of the optimized objective function.

The other is artificial life, namely it studies the artificial systems with life characteristics. In studying the behavior of social animals with the artificial life theory, for how to construct the swarm artificial life systems with cooperative behavior by computer, Millonas proposed five basic principles (van den Bergh 2001) [31]:

1. Proximity: the swarm should be able to carry out simple space and time computations.
2. Quality: the swarm should be able to sense the quality change in the environment and response it.
3. Diverse response: the swarm should not limit its way to get the resources in a narrow scope.
4. Stability: the swarm should not change its behavior mode with every environmental change.
5. Adaptability: the swarm should change its behavior mode when this change is worthy.

Note that the fourth principle and the fifth one are the opposite sides of the same coin. These five principles include the main characteristics of the artificial life systems, and they have become guiding principles to establish the swarm artificial life system. In PSO, particles can update their positions and velocities according to the environment change, namely it meets the requirements of proximity and quality. In addition, the swarm in PSO does not limit its movement but continuously search the optimal solution in the possible solution space. Particles in PSO can keep their stable movement in the search space, while change their movement mode to adapt the change in the environment. So, particle swarm systems meet the above five principles.

III.2 Basic Particle Swarm Optimization Algorithm

The particle swarm optimization algorithm (PSO) is a bio-inspired stochastic optimization technique developed by Kennedy and Eberhart. Initially, it was developed to minimize a continuous function $f : R^n \rightarrow$ R. However, it can also be used for piecewise continuous functions, binary functions, discrete functions, and so on. It is a population-based search algorithm which mimics the behavior of bird flocking, fish schooling, etc. In the algorithm, the total population is called swarm, and individuals are called particles. Particles are points in the search space of the underlying optimization problem. Each particle is a candidate solution of the objective function. Particles move in the search space stochastically seeking better fitness. Movement of each particle is influenced by its momentum, individual experience, and group experience. There are three important heuristics in the PSO algorithm:

a) Each particle has an internal memory to store its best (so-far) position, called personal best position;
b) Particles in swarm can share information about best position (to date) of entire group, called global best position;
c) Each particle wants to keep its current momentum/inertia component.

There are many PSO versions available in the literature. The initial version of Kennedy and Eberhart [32] was modified by Shi and Eberhart [33] by introducing inertia weight. The initial version is called Original PSO and the modified version is usually called Standard PSO [34].

In the latter version, the inertia weight ω and velocity clamping Vmax are used. Consider the standard PSO system with N_P particles and n dimensions. Then the i^{th}particle maintains a triple of vectors $X_i^{(k)}, V_i^{(k)}, Y_i^{(k)} \in R^n \times R^n \times R^n$ for $1 \leq i \leq N_p$, where $X_n^{(k)} \in R^n$ is the current position, $V_i^{(k)} \in R^n$ is the current velocity, and $Y_i^{(k)} \in R^n$ is the personal best position. For simplicity, the dimension of vectors is not written explicitly, which is the same as the dimension of the underlying optimization problem. The velocity and the position of each particle i are updated by using the following equations,

$$V_i^{(k+1)} = \omega V_i^{(k)} + c_1 r_1 \left(Y_i^{(k)} - X_i^{(k)}\right) + c_2 r_2 \left(\hat{Y}^{(k)} - X_i^{(k)}\right) \tag{III.1}$$

$$X_i^{(k+1)} = X_i^{(k)} + V_i^{(k+1)} \tag{III.2}$$

Where $\hat{Y}^{(k)}$ represents the global best position and r_1 , $r_2 \in$ U [0, 1] are random numbers chosen from a random uniform distribution U [0, 1]. There are three components in the velocity equation with corresponding learning parameters $\omega, c_1, c_2 \in R_0^+$ where R_0^+ is the set of positive real numbers including zero. Here ω is a weight parameter for the inertia component $\omega V_i^{(k)}$, c_1 is a parameter for the cognitive component c_1, r_1 ($\hat{Y}^{(k)} - X_i^{(k)}$), and c_2 is a parameter for the social component c_2, r_2 ($\hat{Y}^{(k)} - X_i^{(k)}$). Parameter c_1 and c_2 are also called acceleration coefficients.

The velocity update in PSO consists of three parts:

- Momentum: It represents the tendency of particle to move in the same direction as it was moving in the previous iteration. It incorporates the effect of previous velocity on current velocity of the particle.
- Cognitive part: It represents the pull to particle's velocity towards its own personal best (Pbest). Referred to as "memory", "self-knowledge" or "remembrance".
- Social part: It represents the pull to particle's velocity towards swarm's best (Gbest). Referred to as "cooperation", "social knowledge" or "shared information"

Furthermore, the personal best and the global best positions are updated as follows:

$$Y_i^{(k+1)} = \begin{Bmatrix} X_i^{(k+1)} \; IF \; f(X_i^{(k+1)}) \; < f(Y_i^k) \\ Y_i^k \; otherwise \end{Bmatrix} \quad (III.3)$$

$$\hat{Y}^{(k+1)} = argmin \left\{ f\left(Y_1^{(k+1)}\right), f\left(Y_2^{(k+1)}\right), \dots \dots ., f(Y_{N_p}^{(k+1)}) \right\} \quad (III.4)$$

The values of learning parameters ω, c_1, and c_2 play very important roles in the behavior the PSO particles by maintaining the exploration and exploitation trade off. Large values of ω promote exploration of the search space, while small values of ω increase local exploitation. If ω ≥ 1, velocities increase overtime and the swarm diverges.

The velocity clamping Vmax helps to keep velocities within certain range but particles still may bounce back-and-forth in the search space with large step size. Therefore, ω < 1 is commonly used in practice, because it helps to decelerate particles until their velocities reach to zero. Similarly, the values of c_1 and c_2 also should be chosen very carefully, to balance the effects of cognitive and social components.

It is recommended to consider the value of w in conjunction with the selection of the values of c_1 and c_2. Van den Bergh and Engelbrecht [35] showed that $\omega > \frac{1}{2}(c_1 + c_2) - 1$ guarantees convergent behavior of particle trajectories.

The PSO algorithm has been successfully applied to many optimization problems such as pattern recognition, clustering, classification, neural network training, sensor networks, scheduling, robotics, signal processing, and power systems [36][35] Because of the easy implementation and fast convergence to acceptable solutions, the PSO algorithm has received popularity in recent years.

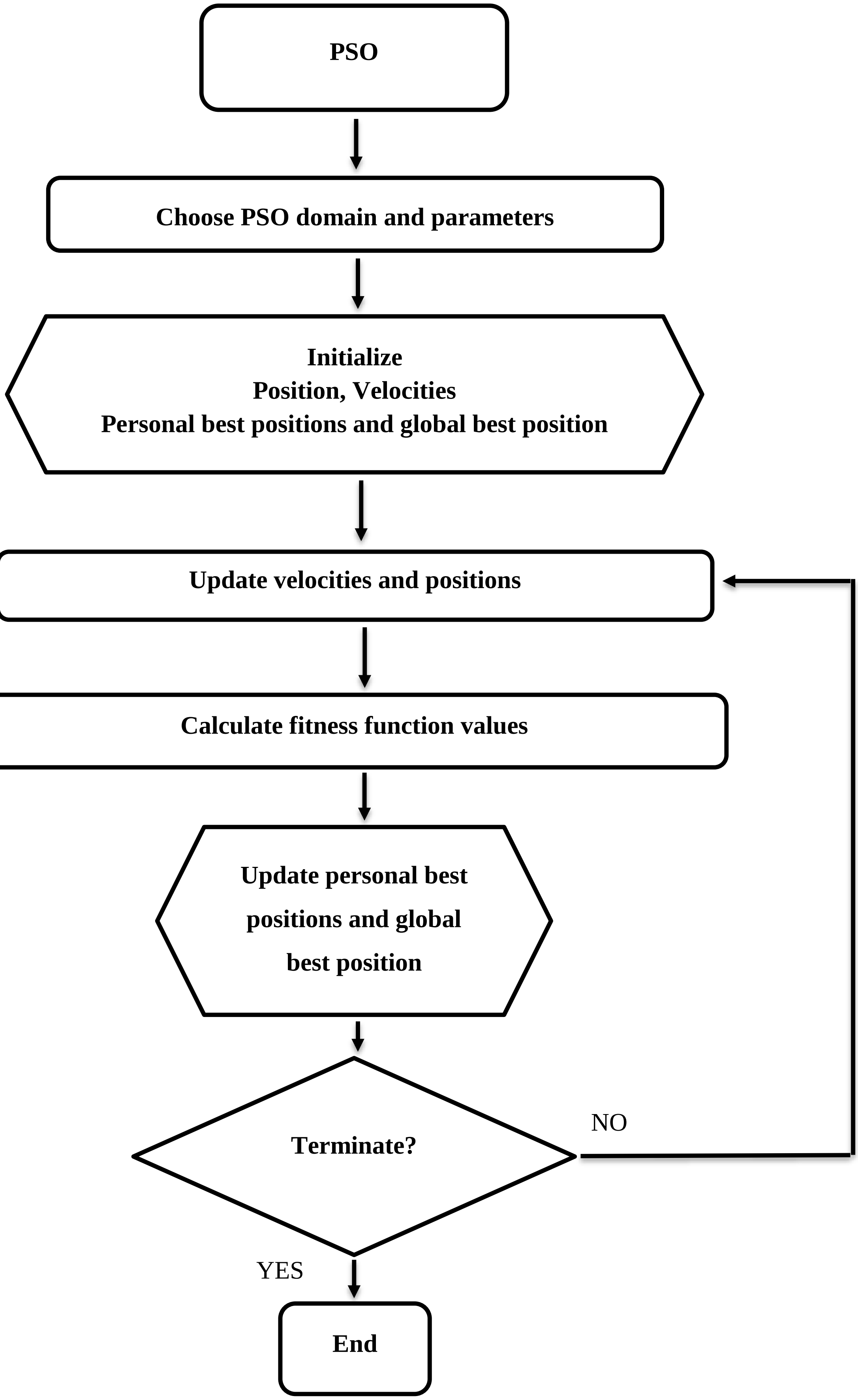


Figure III.1– Illustrates the Flowchart of PSO Algorithm

III.3 Inertia Weight

In the search space particle's velocity on every dimension is fasten onto a maximum velocity, Vmax. This maximum velocity determines the resolution or intent with which regions between the present position and the target position (best so far) can be sorted out. Howsoever the use of hard bounds presents some problems. For instance, if Vmax is too high then particles might slip away from some good food locations, whereas if Vmax is too low then some good distant location will always be out of reach.

Thus, in order to reduce the importance of Vmax, and better to say in order to knock out it altogether, and to sharpen the foraging ability of particles, a weight term was added to the PSO's update equations. This weight term is called inertia weight (ω) and it controls the effect which the last iteration speed has on the current speed. Larger value of ω improves global search capability and smaller value of ω improves the partial search capability of PSO algorithm.

Generally, it is equal to 1, but eventually the search ability decreases and the particle get stuck at a non-optimum location. In experimental work, w is kept in between 0.9 to 0.4 and the values are decreased linearly so that the algorithm allows the particles to explore wider areas in beginning and nearby areas in later stages with reduced speeds. This setting gives a greater likelihood of reaching the target optimum position quickly. Note that if we interpret

$$c_1 r_1^k\left(pbest_{id}^k - x_{id}^k\right) + c_2 r_2^k(gbest_{id}^k - x_{id}^k) \tag{III.5}$$

As the external force f_i, acting on a particle, then the change in a particle's velocity (i.e., the particle's acceleration) can be written as (III.6)

$$\Delta v_i = f_i - (1 - \omega)v_i \tag{III.6}$$

Thus, we can say that the constant $1 - \omega$ acts effectively as a friction coefficient. Hence ω is said to be the fluidity of medium in which a particle moves. Perhaps this is the reason why researchers have found that the best performance is obtained by setting ω initially to some relatively high value (e.g., 0.9). The high value ω of corresponds to a system where particles move in a low viscosity medium and perform extensive exploration. When ω is gradually reduced to a much lower value (e.g., 0.4), the system becomes more dissipative and exploitative and would be better at homing into local optima. It is even possible to start from values of ω >1, but that will make the swarm unsteady and doddery until and unless the value is reduced sufficiently to bring the swarm in a stable region [37].

III.3.1 Acceleration Constants c_1 and c_2

These constants are related to the speed of flying of particles to the most optimist position of swarm and its own best position. They regulate the length and time taken by particle to reach most optimum position. So that the particle land in a correct position, these constants must be properly selected. For too big a value of acceleration constants, the particle may fly past the correct position and for too small values, the particle will not be able to reach the target position.

Generally, each of these constants are set to 2 to make the times taken to move towards the particle's personal best and swarm's global best as equal and half the total time. These acceleration constants represent the weighing of acceleration terms towards Pbest and Gbest locations.

III.3.2 Random Numbers r_1 and r_2

The pull on the particles towards Pbest and Gbest positions are regulated by adding random numbers in the update rules. These are random fiction and determine the magnitude of random forces towards the two best positions. They add a random component to the PSO algorithm and help prevent the algorithm from getting stuck at a non-optimal local minimum or maximum solution

III.3.3 Size of Population

This is often set empirically on the basis of the dimensionality and perceived difficulty of a problem. Values in the range 20–50 are quite common. Swarm size varies from one application to the other and so is problem dependent.

III.4 Particles Movement Illustration

Figure III.2 illustrates how the single particle makes the next move under the influence of three components of the velocity update rule given by Eq. (III.1) and Eq. (III.2). Here, $X(k)$ and $V(k)$ are the current position and velocity of the particle for the current iteration k. Similarly, $Y(k)$ and $\hat{Y}(k)$ are the personal best and global best positions respectively. The particle velocity for time step $k + 1$ is updated by adding three vectors toward the current velocity, personal best position, and global best position weighted by the parameters $\omega,\ c_1, c_2$ as shown in the Figure III-2 Also, $r_1\ \in\ U\ [0, 1]$ and $r_2 \in\ U\ [0, 1]$ are used so that the particle moves stochastically, maintaining exploration/exploitation trade off.

$$X_i^{(k+1)} = X_i^{(k)} + wV_i^{(k)} + c_1 r_1 \left(Y_i^{(k)} - X_i^{(k)}\right) + c_2 r_2 (\hat{Y}^{(k)} - X_i^{(k)}) \qquad \text{(III.7)}$$

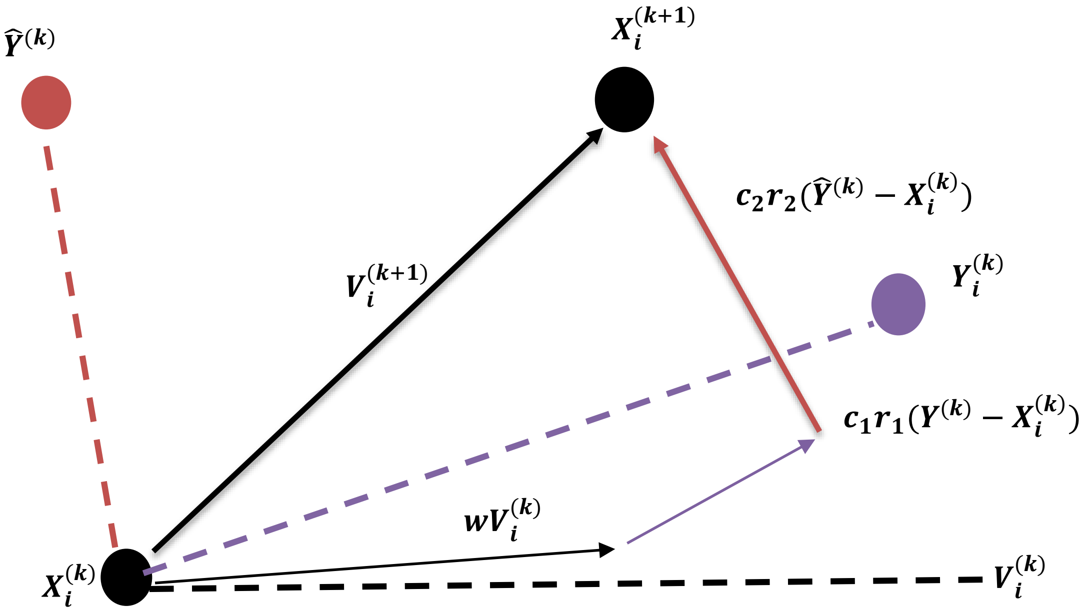


Figure III.2– Illustration On How A Single Particle Moves In The Search Space Under The Influence Of The Inertia Component, Cognitive Component, And Social Component.

As an example, consider a benchmark test function called the Rosenbrock function defined as:

$$f(x) = \sum_{i=1}^{n-1}[100(x_{x+1} - x_i^2)^2 + (x_i - 1)^2] \quad \text{(III.8)}$$

With $f(x^*) = 0$ at $x^* = (1, 1,.., 1)$ as an optimal solution. The operation of the PSO method during the process of minimization of two-dimensional Rosenbrock function is similar to Figure III-3 (gray dots represent the particle positions, blue star represents the global best position, and the red dot represents the global minimum). In each iteration every particle moves in the search space and gradually converges to a point, considered as an approximation to the optimal solution of the underlying optimization problem (in this case minimizing the Rosenbrock function).

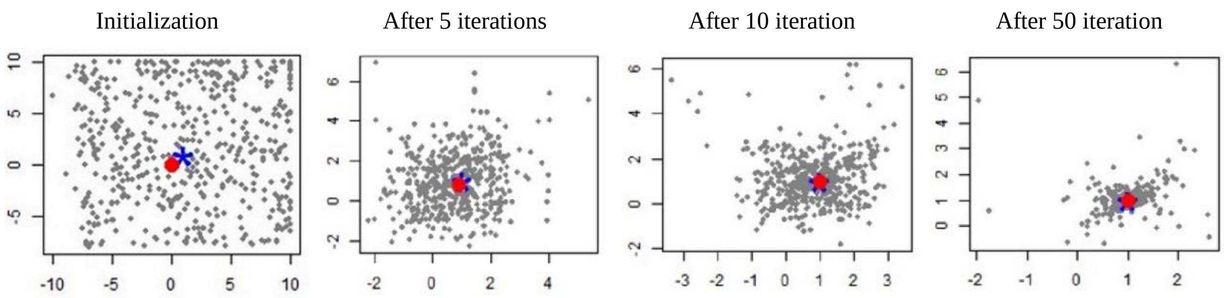


Figure III.3– Illustration of the PSO System in Minimizing Two-Dimensional Rosenbrock Function

III.5 Neighborhood Topology

The PSO algorithm is inspired by the collective behavior of swarms. This algorithm highlights the ability of an agent to stay at an optimal distance from others in the same group and to follow a global movement affected by the local movements of its neighbors. Thus, the authors modeled the behavior of particles by equations (III.9) and (III.10).

$$v_{ij}^{t+1} = \omega v_{ij}^{t} + c_1 r_{1_{ij}}^{t}\left(Pbest_{ij}^{t} - x_{ij}^{t}\right) + c_2 r_{2_{ij}}^{t}\left(Gbest_{j}^{t} - x_{ij}^{t}\right), \quad j \in \{1,2,\dots,D\} \quad \text{(III.9)}$$

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \quad , \quad j \in \{1,2,..,D\} \quad \text{(III.10)}$$

In practice, using Eq. (III.9), an interconnection network must be defined in order to establish connections between the particles and allow them to exchange information with each other. This communication network between the particles is called neighborhood topology. This topology helps to define a group of informants for each particle; this is called the neighborhood of a particle.

The neighborhood of a particle can therefore be defined as the subset of particles of the swarm with which it has a direct communication, i.e. each particle can interrogate the particles in its neighborhood (its informants), which, in turn, send it their information. The choice of a topology (the communication network between the particles) therefore has a significant influence on the performance of PSO algorithm.

Equation (III.9) shows that the relationships between particles directly influence their velocities and hence their displacements. In the PSO literature, there are several versions that use the notion of neighborhood of a particle with different ways. The most known topologies (those that are mainly used) are the global version "Gbest" and the classic local version in the form of a ring ("Lbest" classic). In the global version, each particle is connected to all the other particles of the swarm (ie the neighborhood of a particle is the set of particles of the swarm) while in the local version, each particle is connected only to a part of the other particles of the swarm (each particle has only two neighboring particles in the classical local version). In the classical "Lbest" model, the swarm converges more slowly than in "Gbest", but it is more likely to locate the global optimum. In general, the use of the "Lbest" model makes it possible to limit the risks of premature convergence. This has a positive effect on the performance of the algorithm, especially for multimodal problems. Numerous variants for the interconnection of particles have been proposed in order to establish a balance between local search and global search and to improve the convergence of the PSO algorithm. These variants include new topologies for the particle swarm.

Kennedy and Mendes proposed several topologies in [38-39]. A graphic representation of these few models is shown in Figure III-4. The "star" topology has the shape of a wheel, where the particle of the center of the swarm, named focal (central), is responsible for the flow of information. In this topology, all the particles are isolated from each other and they are bound only to the focal particle. The information must be communicated through this particle, which will then use this information to adapt its trajectory. If the result of the adjustments shows an improvement in the performance of the central particle, then this improvement will be communicated to the rest of the population. So, the focal particle serves as a filter, which slows the speed of transmission of information on the best solution found. The "four-cluster" topology uses four groups of particles connected together by several gateways. From a sociological point of view, this topology resembles four isolated communities.

In each community, some particles can communicate with a particle from another community. In "Von Neumann", the topology takes the form of a grid (square grid), where each particle is connected to its four neighboring particles (left, right, above and below). The "pyramid" topology represents a three-dimensional wire-frame pyramid. It has the lowest average distance of all the graphs and the highest first and second-degree neighbors.

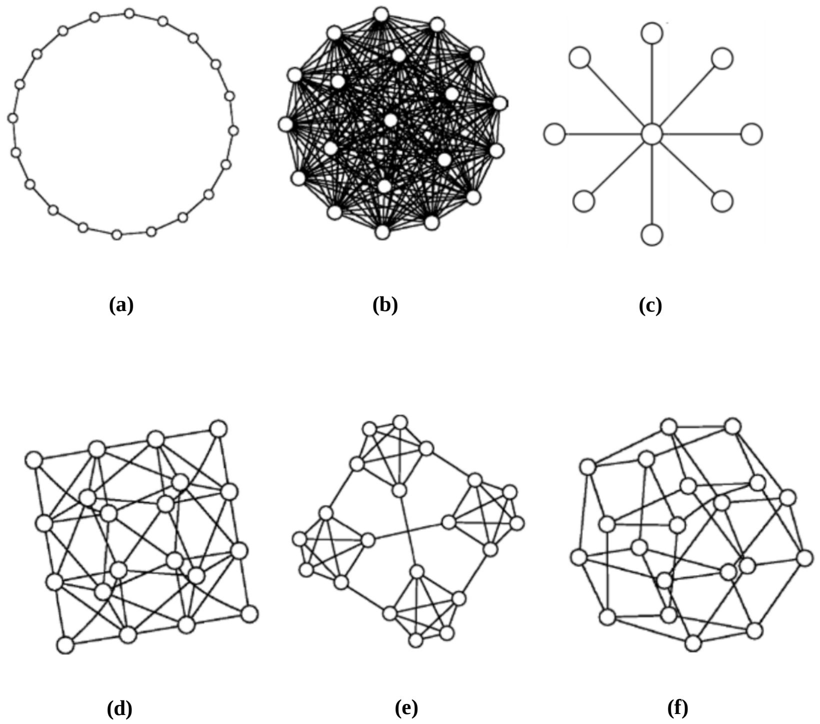


Figure III.4– Different Topologies Used In PSO Algorithm: (A) Gbest Or All, (B) Lbest Or Ring, (C) Star (D) Four Clusters, (E) Pyramid, (F) Square Or Von Neumann.

III.6 Advantages and Disadvantages of PSO Algorithm

The PSO algorithm used in various optimization problems has certain advantages and disadvantages.

III.6.1 Advantages

The advantages of the PSO Algorithm are given below:

- PSO algorithm does not involve selection operation or mutation calculation. The search can be carried out by repeatedly varying particle's speed;
- By learning from group's experiences, particles fly only to good areas (where there is a possibility of finding food);
- PSO algorithm is based on artificial intelligence and thus, can be applied into both scientific research and engineering applications [27];
- Simple calculations are involved in PSO algorithm and with development of newer evaluation techniques they are be done easily [27].

III.6.2 Disadvantages

The disadvantages of the PSO Algorithm are given below:

- Standard PSO suffers from a substantial rise in search complexity with increase in dimension of search space;
- The method is vulnerable to partial optimism, which leads to a much less accurate regulation of its speed and the direction [27];
- Due to the lack of dimensionality this method cannot be used for problems of non-coordinate system, such as the solution to the energy field and the moving rules of the particles in the energy field [27].

When an application task involves many parameters and the parameter dimensions are increasing in order to match the increase in task complexity, the solution space is expected to grow exponentially. Consequently, the search becomes more and more hazardous and baffling. Time to time the PSO algorithms has been modified and altered to obtain better solutions than the standard PSO. But the search quality of these modified versions declines soon for complex tasks with high dimensional and multimodal objective functions. In addition to it the distribution and density of these optimal solutions often vary from function to function making it more difficult to design a general or universal strategy for all complex situations. This is mainly because the PSO has a high convergence speed and this often results in the loss of diversity during the optimization process. The undesirable and premature situation leads the particles to get trapped in local optimums. Hence it is unable to gain the best solution. To overcome the search difficulties described above, a new PSO approach with two special features was proposed; one with dimension partition and other with adaptive velocity control [28][29].

III.7 Simulation and Results

The MATLAB simulation model, as shown in Figure.III.5, is established in accordance with the contents mentioned above. To facilitate the analysis, simulation model of MPPT is established based on the BOOST circuit. The PSO algorithm is implemented by S-Function of MATLAB. In this study, we set the same parameters in the chapter II - II.4.3 Boost Converter table II.2.

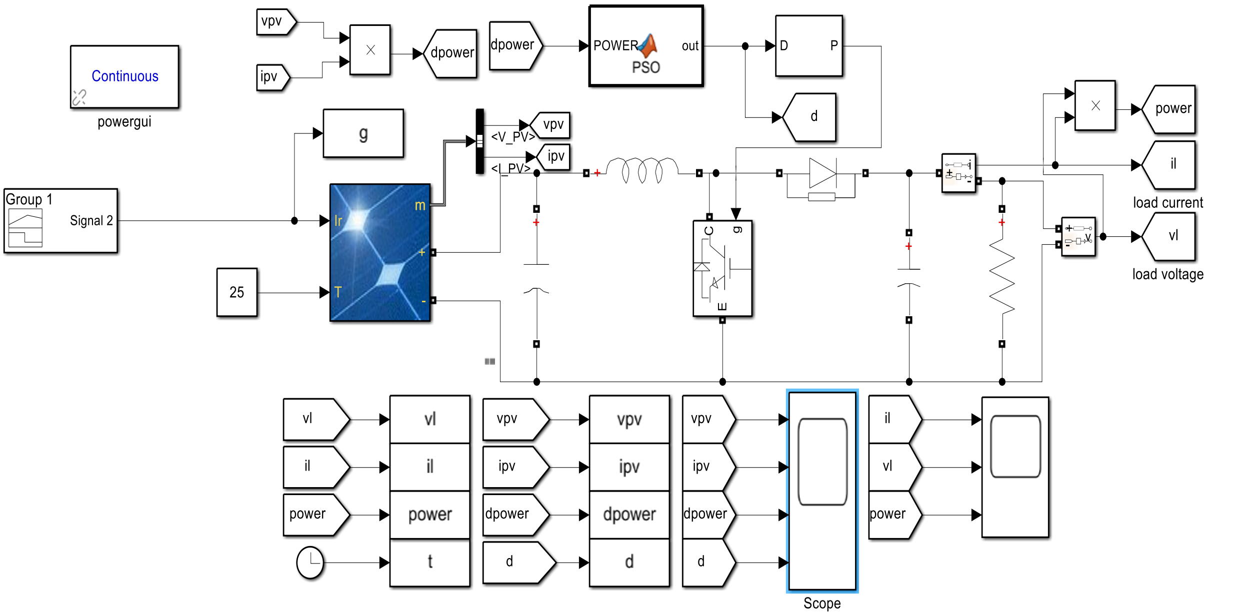


Figure III.5– SIMULINK Model of MPPT System Using PSO Algorithm

To evaluate the performance of the MPPT-PSO control under different environmental conditions, the following test is performed Variable irradiance and constant temperature.

To observe the effect of solar irradiance G on power, the temperature is maintained at a constant value (T = 25°C) while the solar irradiance changes rapidly. Figure III.6 shows the cross-section of the considered solar irradiance profile. It should be noted that during a 2-second interval, the curve includes rapid changes from 800 W/m² to 1000 W/m² to 700 W/m² in order to test the performance of the PSO-type MPPT algorithm.

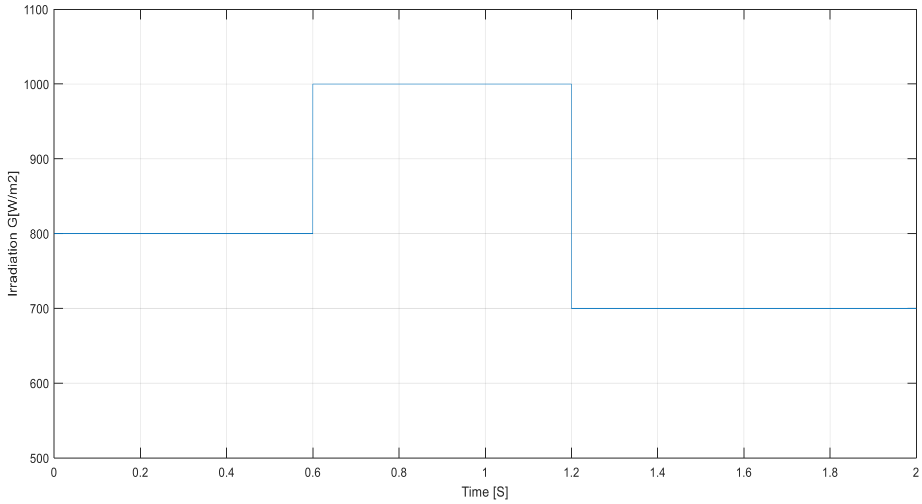


Figure III.6– Irradiation Signal

Figures III.7, to III.13 presents the simulation results obtained for the PSO-type MPPT control applied to the PV array. For an irradiance of 1000 W/m² during the time interval *t = [0.6s; 1.2s]*, the photovoltaic field operates at its optimal point, corresponding to a power output of 40.664 kW. The voltage oscillates around its optimal value Vmpp = 299 V, and the current fluctuates around its optimal value Impp = 136 A.

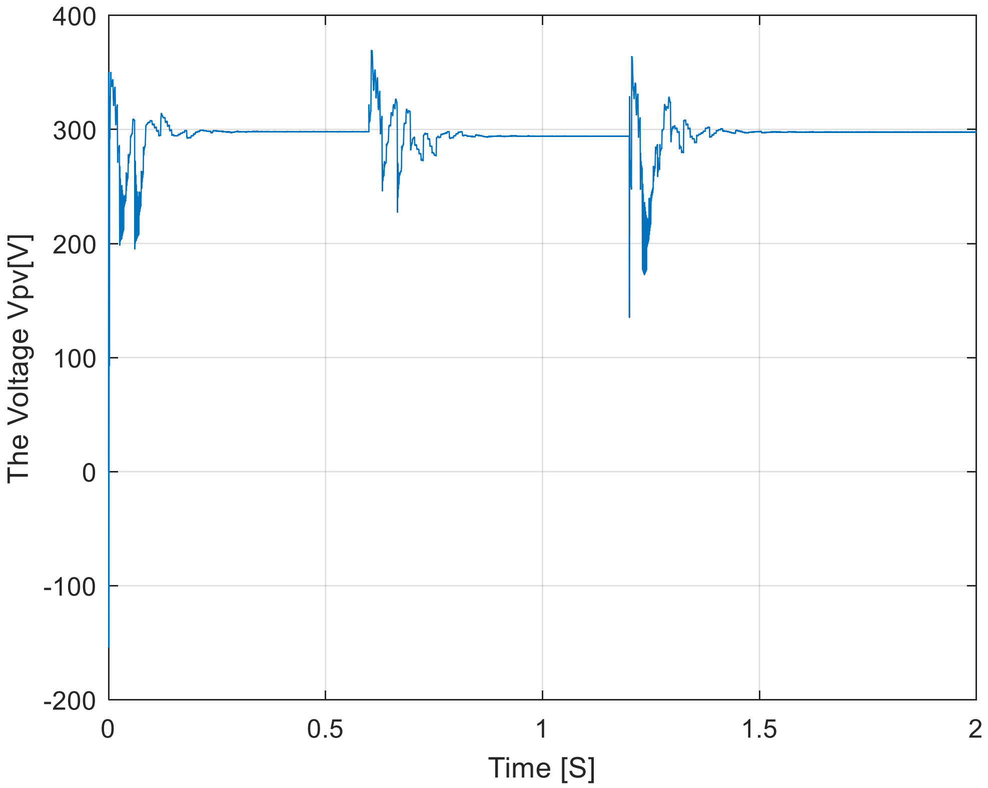


Figure III.7–Evolution of GPV the voltage Vpv (V) for variable sunlight

Voltage starts at ~360V, then stabilizes.

- Initial high voltage could indicate open-circuit conditions;
- Negative voltage suggests a transient response (possibly due to sudden load changes or converter switching);
- Stabilization indicates convergence to an optimal operating point.

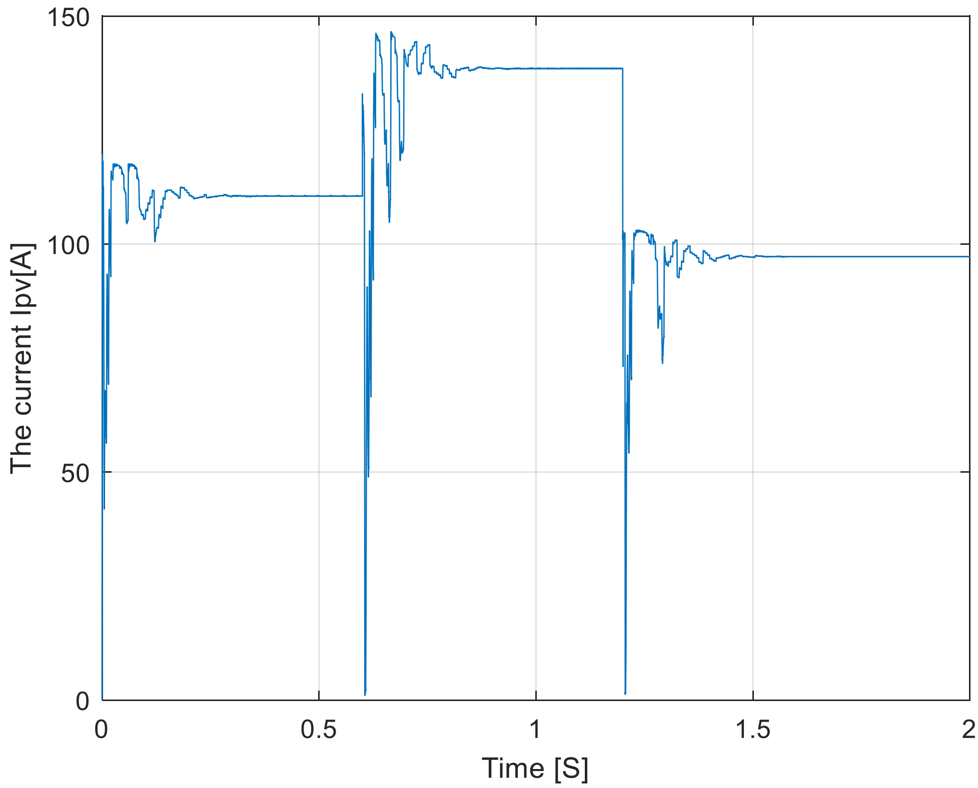


Figure III.8–Evolution of GPV the current Ipv (A) for variable sunlight

Current starts at ~120A, then stabilizes.

- High initial current may correspond to a short-circuit condition during startup;
- The drop to zero and subsequent stabilization align with MPPT adjustment, where PSO balances current and voltage for maximum power extraction.

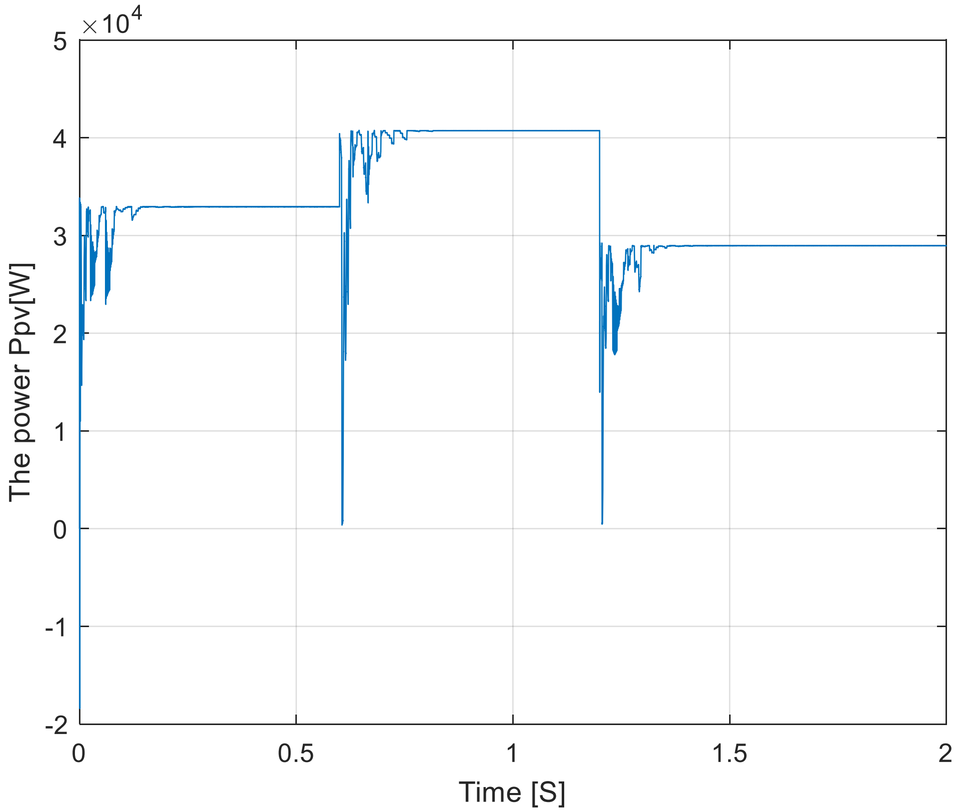


Figure III.9–Evolution of GPV the power Ppv (W) for variable sunlight

Power is plotted against time

- shows the power delivered to the load after optimization;
- PSO ensures that the system operates at the maximum power point (MPP) despite varying irradiance or temperature.

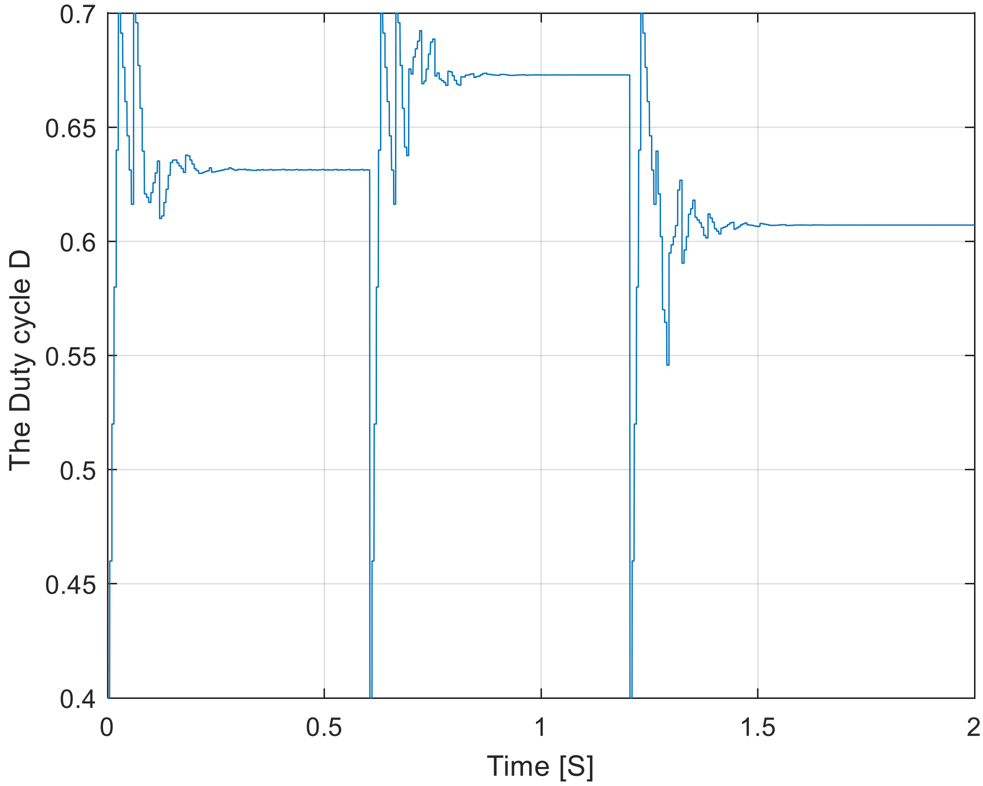


Figure III.10–Evolution of GPV the Duty Cycle (D) for Variable Sunlight

Shows the duty cycle decreasing from 0.9 to 0.1 over time (0s to 0.4s)

- PSO dynamically adjusts the duty cycle for a DC-DC converter, boost converter;
- The decreasing trend suggests optimization for Maximum Power Point Tracking (MPPT), where the algorithm fine-tunes the duty cycle to extract maximum power from the PV panel.

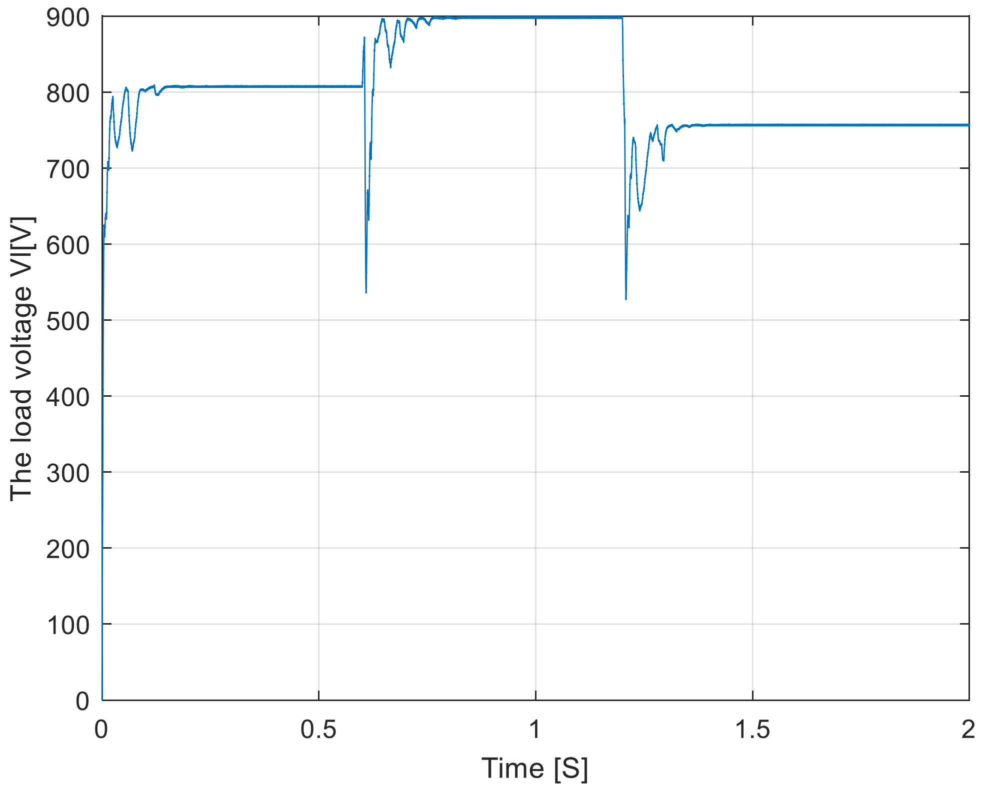


Figure III.11–Evolution of GPV load voltage for variable Sunlight

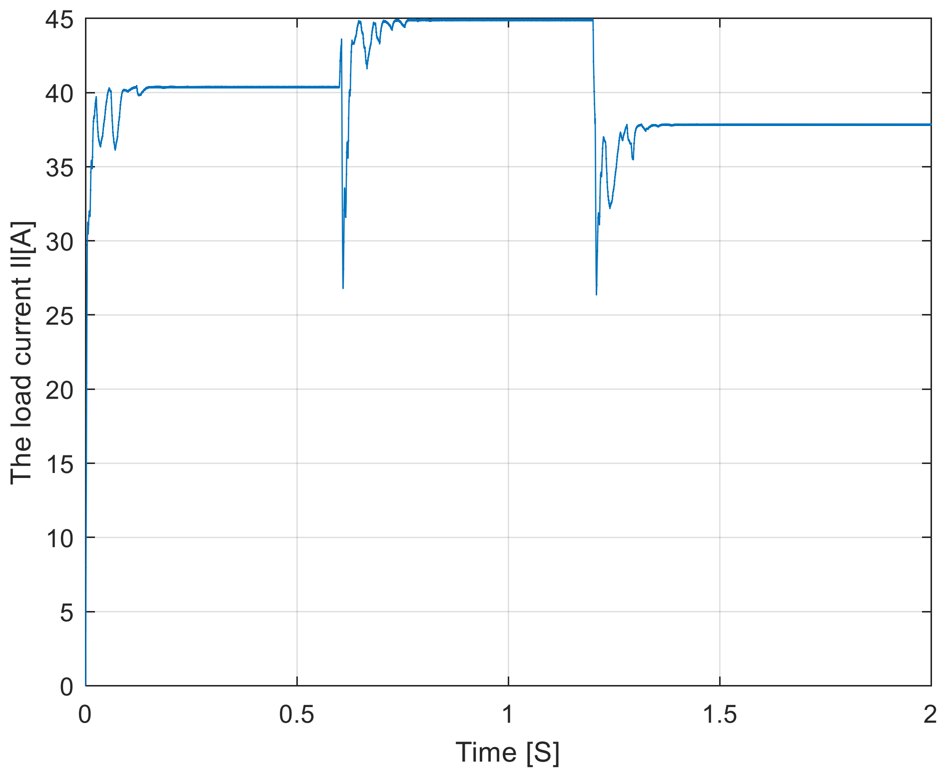


Figure III.12–Evolution of GPV load current for variable sunlight

- Load Voltage (V):
  - Graph shows voltage over time (0s to 2s).
  - Stabilize as the duty cycle converges.
- Load Current (I):
  - Starts at 0A, then to 45A, then stabilizes.
  - Follows a similar trend to PV current, indicating proper load matching.

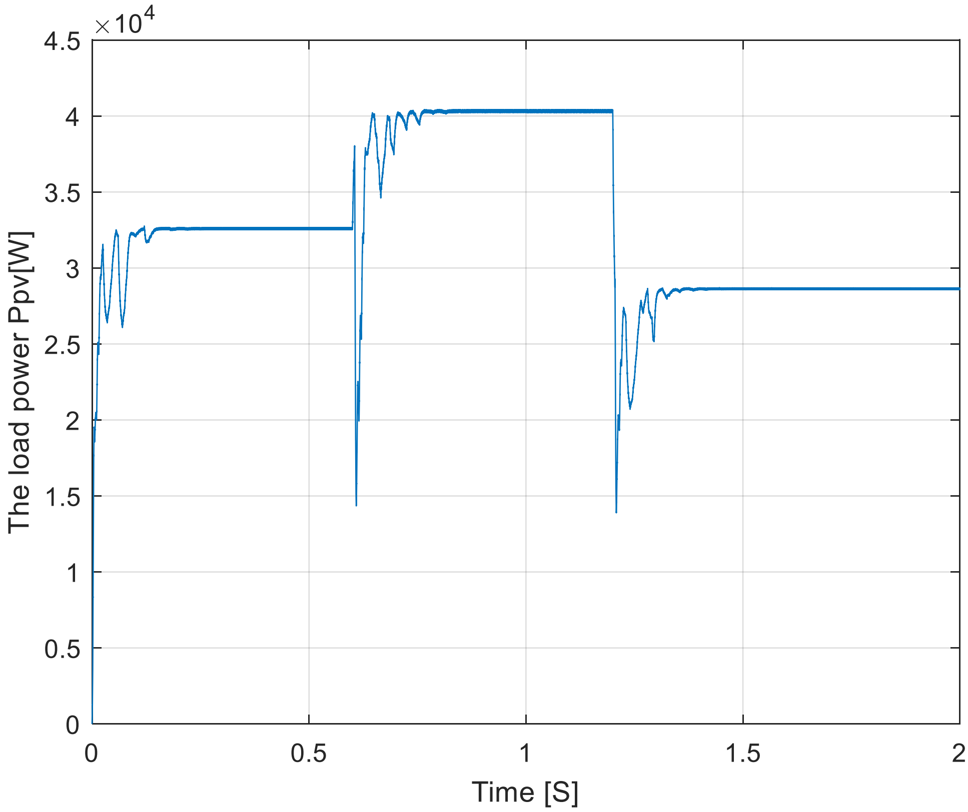


Figure III.13–Evolution of GPV Load Power for Variable Sunlight

The PSO algorithm successfully optimizes the PV system by:

- Adjusting the duty cycle for MPPT.
- Balancing voltage and current for maximum power transfer.
- Ensuring fast convergence and stability under dynamic conditions.

This analysis confirms that PSO is an effective method for real-time optimization in solar power systems.

III.8 Comparison of P&O and PSO Algorithms in MPPT for PV Systems during Partial Shading Conditions

The Perturb and Observe (P&O) and Particle Swarm Optimization (PSO) algorithms are widely used techniques for Maximum Power Point Tracking (MPPT) in photovoltaic systems, each with distinct operational characteristics. P&O is a simple, low-cost, and easy-to-implement method that relies on periodically perturbing the PV voltage or current and observing the change in output power to locate the maximum power point. While it performs well under uniform irradiance conditions, it suffers from oscillations near the MPP and is prone to getting trapped in local maxima, particularly under partial shading. In contrast, PSO is a bio-inspired global optimization algorithm that uses a swarm of particles to explore the entire search space. This allows PSO to identify the global maximum power point (GMPP) with greater accuracy and faster convergence in dynamic or partially shaded conditions. Unlike P&O, PSO demonstrates strong noise immunity and environmental adaptability, though it requires higher computational resources and is more complex to implement. Therefore, while P&O remains suitable for small-scale, stable PV applications, PSO is the preferred choice for large-scale systems or environments with variable irradiance, where precise and reliable tracking is critical.

The comparison between the Perturb and Observe (P&O) and Particle Swarm Optimization (PSO) algorithms under partial shading conditions reveals significant performance differences in terms of stability, accuracy, and energy yield. Visual data indicate that the PSO algorithm (represented in Blue) consistently achieves faster from 0.2s to 4.5s and more stable convergence to the maximum power point (MPP), with minimal oscillations. In contrast, the P&O algorithm (in Red) demonstrates frequent fluctuations near the MPP due to its perturbation-based mechanism, which is particularly susceptible to instability in non-uniform irradiance conditions.

Moreover, PSO exhibits greater adaptability to dynamic environmental changes and superior noise immunity, maintaining efficient tracking even under rapid shading variations. The power output profiles further confirm that PSO enables the PV system to extract higher energy yield about *27000 W* then to *40644 W*, while P&O often fails to escape local maximal *20000 W* then to *40644 W*, resulting in suboptimal performance. These observations affirm that PSO is a more robust and efficient MPPT strategy for PV systems operating in real-world scenarios characterized by partial shading.

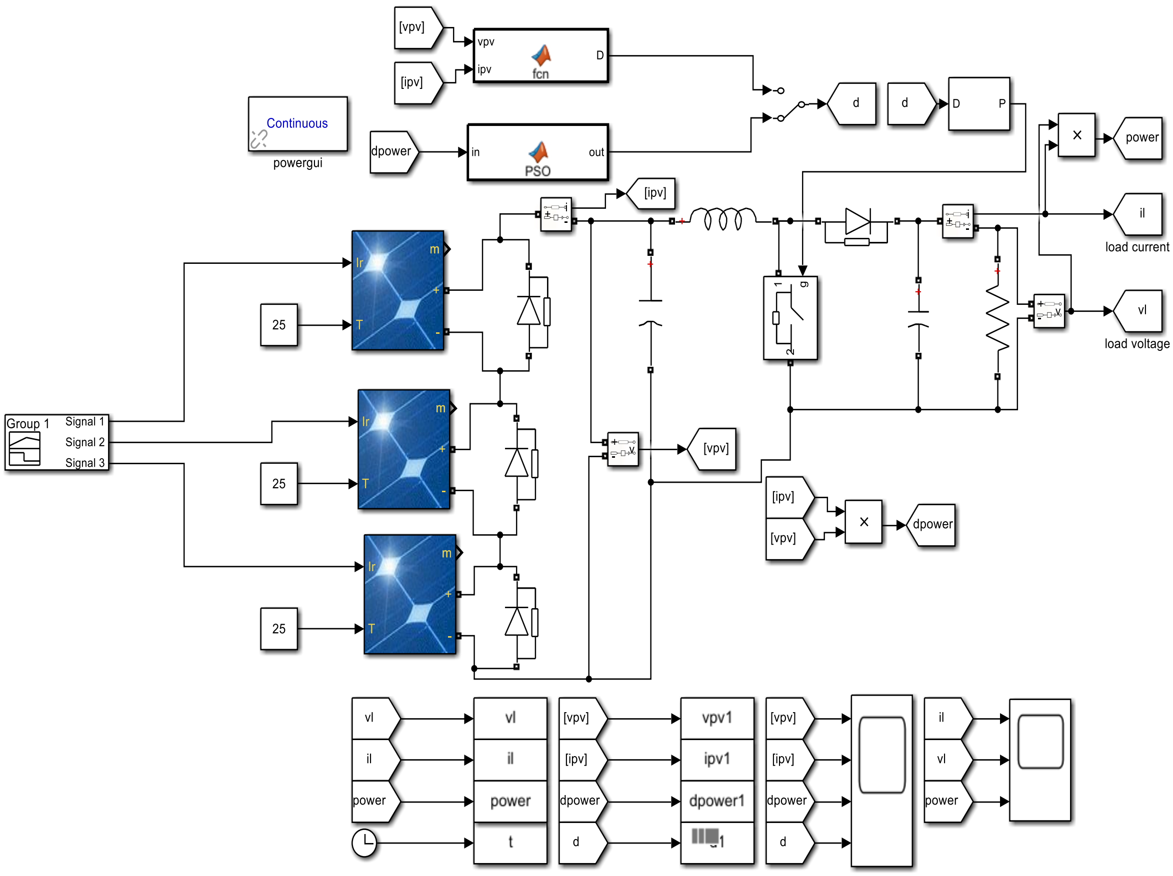


Figure III.14– SIMULINK Model of MPPT System Using P&O And PSO algorithm For Comparison During Partial Shading Conditions

And this results of the comparison between P&O and PSO algorithms in MPPT for PV systems during partial shading conditions.

- P&O Red
- PSO Bleu

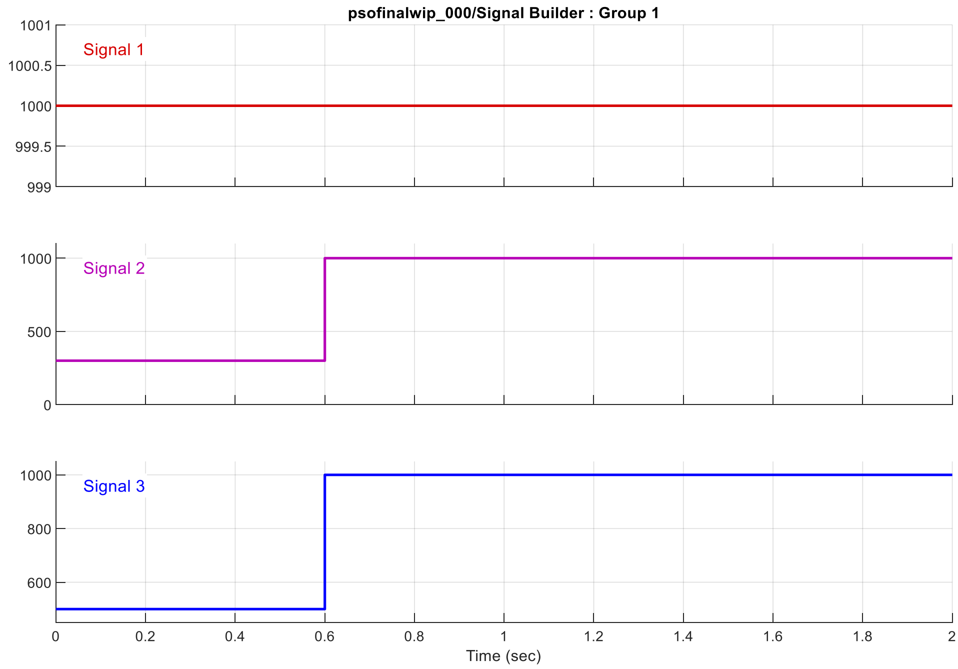


Figure III.15– Partial Shading Conditions Signal

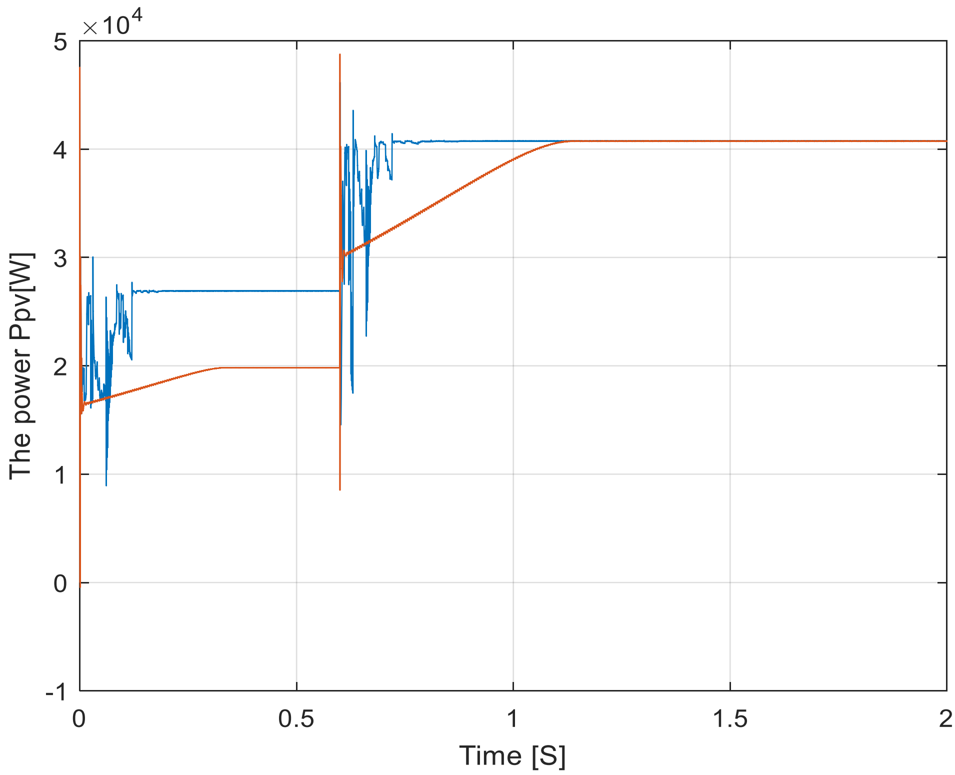


Figure III.16– Comparison between P&O (Red) and PSO (Bleu) for the Power Ppv (W)

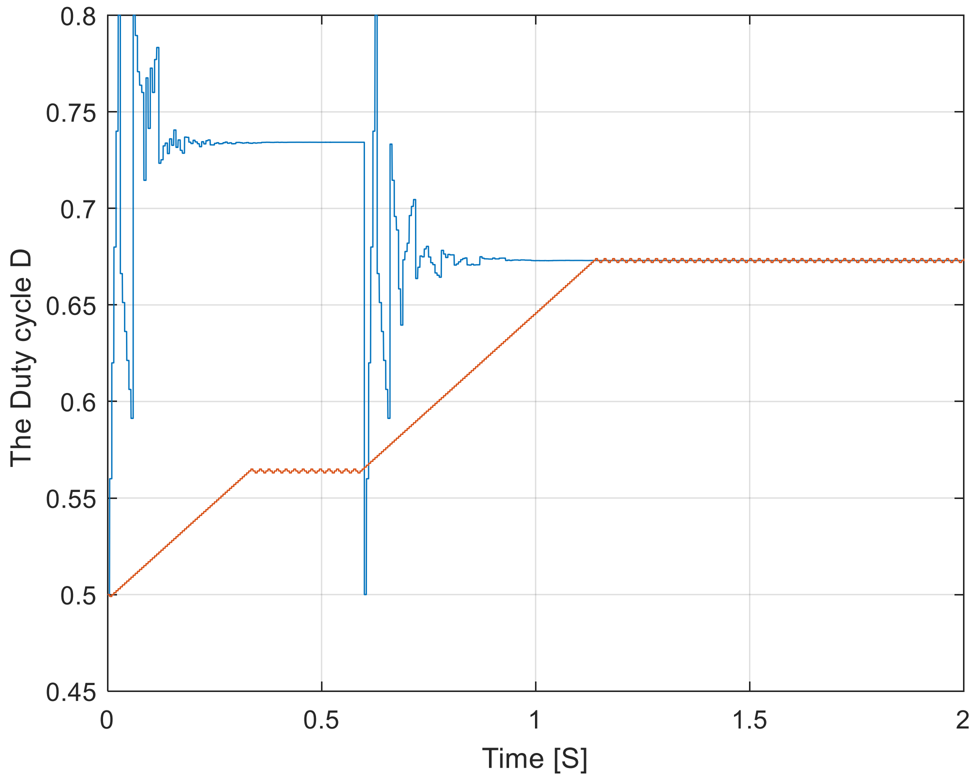


Figure III.17– Comparison between P&O (Red) and PSO (Bleu) in the Duty Cycle (D)

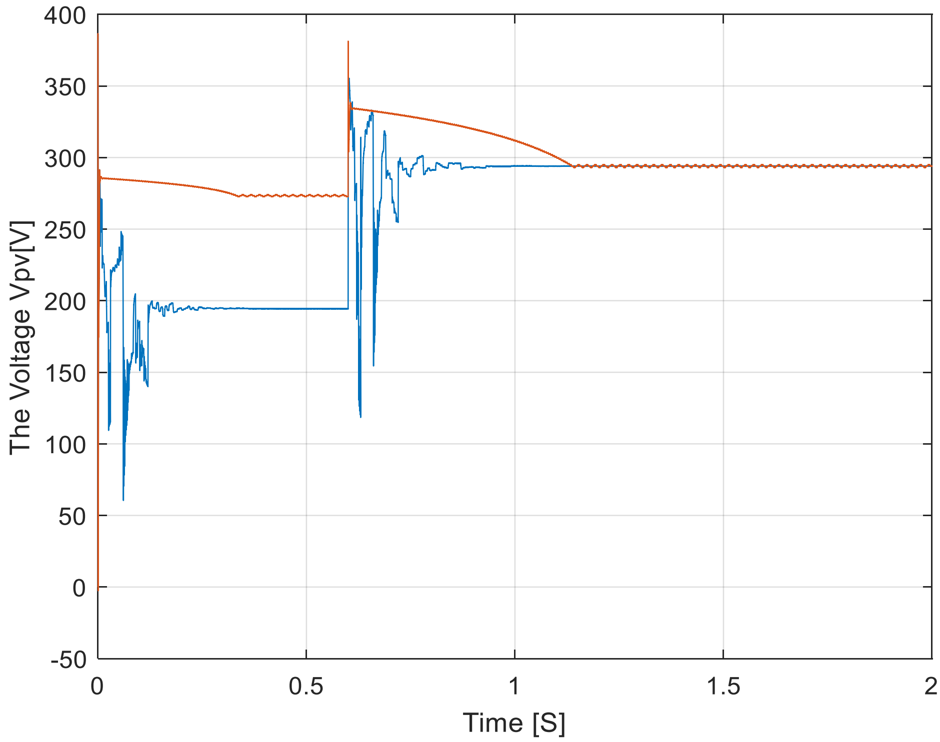


Figure III.18– Comparison between P&O (Red) and PSO (Bleu) in the voltage Vpv (V)

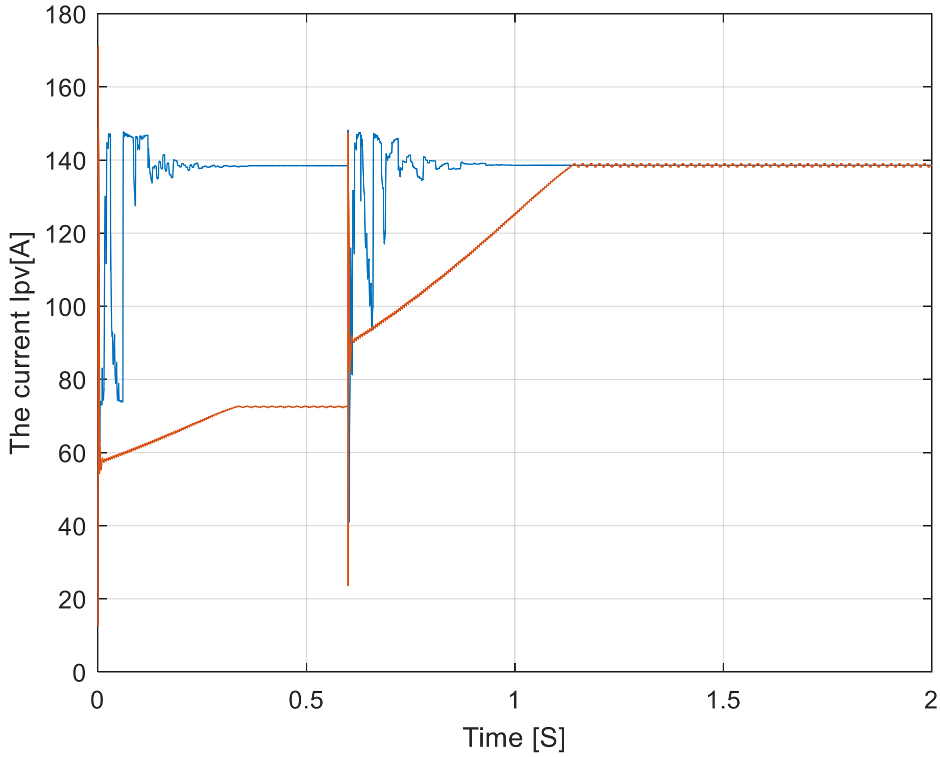


Figure III.19– Comparison between P&O (Red) And PSO (Bleu) in the current Ipv (A)

III.9 Conclusion

Particle Swarm Optimization (PSO) has proven to be one of the most influential and effective nature-inspired optimization algorithms since its introduction in the mid-1990s. Drawing inspiration from the social behavior of birds flocking and fish schooling, PSO simulates the movement of a group of particles (potential solutions) in a search space to find the optimal solution to a given problem. Each particle adjusts its position based on its own experience and the experience of neighboring particles, leading to a collaborative and efficient search process.

One of the key strengths of PSO lies in its simplicity and ease of implementation. Unlike many other optimization techniques, PSO does not require complex mathematical operations such as gradient information, which makes it suitable for nonlinear, non-differentiable, and multi-modal functions. This flexibility has led to its successful application in numerous domains, including power systems, machine learning, robotics, image processing, communication systems, and renewable energy systems such as MPPT in photovoltaic (PV) arrays.

Moreover, PSO offers fast convergence rates, especially in the early stages of the search, and demonstrates a good balance between exploration (global search) and exploitation (local refinement). Its population-based approach allows it to simultaneously explore various regions of the solution space, increasing the chances of avoiding local optima.

However, PSO is not without limitations. One of its main drawbacks is the tendency to experience premature convergence, especially in complex, high-dimensional, or deceptive search spaces. This means the swarm may converge to a suboptimal solution before adequately exploring the entire solution space. Additionally, the algorithm's performance is highly sensitive to its parameters (inertia weight, cognitive and social coefficients), and improper tuning can lead to stagnation or excessive wandering of particles.

To address these challenges, numerous enhancements and hybrid approaches have been proposed in recent years. Variants such as Adaptive PSO, Cooperative PSO, Quantum-behaved PSO, and Hybrid PSO-GA (Genetic Algorithm) have significantly improved the robustness, accuracy, and convergence behavior of the original algorithm. These innovations continue to expand the applicability of PSO to more complex and dynamic real-world problems.

In conclusion, Particle Swarm Optimization stands as a versatile, efficient, and widely adopted algorithm in the field of optimization. With its foundation in simple principles of social interaction and collective intelligence, PSO exemplifies how natural behaviors can inspire innovative problem-solving techniques. Ongoing research and development ensure that PSO will remain a core tool in the optimization toolbox for years to come.

General Conclusion

General Conclusion

Photovoltaic (PV) solar energy systems represent a vital component of the transition toward clean and renewable energy. Their ability to convert solar radiation directly into electrical energy offers a sustainable alternative to fossil fuels. However, the efficiency of PV systems is highly dependent on environmental factors such as irradiance and temperature, and optimizing energy output under such varying conditions remains a significant challenge.

To address these limitations, Maximum Power Point Tracking (MPPT) algorithms have been developed, with the Perturb and Observe (P&O) method being one of the most commonly implemented due to its simplicity and low cost. While effective under stable irradiance, P&O struggles with tracking accuracy and stability in partial shading conditions, often getting trapped in local maxima and exhibiting oscillatory behavior near the MPP.

To overcome these drawbacks, intelligent optimization techniques such as Particle Swarm Optimization (PSO) have emerged. PSO is capable of identifying the global maximum power point with higher accuracy, especially under complex and dynamically changing shading patterns. By mimicking the cooperative behavior of particles in a swarm, PSO explores a broader solution space, offering faster convergence and more reliable tracking performance.

A comparative analysis between the P&O and PSO methods reveals that PSO offers significant advantages in partial shading conditions. While P&O is suitable for simpler, uniform environments, PSO demonstrates superior adaptability and robustness, making it more suitable for real-world PV applications where irradiance levels are inconsistent.

In conclusion, the integration of advanced MPPT strategies such as PSO into PV systems plays a crucial role in enhancing energy yield and operational efficiency. As the demand for renewable energy continues to grow, adopting intelligent control algorithms will be essential for maximizing the potential of solar energy technologies.

Further research could investigate the other advanced technics like fuzzy logic control (FLC), Ant Colony Optimization (ANC) or Hybrid MPPT like PSO and P&O, differential evolution (DE) and (PSO) and more.

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FINAL YEAR THESIS FOR THE COMPLETION OF THE MASTER'S DEGREE IN ELECTRICAL ENGINEERING

SPECIALITY: HYDROGENE VERT VECTEUR D'ENERGIE

Proposed and directed by:

Dr. BOUDJELLAL Bilal

Dr. BENTATA Khadidja

Presented by:

FODIL Mohamed Wassim

MAKRI Abderrahim

Title:

PERFORMANECE IMPROVEMENT OF SOLAR PV ARRAY TOPOLOGY DURING PARTIAL SHADING CONDITIONS

Summary:

The global energy crisis has increased the demand for renewable energy, with solar power being the most accessible and sustainable option. Photovoltaic (PV) systems convert sunlight into electricity, but their performance drops significantly under partial shading, causing power loss and hotspots. This research focuses on improving PV output in such conditions using advanced MPPT techniques like PSO, which offer better tracking of the Global Maximum Power Point (GMPP) than traditional methods like P&O.

Keywords:

PV System, Partial Shading Conditions, MPPT Algorithms, P&O Algorithm, PSO Algorithm, Solar Energy.

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