REPUBLIC OF TÜRKİYE

ALTINBAŞ UNIVERSITY

Institute of Graduate Studies

Electrical and Computer Engineering

SOLAR ENERGY CONTROL SYSTEM BASED ON METAHEURISTIC METHOD

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Master's Thesis

Supervisor

Asst. Prof. Dr. Sefer KURNAZ

Istanbul, 2023

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2023

The thesis SOLAR ENERGY CONTROL SYSTEM BASED ON METAHEURISTIC METHOD prepared by QUTADA JIHAD ABDULQADER and submitted on 19/04/2023 has been **accepted unanimously** for the degree of Master of Science in Electrical and Computer Engineering

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ACKNOWLEDGEMENTS

I sincerely thank my great supervisor Professor Dr. Sefer KURNAZ for helping me conduct the research and prepare the thesis. This thesis is wholeheartedly dedicated to my beloved family, who has been my source of inspiration.

ABSTRACT

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Date: April / 2023

Pages: 56

This thesis examines the issue of figuring out the particle swarm optimization method's maximum power point tracking algorithm for solar energy systems. Before putting a solar cell to use, the manufacturer typically characterizes the device using empirical data. Measurement or detection of a variety of solar energy degradation pathways is important. Thus, it is advantageous to actively measure solar energy factors throughout time. We provide an approach to enhance the maximum power point tracking algorithm for an equivalent model of a typical solar energy system using a smart method based on particle swarm optimization. This technique enables routine updating of the solar energy system, which can be used to identify the system's maximum output power. The 1400 Watt was reached for PV power efficiency, and the irradiation value was 1000 Watt/m2. 95.45% of both the suggested method and the MPPT method were accurate. Its precision is measured in terms of maximum power (252.44 Watts), cells per module (40), and open circuit voltage (35.44 Volts), accordingly.
Keywords: MPPT Controller, Metaheuristic Method, Solar Energy.

TABLE OF CONTENTS

LIST OF FIGURES

Pages

1. INTRODUCTION

1.1 BACKGROUND

Solar technology has been around for a while. A variety of methods were developed between 1860 and the First World War to harness solar energy and create steam, propulsion motors, and irrigation pumps. Since the late 1950s, solar photovoltaic cells, which were developed in 1954 at Bell Laboratories in the United States, have been utilized in space planets to generate electricity.

The development and commercialization of solar energy technology received a lot of attention in the years immediately after the impact of oil in the 1970s. Nevertheless, this newly emerging solar industry failed in the 1970s and early 1980s as a result of the dramatic decline in oil prices and the absence of long-term legislative restraints. From the year 2000, the solar sector has experienced enormous new growth and has acquired momentum.

At the end of 2010, the total installed capacity of solar-based power generation capacity has increased from almost negligible capacity in the early 1990s to over 40 GW (Timilsina, Kurdgelashvili, and Narbel 2022).

A significant technological advancement has also been made in solar electricity. The latest solar technologies are represented by solar intense power and large-scale PV systems that boost energy networks, whereas the earliest solar technologies are small-scale photovoltaic (PV) cells. In the past 30 years, there has been a clear decrease in the cost of solar technologies. For instance, the cost of high-power band solar modules decreased from $27,000 per kW in 1982 to roughly $4,000 per kW in 2006 the installation cost of a PV system decreased from $16,000 per kW in 1992 to approximately $6,000 per kW in 2008. The rapidly expanding solar industry has given rise to a number of useful policy tools, and the prices of fossil fuels are becoming more volatile. Externalities of fossil fuels on the environment, in particular greenhouse gas (GHG) emissions (Kabir et al. 2018).

For the planet Earth, the sun serves as an endless source of free energy (also known as solar energy). Innovative technologies are gaining traction. It is employed to convert solar energy into electricity. These approximations have already been demonstrated to work and are widely used as sustainable alternatives to traditional non-hydro technologies throughout the world. Theoretically, solar energy has the capacity to effectively cover the global energy needs if the means for harvesting and supplying it are already in place. Annually, the earth receives about 4,000,000 exajoules (1EJ = 1018J) of solar energy.

The ability to readily harvest the 5 104 EJ is requested. Despite this enormous potential and rising awareness, solar energy still contributes very little to the world's total energy needs (Sampaio and González 2017). With the present global push to reduce carbon emissions in recent years, for example, 696,544 metric tons of CO_2 emissions, there is yet another significant prospect with solar research.

The installation of 113,533 residential solar power systems in California, USA, has reduced or avoided it. Hence, the use of solar technology will considerably lessen and alleviate the difficulties associated with it, including energy security, climate change, unemployment, etc. Furthermore, it is anticipated that its utilization will have a considerable impact on the transportation industry in the future and eliminate the need for fuel transportation. One of the most promising markets for renewable energy is the use of photovoltaic panels to harness solar energy and produce electricity.

The photovoltaic market is currently widespread, especially in Europe, China, and the United States, thanks to the business's quick growth outlook and high investment levels. Brazil is seeing significant changes, especially with the addition of solar energy. Due to the fall in hydroelectric energy and the increase in power prices for the energy sector, which is currently Brazil's primary energy matrix, the launch of the energy matrix and one-off solar auctions encountered challenges (Nagenborg 2018).

There is an undeniable need for more energy given the tremendous rise in world population. Solar energy is a perfectly eco-friendly alternative to fossil fuels that receives little attention worldwide. The major goal is to collect solar radiation using a high efficiency technology because solar conversion devices have low efficiency.

To close this gap, a new field has been created using nanotechnology. The use of nanofluid significantly boosts the effectiveness of solar energy systems (Ahmed et al. 2014). A sample solar energy system is shown in (figure 1.1).

Figure 1.1: Solar Energy Systems.

1.2 TECHNOLOGIES AND RESOURCES

Solar energy is a term used to describe energy sources that can be linked to direct sunlight or the heat that sunlight produces. The continuum of solar technologies includes passive and active, thermal and photovoltaic, and concentrate and not concentrate. Technology used in passive solar systems just collects energy; it does not change heat or light into other forms. For instance, it entails making the most of heat or light through architectural design. Contrarily, active solar technology—which may be roughly categorized into two groups: photovoltaic (PV) and solar thermal—means that solar energy is employed to store it or transform it for other applications. When light strikes a semiconductor material, it excites electrons and significantly increases conductivity, converting the radiant energy present in the light quantum into electrical energy. This process is known as photovoltaic technology (PV). Solar heat is employed in solar thermal technology, which can produce electricity or be used directly thermally for warmth. Solar energy without electricity and solar thermal energy are the two main subcategories. Applications in the first category include solar cookers, solar water heaters, solar air warmers, solar cooling systems, and agricultural drying (Borchers, Xiarchos, and Beckman 2014).

The latter, also known as concentrated solar power, refers to the utilization of solar heat to create steam for the creation of electricity (CSP). The market now offers four different types of CSP technologies: Parabolic Trough, Fresnel Mirror, Power Tower, and Solar Dish Collector. Our main source of renewable energy is solar energy (Zhang et al. 2013).

In the highest latitudes, effective solar radiation is approximately 0.06 kW/m2, while at low latitudes, it is 0.25 kW/m2. Figure 1.2 uses the present conversion efficiency of existing technologies to assess the technically realistic potential of various renewable energy choices. The technical potential of solar energy in the world's best places is far more than the current total primary energy consumption in those regions, even on a regional scale (Byrne et al. 2010).

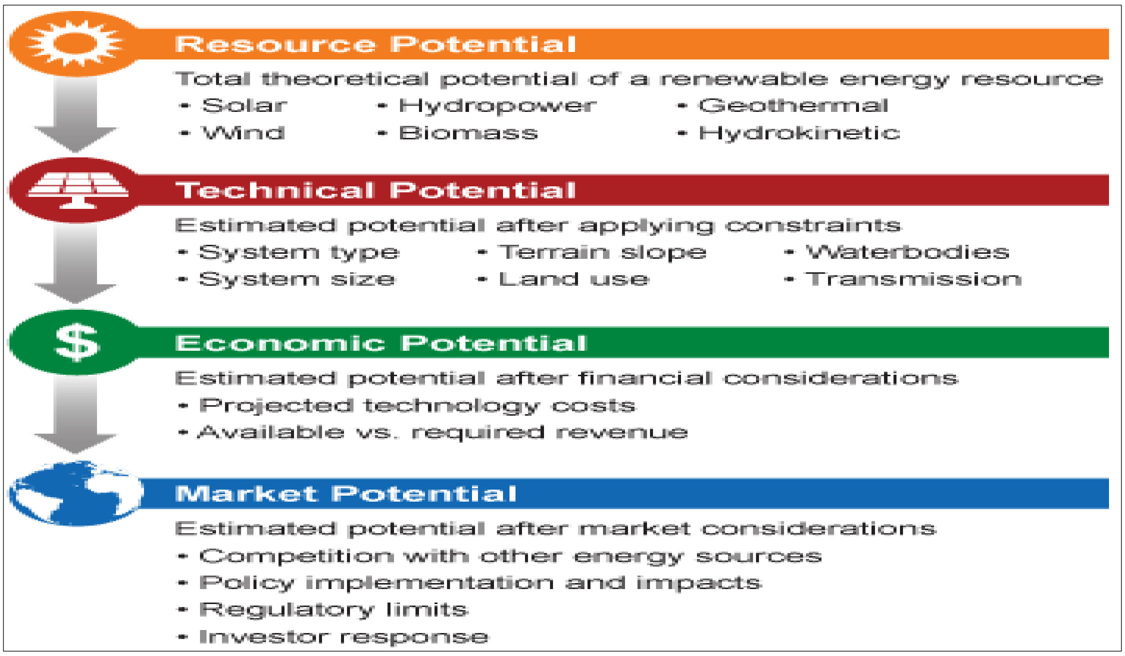

Figure 1.2: Technologies for Renewable Energy have Technical Potential.

1.3 SOLAR PV

Global installed capacity for PV as of December 2010 About 40 GW4, 85% connected to the grid and 15% are off-grid. PV cells made of crystalline silicon today account for more than 80% of the market, and they dominate it.

The rest of the market is dominated by thin film technologies that use photovoltaic cells manufactured by direct deposition on a supporting substrate. Figure 1.3a displays the total installed PV capacity at the worldwide level for Trend of global installed capacity. A handful of countries, the PV market, as shown in figure 1.3b. But in some countries significant market growth. In particular, the Czech Republic, as of December 2010, about 2 GW of solar PV was nearly none in 2008.

In 2010, China had 893 MW of total installed PV capacity, whereas India had 102 MW (Tripathi 2014).

Figure 1.3: Total Installed Capacity of PV at the Global Level.

1.4 CURRENT GLOBAL STATUS FOR SOLAR ENERGY

The majority of renewable energy sources (such as wind, sun, tidal wave, hydro, etc.) are not limited by time of day, season, year, or even place. The use of renewable energy is competitively pursued alongside traditional energy sources in many nations, making a significant contribution to the nation's energy production. In Italy, Greece, and Germany, for instance, solar PV is thought to contribute 7.9%, 7.6%, and 7.0%, respectively, to the need for power. Solar PV capabilities ranged from 3.7 to 225 GW in 2004. It helped develop total solar capacity in 2015, resulting in an additional 59 GW and a $ 161 billion investment. Yet, with an installed capacity of about 100 GW, Europe continues to be the sunniest region. Europe's solar capacity expanded by 8 GW in 2015, but only 5.3 GW (75% more) in the UK, Germany, and France. China, however, has achieved great progress in terms of the overall installed solar capacity. 43 GW have been on the table in Germany's global ranking as of December 2015. China also has ambitions to boost its solar power output to 150 GW by 2020. According to the American Solar Energy Industries Association, in 2017, the nation's total solar PV capacity might reach 45 GW. With 913 MW produced in 2015 compared to 774 MW from wind energy, solar energy has surpassed wind energy as the most major source of new power in Australia. It's interesting to note that Australia stopped using coal power for 1300 Megawatts in the same year. This has been hailed as a great step toward transforming the world's traditional coal-based energy production. The capacity of India's solar power system increased from 3743 MW in March 2015 to 6762 MW in March 2016 to 8062 MW in March 2017. (July 2016). India is currently planning to grow its solar power to an astounding 100,000 MW by 2022 thanks to such breakthroughs. Similar to this, France aims to construct a 1,000 km solar expressway across Europe that could provide enough renewable energy to power 5,000 households each km (Lu et al. 2020).

1.5 AIM OF THESIS

In this thesis we use the particle swarm optimization method to increasing the MPPT performance in solar energy systems.

1.6 CONTRIBUTION OF THESIS

A common technique for maximizing power extraction from photovoltaic (PV) solar systems and wind turbines is called maximum power point tracking (MPPT). The theory is usually applicable to sources with fluctuating power, such as thermophotovoltaics and optical power transmission, even though it primarily deals with solar power. PV solar systems can be configured in a variety of ways with regard to their connections to inverter systems, external grids, battery banks, or other electrical loads. However, the primary problem that MPPT attempts to solve is that the efficiency of power transfer from the solar cell is dependent on the amount of sunlight that hits the solar panels, their temperature, and the electrical properties of the load. No matter where solar energy is ultimately consumed, this is true. When the amount of sunlight and solar panel temperature change, the load characteristic that provides the maximum power transfer efficiency changes as well. As a result, the efficiency of the system is maximized when the load characteristic changes to maintain the power transfer at its highest efficiency. Maximum power point tracking is a technique for locating and preserving the maximum power point (MPP) of this load characteristic (MPPT). MPPT provides a solution to the issue of choosing the appropriate load to apply to the solar cells in order to extract the most useful power. Electrical circuits can be made to provide photovoltaic cells with any kind of load, and then they can change the voltage, current, or frequency to work with different systems or devices. In this thesis the MATLAB-SIMULINK is used to modeling of the PSO method and finding the best MPPT point for the power.

1.7 PROPOSAL OF THESIS

Particle swarm optimization (PSO) is a term used in computers to describe a metaheuristic that mimics the actions of natural particles. The PSO techniques are credited to the researchers Kennedy, Eberhart, and Shi at first. Their original purpose was to simulate social activity, such as the movement of a school of fish or a flock of birds, which are examples of living things. The approach was later made simpler and was discovered to work well for optimization issues. By moving "particles," or candidate solutions, throughout the search space in accordance with mathematical rules that take into account the position and velocity of the particles, PSO enables us to optimize a problem from a population of potential solutions. Each particle's velocity is affected by its current best local position as well as the best global locations attained by other particles as they move across the search space. Making the cloud of particles quickly converge towards the best answers is the theoretical justification for this. PSO is a metaheuristic because it may be used in enormous spaces of candidate solutions and requires little to no hypotheses about the problem to be optimized. PSO does not, however, ensure that an optimal solution will be found in every situation, like all metaheuristics.

2. LITERATURE REVIEW

2.1 BACKGROUND

The history of solar energy control systems can be traced back to the early development of solar power technologies. Here are key milestones in the history of solar energy control systems:

During the period of 1950s-1960s: solar photovoltaic (PV) systems began to be developed for space exploration and satellite applications. Control systems were primarily focused on regulating power output, managing battery charging, and maintaining stable operation in space environments (Pirani, S. 2018).

In the period of the 1970s: As solar energy gained attention for terrestrial applications, control systems were developed to improve the efficiency and reliability of solar power systems. MPPT algorithms emerged to optimize the power output of solar panels. Battery management systems were also introduced to enhance energy storage performance (Sankaran 2022).

The duration of 1980s-1990s: With the growing deployment of grid-connected solar power systems, control systems were developed to ensure safe integration with the electrical grid. Grid interaction control mechanisms, including synchronization and grid code compliance, were implemented to enable seamless connection and power injection into the grid (Farivar,2020).

In the 2000s: Advancements in electronics and microcontrollers enabled more sophisticated control systems for solar energy. The integration of digital control techniques, such as advanced MPPT algorithms, allowed for precise tracking of the maximum power point and improved system efficiency. Monitoring capabilities expanded with the use of communication technologies, enabling remote monitoring and data analysis (Ahmad 2020).

In the present current solar energy control systems continue to evolve with advancements in technology. The use of advanced algorithms, machine learning, and artificial intelligence techniques is being explored to further optimize energy production, improve system performance, and enable predictive maintenance. The integration of energy management systems and smart grid technologies allows for more effective load management and grid interaction (Alassery 2022).

Throughout the history of solar energy control systems, there has been a continuous focus on improving system efficiency, reliability, and safety. The advancements in control systems have played a significant role in the widespread adoption of solar power as a clean and renewable energy source, contributing to the global transition towards sustainable energy systems.

2.2 SOLAR ENERGY CONTROL SYSTEM

A solar energy control system, also known as a solar power control system, refers to a set of components and algorithms that manage and optimize the generation, distribution, and utilization of solar energy within a solar power system. It involves various control mechanisms to ensure efficient and safe operation of the system. Here are some key aspects of a solar energy control system (Liu,2021).

a. Solar Panel Control: The control system manages the operation and output of solar panels or modules. It includes mechanisms to track and optimize the position and orientation of solar panels to maximize solar energy absorption. This can be achieved through solar tracking systems that adjust the tilt and azimuth angles of the panels based on the sun's position (García 2020).
b. Maximum Power Point Tracking (MPPT): MPPT algorithms are used to optimize the power output of solar panels by continuously adjusting the operating point to the maximum power point. MPPT controllers track changes in environmental conditions and adjust the voltage and current levels to extract the maximum available power from the solar panels (Babes 2022).
c. Battery Management: In solar energy systems that incorporate energy storage, the control system manages the charging and discharging of batteries. It monitors battery voltage, current, and state of charge to ensure optimal battery performance and longevity. The control system regulates charging rates, prevents overcharging or deep discharging, and may implement temperature compensation for battery operation (Sangswang, 2020).
d. Grid Interaction Control: For grid-connected solar power systems, the control system manages the interaction between the solar system and the electrical grid. It includes mechanisms for synchronization with the grid's frequency and voltage, as well as monitoring the power injected into or drawn from the grid. Grid interaction control

ensures safe and reliable operation while adhering to grid codes and regulations (Chakir, 2022).

e. Load Management: The control system may also incorporate load management functionality to optimize the utilization of solar energy. It may prioritize the supply of solar power to specific loads, manage energy storage based on load demand and availability, and implement demand-response strategies to balance energy consumption and generation (García,2019).

f. Monitoring and Data Analysis: A solar energy control system often includes monitoring capabilities to collect and analyze data from various components, such as solar panels, inverters, batteries, and loads. Monitoring helps assess system performance, identify faults or inefficiencies, and facilitate maintenance and troubleshooting activities (Herraiz,2019).

g. System Protection: The control system incorporates protection mechanisms to ensure the safety and reliability of the solar power system. This includes overvoltage protection, overcurrent protection, short-circuit protection, and other safeguards to prevent damage to system components and ensure the safety of personnel (Anderson,2022).

Overall, a solar energy control system plays a crucial role in optimizing the performance, reliability, and safety of solar power systems. It enables efficient utilization of solar energy, ensures seamless integration with the grid, and facilitates effective management and monitoring of the system's components.

3. PARTICLE SWARM OPTIMIZATION

3.1 BACKGROUND

Like all optimization techniques, the Particle Swarm Optimization method looks for a range of input values for a particular function. The technique seeks for the best possible combination of inputs within the domain in order to generate the highest (or lowest) viable output value within the range of possible values for the function. Whereas the parameters for the output values could be things like performance, efficiency, or cost, the parameters for the input values could be things like power, force, or position. For example, these input values could be power, force, or location. Sensor data from a robotic prospecting mission to an extraterrestrial world reveals the location of a desired resource's concentration. The input-output relationship that this function depicts is denoted by the fitness function. In the event that it is not already a discrete function, this Fitness Function needs to be discretized before the optimization process may begin. Because discretization eliminates the need for floating-point calculations, errors in the observation of fitness function values are not affected. When there are N input parameters (variables that aren't controlled by anything else), the fitness function will also have N dimensions. The number of discrete points that should be placed along each input axis, as well as a maximum value and a minimum value, must be chosen before the fitness function may be discretized (Kotsiantis and Kanellopoulos 2006). The kind and amount of any noise present in the input parameters, for instance, if sensor data samples are used to create fitness function samples. This is something that must be kept in mind during the process of selecting these parameters.

a. When the output of the fitness function may be periodic, the Nyquist Sampling theorem is relevant.
b. the nature and severity of any noise, such as if fitness function samples were taken from a sensor. In this scenario, the noise may take the form of random fluctuations.
c. The development of an N-dimensional grid of discrete spots inside the search space, which are also referred to as "bins" occasionally, is the end result of the discretization method known as "discretization." In the context of the two-dimensional example, the concept is graphically represented as shown in Figure 2.1.

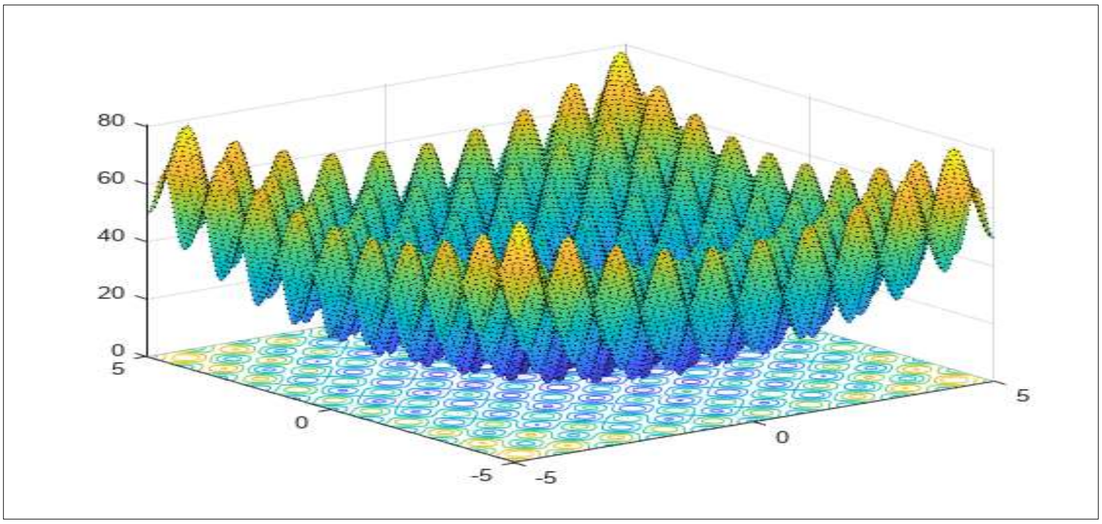

Figure 3.1: A Discretized Two-Dimensional Fitness Function in Which the Height of the Plot Represents the Fitness Value.

During this phase of the discretization process, it is necessary to strike a balance. The fitness value will be extremely variable inside the discrete bin if the bin is also big. The Fitness Functions would be considered an alias in this scenario. If the separate bin is not large enough, the noise in a particular place may cause the reading from a sensor to span more than one bin (Kotsiantis and Kanellopoulos 2006). The memory is used to store this discretization of the search space while the optimization procedure is being carried out. The values of the points that are sampled along the fitness function are saved as they are obtained. Memory is the limiting factor for both the number of dimensions N and the number of discrete points on an axis, for systems that retain this discretization in memory. This means that the maximum number of discrete points on an axis cannot exceed the memory capacity of the computer. Because this implementation is only intended to serve as proof-of-concept, the simulations that are being provided Use caution while utilizing Fitness Functions with parameter spaces that exceed the system's memory capacity. In systems that use Fitness Functions with vast parameter spaces, the discretization data must be saved using techniques with a greater latency, like files, databases, or network ports. This is true because these methods take more time to complete.

3.2 OPTIMIZATION PROCESS

The region on the fitness function that will be sampled during the subsequent optimization step is referred to as a particle. On the following optimization cycle, this place will be sampled. These Particles are individual robots that, as part of our exploration mission to find natural resources on other worlds, are tasked with selecting sites within the search space in which to conduct their investigations. There is a possibility that the movement of these Particles across the Fitness Function will appear to be rather chaotic. The name "Particle Swarm Optimization" comes from the chaotic movement of the particles.

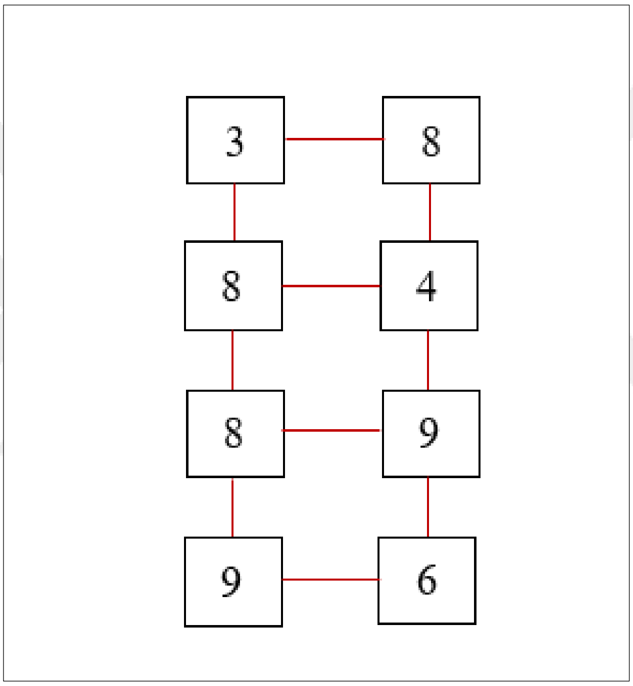

Figure 3.2: The "Survival of the Fittest" Mechanism is Shown in A Visual Way. New Samples are Discovered and Compared to the Finest Samples Already Available (Each Row) to the Following Comparison.

The sample with the highest fitness value is chosen using a "survival of the fittest" approach in particle swarm optimization. When the optimization process determines the fitness function's maximum value, The highest fitness value has the best value. The best fitness value is the lowest when the optimization procedure determines the fitness function's least value. There is a straightforward process for each particle that identifies the specimen with the best fitness rating. The "best fitness" sample from the past is compared to the fitness values of freshly discovered samples. When the fitness score rises, the new sample becomes the "best fitness" sample. If the fitness declines, the previous value remains. The old or new sample is picked at random using a uniform distribution if the fitness values are precisely equal. Figure 2.2 depicts this procedure. Each particle is able to locate the best fitness sample they have ever found thanks to this process. This best illustration is referred to as The Area's Finest. The collection of Local Best samples is repeatedly subjected to this "survival of the fittest" methodology in order to determine the best sample that all Particles have discovered. The Global Best or Local Best is the name given to this top sample. The multiple Local Best locations identified in each comparison serve as the "New Samples" input values in the following "survival of the fittest" approach shown in Figure 2.2. This demonstrates that, among the several Local Best samples, the Global Best sample is the most suitable and that, for at least one particle, the Global and Local Best samples are identical. Due to centralized implementation, each Particle in the simulations performed here has access to the same memory space on the computer. Information about the locations and values of recently discovered sample data, however, must be sent to the other robots during a robotic prospecting trip utilizing radio communications. This communication creates a setting similar to the centralized simulation while each robot executes the algorithm independently (Helwig, Branke, and Mostaghim 2012)(Bratton and Kennedy 2007)(Clerc and Kennedy 2002)(Jin'no 2009)(Jin'no and Shindo 2010)(Jin'no and Shindo 2010)(Clerc and Kennedy 2002)(Clerc and Kennedy 2002)(Jin'no 2009)(Jin'no and Shindo 2010)(Shindo and Jin'no 2013)(Trelea 2003). Adding dashed lines to Equation 2.11 to draw attention to the broader case's symmetry with the one-dimensional state-space model. The complete decoupling of the dynamics of each fitness function dimension is the main characteristic of this equation system. The interdependence of the states must be kept in mind. The two states for each fitness function dimension are the present location along each axis and the most recent position. While being related, these two states are apart from one another in all other dimensions. Additionally, because the inputs for each dimension are independent of one another, A y-axis input only affects the y-axis, and an x-axis input only affects the x-axis. As the whole analysis done for the one-dimensional system still holds true for the entire scenario, this decoupling is crucial. Each axis' dynamics can be thought of as a separate one-dimensional system. The dynamics need not be limited to being similar for each dimension because they are decoupled for each dimension of the fitness function. by vectorizing the inertia weight.

3.3 CLOSED LOOP DYNAMICS

The closed-loop dynamics will be looked at now that a generalized N dimensional form of the state-space representation has been created. The decoupled character of the open-loop system is maintained by setting the gain matrix to have these terms zero, even though the off-diagonal components of K need not be 0. The B and K matrices' entries for these locations are zero because the state vector's final point is missing. It is crucial to note that the entire state vector feedback complies with the matrix multiplication requirements (ABK equals 2N 2N). By changing the gain levels for the feedback terms, the conventional version of PSO tries to generate a Brownian (random) motion for the particle dynamics. Previous studies have used the constriction factor, local weight, and neighbor weight selection to ensure that the stability of that particle is not jeopardized by the random vectors (Clerc and Kennedy 2002)(Jin'no and Shindo 2010). It is not advisable to use this technique to create randomness in the output signal since changing the closed-loop gains has an impact on the system's performance and stability. Instead, constant K and M gain values are chosen in this instance as a more conservative method. These values are recognized to be stable, function well, and be resistant to a given level of noise. The signal is then modulated with randomness using this deterministic output.

3.4 DESIRED LOCATION

The choice of the preferred sample site for the PSO Equation in state-space is covered in this section. The closed-loop dynamics from the prior section will be applied at this position. The PSO algorithm's optimization component depends on the choice of this site. The equation that selects the target position in the original PSO technique determines the location using randomly generated closed-loop gains. While the analysis conducted up to this point has decided to employ a constant closed-loop gain K, the standard form of the PSO equation contains a gain that changes with time. This is crucial for the reader to comprehend. The random vectors r1(k) and r2 are responsible for this change (k), They are produced at every k-th timestep. The desired position will be determined using the equation K(k). To demonstrate to the reader how the intended location is utilized in both the conventional and state-space implementations of the PSO algorithm, this is done. It is important to keep in mind that the division symbols used here reflect the Hadamard product, which is vector division done element by element, as K is a vector. This relationship has been discussed in the past, and research has looked into how C1 and C2 are weighted. If C1 is given a bigger weight, each particle is more likely to track its own distinct Local Best position. This suggests that a better investigation of the search space is warranted. If C2 is given a bigger weight, All Particles are more likely to choose the Global Best posture. As a result, the swarm will finally converge at the site of the Global Best. The behavior of the swarm of particles can be managed by adjusting the ratio between C1 and C2 (Kameyama 2009). Nevertheless, because C1 and C2 have an impact on the closed-loop gain, they also have an impact on the system's performance and stability. This makes it foolish to try and use these settings to influence the swarm's behavior. Once more, it is preferable to keep C1 and C2 at constant values while controlling the behavior of the swarm with a different approach suggested in this study that is similar to the plan outlined in the previous section. The Resident Finest location is used as the intended location in all of the proof-of-concept simulations described in this study. Robotic prospecting for natural resources aims to locate areas having significant target resource concentrations. The robots are not desired by the software. congregate in the region of the search space where there is the greatest concentration. Due to this, C1 = 1 and C2 = 0 are used for tracking the Local Best location. This design, as opposed to following merely the Global Best, is what previous work indicates leads to improved exploration of the search space (Kameyama 2009). Choosing to track the Local Best location ensures that the intended position is independent of a closed-loop gain that varies over time. This is an important consideration. So, using this configuration with the PSO state-space representation is appropriate. A future work implementation may decide to employ a function approximation technique, such as Bayesian Regression, to pinpoint the areas in the search space where the fitness value confidence is the lowest in order to more thoroughly explore the search space.

4. PHOTOVOLTAIC SYSTEM

4.1 BACKGROUND

Fossil fuels have been a mainstay of the global energy market for centuries. Due to the implications of reliance on fossil fuel imports and the effect of fossil fuels on the environment, there is high demand for renewable energy resources as a replacement for fossil fuel-based power generation. Some of these renewable energy resources include solar, wind, and hydroelectric. Solar power, also known as a photovoltaic power, is a popular renewable energy resource due to its availability and low maintenance costs. As shown by the map in Figure 3.1, solar power may be generated anywhere. Though not a continuous supply of power, solar power can be used to regularly generate electricity. Solar panel can be an important resource for remote regions. For example, solar power may be used to provide electric power to a remote location not connected to a utility grid (Boveri 2016). Solar may even be combined with other renewable energy resources to form a reliable microgrid (Ratsame 2012).

A photovoltaic (PV) system, also known as a solar power system, is an arrangement of solar panels or modules that convert sunlight directly into electricity. PV systems are designed to harness solar energy and generate clean and renewable electricity (Mugha 2018). Here are some key components and aspects of a typical photovoltaic system:

a. Solar Panels/Modules: Solar panels or modules are the primary components of a PV system. They consist of interconnected solar cells that convert sunlight into direct current (DC) electricity. These panels are usually made of semiconductor materials like silicon (El Hammoumi).
b. Inverter: The DC electricity produced by the solar panels needs to be converted into alternating current (AC) electricity, which is used to power electrical appliances and is compatible with the electrical grid. An inverter is used to perform this conversion (Nwaigwe,2019).
c. Mounting Structure: Solar panels are typically mounted on structures or rooftops to maximize their exposure to sunlight. Mounting structures provide support and orientation for the panels, ensuring optimal solar energy absorption (Dörenkämper, 2021).
d. Electrical Wiring: Electrical wiring connects the solar panels, inverter, and other system components. It facilitates the flow of electricity within the PV system and allows for the

integration of the system with the building's electrical system or the electrical grid (Khan 2022).

e. Batteries and Energy Storage: Some PV systems include batteries or energy storage systems to store excess electricity generated during periods of high solar availability. These stored energy reserves can be utilized during times when solar generation is lower, such as at night or during cloudy days (Kumar 2022).
f. Monitoring and control: PV systems often have monitoring and control systems that allow users to track the performance and output of the system. These systems provide real-time data on energy production, system efficiency, and potential issues, enabling maintenance and optimization of the system's performance (Shapsough 2021).
g. Grid connection: PV systems can be grid-connected or off-grid. In grid-connected systems, excess electricity generated by the PV system can be fed back into the electrical grid, earning credits or revenue through net metering or feed-in tariffs. Off-grid systems, on the other hand, are standalone systems that are not connected to the electrical grid and rely on batteries or other energy storage methods for electricity supply (Jasuan 2021).

Photovoltaic systems have numerous applications, ranging from residential and commercial installations to utility-scale solar power plants. They offer a sustainable and environmentally friendly source of electricity, reducing dependence on fossil fuels and contributing to the transition to clean energy.

4.2 DESCRIPTION OF HARDWARE COMPONENTS

The following section is an explanation of the basic components used in a photovoltaic energy collection system. A photovoltaic system usually includes a photovoltaic (PV) source and a converter structured to receive the DC power from the PV source and convert the DC power to AC power or DC power with a higher voltage.

4.3 PHOTOVOLTAIC PANEL

A PV panel is a means for generating direct current power using a light source. A PV panel is often modeled as a current source (Rahman et al. 2016).

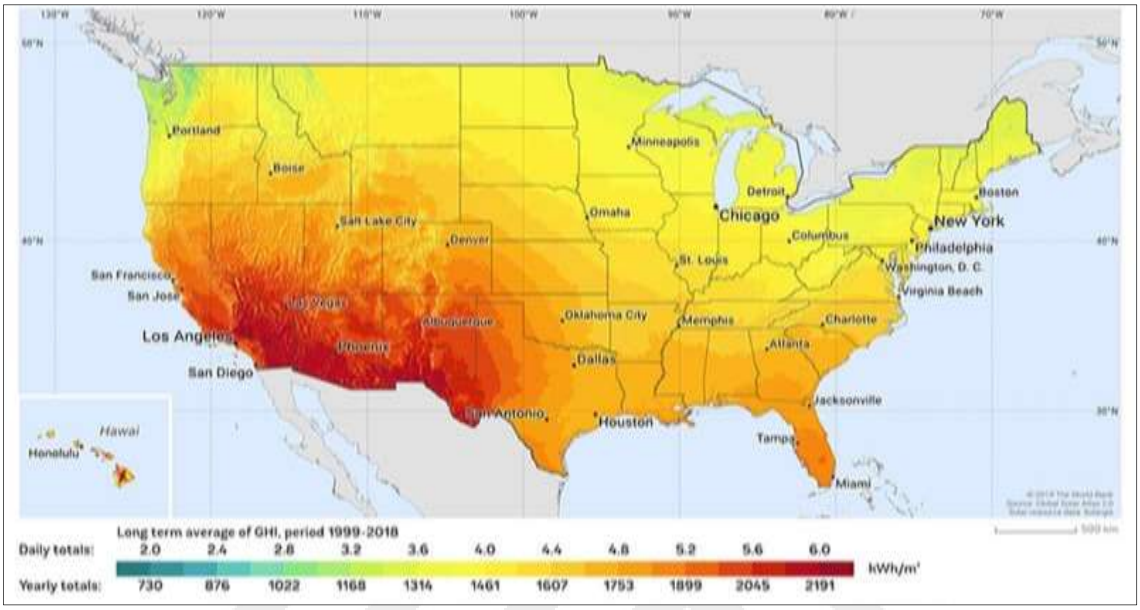

Figure 4.1: Solar Map of the United States (Martins, Pereira, and Abreu 2007).

An equivalent circuit is show in Figure 3.2 where I_{pv} represents current generated by the solar panel, D_1 represents the voltage-dependent current lost, R_{sh} represents the current lost due to shunt resistance, and R_s represents series resistance. Since the output current and output voltage of a solar panel are co-dependent, the output power of a solar panel is represented with an I-V curve.

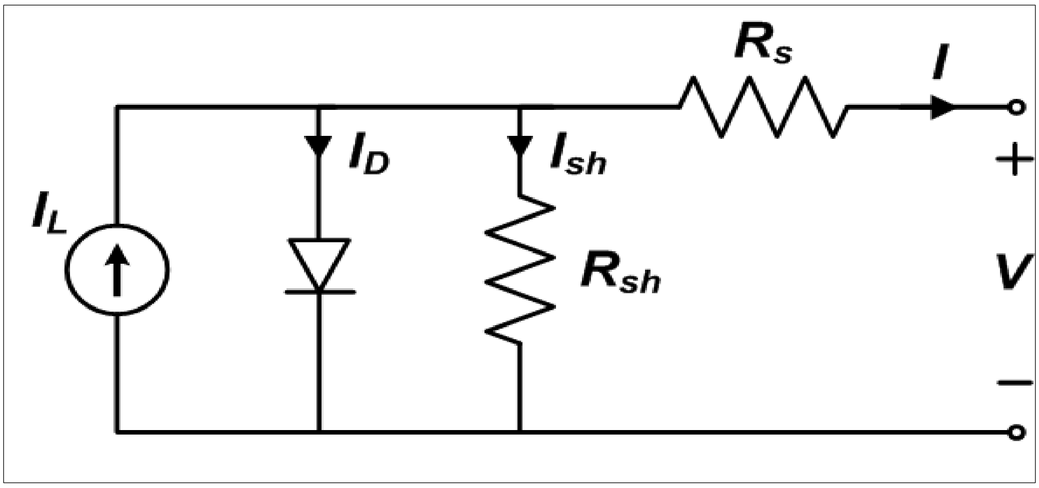

Figure 4.2: Solar Panel Equivalent Circuit.

The maximum current (short circuit current) and maximum voltage (open circuit voltage) generated by a solar panel are dependent two main variables: panel temperature and solar irradiance. Irradiance is the measure of light intensity absorbed by the solar panel, measured in watts per meter squared (W/m^2). Solar irradiance primarily affects the maximum current produced by the solar panel. As shown in Figure 3.3, maximum current increases as irradiance increases and decreases when irradiance decreases. The rate of change of irradiance with respect to sunlight typically does not exceed 60% per second (Huque, Coley, and Key 2013). Changes in irradiance may be due to cloud cover, which affects the entire solar panel evenly, or due to shading, which affects a portion of the solar panel (Dhople et al. 2012). Irradiance is also affected by the position of the solar panel with respect to the sunlight. Some PV systems use a sunlight tracker to physically move the solar panel to face the sun throughout the course of a day (Gupta and Saxena 2016).

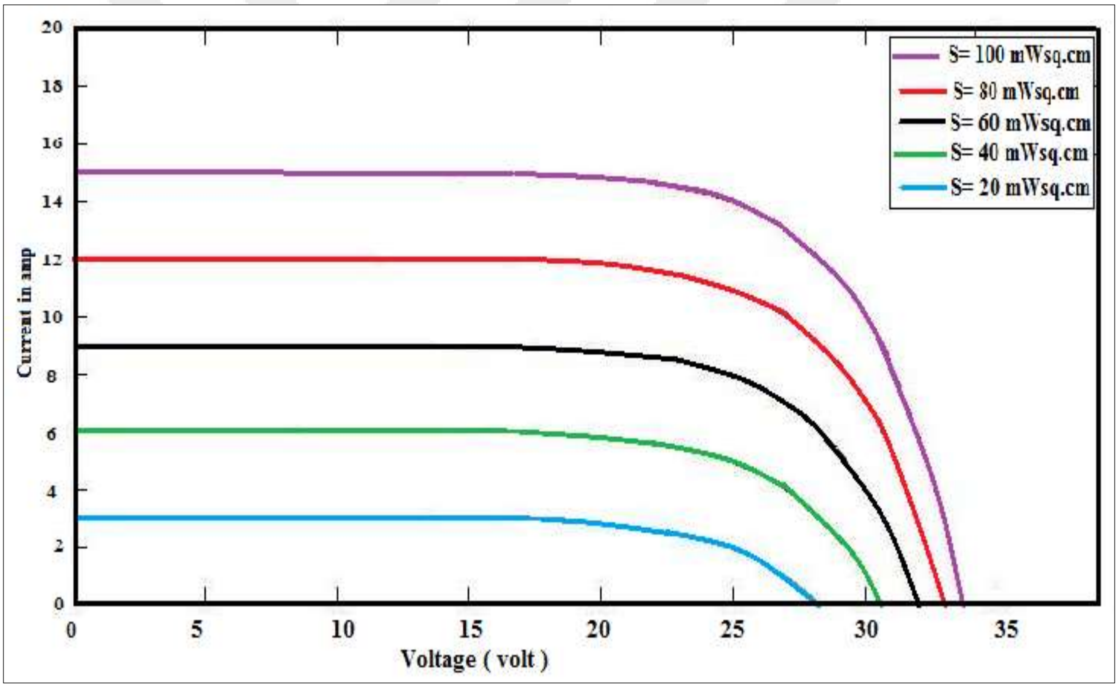

Figure 4.3: IV Curves for Different Irradiance Levels.

Panel temperature mainly affects the maximum output voltage. As shown in Figure 3.4, maximum output voltage increases as temperature decreases and maximum output voltage decreases as temperature increases (Hussein et al. 1995). Weather conditions such as ambient temperature, wind, and rain affect the panel temperature. Solar irradiance also affects the panel temperature.

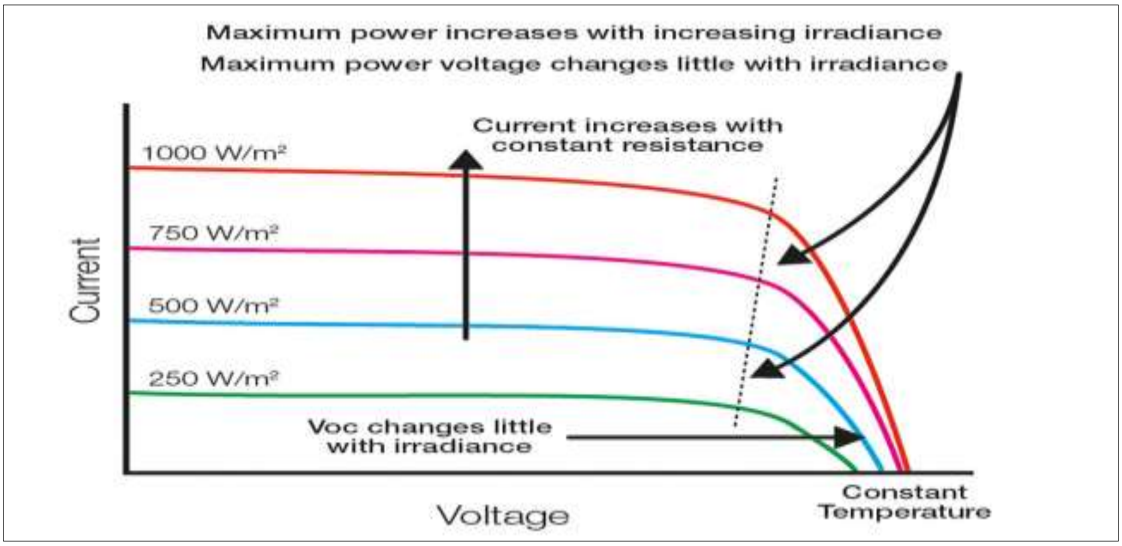

Figure 4.4: IV Curves for Different Temperature Levels.

Some companies have begun to incorporate circuitry into the solar panel itself. For example, some solar panels now include small DC-DC optimizers to maximize output power (Hester, Dhople, and Sridhar 2015)(Har-Shai et al. 2018). Other solar panels include data loggers which collects power output and fault data. Solar panels may be combined into arrays based on desired output current and output voltage. For example, solar panels may be coupled in series to increase output voltage. Solar panels may be coupled in parallel to increase output current.

4.4 DC/DC CONVERTER

A converter is coupled to the output of the solar panel to receive the DC power generated with the panel. This converter commonly includes a DC-DC converter, also known as a DC-DC optimizer. The DC-DC converter is employed to change the load characteristics according to the requirement by varying the duty cycle of a switching device within the DC-DC converter (Al-Gizi 2016). A circuit diagram for a DC-DC converter is illustrated in Figure 3.5. The illustrated DC-DC converter is a boost converter, meaning the voltage of the power output by the DC-DC converter is greater than voltage of the power received with the DC-DC converter. Another type of DC-DC converter commonly coupled to a PV source is a buck converter, which outputs DC power with a voltage less than the voltage of the input power.

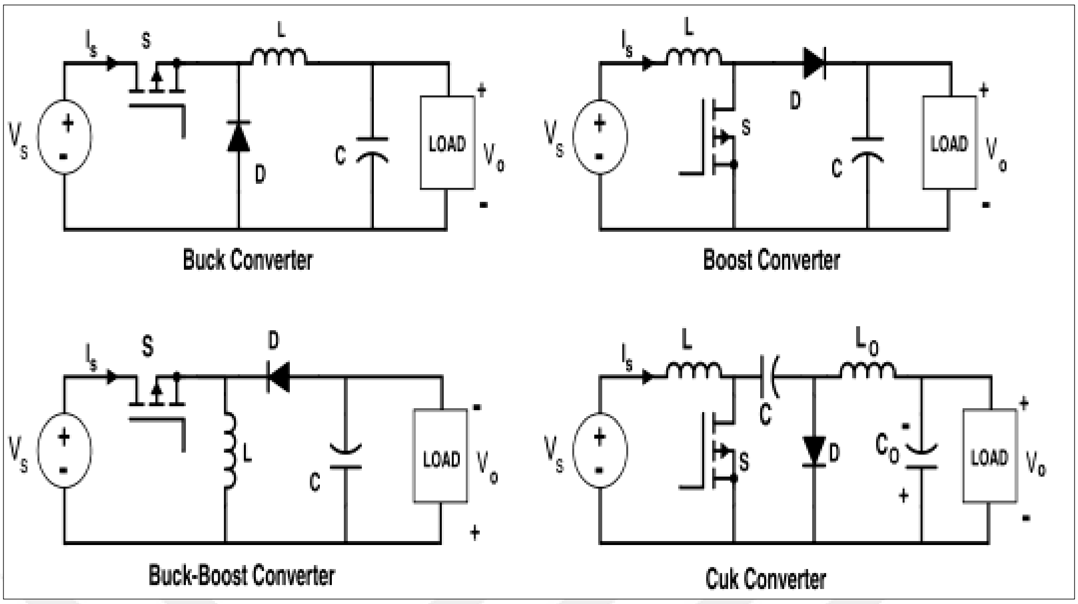

Figure 4.5: DC-DC Converter Circuit Diagram.

The effect of operating the switch of the DC-DC converter is illustrated in Figure 3.6. The top graph represents the switching state of the DC-DC converter switch. A high value means the switch is close and a low value means the switch is open. As show in the second graph, the input voltage V_i is less than the output voltage V_o. The third graph illustrates the current through the inductor of the boost converter. The relationship between the input voltage and output voltage of a boost converter can be expressed with the following equation, where V_{out} is the output voltage, V_{in} is the input voltage, and D is the duty cycle.

$$V_{out} = \frac{V_{in}}{1 - D} \tag{3.1}$$

A boost converter coupled to a voltage source will have a constant input voltage. However, as we will see in more detail below, a boost converter coupled to a PV panel may control the solar panel output voltage by adjusting the duty cycle of the DC-DC converter.

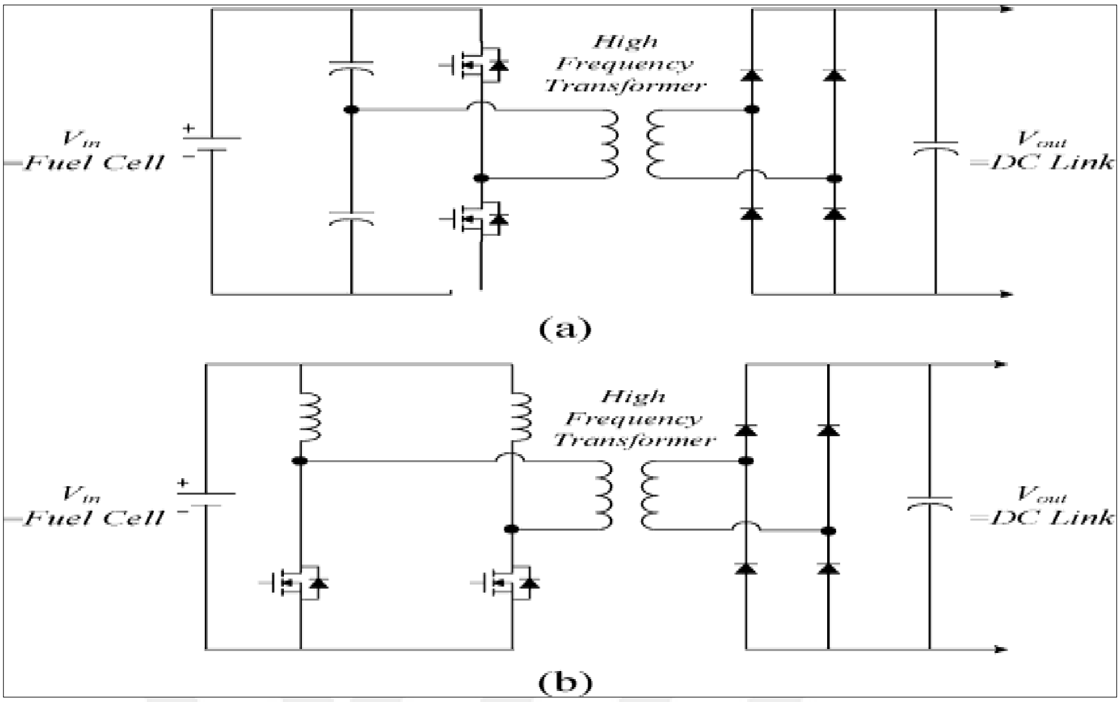

Figure 4.6: C-DC Converter Voltages and Currents, (a) Voltage, (b) Current.

DC-DC converter may be arranged in different configuration depending on the desired efficiency of the system. For optimal efficiency, each solar panel is coupled to a separate DC-DC optimizer. In other arrangements, a single DC-DC optimizer may be used for a string of panels (Libo, Zhengming, and Jianzheng 2007).

4.5 INVERTER

The converter coupled to the PV source may also include an inverter which converts DC power from the DC-DC converter to AC power (Marouani and Bacha 2009). Figure 3.7 illustrates a three-phase inverter topology. Each switch of the inverter is controlled so as to generate sinusoidal current wave for Phase A, Phase B, and Phase C.

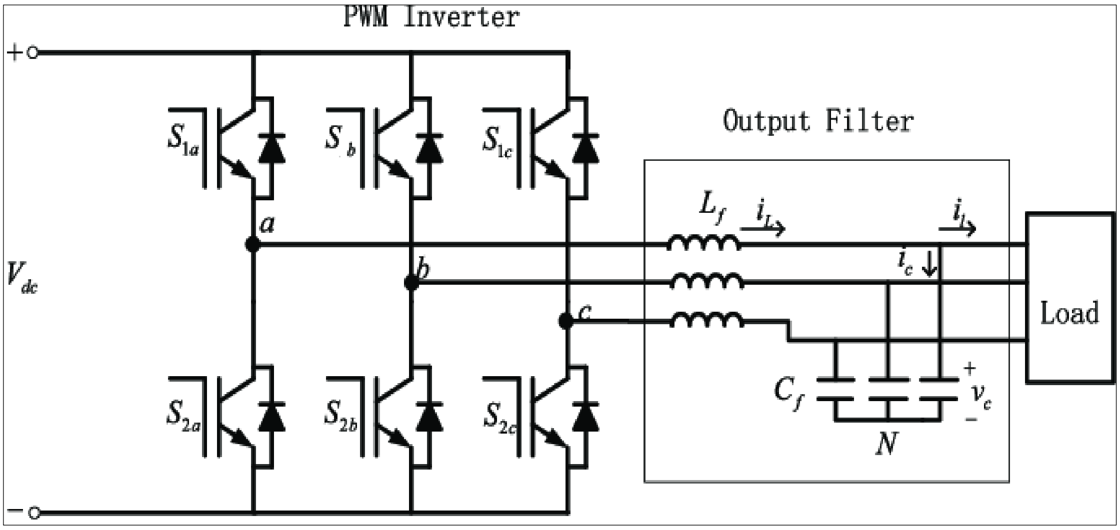

Figure 4.7: Three Phase Inverter Topology.

The switches of the inverter and the switches of the DC-DC converter may be controlled using a control strategy called pulse width modulation, or PWM (Liu and Sánchez-Sinencio 2015). A comparator receives a modulating signal and carrier signal, such as the signals in the first graph of Figure 3.8, and produces an activation signal as depicted in the second graph of Figure 3.8. A triangle or sawtooth wave, which is a high frequency waveform, serves as the carrier signal. To obtain the required converter output, the modulating signal may be controlled. A sinusoidal modulating signal, for instance, might be used by an inverter to produce the desired output frequency. The switch's activation signal is switched on and off each time the carrier signal crosses the modulating signal. The operation of a three-phase inverter using PWM is illustrated in Figure 3.9. A sinusoidal current is generated by operating the inverter to produce the illustrated voltage outputs. Inverters may also incorporate additional elements such as passive components for soft switching or MPPT (Chen et al. 2013). Just as the DC-DC converters may be coupled to one or more solar panels, an inverter may be coupled to a single solar panel or a solar panel array. Inverters coupled to solar panel arrays are called string inverters. While connecting one inverter to many solar panels is cheaper, output efficiency may.

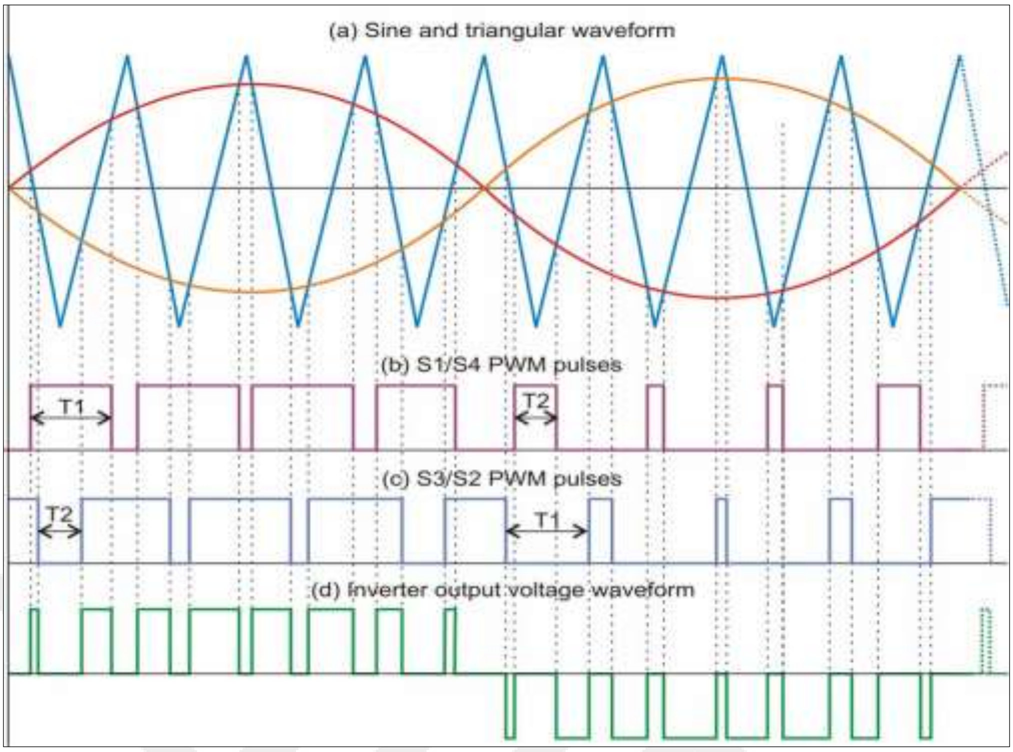

Figure 4.8: PWM Signals for Inverter Control.

be reduced if one of the panels is shaded. An inverter is called a microinverter, also known as a micro converter, when the inverter receives power from a small number of solar panels. Microinverters are generally more efficient than string inverters, and when arranged together in series, may be controlled individually so as to maximize the output power of a larger array (Chiu et al. 2012).

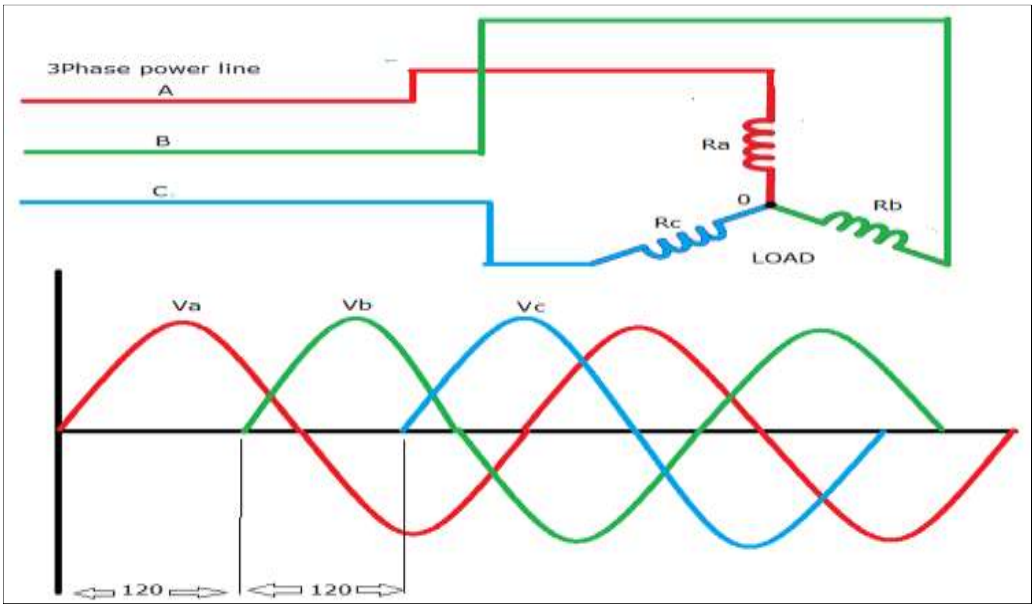

Figure 4.9: Three Phase Inverter Output.

4.6 LOAD

A load is coupled to the power converter and receives power generated by the solar panel. The load may be any device structured to receive electric power such as a utility grid, a battery, a microgrid, or a motor (Dubovsky 2012).

4.7 MAXIMUM POWER POINT TRACKING

Since power is equal to current times voltage, there exists a point on the I-V at which power is maximized. This point is called the maximum power point. A controller is used to operate the DC-DC converter so that the output voltage of the solar panel is the voltage corresponding to the maximum power point. Although a current reference may be used to track MPP, it is often viewed as too unstable. The process by which the controller operates the DC-DC converter to track MPP is called maximum power point tracking. As the solar panel experiences changes in irradiance and changes in temperature, the maximum power point changes. Thus it is the objective of the controller to quickly detect changes in the I-V curve of the solar panel and determine the new maximum power point (Urtasun, Sanchis, and Marroyo 2013). The controller configured to operate the DC-DC converter is commonly called an MPPT controller. One or more sensors may be used by the MPPT controller to track MPP. Some of the sensors used in known MPPT algorithms include voltage sensors, current sensors, temperature sensors, and irradiance sensors (Cuiping et al. 2016). While most MPPT controllers include digital circuitry, some MPPT controllers use only analog circuitry. In some cases, the MPPT controller can be used to control an inverter instead of a DC-DC converter (Wareesri and Po-Ngam 2016). Some MPPT controllers adjust the control strategy based on the type of load. For PV systems with multiple MPPT controllers, coordination using a wireless network may prevent power fluctuation. Each MPPT controller executes a stored algorithm in order to track the maximum power point. Numerous MPPT algorithms exist (Subudhi and Pradhan 2012). Particular MPPT algorithms will now be discussed, with particular attention paid to MPPT algorithms executable by a microcontroller with limited processing power and memory storage.

4.7.1 Perturb and Observe

One of the most common MPPT algorithms is perturb and observe (Zhang, Chen, and Chen 2014). The algorithm is illustrated in Figure 3.10.

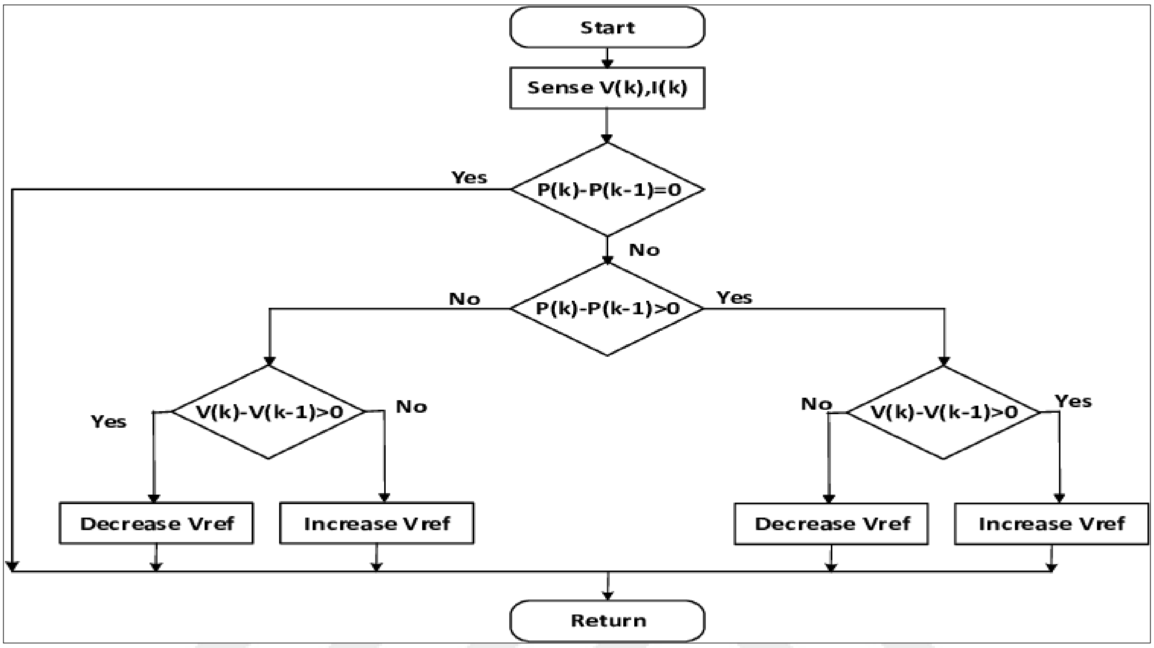

Figure 4.10: Flowchart of Perturb and Observe Algorithm.

Using measurements from a voltage sensor and a current sensor, solar panel output power is calculated. The current power value is compared to the most recent power value. If the current power value is greater than the previous power value, the same duty cycle adjustment is made as the previous duty cycle adjustment. If the current power value is less than the previous power value, the opposite duty cycle adjustment is made. For example, if the power increased from the previous measurement and the last duty cycle adjustment decreased the duty cycle, the duty cycle is again decreased. The algorithm is executed continuously in order to track MPP. perturb and observe may track inaccurately during periods of rapid changes in irradiance or temperature. The algorithm may be optimized by changing the value of the duty cycle adjustment or delaying the time period between duty cycle adjustments (Manganiello et al. 2015). Multiple variations of the perturb and observe method exist (Osako and Sato 2016). The variations include using perturb and observe during changes in irradiance and another algorithm during steady state; measuring motor frequency instead of voltage for pumping applications; and executing three perturbations at one time to evaluate the proximity to MPP.

4.7.2 Incremental Conductance

Another popular two sensor approach is incremental conductance (Elgendy 2016). Figure 3.11 provides an illustration of the algorithm. The dP/dV at MPP is zero, positive when the voltage is below Vmpp, and negative when the voltage is higher than Vmpp. This is the foundation for the algorithm. To calculate the value of dP/dV, current and voltage are sampled. Incremental conductance is subject to noise, just like perturb and observe.

4.7.3 Variable Step Incremental Conductance

Variable step inductance is another MPPT algorithm which is similar to incremental conductance (Ravari and Zarchi 2015). One of the disadvantages of incremental conductance is that duty cycle adjustments are equal, regardless how far away the converter is operating from MPP. Variable step incremental conductance determines the duty cycle adjustment based on the proximity to MPP. Some variations of the algorithm use the relationship between power and current to determine step size. Other variations combine the algorithm with perturb and observe such.

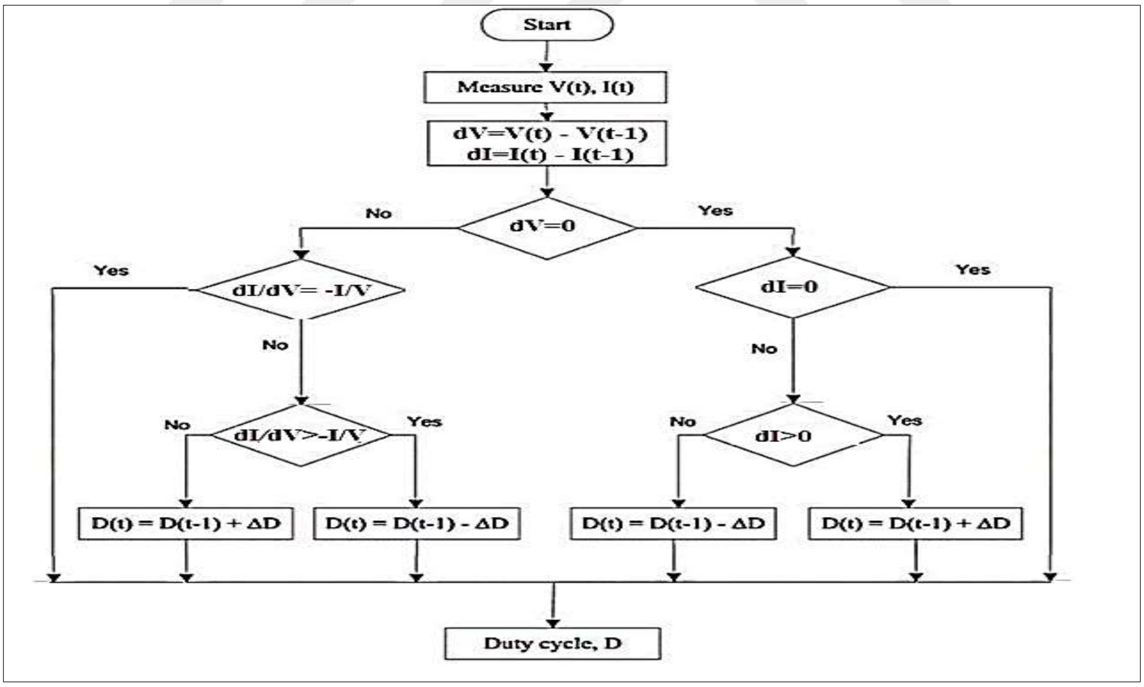

Figure 4.11: Flowchart of Incremental Conductance Algorithm.

that variable step is used for transient states and perturb and observe is used for steady state (Sturm 2017)(Hsieh, Hsieh, and Chan 2015)(Pulli and Hellberg 2016). In still other variations, variable step is combined with a technique called fractional open circuit voltage, which is explained in more detail below.

4.7.4 Weather Sensor-Based Algorithms

Weather sensor-based algorithms refer to computational methods and techniques that utilize data collected from weather sensors to analyze, model, and make predictions about weather conditions (Frnda ,2019). These algorithms are typically employed in weather forecasting, climate modeling, and environmental monitoring applications. Here are a few examples of weather sensor-based algorithms:

a. Numerical Weather Prediction (NWP): NWP algorithms use mathematical models and data from weather sensors to simulate the Earth's atmosphere and predict future weather conditions. These models utilize principles of fluid dynamics, thermodynamics, and other physical processes to generate forecasts. NWP algorithms assimilate observations from weather sensors, such as temperature, humidity, wind speed, and atmospheric pressure, to initialize and update the models (Hewage 2021).
b. Data Assimilation: Data assimilation algorithms combine observations from weather sensors with model predictions to create more accurate and reliable weather forecasts. These algorithms employ statistical techniques, such as Kalman filtering or variational methods, to merge the model output with observed data, adjusting and updating the model's initial conditions or parameters (Abbasi 2018).
c. Machine Learning for Weather Prediction: Machine learning algorithms, such as artificial neural networks, decision trees, or support vector machines, can be used to learn patterns and relationships between weather sensor data and weather outcomes. These algorithms can identify complex non-linear relationships and make predictions based on historical data from weather sensors, including temperature, humidity, wind, precipitation, and cloud cover (Rahman 2022).
d. Image Processing for Weather Monitoring: Image processing algorithms can be applied to data collected from weather sensors, such as satellite imagery or radar data. These algorithms analyze the images to detect and track cloud formations, identify storm systems, estimate rainfall intensity, and monitor other weather-related phenomena (Amani 2022).

e. Extreme Event Detection: Algorithms can analyze data from weather sensors to detect and predict extreme weather events, such as hurricanes, tornadoes, or flash floods. These algorithms employ statistical methods and pattern recognition techniques to identify precursors or indicators of severe weather conditions, allowing for early warnings and preparations (Salcedo 2022).
f. Climate Modeling: Climate models incorporate data from weather sensors to simulate long-term climate patterns and study climate change. These models use algorithms to represent various physical processes, including interactions between the atmosphere, ocean, land, and ice. By assimilating observational data, climate models can simulate historical climate conditions and project future climate scenarios (Kashinath 2021).

A plurality of MPPT algorithms use temperature and irradiance measurements to calculate MPPT (Min 2014). For example, one algorithm identifies a voltage reference value from a lookup table using a temperature and irradiance measurement. Other method generates a system model using temperature measurements, irradiance measurements, and system parameters to determine MPP.

4.7.5 Processor Heavy Algorithms

A number of MPPT algorithms require a hardware configuration with significant processing capabilities (Mao et al. 2016)(Marquez et al. 2016)(Li et al. 2016). These algorithms include generating a system model or performing complex calculations. For example, some controllers use fuzzy logic or fish swarm algorithm to track MPPT. Since the objective of this thesis is to develop an MPPT method for a low-cost microcontroller, these hardware heavy algorithms will not be explained in further detail.

4.7.6 Single Sensor Algorithms

A small subset of MPPT algorithms use a single sensor to track maximum power point. One of the benefits of using a single sensor is the reduction of measurement errors compared to a two sensor system (Abdourrziq, Ouassaid, and Maaroufi 2016) Some single sensor algorithms use a current sensor, the most well-known being the fractional short circuit algorithm. The algorithm identifies a current reference value by measuring the short circuit of the solar panel and multiplying the measured short circuit current by a gain. The algorithm has been criticized for not tracking maximum power point over a wide range of irradiances and temperatures. Other single sensor methods use current measurements and the duty cycle value to track maximum power point. In one algorithm, the current measurement and the duty cycle value are used to estimate voltage. In another algorithm, the current measures current between the converter and the load to track maximum power point. The single sensor algorithms that do not use a current sensor instead use a voltage sensor.

Voltage sensors are preferred over current sensors due to their low cost and simplicity. A voltage sensor, for example, may be as simple as two resistors coupled in series which divides the measured voltage into a voltage range between 0 and 3.3V.

The output of the voltage divider can be transmitted directly to an analog to digital channel of a microcontroller. The most well-known single sensor algorithm using one voltage sensor is the fractional open circuit voltage (FOCV) method (Bekker and Beukes 2004).

The FOCV method is illustrated in Figure 3.12. First, the solar panel is temporarily disconnected from the load. Before the load is reconnected, the open circuit voltage is measured. The measured voltage is multiplied times a fixed gain in order to obtain a voltage reference value.

Like other single sensor algorithms, the fractional open circuit voltage algorithm does not track maximum power point over a wide range of irradiance and temperature levels. In some variations, measurement frequency and step size is adjusted to track MPP more efficiently (Sivaramakrishnan 2016).

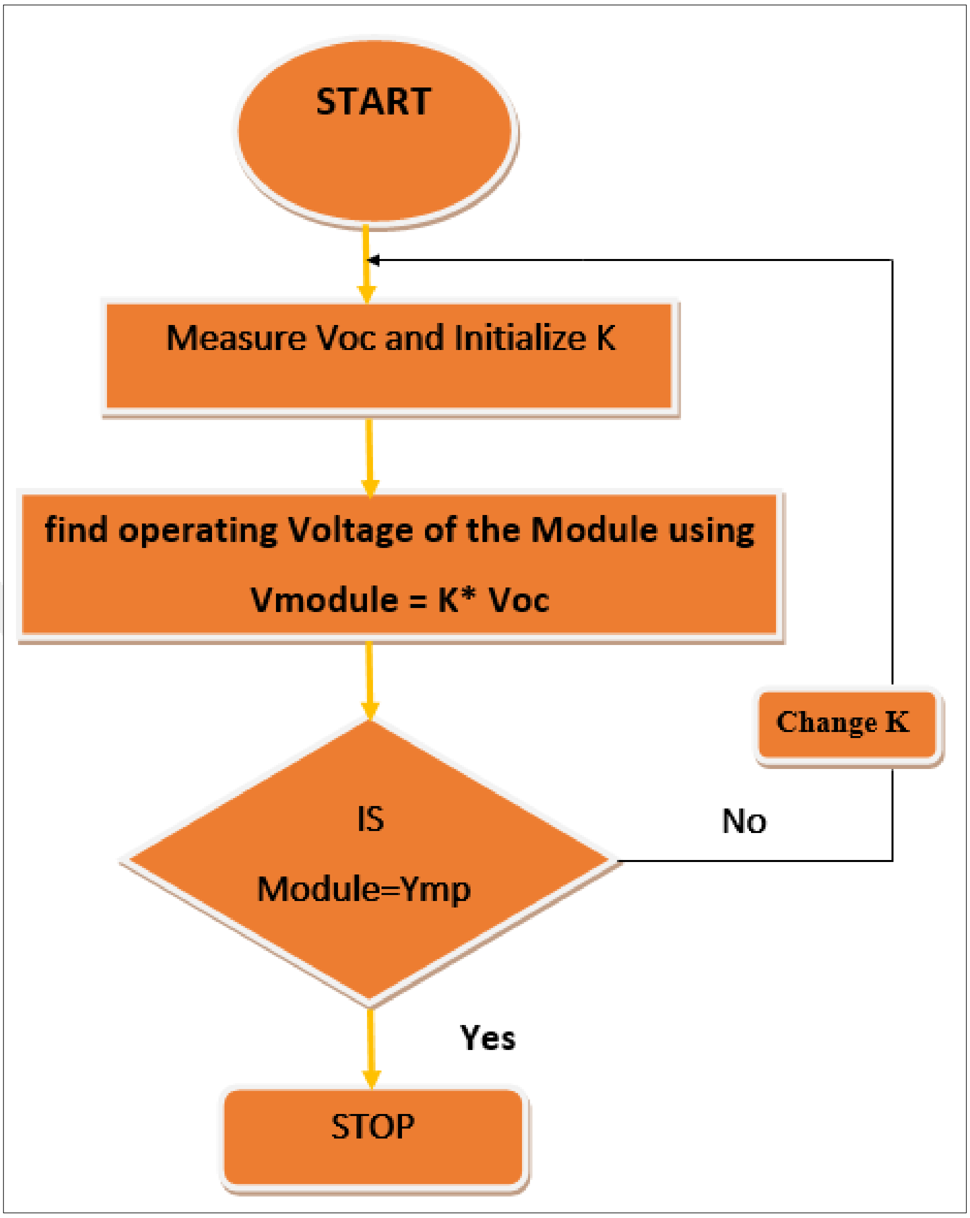

Figure 4.12: Flowchart of Fractional Open Circuit Voltage Algorithm.

Other single sensor algorithms use a voltage measurement and the duty cycle value to track maximum power point (Chen and Lai 2014). One of these algorithms developed by Yie-Tone Chen is illustrated in Figure 3.13. Chen uses the difference in voltage measurements, the difference in duty cycle value, the current voltage measurement, and the current duty cycle measurement to track MPP.

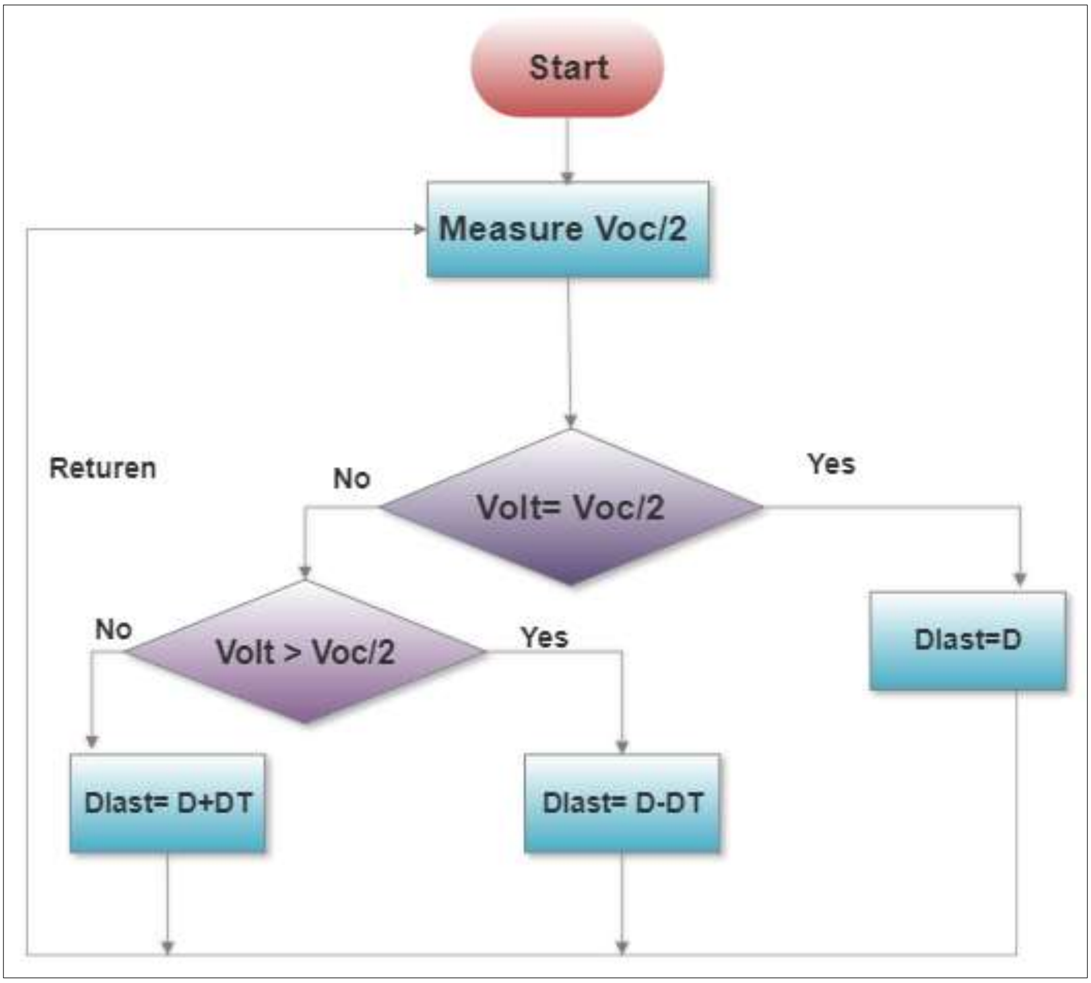

Figure 4.13: Flowchart of Chen Single Sensor Method.

5. SIMULATION RESULT

5.1 Particle Swarm Optimization Algorithm Based MPPT

In order to enhance maximum power point tracking performance of the PV system under partial shading situations, a PSO algorithm based MPPT algorithm is provided in this thesis. The maximum power point tracking converter (Boost converter) and firefly algorithm are the key components of the proposed control strategy for PV panels operating in partial shadowing. The block diagram of the full PV system is displayed in Figure 4.1.

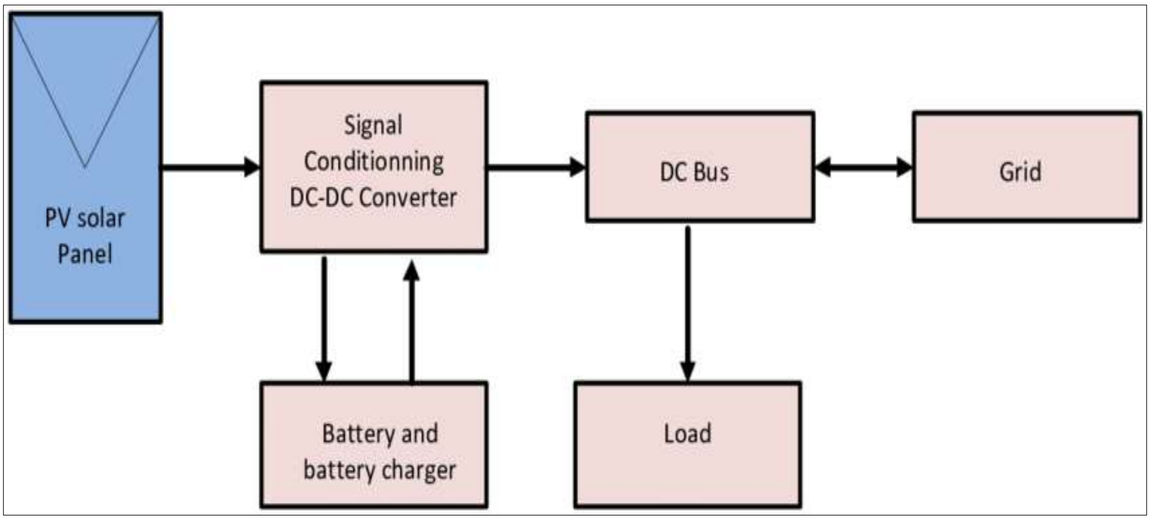

Figure 4.1: The Functional Organization of the Complete PV System as A Block Diagram.

The PSO algorithm generated the set of duty cycles for the boost converter in a random fashion.

5.2 Boost Converter

Switched-mode power supplies are a type of system that can be utilized for a variety of reasons, one of which is the creation of DC-DC converters. Even though there are sources that generate DC electricity in today's energy systems, the voltage values that are produced by these sources are not sufficient for some buildings since some constructions require higher voltages. The desired voltage values can be achieved by forming battery packs in DC circuits where high voltages are required; however, despite being a solution that offers sufficient parameters, this provides theoretically sufficient disadvantages in many ways, such as building material, usage area, and weight. In DC circuits where high voltages are required, battery packs can be formed to produce the desired voltage values. To get the necessary voltage values at this point, direct current to direct current (DC-DC) converters are used. DC converters as well as Boost Converters. The design of the inverter is based on obtaining the output voltage by increasing the applied voltage value. The DC-DC Boost converter is shown in figure 4.2.

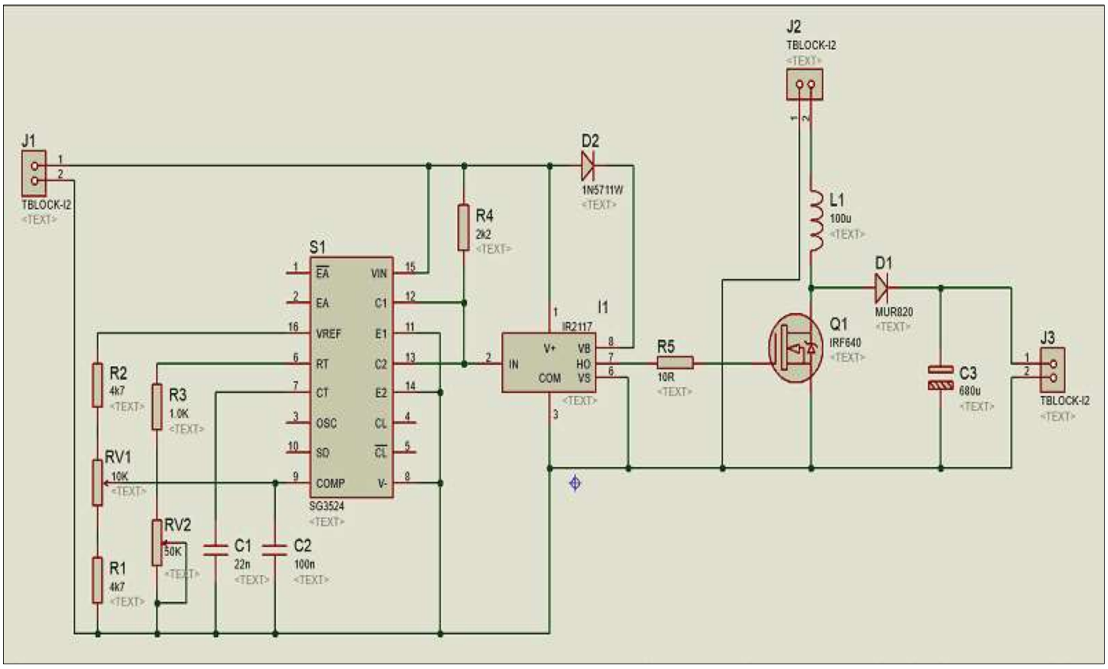

Figure 4.2: DC-DC Boost Converter.

The Simulink model of proposed method is shown in figure 4.3.

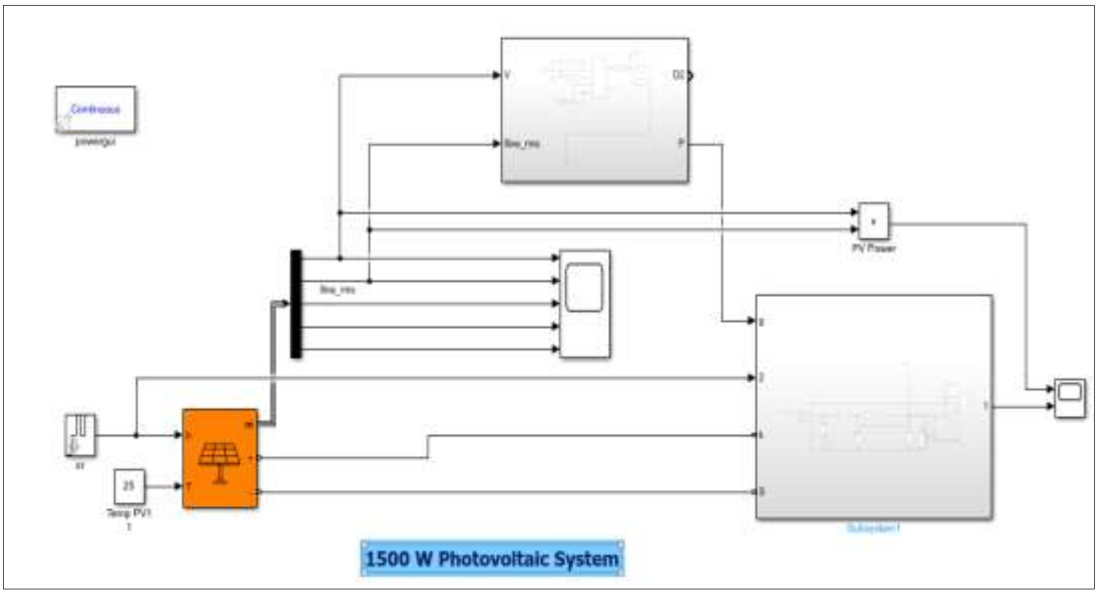

Figure 4.3: Simulink Model of Proposed Method.

The Sample code of the PSO for MPPT is shown in figure 4.4.

```
    current_power=zeros(1,3);
end
if isempty(local_best_power)
    local_best_power=zeros(1,3);
end
if isempty(local_best_dutycycl)
    local_best_dutycycl=zeros(1,3);
end

function [D1,D2] = PSO(q,i,b,V,I)
persistent   P W D j k count current_dutycycl velocity current_power

D2=0;
D1=0;
if isempty(j)
    j=1;
end
if isempty(k)
    k=1;
end


if isempty(P)
    P=zeros(1,3);
end

if isempty(D)
    D=zeros(1,3);
end

if isempty(count)
    count=0;
end

if isempty(current_dutycycl)
    current_dutycycl=zeros(1,3);
    W=0;
end
if isempty(velocity)
    velocity=zeros(1,3);
end
if isempty(current_power)
```

Figure 4.4: Sample Code of the PSO for MPPT.

The PV power – PSO, irradiation PV and boost converter voltage against of time is shown in figure 4.5.

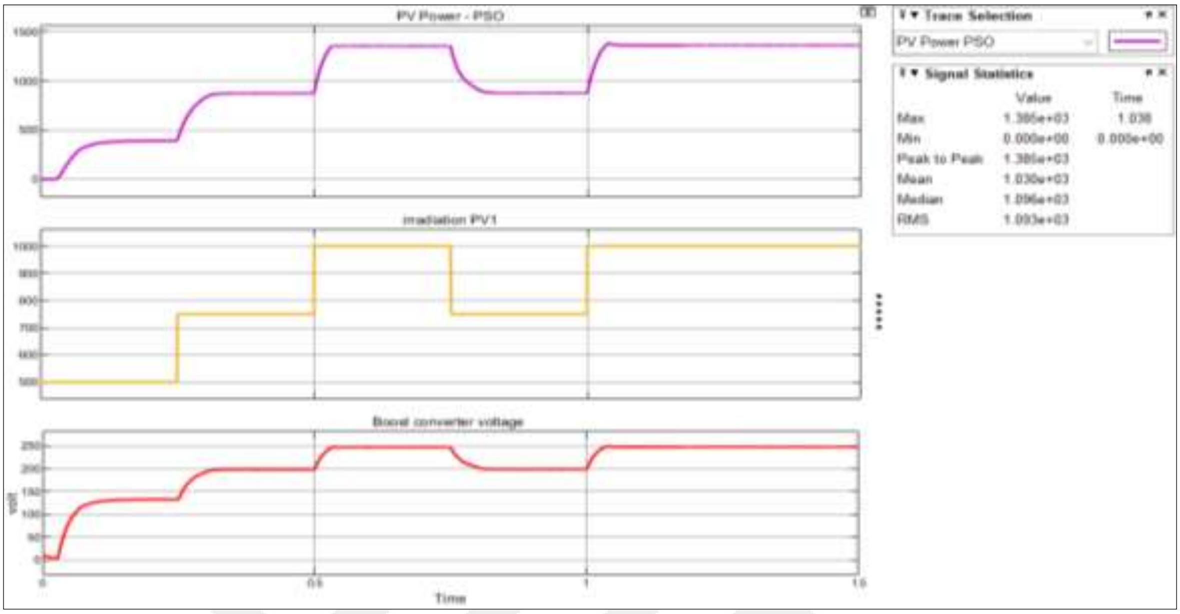

Figure 4.5: PV Power – PSO, Irradiation PV and Boost Converter Voltage Against of Time.

The output of demux is shown in figure 4.6

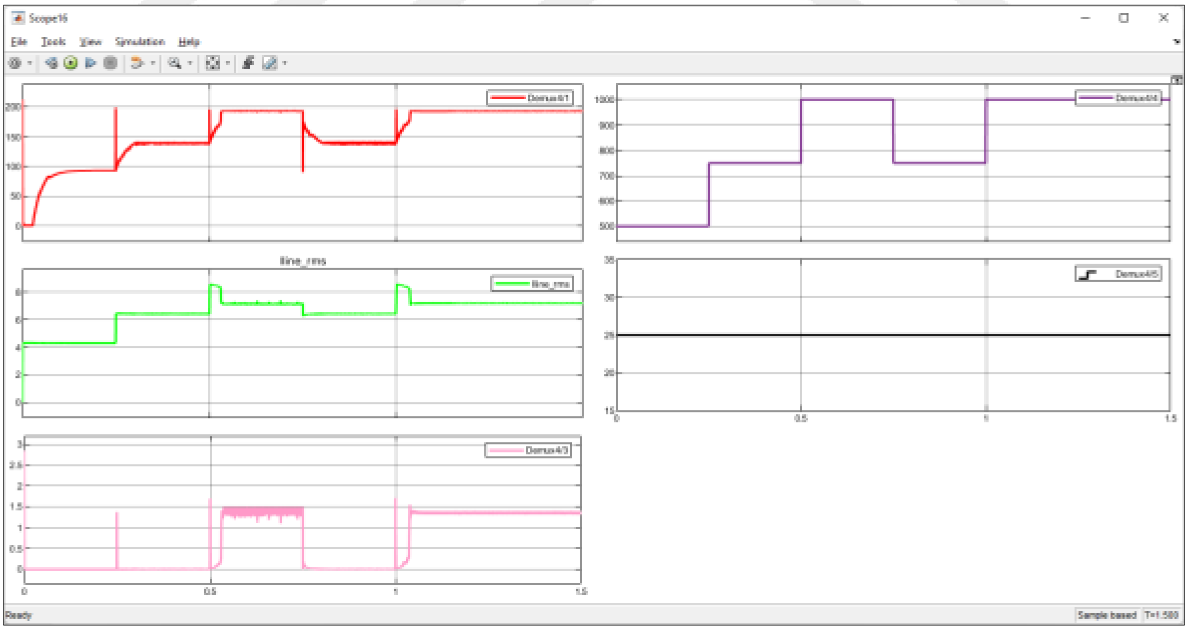

Figure 4.6: Output of Demux.

The comparison between PV power with PSO and without PSO is shown in figure 4.7

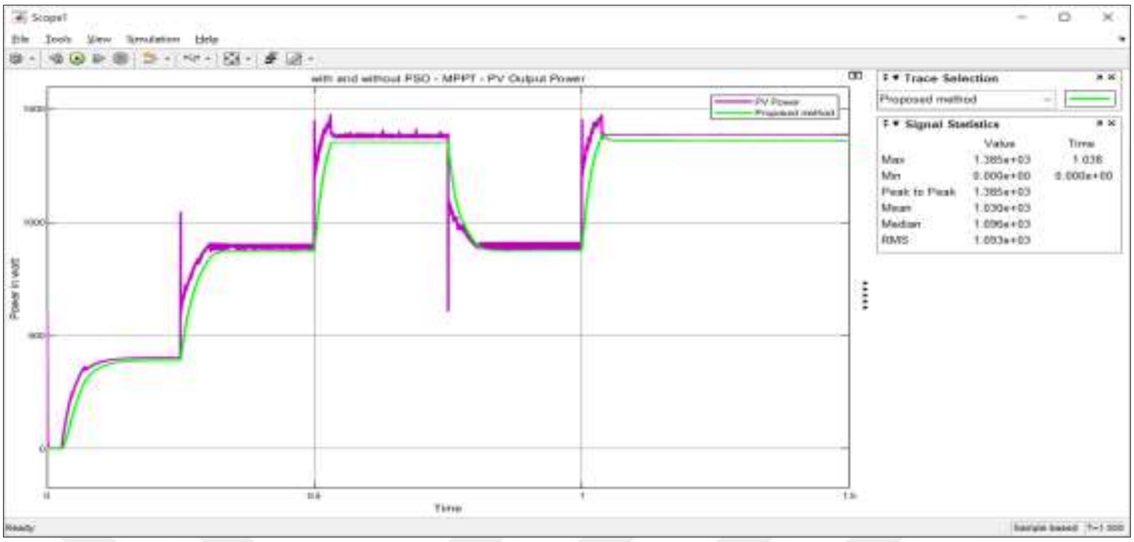

Figure 4.7: Comparison Between PV Power With PSO and Without PSO.

The PV boost converter voltage and current is shown in figure 4.8.

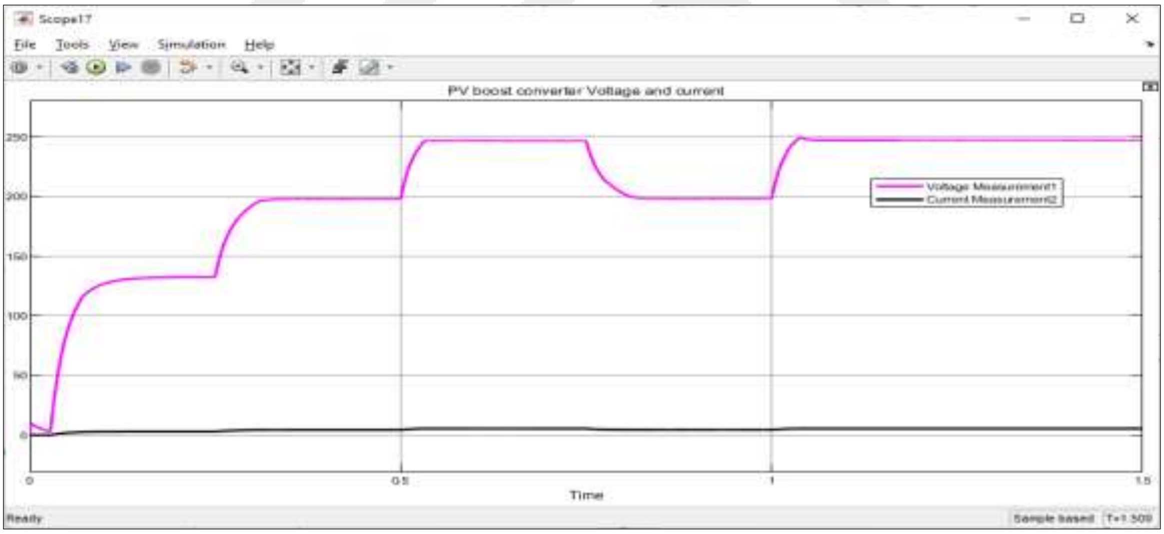

Figure 4.8: PV Boost Converter Voltage and Current.

The specification of the PV panel is shown in figure 4.9.

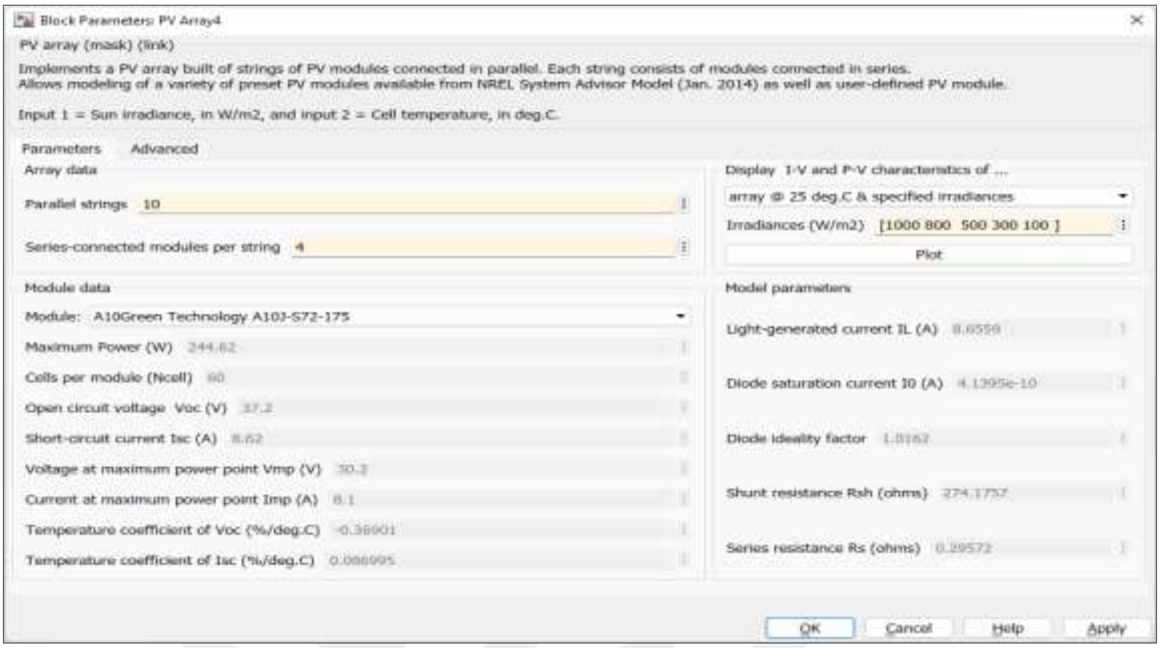

Figure 4.9: Specification of the PV Panel.

The I-V and P-V curve for the irradiation situation is shown in figure 4.10.

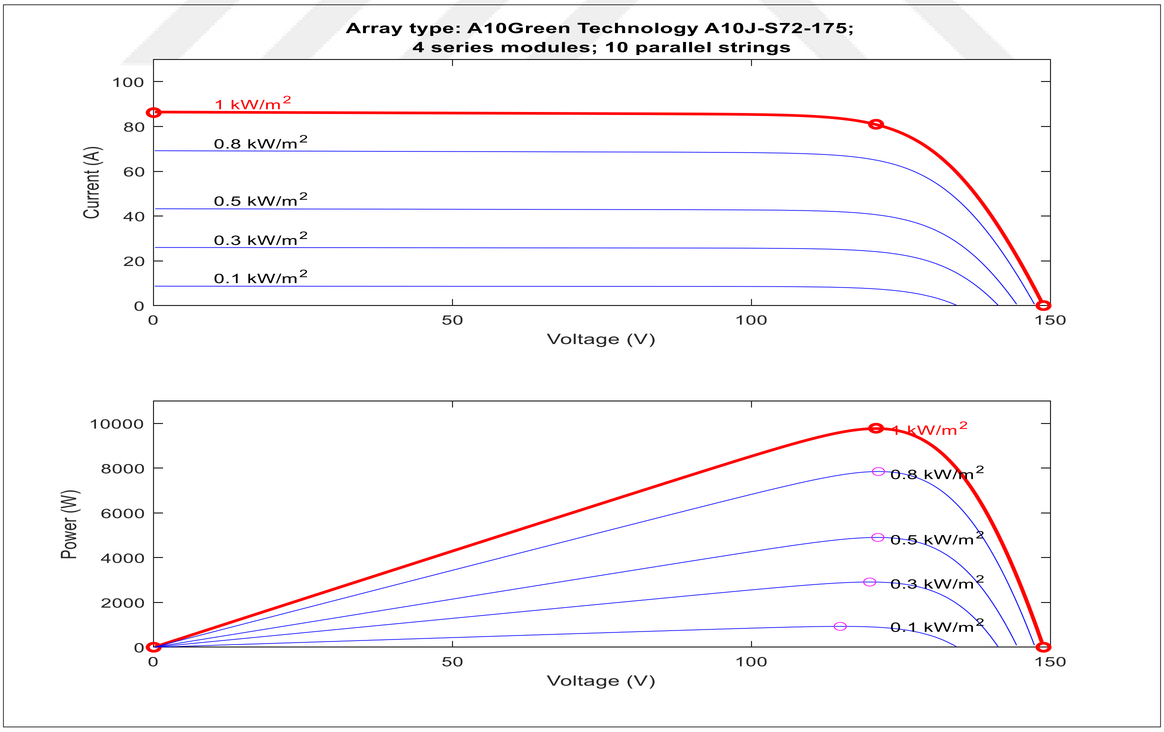

Figure 4.10: Current – Voltage and Power – Voltage for Different Radiation Values.

The I-V and P-V curve for the temperature situation is shown in figure 4.11.

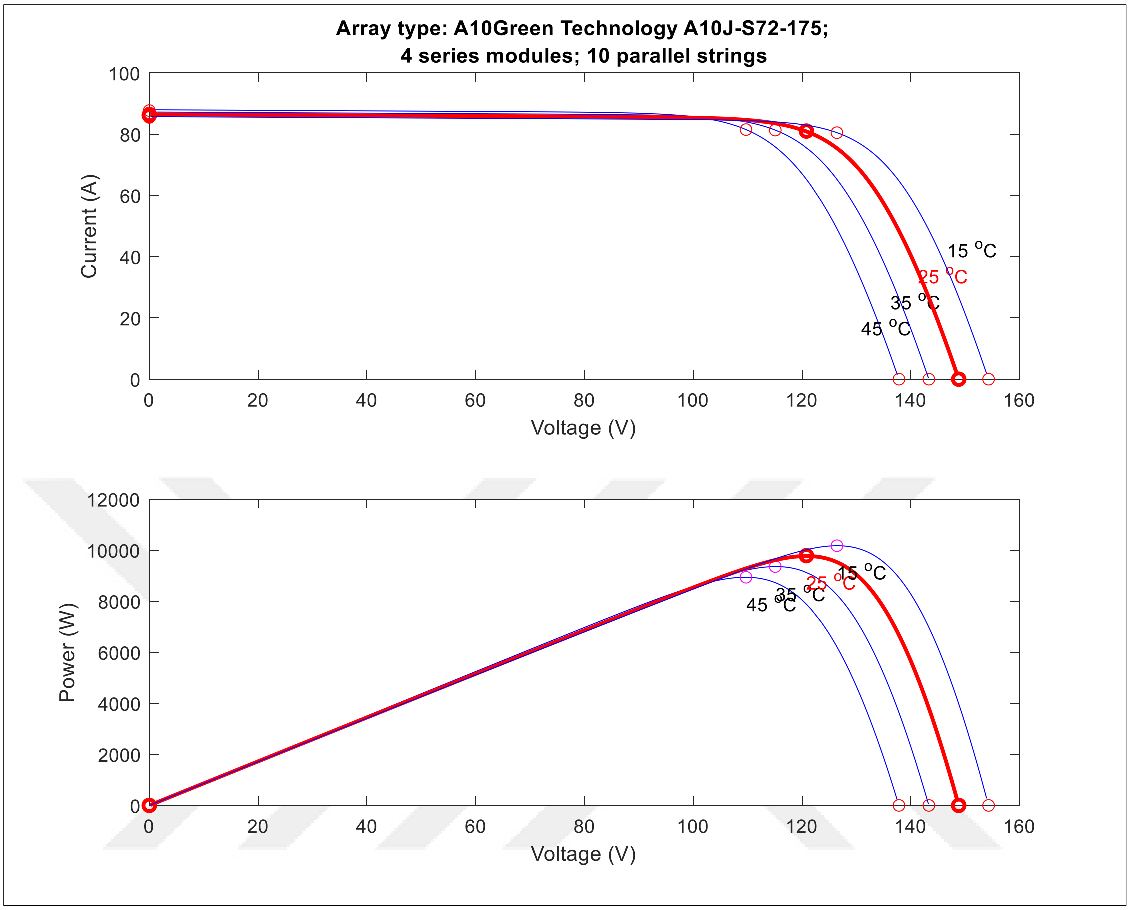

Figure 4.11: Current – Voltage And Power – Voltage for Different Temperature Values .

6. CONCLUSION AND FUTURE WORKS

6.1 CONCLUSION

Solar power generating is a good example of how the notion of distributed energy generation may be applied. Solar energy is the process of generating heat by exposing a surface to the sun's rays, allowing the heat to be collected, distributed, and utilized. It is common practice to classify solar power plants that utilize concentrating solar arrays (also known as CSP or concentrated solar power) as a distinct subcategory of solar energy stations. A system of lenses and mirrors is utilized in these installations to concentrate the light that is generated by the sun's beams into a single, focused beam of light. This beam is a source of thermal energy that is used to heat the working fluid, and it is utilized in that process. Particle swarm optimization (PSO) is a technique for optimizing a problem by moving a population of candidate solutions, also known as "particles," around in the search space in accordance with a set of mathematical rules that takes into account the position and velocity of the particles. Particles are referred to in this context. The motion of each particle is affected not just by the best location it has found for itself locally up to this point, but also by the best positions other particles have discovered for themselves globally as they move across the search space. The purpose of this, from a theoretical standpoint, is to hasten the process by which the cloud of particles converges on the optimal solutions. PSO is considered a metaheuristic because it makes very few or no assumptions about the problem that has to be optimized and because it may be applied to problems with very vast candidate solution spaces. However, similar to other metaheuristics, PSO does not provide an absolute assurance that an optimal solution will be found in every circumstance. In this thesis, the problem of determining the maximum power point tracking algorithm for use in solar energy systems through the application of the particle swarm optimization approach is investigated. Before a solar cell is put into use, the manufacturer will often characterize the device using empirical data. This occurs before the solar cell is put into service. There are many other ways that solar energy can be degraded, and it would be interesting to quantify or detect as many of these as possible. Hence, conducting active measurements of solar energy characteristics on a regular and consistent basis over time is beneficial. To enhance the maximum power point tracking algorithm for an equivalent model of a typical solar energy system, we offer a method that was derived from an intelligent method based on the particle swarm optimization method.

This method allows for the solar energy system to be periodically updated, which can then be used to update the finding of the maximum power in output that the system can produce.

6.2 FUTURE WORK

For future study the authors recommend to use the other metaheuristic methods such as gray wolf optimization method, ant colony optimization method in finding of the duty cycle and find the optimum values of the controller.

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