School of Electrical Engineering, Computing
and Mathematical Sciences

Development of Hybrid PS-FW GMPPT Algorithm for improving PV System Performance Under Partial Shading Conditions

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgement has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature: ....

Date: ....

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Abstract

Under partial shading conditions (PSC), conventional Maximum Power Point Tracking (MPPT) algorithms are unable to reach the Maximum Power Point (MPP) due to non-linear characteristics of the curve. In the literature, some algorithms, such as Fireworks algorithm (FWA) and Particle Swarm Optimization (PSO), have been used to obtain the MPP. However, they provide less than optimal convergence rate and tracking accuracy of FWA which impair the MPPT performance.

In this thesis, an application of the hybrid method of PSO and FWA (PS-FW) algorithm for GMPPT is proposed. The difficulty of balancing exploration and exploitation is alleviated within the PS-FW through the PSO velocity operator and the FWA mutation and explosion sparks operator. The population health is maintained through abandonment and supplement strategy and an adaptive modification to the operators to enforce convergence is also described.

The proposed GMPPT algorithm performance is verified within a simulation environment under a PV system facing four irradiance patterns. Comparisons are made against singular versions of the hybrid algorithm and another hybrid algorithm. Simulation results verify that the PS-FW algorithm outperformed the PSO, FWA and Differential Evolution-PSO (DE-PSO) algorithm in terms of tracking speed, accuracy and efficiency under PSC. In all shading patterns applied to verify the PS-FW, the algorithm is able to obtain at least a minimum of 7.59% better tracking speed of the GMPP under simulation verification at one initial population setting. Experimental verification further validates the hybrid PS-FW algorithm. PS-FW is able to achieve at least a minimum of 24.69% better tracking speed of the GMPP in two initial population settings. The hybrid PS-FW algorithm proves itself as an alternative to the singular PSO and FWA algorithms and builds upon the good aspects of the counterparts capable of good tracking speeds and accuracy in GMPPT application.

List of Publications

Parts of this thesis and concepts from it is submitted to the following journal which has been published.

Journal Papers

[1] L.G.K Chai, L. Gopal, F.H. Juwono, C.W.R. Chiong, H.C. Ling, T.A. Basuki, "A novel global MPPT technique using improved PS-FW algorithm for PV system under partial shading conditions" *Energy Conversion and Management*, Volume 246, 114639, 2021.

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List of Acronyms

ADC	Analog-To-Digital
BWO	Black-Widow Optimization
CCM	Continuous Conduction Mode
CS	Cuckoo Search
DAC	Digital to Analog Converter
DC-DC	Direct Current to Direct Current
DCM	Discontinuous Conduction Mode
DE	Differential Evolution
EA	Evolutionary Algorithm
EP	Evolutionary Programming
FA	Firefly Algorithm
FWA	Fireworks Algorithm
GLS	Guided Local Search
GP	Genetic Programming
GWO	Grey-Wolf Optimization
I-V	Current-Voltage
IC	Incremental Conductance
ILS	Iterated Local Search

L-PSO	Leader Particle Swarm Optimization
LMPP	Local Maximum Power Point
LNS	Large Neighborhood Search
MFO	Moth-Flame Optimization
MOSFET	Metal–Oxide–Semiconductor Field-Effect Transistor
MPPT	Maximum Power Point Tracking
NSC	non-shading conditions
P-V	Power-Voltage
P&O	Perturb and Observe
PWM	Pulse Width Nodulation
SFO	Sailfish Optimizer
SI	Swarm Intelligence
SSO	Salp Swarm Optimization Algorithm
STC	Standard Test Conditions
TS	Tabu Search
VNS	Variable Neighborhood Search

Chapter 1

Introduction

Due to the massive installation of solar photo-voltaic (PV) and wind turbine, the use of renewable energy-based electricity generation increased by 3% in 2020 when compared to previous year. As reported in [1], the share of renewable energy sources rose to around 28% in Q1 2020, increasing from 26% in Q1 2019. Moreover, the share of renewable energy sources is projected to grow from 15% in 2015 to 63% of total primary energy supply in 2050 as stated in [2]. In tropical countries, e.g. Malaysia, where solar energy is abundant, PV systems are suitable for exploration as renewable-energy sources. Malaysia's geological location is well suited for solar power generation as the country is located on equator, where irradiation is favourable and average daily solar radiation is at 4500 Wh/m^2 with sunshine duration of 12 hours [3]. In addition, PV systems barring just the benefits from reducing ecosystem pollution also includes advantages from low maintenance cost, scalability, and ease of installation [4].

To this end, methods of improving PV solar systems are implemented through controlling the Direct Current to Direct Current (DC-DC) power converter side of the system with an optimization algorithm which is able to control the duty cycle of the chosen converter switch. The maximum power point (MPP) can be found at a correct duty cycle where the power conversion efficiency of the PV system is at its maximum. Implementations of the DC-DC converter configuration dictate the output voltage from the conversion, voltage can be either stepped up, stepped down or both within a single configuration. An example of such methods out of many can be singled down to both Maxmimum Power Point Tracking (MPPT) and Global MPPT (GMPPT) algorithms. The GMPPT algorithm is a preferable design choice as cases of partial shading conditions (PSC) which causes multiple maxima and minima to appear on the PV curves, which is the main advantage of the global tracking capabilities found in GMPPT algorithms. The global capabilities stem from strategies employed in the design of a GMPPT algorithm. These algorithms are implemented to control the switching in most PV systems which install the DC-DC converter. However, a conducted review of methods used for GMPPT has shown that converters are commonly boost or buck converters, thus the chosen converter application must be determined beforehand [5] based on system requirements. Regardless of the configuration, conversion of voltage stepping up or down both, are dependent on the frequency of switching the switch, duty cycle ratio, inductance of the inductor, capacitance of the input and output capacitors, and finally the load resistance [6].

Hence, the requirement of a form of control towards this duty cycle is required using an algorithm. To provide voltage or current conversion, filtering, and regulation for driving various loads, including power grids or motors; PV systems will typically be integrated with algorithm controllers which implement a respective algorithm [7]. The implemented algorithm is an optimization algorithm that can include meta-heuristic methods which act as a black box to any given engineering solution due to their stochastic and iterative problem solving nature. To obtain maximum power for any given environmental conditions, the MPPT or GMPPT algorithm samples the output of PV cells and apply various duty cycles to obtain information of the power obtained which will assist in further search in later iterations of the algorithm.

1.1 Maximum Power Point Tracking

The operating point of the panel dictates the output power at the time. This point is rarely at its peak when directly connected to the PV panel. Impedance of the entire connection strictly determines the operating point of the PV panel, when modified; the operating point is able to move towards the MPP [8]. Since PV panels output in DC power, a form of impedance transformation must be implemented using DC-DC converters. The impedance of the PV panel (source) can be matched with the load to adjust the operating point. To match the impedance of the system, a change of the duty cycle or ratio of the DC-DC converter is required. At a particular duty ratio, the operating point will be the MPP where the power transfer from the PV panel or conversion efficiency of the entire system is highest. The P-V or I-V curve characteristics of the PV panel vary with adjustments of atmospheric conditions such as irradiance and temperature. The influence of the dynamically changing operating conditions render it non-feasible to fix on one duty ratio for the DC-DC converters.

PV system MPPT implementations utilize MPPT algorithms that frequently sample panel voltages and currents, then adjust the duty ratio as needed. These algorithms perform favorably under a uniform irradiance level where there is only one MPP in the power-voltage (P-V) or current-voltage (I-V) curve of the PV panel [9]. However, the current PV system problem at hand can be expressed as a difficulty in choosing the right duty or switching ratio for the switch in a converter to overcome the existence and occurrence of PSC the PV panels. When the PSC affect the PV panel, the conversion of solar energy is diminished as the solar cells become reverse biased and drain the power generation from other solar cells in the panel.

Figure 1.1: Example of PSC on a PV Panel

A figure describing the PV panel with PSC on it panels or cells is shown in Fig. 1.1. The shaded cells depreciate the output power of PV modules due to reduced operating short-circuit current (I_{sc}), moreover these shaded cells can cause hot spot phenomena, where the reverse biased cells cause heat dissipation at the affected cell and cause permanent damage if high temperatures are reached. However, the solutions of mitigating hot spot phenomena damage on the solar cells is not the main research objective of this research project. The damage on the cells could be mitigated using an bypass diode for each cell as proposed by [10] or complex designs in the power control system in [11]. The implications for these methods, however, suggest the inclusion of more expensive electrical components by increase of diode, capacitors and MOSFETs. That could spike the development cost for a more complex design of the DC-DC converter. The selection of methods to improve the PV system implementation and its power conversion efficiency in this project lies in the design of the GMPPT algorithm which controls the DC-DC converter selected. The design of the GMPPT algorithm and implementation of the PV system for the proposed application, in simulation and real experimentation conditions is conducted.

MPPT algorithms, as the name implies must keep the solar panels at the MPP where the power gain is highest [12]. The solar panel of a PV system has a unique MPP that varies with different irradiance and temperature values where the power generation is at maximum. A DC-DC converter controlled by the MPPT algorithm is inserted between the PV panel and the load, which is controlled by the pulse width modulation (PWM) signal from the micro-controller. Duty cycle from the PWM is then changed according to the voltage and current by for example, a micro-controller or a signal processor. The micro-controller maximizes the power output from the solar panel by controlling the duty or step-up ratio to always keep the solar panel operating at its MPP. The methods all differ from each other through their tracking and convergence speed, complexity of the implementation, sensor requirements, hardware implementation costs as well as their control parameters [13].

Some simple and low-cost techniques for MPPT have been proposed in the literature, such as Incremental Conductance (IC) [14] and Perturb and Observe (P&O) [15]. The relationship of the P-V or I-V curve describes the relationship of the output power, current and voltage that the PV panel or array setup is able to extract at whichever point. The curve itself arcs to a maximum on the graph and no matter how much more voltage or current is extracted, the setup is only able to generate at this MPP at the apex of the curve. Thus, the PV cells produce a nonlinear characteristic of output based on the temperature and the total resistance within the cells which are analyzable through the P-V or I-V curves [16]. The MPPT algorithms allow the highest efficiency for the PV system through the tracking of Global MPP (GMPP). However, the conventional MPPT techniques risk being unable to track the local peaks and true GMPP when partial shading conditions (PSC) occur, thereby greatly disrupting power generation [13]. PSC happens when PV panels are shaded to non-uniform degrees of irradiance, lowering the efficiency of power generation while multiple MPP appear on the curves. Reduced MPPT performance greatly hampers both the power generated and the reliability of the PV system [17].

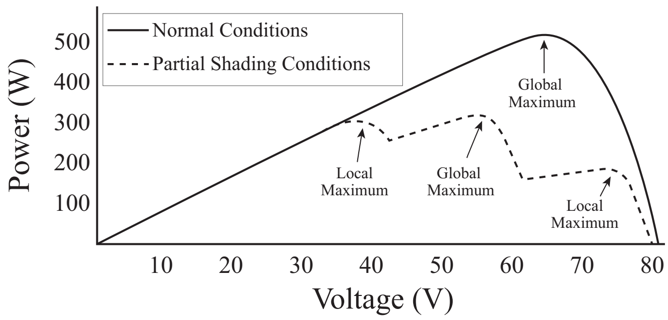


Figure 1.2: P-V Curve Under PSC

The Fig. 1.2 demonstrates multiple data points on a P-V that are referred to as local or global maximum points for the PV system, the appearance and non-linear characteristic of this type of curve correlates to how the proposed optimization algorithm must perform in order to seek the true global maximum point and is detailed in Chapter 2. The optimization algorithms must apply design theory of particular functions and methods that avoid choosing the local maximums as a proper solution.

GMPPT methods are required to seek out the correct global maximum point among multiple incorrect local maximums for PV panels under PSC. The GMPPT methods are categorized as optimization-based algorithms, hybrid approaches combining multiple optimization algorithms, and other methods such as curve fitting and fuzzy controller. The optimization-based algorithms include swarm intelligence- and evolutionary-based algorithms which reiterate upon a set of solutions to find the global best solution. In particular, the commonly implemented optimization-based methods are Particle Swarm Optimization (PSO) [18], Firefly Algorithm (FA) [19], and Simulated Annealing (SA) [20]. Moreover, enhanced versions of these algorithms, enhanced PSO [21] or Modified Firefly algorithm [22] will have superior performance than their originals [5]. Other than enhanced versions of algorithms, hybrid methods which consist of combination of two optimization algorithms or optimization method and conventional method exist. It has been shown that the hybrid methods are able to improve the system performance [23].

1.2 Problem Statements

As stated in papers [24],[25], MPPT algorithms improve the efficiency of PV systems; however, they suffer from cases of PSC. Several aspects must be considered, such as the advantages and disadvantages of each algorithm and application system characteristics [26]. However, slow convergence rates that could result from improper parameter adjustment and risk of falling into local maxima could still occur in enhanced or hybrid methods [27]. The chosen algorithm may also not perform well in a different system despite possessing a black-box nature [5]. A form of performance validation for GMPPT must be known.

From the selection of GMPPT algorithm of literature review conducted in this project, the PSO algorithm and Fireworks Algorithm (FWA) are subjects of improvement. PSO and FWA have demonstrated their capabilities to overcome conventional MPPT methods as seen in [28] and [5], the algorithms are also simple to implement. However, PSO algorithm is hampered by initialization problems where an improper velocity update can severely slow down the convergence rate [29]. Moreover, PSO has a tendency to fall into premature convergence into local maxima [30]. The weakness of the PSO in local search and the weakness of FWA in global search were also prime selection choices that attributed to the implementation of a hybrid algorithm based on PSO and FWA. In [31], Chen et al. introduced a hybrid algorithm based on PSO and FWA called Particle Swarm Fireworks Algorithm (PS-FW). The algorithms are combined to alleviate the weaknesses of both PSO and FWA as discussed earlier. The performance of PS-FW is proven on 22 benchmark functions which show that PS-FW is accurate and converges relatively fast in global optimization problems. An implementation of the PS-FW algorithm has not been used for solving GMPPT problems. Henceforth, a GMPPT algorithm will be implemented and tested under simulation and practical cases that bring greater performances in tracking speed and accuracy than that of commonly used GMPPT algorithms. Through this research, a gap is closed within GMPPT algorithm development through design of the PS-FW hybrid algorithms that applies the strategies unused within GMPPT application and having better performance than the singular versions of PSO and FWA.

A simulation model and an experimental setup of a PV system built must be used to determine to evaluate and validate the effectiveness of the proposed GMPPT algorithm and designed boost converter. Implementation of PV arrays under PSC with various different shading patterns are required which can reflect the P-V and I-V curve performance. The algorithm search behavior and performance determines the tracking of the GMPP which is found in these two curves of the PV panel using the balance of exploration and exploitation of the algorithm. Hence, a boost converter topology that is suitable for the GMPPT algorithm to be incorporated under PSC in simulation and experimental setup is required to be developed. The algorithm determines the output or duty cycle in its search process which accompanies the boost converter in stepping up the voltage level while finding the GMPP. The maximization and minimization of an algorithm process, the duty cycle can be found through each of the tracked performance in MPPT. An improper boost converter does not accurately reflect the GMPPT algorithm's tracking performance. Thus, the boost converter must be calculated according to requirements of the PV system [32].

The exploration and exploitation both refer to the accumulation of the capability of local search and global search of an algorithm during the algorithm search process in early, middle and late stages. With a good balance, it can be declared that a good convergence speed and accuracy is obtained [33]. The problem that is stemmed from all optimization algorithms are the trade-offs and balancing of these two aspects while solving the optimization problem [33]. Thus, an algorithm that is designed in mind with the application of seeking GMPP under PSC in a PV system is obtained with the hybridization of two algorithms; it maintains a good balance of exploration and exploitation that allow it to be properly optimized in its objective.

1.3 Aim and Objectives

The project aims to implement a GMPPT algorithm that is able to maximize power conversion efficiency for the PV system. This algorithm will be able to track the GMPP among many power points which may or may not exist on the P-V curve. If there are PSC affecting the solar panel arrays, then the conventional maximum power point algorithms are ill suited to track the correct maximum power point which brings the need to implement a GMPPT algorithm in the PV system.

The GMPPT algorithm is an implementation of hybrid PS-FW algorithm; which combines both the PSO and FWA algorithm. Methodology of implementing this algorithm from simulation uses MATLAB/Simulink software. To support the GMPPT application, an adaptive control of the spark number generation from FWA stage is also proposed in this thesis which controls the explosion sparks generated in later stages of the algorithm. The testing stage consists of the experimental setup which utilizes a digital signal processing board, dSPACE1104 and the CP1104 board that will output the duty cycle from PWM signal alongside receiving any voltage or current sensor values through the Analog to Digital Converter (ADC) Channel. In addition, verification of the PS-FW algorithm for GMPPT application is conducted with different shading patterns under both simulation and experimental setup.

This algorithm will be compared to PSO, FWA and DE-PSO GMPPT algorithms based on their performance in speed, accuracy and implementation complexity under non-shading conditions (NSC) and multiple patterns of PSC. Notably, the algorithms must perform accordingly in order to prove convergence or exploitation, and good exploration in the population which results in better overall GMPPT performance. A research based on the extent of algorithm design and the application of said algorithms is required.

The completion of the research project requires the fulfillment of the following objectives.

1. Designing and implementing a novel GMPPT algorithm for PV arrays which are able to track the local and global maximum respectively and identify the GMPP under NSC and PSC.

2. Designing and building a simulation model and an experimental setup of a PV system to evaluate and validate the effectiveness of the proposed GMPPT algorithm and boost converter under NSC and PSC with various different shading patterns on the PV systems.

3. Proving and comparing the implemented GMPPT algorithms under the proposed PV system application in terms of performances based on the balance of exploration and exploitation.

With completion of the aim and objectives, the contributions of this thesis are made clear and as follows:

- The proposed PS-FW hybrid algorithm for GMPPT under NSC and PSC is implemented.

- An adaptive spark control to speed up search process of PS-FW algorithm for GMPPT is proposed.

- The results are validated through both simulations and experimental setup.

With the contributions of the research project, the project itself would also serve to assist whoever is interested in the design of PV systems with the use of meta-heuristic GMPPT algorithms. The concept of the algorithms are explained in detail and the PV system is also shown in both simulation and experimental setup. Thus, the proposed research aims to further the development of GMPPT algorithms for the future.

1.4 Research Scope

The research scope of this project involves the design and implementation of a hybrid GMPPT algorithm in a PV system that faces PSC. The PV system itself is comprised of multiple components, which may be differ according to the extent of the implementation towards off-grid or on-grid systems. However, in this research, the PV system only requires to the research of PV panel model that can reflect the cases of PSC happening on them and the current DC-DC boost converter configurations and components needed. The GMPPT algorithm is implemented into the PV system to control the boost converter's duty cycle. The PV panel model equations are only derived to the point that irradiance values and temperature may properly reflect the desired characteristics on the P-V or I-V curves which include power values and any peaks that may appear. The methodology for calculating the values of electrical components of the chosen boost converter; the inductance, capacitance and load resistance are all understood which can handle the input and output of the PV system under PSC. The boost converter is only limited to boost converter configurations that appear in literature, thus there are no new designs of the configurations proposed.

Currently, the GMPPT algorithms fall into a subcategory of meta-heuristic algorithms; which are mostly evolutionary and swarm intelligence based. The research extends to the understanding of most concepts involved in only these two subcategories, which are the terminology, framework and operators involved which ultimately influence the algorithm search process. With the research conducted, the proposed implementation is modified for GMPPT purposes.

The research does not focus on other sub categories of the meta-heuristic family; however, the other GMPPT methods that are not meta-heuristic in nature are mentioned if they are relevant to the literature review. Other GMPPT methods may be mentioned as well as they share terminology or design choices or are involved in modification and hybridization. The literature review is conducted on only GMPPT methods in literature, they are explored as well to determine the performance criteria that validates each GMPPT method. The performance criteria only involve the measurement of speed and accuracy, while also mentioning the global search and local search capabilities of a GMPPT method. The review is also conducted on strategies and operators of the GMPPT method that determine or aid in the tracking process of GMPP under PSC.

Moreover, the literature review conducted influence the methodology of simulation and experimental setup. Only the simulation and experimental tools that are adopted by the literature are considered as the results from the papers reflect their validity. There is no research of untested software or hardware in the proposed project. Thus, the simulation and experimental setup is then complete with the PV panel, boost converter and the GMPPT algorithms, creating a PV system under PSC with GMPPT.

1.5 Thesis Structure

The remaining of this thesis is organized as follows.

In Chapter 2, the background of the proposed PV system which includes the partial shading, PV panel, DC-DC converter topology and the methods or techniques used in the meta-heuristic optimization algorithms are expanded. Reasoning of meta-heuristic usage chosen for the PV system application is given.

In Chapter 3, a literature review of implemented GMPPT algorithms, that are able to track GMPP under PSC, is made. The literature review assists the proposed research in simulation and experimental tool selection to contribute towards the design of the methodology. Moreover, the performance criteria that denotes the performance of a GMPPT algorithm is given. The chapter also focuses the concepts on hybridization as the motivation for the hybrid algorithm is drawn from PSO algorithm and FWA.

The Chapter 4 focuses on the proposed research work regarding the design of PV panel model, conventional boost converter specifications in terms of calculations and the hybrid PS-FW GMPPT algorithm. The process and explanation of implemented PSO algorithm and FWA mathematical operators, alongside the detail and operators used for the hybrid PS-FW are presented.

Chapter 5 briefly introduces the hardware and software used for the simulation which is the proposed simulation model of PV panel, simulation software for the PV system, experimental software and experimental setup of the PV system. The methodology to be proven in this Chapter will validate the performance results of designed GMPPT algorithm.

In Chapter 6, the validation of PSO, FWA and DE-PSO GMPPT algorithms and all methodology of simulation and experimental setup is conducted. Performance criteria regarding the GMPPT algorithms need to be given first, supplementary validation is also made upon the power threshold and seed settings. The simulation results of the performance of the hybrid PS-FW algorithm are shown and discussed with comparison against other singular GMPPT algorithms. Then, the proposed PS-FW GMPPT algorithm results are presented and discussed with terms to the performance criteria. A complete summary of research objectives completed is also made.

Finally, the conclusion and future work are given in Chapter 7.

Chapter 2

PV System and Optimization Algorithms

The relation to the background of the proposed PV system includes, PV panel, partial shading on the PV panels, DC-DC converter topology and the methods or techniques used in the meta-heuristic optimization algorithms. The mentioned background are given in both Section 2.1 and Section 2.2.

There exist many other MPPT techniques in the field of PV system MPPT which may be applicable to a simple PV system application. However, the reasoning of meta-heuristic utilization for the PV system application itself is given through the culmination of concepts in Section 2.3. As the MPPT or GMPPT problem is harder to solve, these soft computing methods are suggested and justified as the meta-heuristics are able to estimate a solution for the problem without sacrificing too much time or is able to supply the best possible results.

Moreover, the operators which are sets of strategy and equations form a basic description of a section inside the operator's framework. By denoting the operators, the operators can be generalized as the main factors in modifying the population of individuals to find the best solution. As such, a modification to the operator as a whole can also be easily recognized. Details regarding the operators are explained further in Section 2.3.

Exploration and exploitation are commonly designated as the performance validation of an algorithm. The Section 2.4 explains the exploration and exploitation (global search and local search) further detail with context regarding the difficulty of balancing the two aspects.

2.1 Solar Panels and Partial Shading

A PV device may be any element that converts sunlight into electricity. The elementary PV device is the PV cell. A set of connected cells form a panel. Panels are then composed of PV cells series in order to obtain large output voltages. Panels with large output currents are achieved by increasing the surface area of the cells or by connecting cells in parallel. A PV array may be either a panel or a set of panels connected in series or parallel to form large PV systems. Solar energy obtained from a solar PV cell is not constant at all times as the amount of extracted power from a PV system is affected by external conditions like solar irradiance and temperature [34].

When the photons in sunlight contact the PV panels, they are absorbed by semiconducting materials. The electrons (which are negatively charged) are separated from their atoms as they are charged. Due to their unique structure as well as the materials in the solar cells, electrons can only move in a single direction. For this process to work, it is vital that the materials used in the electronic structure such as silicon contain small amounts of boron or phosphorus and used in different layers. Solar cell arrays help convert collected solar energy into usable amounts of direct current (DC) electricity. Occasionally the performance of a PV panel is provided by manufacturers at Standard Test Conditions (STC) where irradiance is at 1000 Wh/m^2, temperature is at 25 degrees Celsius and the angle of degree for the PV panel towards the sun is 45 degrees. During this state, the P-V or I-V curve shows only one single peak MPP that is the optimal operating point of the PV panel or array [35]. This point denotes the performance of the specific PV panel with given maximum current I_{mpp}, voltage V_{mpp} and power P_{mpp}.

Partial shading on the PV panel is mostly caused by surrounding buildings, passing clouds or trees, the P-V curves of the entire panel is affected drastically as the characteristics vary due to multiple MPP existing on the curve [36]. As the PSC cases affect the generation of power within the PV system, it is of advantage to use a simulation model to understand the behavior of a PV panel or array under different solar irradiance and temperature conditions. Thus, only the measurements made at the time via the I-V and P-V curves allows us to accurately determine the electrical parameters of the PV panels.

The following issue is resolvable by utilizing a DC-DC converter which implements a way to control the converter either through the use of integrated circuits or programmable devices such as micro-controller or field programmable gate arrays. Through control of the switching at the converter, the method of maximizing the power of conversion in the PV panel is applicable. Depending on the DC-DC converter configuration applied in the system, desired voltage or current levels can also be obtained based on the component values and proper control of the switching.

2.2 DC-DC Converter

On the topic of converters for PV systems, it is regarded that switching regulators, which DC-DC converters are categorized as, are utilized in favour of other methods of voltage or current regulation. For example, in linear regulators, the lack of inductors to store electrical energy is discharged off through heat dissipation, greatly increasing risk of damage to passive components in the system.

The DC-DC converter is a component used to match the input to the load output of electrical systems either during current or voltage levels. This can be done by storing the electrical power into inductors or capacitors then using various MOSFET, IGBT switches and diodes. However, the efficiency of a DC-DC converter is dependant on proper switching rise and fall times which can dictate the resultant parasitic excess of electrical energy in the given circuit. There are two modes that a DC-DC converter may operate in, the two modes being either discontinuous conduction mode (DCM) or continuous conduction mode (CCM). A power stage can operate in both modes. The primary characteristic of a continuous inductor current mode is that its current is flowing continuously in the inductor during the entire switching cycle while in steady state operation. The other mode, discontinuous inductor current mode, is characterized by the inductor current flow of power reaching zero for a portion of the switching cycle.

The current initially starts off at zero then reaches a peak value before finally returning to zero during each switching cycle. In addition, as DCM allows for the fall of the inductor current to zero level, this means that the value of the inductance required for DCM is lesser when compared to CCM. However, DCM has the disadvantage of high peak current when at the switch terminal and high peak voltage at the load resistor, which may result in strain on component durability. Regardless, the conventional boost converter is able to operate in any mode of current operation under changed power levels. Certain topology exist to categorize the usage of the different types of converters. The most basic of these include, buck, boost and buck-boost converters. PV system applications may range from small scale battery charging applications to large scale on-grid solar farms. Thus, the need to choose a suitable topology to fit the chosen application is needed. Boost or buck converters have the advantage of being used in design implementation and manufacturing compared to buck-boost converter in the application due to the low number of electrical elements implemented inside the topology [37].

Boost converters will obtain higher output voltage from lower input voltages, making the converter appropriate for a PV system as the voltage values will be maximized [38] [39]. Moreover, the boost topology is proven to maintain a balance in qualities in comparison to buck and buck-boost by obtaining higher efficiencies when used for PV system [40]. Given the previous statement, designs of boost converter topology can be considered from then on for PV systems.

Boost converter configurations implemented may include but not limited to the following;

1. **Boost Converter**

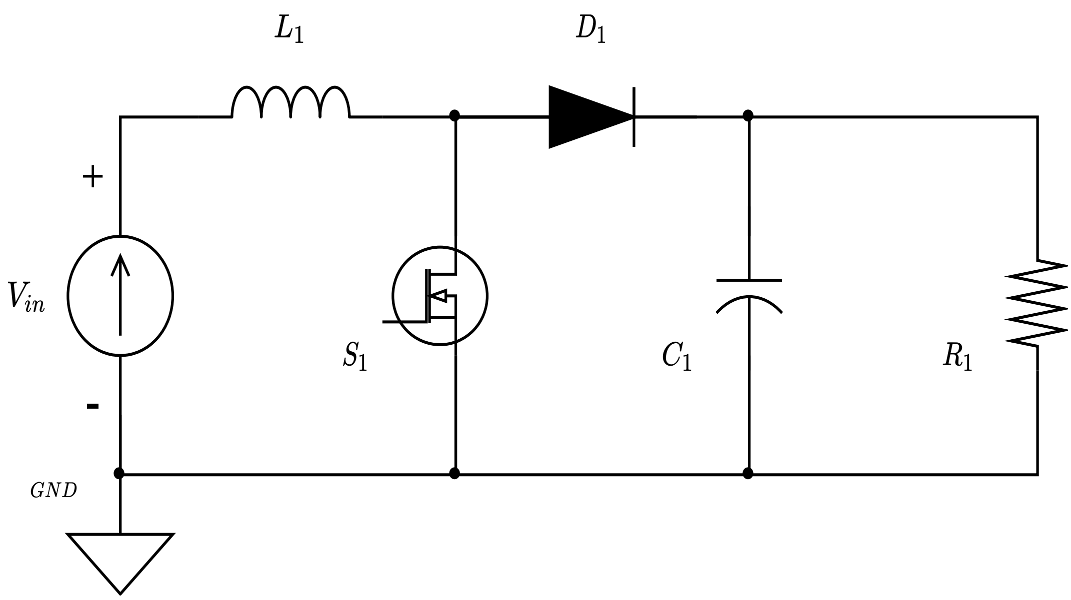


Figure 2.1: Conventional Boost Converter Schematic

Conventional topology that is commonly used in PV system for their use in stepping up voltage from the PV panel. The principle operation of the DC-DC conventional boost converter shown in Fig. 2.1. When the switch is on, the diode becomes reverse biased, thus, isolating the load stage. The input from the PV source will store electrical energy in the inductor constantly during on and off states. As the switch turns off, the inductor discharges to the resistor load as well as from the input source, resulting in a greater load voltage than the source voltage.

The conventional boost converter configuration proves its simplicity and low cost in design which makes a common choice in PV systems/ has a simple circuit and low cost [41]. However, the conventional boost converter topology may consist of undesired disadvantages which will need to be overcome through careful selection of components. There are high ripple currents in the circuit that can damage the active and passive components, high voltage stress may damage the power switch and a sufficiently large capacitance value is needed to keep the output voltage steady from voltage ripple [42].

2. **Inter-leaved Boost Converter**

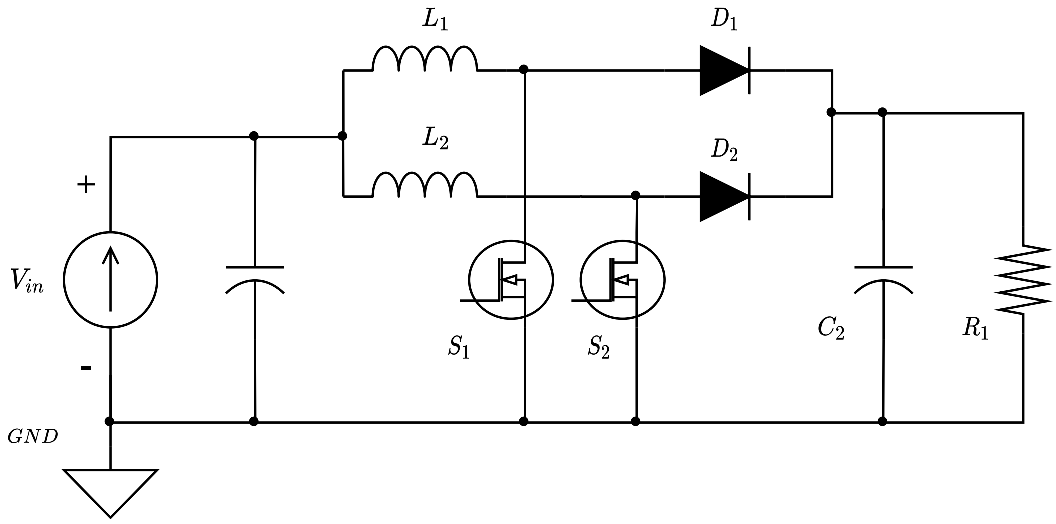


Figure 2.2: Inter-leaved Boost Converter Schematic

The Fig. 2.2 shows the design of an inter-leaved boost converter, an extra set of a component from the conventional boost converter used before the load. An extra switching element is inserted with its own inductor and diode. Hence, the load will be in series with double the switching provided by the two switching elements. One drawback of the conventional boost converter is that high current ripples can be drastically reduced by adopting the interleaved boost converter configuration [43].

The topology works with binary branches that operate 180 degrees out of phase from each other. Each phase operates as a separate conventional boost converter described earlier. Because the two phases are combined at the output capacitor, effective ripple frequency is doubled, making ripple voltage reduction much easier in the entire circuit. However, the number of passive and active elements increase in the configuration, which increase cost and complexity.

3. **Cascaded Boost Converter**

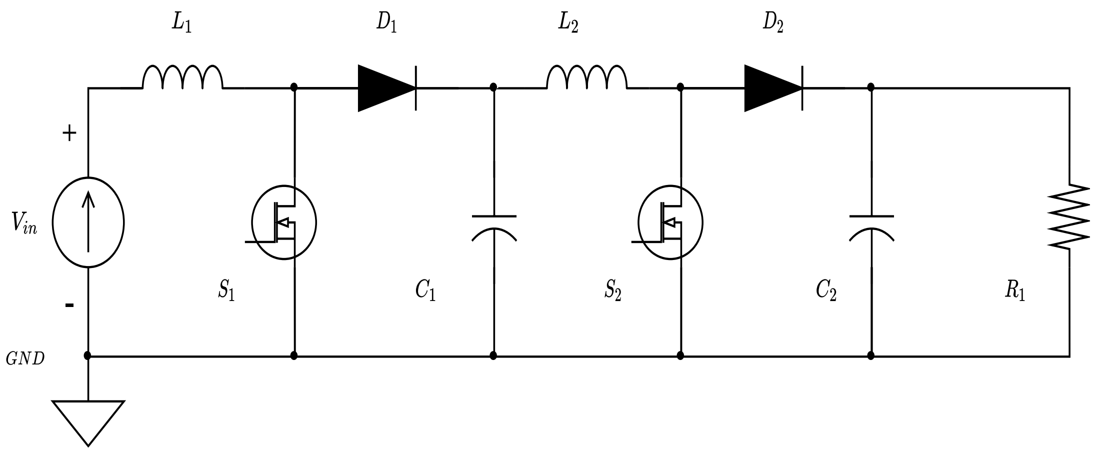


Figure 2.3: Cascaded Boost Converter Schematic

High voltage applications that require outputs that start from kilo-volts can utilize cascaded boost converters in comparison to single stage boost converters which may not have sufficient voltage gain for high voltages [44]. The input voltage is stepped up in several stages which cascades at the end of the output. Fig. 2.3 describes the cascaded boost converter configuration.

4. **Boost Converter with Voltage Multiplier**

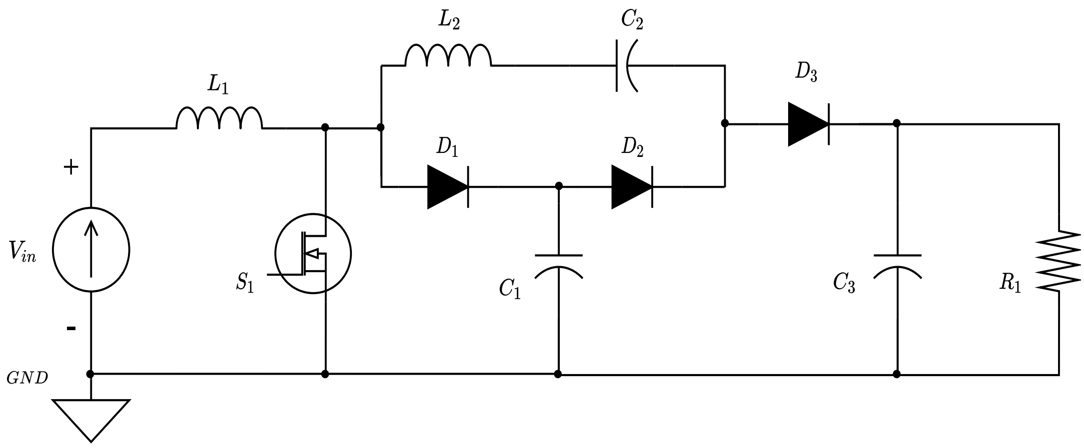


Figure 2.4: Boost Converter with Voltage Multiplier Schematic

If higher voltage gain is desired instead only then the voltage multiplier topology can be utilized [45]. An addition of multiplier cells count to achieve the required duty ratio for larger gain is implemented for the configuration, the multiplier cells can be increased for further gain as well.

In a conventional boost DC-DC converter, the switch is powered by a high frequency pulse-train current waveform that is also referred to as the pulse width modulation (PWM). Frequency dictates the amount of pulses that occur per second according to the (2.1).

$$f = \frac{1}{T}. \tag{2.1}$$

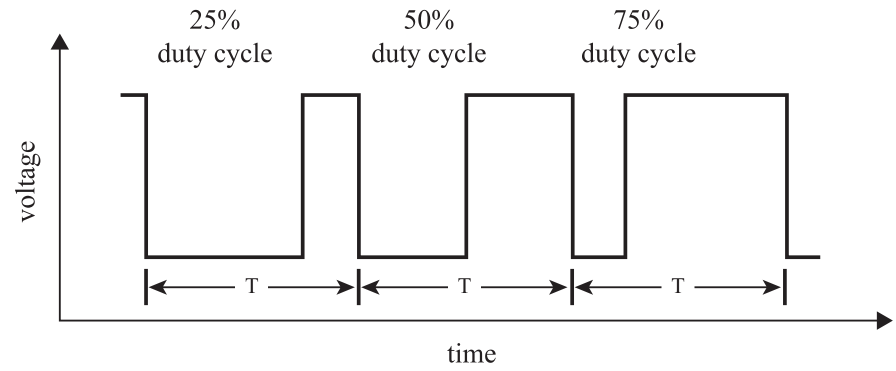


Figure 2.5: Duty Cycle On-Times

where f is the frequency, T is the time or period. In this pulse, a set duty ratio will determine the time in the pulse where it is V_{on}, so for example a 30% duty ratio will turn the pulse on for 30% of its cycle. The Fig. 2.5 describes various duty cycle ratios.

The conventional boost converters require large switch duty ratios to obtain a higher voltage gain, which results in risk of higher current stress in the boost switch. The maximum possible voltage gain is determined based on the resistive components within the circuit which can constrain the voltage gain. In turn, the power loss is potentially reduced for large duty ratios. How many times the switch pulses at the chosen frequency and for how long at the duty ratio will affect the electrical energy in inductor being pulsed through the resistor load.

Various risks in the design of a boost converter can be determined which must be resolved or compensated for. There are diode reverse recovery problems because the diode conducts for a short period of time when switching from the conducting to the blocking state, a diode or rectifier has stored charge that must first be discharged before the diode blocks reverse current. The frequency and duty cycle ratios affect these timings, if improper amount of time is given in the circuit then there will be excess electrical energy in the circuit, damaging all the components. Furthermore if large current ripples exist in the input, it will further degrade the efficiency of the converter due to the stresses that occur on the switches [46]. The term ripple voltage or current are synonymous with other and the terms will be commonly shared.

Coupled inductors or high frequency transformers are usually used to obtain high conversion ratios of voltage in a converter [47]. The inductor selection would be complicated if large gains are required as the inductor will require a higher number of winding turns. The leakage inductance for the inductor will increase which increases the voltage stress on the switch, making the design more complicated [48].

Nevertheless, the boost converter usage is commonly found as seen in multiple reviews of MPPT implementations [5][23] for both on grid and standalone PV systems. As discussed, the boost converter's specifications are suggested for grid-connected systems due to its ability to step up and maintain voltage levels while taking into account unpredictable input PV levels [49]. A conventional boost DC-DC converter will hence be utilized in the design for the PV system in this project. By utilizing less components in the design, it will improve accessibility and distribution of the experimental setup. As such, for the design of the current research application, the switch must be able to maintain a high frequency of switching or large enough capacitor implemented to reduce the ripple current. Furthermore, the inductance of the inductor and capacitance of the capacitor must be high enough to satisfy the leakage of inductance. The selection of the components in the proposed boost converter can be calculated from equations which will be detailed in Chapter 4.

2.3 Meta-heuristics and Optimization Algorithms

Optimization algorithms are part of computational optimization techniques. Such algorithms are also commonly referred to as methods or techniques within the application scope. Optimization algorithms can be roughly divided into two categories: deterministic algorithms and heuristics. Deterministic algorithms are designed in such a way that it is guaranteed that they will find the optimal solution in a finite amount of time. However, for very difficult optimization problems like global optimization, the dimension of these problems can drastically and exponentially increase the time needed to find an exact solution.

Heuristics are not guaranteed to find an optimal solution, and therefore generally return solutions that are not the exact solution, but is the current best possible solution given in that time frame. The primary goal of a heuristic algorithm is to find the most optimal solution in the given time for the current problem which makes them specific and problem dependent. Normally, heuristic algorithms are easily trapped in local optimum where the solution found is not the globally best solution.

Thus, meta-heuristic methods or algorithms which are more complex and high-level exist that are able to seek the global optimum solution. The meta-heuristics allow themselves to explore the search region of a problem and thus avoid the chance of trapping within local optimum [50]. This means that, meta-heuristic are problem independent implementations of a method, technique or optimization algorithm. However, fine tuning of the system is still required for the specific parameters are always dependent on the application. Optimization algorithms are deemed as algorithms that find solutions to the engineering problem at hand. An exact algorithm is usually defined as an algorithm that always finds the optimal solution in the optimization problem; given that, the application at hand where the input variables always differ, it will be difficult to prove that the algorithm perform suitably in the PV system as the aim is to maximize power generation efficiency under fast speeds. The meta-heuristic methods as defined beforehand therefore will perform adequately in the PV system that requires best possible optimal solution only; since, a good selection choice can also be made to improve the performance of the PV system by implementing good meta-heuristics and their practices fitting to the PV systems application.

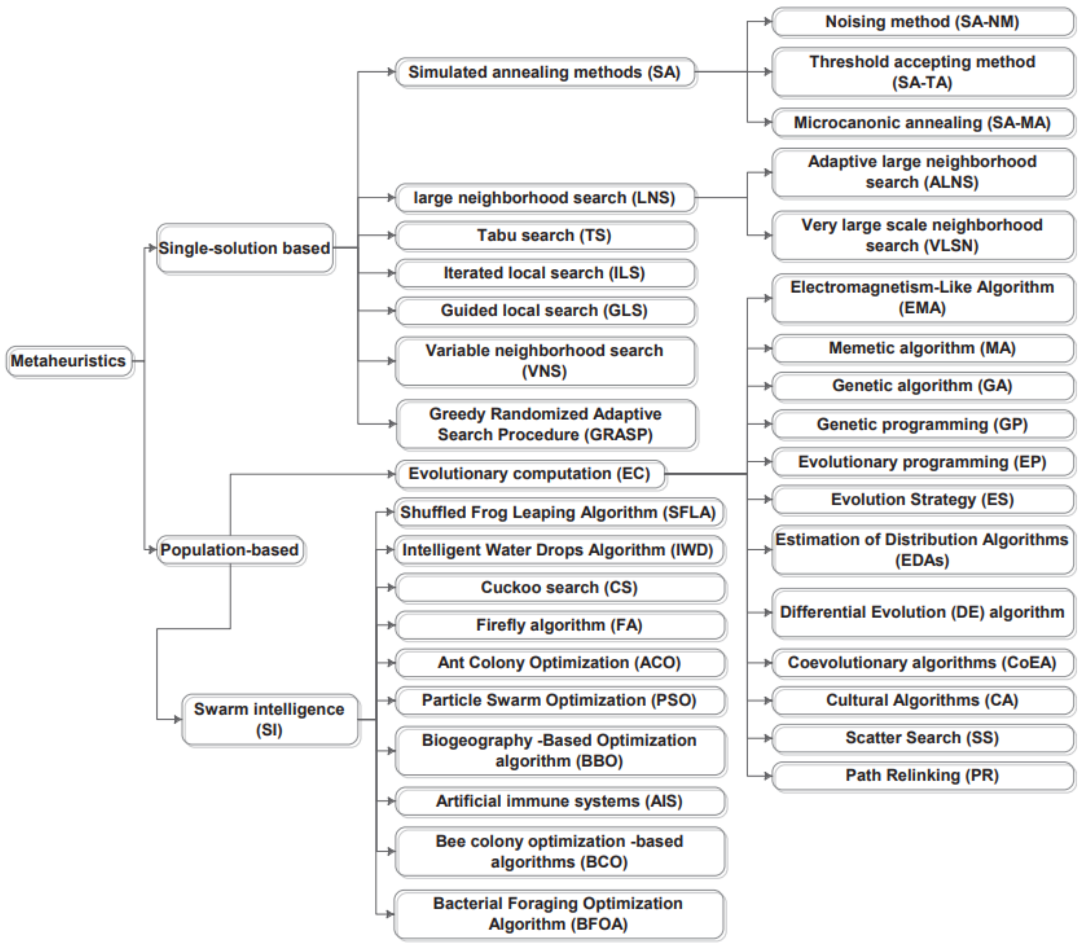


Figure 2.6: Taxonomy of Meta-heuristics [51]

The performance capability of meta-heuristics in their problem solving have been proven to be efficient and feasible approaches to solve hard optimization problems [52]. A depiction of generally widely used meta-heuristic methods and techniques in literature are presented by [51] in Fig. 2.6. The introduced taxonomy has classified the optimization methods based on the theoretical principles. Based on the taxonomy, meta-heuristics are mainly grouped in single solution based, population based and swarm intelligence (SI) based methods. Including the methods presented by the paper, single solution based heuristics include SA, LNS , TS , ILS , GLS and VNS . Population based methods can also fall into GP, EP, ES, DE and EDA. Finally, there are SI methods which include the popular PSO, ACO and FA.

Outside of the presented taxonomy, several meta-heuristics have also appeared recently. Single-solution based algorithms have no current recent developments. Single-solution algorithms experience popularity in enhanced or hybridized algorithms for optimization problems as shown in [53] and [54]. For example, the Jaya algorithm by [55] introduced in 2016 is quite popular as it has shown improved versions over the years in 2018 by [56] and in 2021 by [57]. In population based algorithms, Black-Widow Optimization Algorithm from [58] in 2020, Aquila Optimizer by [59] in 2021, Sailfish Optimizer (SFO) by [60] have emerged recently to solve optimization problems.

The details, application and benchmark of these algorithms are referred to in other recent reviews of meta-heuristic methods as well. As such, the methods just mentioned but not limited to, have been proven to be impeccable for the design of not just hard optimization problems but the application into real-world solutions by Abdel et al. [61], Wong and Chew in [62] and Paulo et al. in [63].

2.3.1 The Optimization Process

The optimization process is generalized in this subsection for most meta-heuristic methods. However, the specifics of implementation and terminology may not be shared between other classes of meta-heuristics. The description of the process is only basic and will be expanded upon in Chapter 3 where the selection of meta-heuristic subclass is decided on.

The goal of global optimization is to find the best possible elements x_n from a set $\mathbb{X}$ according to a set of criteria $F = f_1, f_2, .., fn$. However, in the case of single-objective algorithm where the solution is already re-presentable with one objective function, f or f_1 then the quantifiable elements from $\mathbb{X}$ map themselves with respect to the objective function and in turn fulfill the single objective. When the set of criteria F includes elements of more than one f_n, it is referred to as a multi-modal objective where the multiple objective functions must be evaluated. Global optimization comprises all techniques that can be used to find the best elements x_n in $\mathbb{X}$ with respect to such criteria $f \in F$.

The domain $\mathbb{X}$ of f is the problem space and contains the solution or answers to its objective function, f. Depending on the type of optimization, elements inside $\mathbb{X}$ are most commonly termed as individuals, candidate solutions and $\mathbb{X}$ itself is termed as population or swarm. Hence, for this research project, the terms; such as, 'population', 'individuals', 'solutions' and 'swarm' are terms that remain synonymous with each other as the meaning is shared. The solutions are sometimes denoted as genotypes which are comprised of numerable distinguishable individual characteristics that can be symbolized as the DNA of a genotype. Typically, most meta-heuristics maintain a stochastic generation and modification of solutions due to the non-deterministic behavior of the objective function, which is what global optimization techniques strive to solve.

$$y = f(x). \tag{2.2}$$

Equation (2.2) refers to the objective function of said optimization problem. Any given x element will be able to fulfill the function and the amplitude of the evaluated fitness is given.

$$x_i = (x_1, x_2, ..., x_n)^t. \tag{2.3}$$

Equation (2.3) refers to the set of elements that fulfill the objective function. An x_n element is a vector of size with dimensions that is dependent on how many variables the element needs to answer the function and at whichever iteration or generation, t. For example, if an element requires two variables to compute the amplitude or result of the objective function, f then it is a two-dimensional problem. The dimensionality of a problem increases the difficulty of solving the algorithm as more variables are needed to be optimized and changed to seek the desired maximum or minimum. Even so, even in one dimensional functions there can exist more than one global maximum, multiple global minima or even both within the problem search space [64].

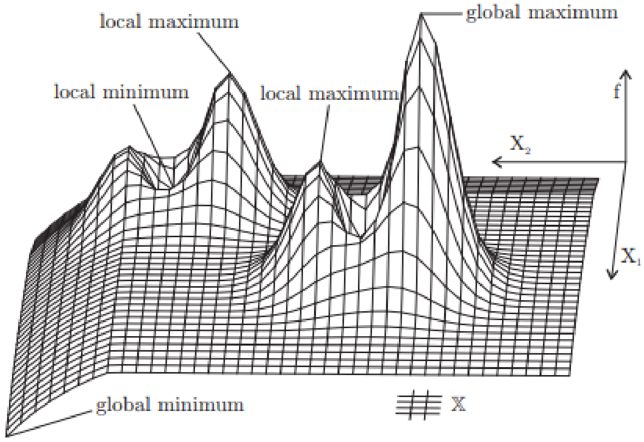


Figure 2.7: Local and Global Maximums in Fitness Landscape [64]

The Fig. 2.7 describes a 3-dimensional optimization problem and its fitness landscape. The differentiation between local maximum, local minimum, global minimum and global maximum are given. In optimization, the maximum and minimum represent the objective of the problem solving. A solution to the objective function is reflected onto a fitness landscape.

With a single criterion f fulfilling the optimization problem, an optimum consists of either the maximum or minimum depending on the user requirements for the algorithm. To give an example, there is an engineering problem which requires the minimization of time spent doing a certain task by optimizing the task routing and scheduling, while there is another business problem that requires the maximization of profit gained by changing the sales price of stock. Though many algorithms build their process and behavior upon the objective of minimization, maximization of objective function can be done by simply reversing the fitness value initial comparison to a negative value.

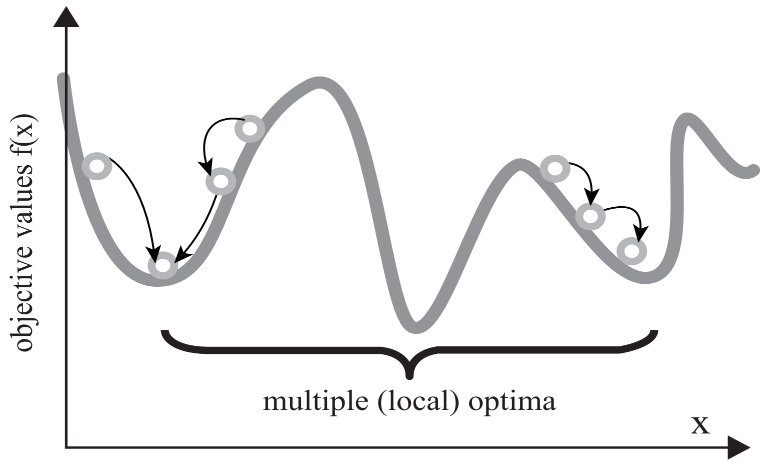


Figure 2.8: Multimodal Fitness Landscape [64]

In [64], different possible properties of fitness landscapes have been presented that an optimization problem may fall under. The implication is that the optimization problem can have different shapes in their landscape based on the objective function. An objective function that is hard to solve will typically exhibit an alteration or mismatched shape in the fitness landscape of objective values with respect to solution of the elements. A simple optimization problem would have a linear ascending or descending shape in their fitness landscape making the maximum or minimum seeking easy to solve.

According to the definition of fitness landscape of a one dimensional problem from [65], the algorithm's search operations within the search space influence the efficiency of the algorithm. The Fig. 2.8 shows a fitness landscape that similarly represents the problem if the solutions are mapped to the objective functions in this research project. The mapping of the objective function for GMPPT is shown in Chapter 1 Fig. 1.1, that shape can be exactly defined as a multi-modal problem. Since optimization algorithms are guided by objective functions, the optimization problem is identifiable and solvable through a mathematical perspective in this context if it is not continuous, not differentiable, or if it has multiple maxima and minima. Through understanding of a problem's difficulty, the applied methods and techniques of the optimization algorithm may balance the local search (exploitation) and global search (exploration) abilities while taking into account the characteristics of the objective function. It is a long proven fact that the exploration and exploitation of solutions in the search space, fitness landscape or solution range dictate an algorithm's performance in global optimization [66] [67]. The balancing of these two criteria are essential in any optimization algorithm objective. The applied methods are different for each optimization algorithm subclass as already shown in Fig. 2.6, thus the method would be chosen based on application needs. Given that the fitness landscape is non static in most cases, the difficulty of solving an objective function with unknown fitness landscape at the time is resolved through balancing the exploration and exploitation capabilities of an optimization algorithm for the GMPPT problem at the chosen approaches which is either SI based or population based evolutionary computation methods.

2.3.2 Improvement Aspect of Optimization Algorithms

While the use of optimization algorithm within engineering problems is widespread, academic research into the improvement of the algorithms can be stemmed from the addition of new behavior or operators that describe a method or feature in the algorithm process in its determination of the minimization or maximization of objective values. Moreover, the determination of algorithmic specific parameters is also a subject of optimization.

The common parameters in evolutionary algorithms (EA) themselves mainly consist of population size, coefficients that determine crossover or mutation which modify the solution in each of their respective iterations, convergence criteria and initial randomized population solutions. While similarly, the algorithms will also have other parameters that are exclusive to them, for example PSO utilizes a velocity inertia that controls the change of position on the solution. But, CS uses random values in Lévy flights for the step sizes determination. A parameter deployed in one algorithm may not be present in another. While an example was shown earlier, an algorithm may utilize elite or random selection processes, random searches of solutions, solution limit search, complete abandonment of weaker solutions through the removal of population size as shown in FWA and adaptive control of parameters such as maximum allowed searches for weaker population, and minimum searches for stronger solutions. Under the guise of all these complex and unique differences between every type of implementation; however, the basic principle of the evolutionary algorithm employed is a common point in which maximization or minimization of objective function values must be determined regardless if the problem was constrained under time, complexity or cost.

In practicality, an approach to any method is sought after for its features such as speed and precision rather than the design. Speed and precision are highly conflicting objectives in the realm of meta-heuristic optimization given their probabilistic nature of the algorithms. A common viewpoint that can be gathered is improvements would only occur from the trade off between either improving accuracy or investing more time [64]. Whether the methods of any algorithm are useful in the application must be compared in between the application specific implementations of any algorithm as well; since, it is proven that an algorithm cannot perform equally in all optimization problems unless modifications to parameter values through tuning or unique features for application specific implementation are made [68].

2.3.3 Hybrid Optimization Algorithm

A method of improving the efficiency of algorithms through the use of capitalizing on the strengths and weaknesses of each certain algorithm technique or methods has been a popular subject of research recently [69]. The method of hybridizing different algorithm techniques is able to combine the good strategies of each algorithm technique and produce the solution with performance that is greater than what a singular algorithm is capable of. The hybrid algorithm usually combines a part of the behaviour or process of two respective algorithms. Typically, a design of hybridization would stem from the requirement of specific methods in other algorithms that is desirable for the application problem at hand. Hybridization may lead to the combination of equations and operators from its algorithms in a bid to find an equal balance point between exploitation and exploration of the solution search space.

1. **Hybrid Harmony Search Algorithm With Grey Wolf Optimizer**

   The proposed hybrid algorithm for global optimization problems is called GWO-HS [70], which combines Harmony Search (HS) with the Grey Wolf Optimizer (GWO) to resolve HS parameter selection problem. Moreover, a form of opposition-based learning technique is implemented within their hybrid algorithm to improve HS exploration due to HS behavior that commonly traps it within local optima. Moreover, two of HS parameters were updated using the GWO instead, which are pitch adjustment rate and bandwidth. The demonstration of hybridization benefits can be observed from the mutual benefit for the entire algorithm. The author conducts an evaluation of the GWO-HS hybrid which has proven its performance exceeding in speed and accuracy against other algorithms in literature while using 24 other classical benchmark functions and 30 state-of-the-art benchmark functions from CEC2014.

2. **Hybrid Algorithm Based on Grey Wolf Optimization and Crow Search Algorithm**

   A hybrid algorithm proposed by Arora et al.[71] which combines the GWO and Crow Search Algorithm (CSA) to form GWOCSA. CSA is a meta-heuristic algorithm that mimics the intellectual conduct of craws is aptly called Crow search algorithm (CSA). The author proposes their hybrid algorithm that combines the strengths of algorithms effectively with the aim of generating promising candidate solutions to achieve global optima efficiently. A widely utilized set of 23 benchmark test functions with a wide range of dimensions and varied complexities is used in their paper to validate the competence of the proposed hybrid GWOCSA. For verification, the results of the proposed algorithm are then compared to 10 other algorithms. In terms of high local optima avoidance ability and fast convergence speed, the statistical results obtained show that the GWOCSA outperforms other algorithms, including recent variants of GWO called enhanced grey wolf optimizer (EGWO) and augmented grey wolf optimizer (AGWO).

3. **Hybrid ACO with PSO Algorithm**

   Pal et al.[72] presents their ACO-PSO hybrid algorithm which combines ACO and PSO together for enhanced performance capabilities. To create an initial population from the existing population from the existing population applied in the hybrid ACO-PSO (second stage), genetic algorithm (first stage) is used. This implementation of the hybrid optimization algorithm makes complete use of parameter of both algorithms unlike the traditional ACO-PSO. In the given algorithm, the PSO is used to enhance the attributes in the ACO which defines that the selection of parameter does not depend on artificial experience but instead relies on the robust search on the particles in the PSO. In this paper, an enhanced utilization of ACO was also used and by this technique the shortest path or routes of ants was found. In the output of the experiment it is shown that the optimize algorithm not only reduced the number of paths in the ACO, but it also found the shortest path at the largest path. Overall, the simulation result shows that the combination of ACO-PSO performs better than ACO and PSO.

4. **Hybrid Whale Optimization Algorithm with DE**

   Whale optimization algorithm (WOA) was initially presented in [73] as a biological-inspired optimization algorithm. Initially, the algorithm promoted itself with the usage of less control parameters and relatively simple implementation. However, WOA can easily get stuck in the local optimum and may lose the population diversity, suffering from premature convergence in the later stages due to the presence of elite vector [74]. Hence, the authors in [74] proposed a hybrid whale optimization algorithm called MDE-WOA, which utilizes aspects from both the Whale Optimization Algorithm and DE. The main change in the DE operators was a modified differential evolution operator (MDE). A lifespan mechanism is introduced to the whales in WOA, which when the MDE operator is applied to whales in the population which will enhance local optima avoidance ability. Moreover, an asynchronous model is utilized to accelerate the algorithm's population convergence and improve its accuracy. Their proposed MDE-WOA, is verified with testing against 13 numerical benchmark functions and 3 structural engineering optimization problems. The benchmark results prove that their proposed MDE-WOA successfully obtains better performance than WOA, basic DE and three DE variants, PSO, Sine Cosine Algorithm, Chaotic Squirrel Search Algorithm and Adaptive Fireworks Algorithm in terms of accuracy and robustness on a majority of cases.

5. **Hybrid Meta-Heuristic Algorithm Based on Cross-Entropy Method and Firefly Algorithm**

   The FA inspired by bionics is initially presented in [75]. In the original cross-entropy method by Rubert in [76], the authors in [77] claim it has disadvantages of large computational cost and slow convergence rate. While in FA, the algorithm produces advantages of strong local search ability and fast convergence but risks the possibility of falling into a local optima rather than obtaining the global best solution. A novel hybrid meta-heuristic algorithm is proposed by [77] through embedding the cross-entropy (CE) method into the FA to enhance the global searching ability to form the Cross-Entropy Firefly Algorithm (CEFA). The new method utilizes both CE operator and FA operator which has introduced individual information sharing between the CE sample and the FA population through co-evolution in each iteration. In the validation of this proposed hybrid, the authors have applied 23 standard testing functions onto their work. Comparisons were made against conventional FA, CE, PSO, GA , SSA, Butterfly Optimization and another Hybrid Firefly Algorithm. In the results, their proposed hybrid algorithm minimizes the risk of falling into a local optimum, enhances the algorithm global searching capability and finally improves its convergence rate. The algorithm can be deemed to successfully balance between exploration and exploitation.

The described hybrid algorithms serve to prove a demonstration of the implementations conducted by various authors in implementing hybrid algorithms. Through the results provided the concept of hybridization is visualized through results proven in general engineering problems.

2.3.4 Applications in Engineering Problems

Algorithms have already applied their methods onto various optimization problems, namely engineering in specific. The engineering problems entail processes which are either time constrained or face dynamically altered environmental changes, such problems forego a deterministic approach to their solving in favour of employing the different optimization algorithms in their design. Without the meta-heuristic optimization algorithms, the objective functions become substantially difficult to solve which affects effectiveness of applied real-world systems due to improper control of the system [78].

The authors in [79] have utilized Moth-Flame Optimization Algorithm (MFO) to solve minimization of speed design for gears or brake shafts while constrained under stress of the components, design of car side impact based on the measurements of the material used. Recently, big data has been a subject of interest in academic fields and optimization algorithms are utilized in the subject. The authors in [80] have employed Parallel Random Forest Algorithm (PRF) with the objective of determining useful data sets in the sea of big data; the algorithm has also utilized operators to reduce the dimension of the data sets and a weighted voting method to increase the accuracy of choosing among high dimensional noisy data. Yongmin Zhang et. al in [81] has developed their own data gathering optimization algorithm for the purpose of dynamic sensing and routing of its rechargeable sensor network. The algorithm will balance energy allocation of its sensors and then optimize the sensing and routing of its sensor data in order to optimize the energy efficiency.

The algorithms above are examples of meta-heuristic optimization algorithms employed in engineering problems for problem solving, in the literature they are compared using the average value of the speed and best solutions in respect to the specific application at hand against other algorithms. Majority of the algorithms, however, always propose that their algorithm performance is evenly matched or superior against others, due to this fact the proposed algorithm in this project must be compared against other algorithms in literature within the proposed simulation and physical experimental system to ensure a fair comparison without bias.

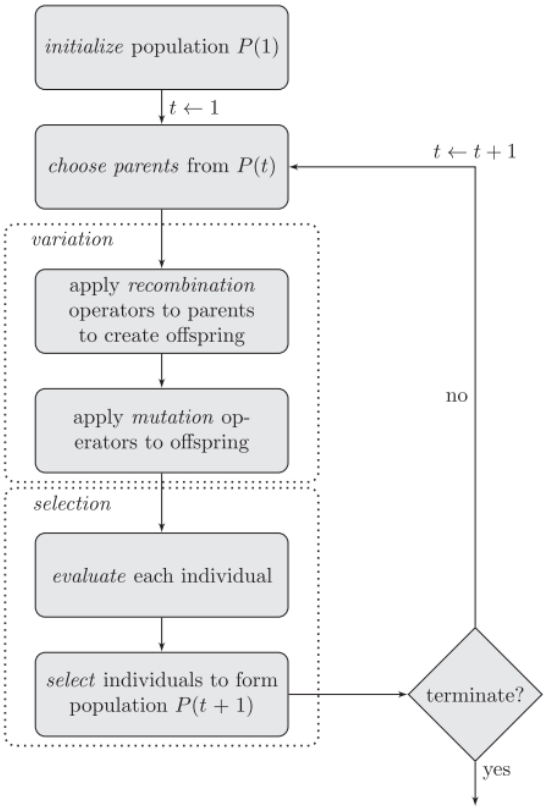


Figure 2.9: Framework of Basic Evolutionary Algorithm [82]

The framework of an evolutionary algorithm can be observed in Fig. 2.9. In its core, evolutionary algorithms, their derivatives and sub-classes function in the same behavior are described in the figure.

The term population refers to the candidate solutions of an optimization problem. The candidate solutions share the name synonymously with individuals or phenotypes in literature; since, each solution contains properties which can be modified or mutated. The properties are also synonymously called chromosome or genotypes. In the context of the application in this research project, the population of individuals contain solutions of the duty cycle property. A chromosome in the typical GMPPT solution is denoted as the duty cycle as the value itself is able to completely represent the candidate solution. Each solution has a duty cycle that answers the PV system's objective function.

In each generation, the evolution of an initially randomly generated individual progresses iteratively per generation. The fitness value of the solutions are values obtained from evaluating an individual solution against the objective function for the optimization problem being solved. Then, individuals are chosen using the selection operator to be modified to form the new generation with different properties. The next iteration will be evaluating these new individuals. Finally, the algorithm terminates upon maximum number of generations or when a certain fitness required is reached.

The terminology used in meta-heuristics was a large topic of discussion if not so today where as meta-heuristics appeared in literature, their classification can be loosely extended as a variant of evolutionary algorithm [83].

Take for example in the research topic of GMPPT algorithm and the application, it is known that the duty cycle is represented as the candidate solutions and the duty cycle can be evaluated using the objective function, which is a real-world model PV system connected to the DC-DC boost converter to measure the quality (fitness) value. An initial solution set is introduced to modification from a few variation operators which modify the current solutions, creating a new set of candidate solutions; then, after the evaluation of current, then new duty cycles, finally, a selection scheme such as tournament or replace method at the end of one iteration. If needed, the introduction of an extension of the algorithm with non-standard features like constraining the time allowed for reaching a GMPP or assign penalties to weak candidate solutions. Search processes repeat until the method ends. Finally, the parameter tuning is conducted in the algorithm for maybe population size and the rates of the operators. The rates of the operators can be deterministic or stochastic values; nevertheless, they are modified to improve that operator or the method in a whole. If a term would be describing this set of methods, it can be defined into a variant of evolutionary algorithm, it could be a variant of evolutionary algorithms from SI because the behavior of the method can be extended into PSO.

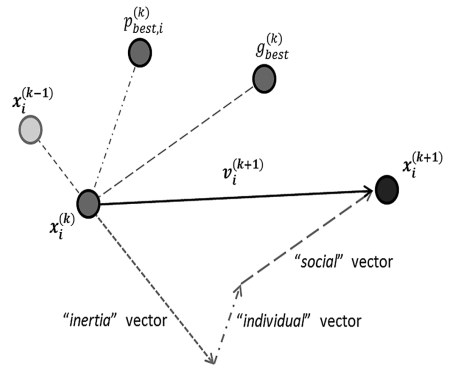


Figure 2.10: PSO Iterative Movement [84]

In PSO, a set of candidate solution particles, are first initialised, evaluated and modified using velocity and inertia operators. The entire particle swarm is brought over into the next generation and inertia is decreased as iterations go on. The whole search process obeys the criteria to be deemed an evolutionary algorithm, but why would PSO be termed as a method of SI? The answer can be found in the intricacies or strategy of the design in any method, a consideration of individual and group observations within design such as PSO and FFA individuals would act in a collective behavior as a group by moving to the best solution iteratively. For example, Fig. 2.10 describes this collective behavior of improvement over the course of several iterations in PSO, the group utilizes information from each other, as a group to search for the best solution. Other than that, evolutionary algorithms rely on the selection of parents and or without crossover, as it follows the rule of survival for the selection of best candidate solutions where surviving individuals are the most likely to be chosen from selection scheme.

For this sake and within this research project application, an evolutionary algorithm is defined so as long as it is able to represent the behavior of multiple evolutionary processes; such modification of solutions using variation operators may include combination, crossover, mutation and selection of populations into a compilation that obeys a mathematical process structure. Differences in the strategy of search process in the objective of searching and convergence to the best possible solutions in the interests of user or application needs cause differences between many other metaheuristic methods. Thus, the design of the proposed algorithm is still seeking the best possible performance for the GMPPT application and system requirements. When evaluating the performance of an algorithm, two factors are taken into account which are the quality of final solution and the time taken to reach this final solution. The efficiency of the whole process is problem dependent and relies heavily on the successful strategy, parameter usage, its tuning and the plethora of variation operators used.

2.4 Operators

Variation operators will be defined in terms of evolutionary algorithms, genetic operators represent an analogy from but not limited to mutation, crossover, reproduction and competition. Individuals henceforth evolve from the set of initial candidate solutions that are modified by the operators. Genetic variation is a necessity for the process of evolution to prevent genetic stagnation, computational programming applies the variation by reiterating its calculations with modified variables. The result is analogous to evolution in nature with how the genetic operators modify the solutions in every generation or commonly known as iterations.

With a set of mathematical expression and equations, the operator is built. Operators are aptly defined by their mathematical expression and how it utilizes information from the populations, from known or unknown parameters. They are also sometimes called or named depending on a description of its process; e.g Differential Operator, Velocity Operator and any terms that can represent the process. Resultant population of individuals are iteratively modified again using operators until the set convergence criteria is resolved or fulfilled. Through manipulation of the individuals of a population by the genetic operators, evaluated solutions can be assigned a fitness value that represents their position as good or strong solutions within that population and vice versa for weaker solutions. Utilizing the best solutions are the basis of the evolution process in any form of meta-heuristics; usually best solutions in the operators decide the next generation of solutions by mainly choosing them as parents and then creating offspring solutions using crossover or combination; mutation solutions are also produced if diversification of individuals are desired in the application, especially in dynamic environments where objective functions are even more non-linear.

The mutation operator introduces or forces a change in the solutions, or a form of genetic diversity in solutions. The mutated solutions, attempt to prevent the GA into converging to a local minimum by stopping the solutions becoming too close to one another, hence avoiding stagnation. Mutations, typically change the solutions entirely to be different than the current population's solution values. By mutating the solutions, a GA can also seek the improved solution solely through the mutation operator [85].

Different methods of mutation exist; the mutations may, modify the single chromosome or bits in the solution individual to a certain rate or to more complex mutation methods, which may replace entire values in the solution with random values chosen from the uniform distribution or the Gaussian distribution. As mentioned before, after a complete generation of evaluated population, a set of existing individuals are selected for the creation of new generation. By ranking individual solutions based on their performance in the maximization or minimization of fitness process within the algorithm, the individual solutions are ranked using a fitness function after obtaining their fitness by subjecting them against the objective function. This is important for high dimensional problems where the properties of the individual increase in number, thus the evaluation of a solution must be weighed with the fitness function. Well performing individuals dominate the selection process with preferential choice by the selection method or operator as their fitness is higher than others in the population. Some methods, however, do forego the former in favor of stochastic selection to save time and reduce complexity.

Different methods for choosing the solutions exist, the methods are listed as follows:

1. **Roulette wheel selection**: This scheme is sometimes denoted as a Fitness Appropriation Scheme in which the fitness values of each individual in the population in the current generation is summed together. Then, the fitness of each individual is divided against the resultant sum from before, the value computed as a ratio becomes a probability of being chosen for the next generation.

2. **Tournament Selection**: A number of tournaments, as the name is implies, are conducted based off the objective function, the fitness values are used for competition between two individuals according to a subset and number of tournaments allowed. Among a subset of individuals created from the population, the highest fitness individual is chosen for surviving the next generation.

3. **Replace selection**: A class of selection operators which work on populations with size of 2, treating the population as a sequence instead of set. In this method, the fitness value between two individuals are competed against each other to denote a survivor to carry over the next generation.

4. **Elitist selection**: An operation which falls under the elitism strategy prevalent in design of evolutionary algorithm operators or methods where the best individuals of the population are directly used in crossover, mutation and selection. In

elitist selection, the best solutions are immediately brought over from the current generation into the next generation with no contest.

2.5 Exploration and Exploitation

Exploration and exploitation guide the evolution of a set of stochastically selected individuals towards good near optimal or optimal solutions. Two fundamental processes drive the evolution of any population: the variation process, which enables exploring different regions of the search space, and the selection process, which ensures the exploitation of previous knowledge about the fitness landscape. As the algorithm runs, if not balanced well, its search process will heavily skew towards either weak local search or weak global search. If the chosen operators and other methods in an algorithm are not balanced well, the solutions will skew towards either weak exploration or weak exploitation. Weak exploration is denoted mostly from a lack of global search in the search process that causes the individual solutions to not explore other potential search areas for a better candidate solution. In selection process, if an elitist behavior is adopted to select the solutions every iteration, it will bring the risk of weaker search due to only focusing operators to modify solutions around good potential search areas. The disadvantage of this generates the possibility of not being to explore the search area properly, which will indirectly cause weak exploitation.

There are methods to alleviate this flaw, introduction of initially more weighted initialization of the solution towards a proper known average can usually result in a good candidate solution search area; however, it will require prior research into the problem or system. The known knowledge if unavailable can be substituted with an initialization towards the normal distribution in a solution range applicable to the system. Otherwise, introduction of mutation in the framework, as the name implies, is able to genetically alter the solution. However, its role in the algorithm is able to inject solutions with drastic modification that do not obey common crossover operator equations. In terms of mathematical expression, exploration must spread away from current global best solution so it must be designed without using historical global best values.

For example, the solution values can be given a minimum change in movement to ensure the change difference from global best in the search area, otherwise it can be randomly initialized again based on design needs. If the crossover operator is used for exploitation, the mutation operator is more commonly used for exploration due to the ability to produce solutions which are inverted and away from the current best solutions. Typically, only a low number of mutation solutions are generated to not prolong the search process with sometimes useless searches that cannot be profited due to the loss of time in favor of more exploitation than exploration. An adaptive control of the amount of mutation to be generated can be also suggested through the use of iteration count and limit, the longer the search process goes the less mutation can happen. The mutation operator in mind must be beneficial to the system and be able to search as many other areas in the search range that the current convergence has not explored.

Exploitation on the other hand functions as an inverse to exploration in the role of evolutionary algorithm search process by its focus on intensification of individuals. Exploitation is akin to what is described as an algorithm's prowess towards local search whereas exploration is also commonly known as the capability of global search. As exploration is explained beforehand, exploitation aims to search in the region of the currently global best solutions; the exploitation behavior is replicated through the use of operators that calculate output solutions close by the current best solution. Crossover operators primary objective are aligned with exploitation, the careful selection of which individuals to undergo crossover in reproduction of offspring, produces and derives a new solution for the current individual of the new iteratio. Typically when two individuals are utilized for crossover, the two values are crossed together in respect to the mathematical expressions designed for it, which include but not limited to multiplication with random numbers, movement towards global best solution by assigning the global best solution with a coefficient to denote its weight in the expression and use the current iteration count or iteration limit to decide the step size. Much like the exploitation where adaptive control can be applied, searches down the line in the search process should not have large step sizes so the accuracy of the solution can be pinpointed.

2.6 Chapter Summary

In this chapter, the background regarding the PV panels and the partial shading problem is given which arises the need of a method of alleviating the PSC problem; it drastically hampers power generation efficiency in PV systems. A background of current DC-DC converter topology in literature is reviewed which justifies the DC-DC converter as a switching regulator to be commonly implemented into PV systems The conventional boost converter topology is suggested to be utilized in the PV system for this research project, and is finalized in the literature review of Chapter 3.

In the aspect of optimization, the applications have applied machine learning or search methodologies in the design of such system [86]. Evolutionary algorithms are these search methods that mimic the behavior of nature in their algorithm process. Its evolution ideology and methods are the main basis of the evolutionary computation techniques, genetic algorithms, evolutionary strategies or any form of programming that is loosely based on the evolutionary nature. Classification of evolutionary algorithms fall under the meta-heuristic category by which the likes of SI, SA and differential evolution (DE) are included in their categorization due to the similarity in sharing methods, search behavior and the stochastic nature in their by reiterative problem solving through the use of random generation in the range of possibilities. The evolutionary algorithms can be described as a rapidly developing associative analysis, by which the collection of techniques and systems manage a complex problem or if applied, a complicated application system [87]. The techniques under the term of evolutionary algorithms differ in the representation of its form of deriving the solution and how the implementation of the algorithm changes based on the applied problem. As such, the GMPPT problem is declared to be an engineering problem that is susceptible to the advantages of implementing a meta-heuristic evolutionary or SI algorithm.

The operators of these algorithms have also been heavily detailed that state the design of the operators must be taken into account. The operators influence the individual solutions and the results obtained, with the proper strategy conducted based on the engineering problem at hand, design of the operator itself can be improved. Chapter 3 reviews the operators adopted by GMPPT implementations in literature, which will prove the background provided in Chapter 2.

Exploration and exploitation describes itself as a delicate balance of the capabilities in a meta-heuristic algorithm to conduct the global search and local search effectively. With regards to the background given, the proposed GMPPT algorithm design will base itself off maintaining this balance while obtaining better convergence speeds and tracking accuracy.

Chapter 3

Overview of GMPPT Algorithms

As stated earlier in Chapter 2, evolutionary and SI approaches dominate the field in problem solving for implemented applications which also include the GMPPT and MPPT optimization problem. The applied methods of these GMPPT algorithms are compared and evaluated in this Chapter to validate the improvement that can be made to the PV system problem with the proposed designed GMPPT algorithm. The properties that define the framework of a GMPPT have been shown in Chapter 2.4 are the variation operators which can nudge, mutate or shift the solutions in a population in the domain range to balance local and global search capabilities.

The proposed algorithm will retain, qualities that are beneficial to the GMPPT problem. These qualities include fast tracking speeds, accuracy and complexity which will are outlined in the following Chapter. Through the retention of good algorithmic behavior in exploration and exploitation, the balance of these two aspects is able to guarantee the performance of GMPPT. The design of the proposed method has already assumed the above aspects into consideration for the objective of GMPPT performance and the closing of any research gaps in current literature. How the GMPPT algorithm's performance relates to the exploration and exploitation balance is given in Section 3.1 which also derives the performance criteria related to this balance.

In the Section 3.3, applied GMPPT algorithm methods are detailed and compared between each other. Regardless of method or algorithm used, the process of GMPPT commonly shared is shown. A method in this chapter can denote a meta-heuristical optimization evolutionary algorithm or any other form of control and generation for the duty cycle, D. Henceforth, methods and algorithms will share the same synonym following their similarity in process behavior.

In Section 3.4, the adjustment of parameters in the chosen GMPPT technique, operators and hybridization, and modifications made to improve performances are detailed. Variation operators within each algorithm are also categorized based on their type and usage. Other variables or techniques utilized that are unique to the algorithm implementation are also found and detailed in comparison. Ultimately, the specific advantages and weaknesses of the algorithms and their techniques applied to the GMPPT problem will be shown.

3.1 Global Maximum Power Point Tracking

Given that optimization algorithms are used to solve difficult computational problems, they are widely used in many applications that need to solve a specific objective function which are mostly engineering problems. As explained previously, DC-DC converters require switching control or regulation of the duty ratio at any form of switching electrical component such as transistor, MOSFETs and IGBTs. However, since the solar panels which are the input side of a converter are always under dynamically changing irradiance and temperature values which greatly affect generated power due to the solar conversion, the duty ratio cannot be controlled using an exact or deterministic optimization algorithm. An implementation of a meta-heuristic optimization algorithm is needed to solve the problem by searching for the GMPP.

GMPPT algorithms control the duty ratio after evaluation through the objective function, which is the obtained power at its current time and seek out the greatest possible power to maximize power conversion efficiency. The implementations of GMPPT algorithms include the use of programmable devices or, a micro-controller to measure the current and voltage to compute the current power generated of the input side of the converter. The algorithm will determine the best duty cycle ratio for finding the best possible power generation at the GMPPT. In the case of GMPPT where the name applies, PV systems face dynamic environments where the power generation will never be static, thus the algorithm is needed to actually calculate a duty ratio during the time the system is running while facing PSC.

The details of initialization, crossover or mutation operators, selection strategies, termination criteria from the evolutionary computation and SI methods are sub-classes of meta-heuristics. A review of employed GMPPT algorithms in literature is laid out in this Chapter 3 or literature review to pronounce the design and performance capability of modern GMPPT methods. The review of the GMPPT algorithms is made in order to evaluate the algorithm for comparison for their design choices that must be considered in the proposed design of the GMPPT algorithm.

3.2 GMPPT Algorithm Performance Evaluation

Algorithms differ on certain parameters depending on the application, and it is no different for the application of MPPT. Many conventional evolutionary and soft computing GMPPT algorithms exist in literature; such as, PSO, GA and Fuzzy Logic which have good performance but no capabilities to counter the occurrence of local trapping which causes local maximum power points (LMPP). The assumption of these algorithms being able to search for GMPPT effectively comes from the inherent nature of the algorithm framework and more of a luck rather than actively seeking to escape local traps. Of course, to alleviate such weaknesses the improvement of the aforementioned GMPPT methods are improvable with modifications or additions of new methods [23]. The algorithm designs have varying range of complexity from low to high of implementation. The complexity of a given algorithm is characterized from its usage of parameters of variables and the amount of operators utilized just to search for the solution and assemble the framework, it is important to note that complexity does not guarantee a performance standard. Certain strategies of algorithms that are not limited to the operator category include range limitation of solutions, different initialization of initial population duty cycles, re-initialization strategy and adaptive modification of parameter or variable values.

In canonical and generic implementations of most GMPPT methods, the aforementioned strategies are unused or niche in other applications, the strategies must be applied to the design of the proposed method to improve the performance of the overall PV system under PSC. As the algorithm must consider PSC, methods that are able to implement strategies that in turn improve tracking speed and accuracy of solutions ultimately prevent the DC-DC converter from converting power at less than optimal values. However, fine tuning of the algorithms is still required as specific parameters are always dependent on the application. To summarize, the framework of a method or algorithm depends on the operators it applies for the solutions; as such, any strategies outside of operators used for modifying aspects of the framework, and the fine tuning of parameters and variables of these two points are the most important to be focused on for the improvement of performance capabilities in GMPPT problem.

As the algorithm must take into account PSC, the referred techniques are ones that are able to perform adequately as they possess features that allow the individual solutions to spread out the search space, avoiding local traps and seeking the true GMPP. Thus, these techniques must have suitable exploration and exploitation capabilities for their application in GMPPT.

It is understood that based on the design of a GMPPT as said before with the operators and strategies, any application of the GMPPT for a PV system should fulfill most of the following criteria while designing the framework:

- Performance Accuracy
- Convergence Speed
- Sensor Requirements
- Complexity level of Design
- Control Parameters
- Hardware Implementation Costs

Accuracy will dictate the capability of the algorithms to find the GMPP among a set of patterns of PSC that is applied or caused to the PV system during its run-time. The convergence speed of an algorithm determine how fast the GMPPT algorithm is able to perform while following the desire of the earlier requirement, a well sought after algorithm must be fast and accurate. The GMPPT algorithm's convergence speed is split into two work flows, the population of solutions within the algorithm must be able to converge to a current leader that obtained the best fitness value, the other is that the algorithm must not converge too fast to this current leader to avoid local trap which resulted from the inadequate and superficial search. Though extraneous search does penalize the time in a constrained system, the balance of exploration and exploitation is a huge hurdle to tackle in the GMPPT problem. Sensor requirements denote the use of voltage or current sensing sensors in the PV system, typically two sensors are used in the DC-DC converter; however, some algorithms can observe the fitness value solutions with either voltage or current given that the component values in the DC-DC converter are known beforehand; such as, resistor load value which allows only one sensor requirement and sense the other value through Ohm's law. However, this limits the delivery and commercialization of the algorithm as a universal solution to GMPPT problems as the converter values must be assumed or known.

Moreover, the complexity of GMPPT algorithms are considered at times where the deployment of them into low-power or weaker micro-controllers are demanded. The criteria go hand in hand with control parameters as lesser control parameters are always desirable to reduce the memory storage needed from the computing devices; therefore, they also reduce complexity as the algorithm uses less parameters to calculate the solution values. Ultimately, less complex design could result in less control parameters needed which in turn reduce hardware implementation costs where weaker and cheaper devices can be utilized instead.

3.3 Types of GMPPT Algorithms

The section dedicates itself to the review of GMPPT methods in literature. Compilations of the methods utilized and their popularity, capability with performance is made. Furthermore, the compilations of the methods under real world scenarios and real experimental setups are undoubtedly required to prove themselves. The following section lists and describes the GMPPT techniques that have been reviewed for the purpose of research into the development and design of a boost converter installed PV system with GMPPT algorithm tracking that fits out application needs. Conventional MPPT techniques include the Perturb & Observe (P&O) method and the Incremental Conductance (IC) method. As seen during this literature review, these methods are not detailed due to already set precedence of their weakness in GMPP. P&O and IC methods already fall into local traps easily, choosing only LMPP and their GMPP searching is mostly reliant on luck of not observing other peaks in the P-V curve. Even so, more modern MPPT methods have adopted features of global search to accurately detect GMPP among LMPP in the P-V curve. For this reason, conventional MPPT methods with weak GMPP or global search are abandoned and not considered for further study while MPPT methods that have developed themselves further to overcome the PSC weakness, are reviewed.

The applications requirements in this case answer to the implementation of GMPPT method that is able to function with the simulation software, experimental setup, according to the specified PV parameters, cases of PSC and DC-DC converter component values. Exclusivity of testing most methods do cause the lack of confirmation or trust in the results, hence the confirmation of the GMPPT methods result would need to be met with an application and implementation of them in the proposed PV systems if needed. The stigma is unfortunately justified due to the nature of meta-heuristics where the application or problem at hand is just as important as the method choice.

The methods or algorithms are classified in the list below, they are the works of other authors to solve the GMPPT problem. Results of these algorithms in tracking speed, efficiency and the complexity are compiled in a table below the section.

3.3.1 Bat Algorithm

The authors in [88] have presented the Bat algorithm for utilization in MPPT problem under PSC. Bat algorithm is a population based optimization algorithm inspired by the echolocation features of microbats in locating their foods. It is developed by Yang in [89]. Bat algorithm maintains a swarm of N microbats, where each microbats flies randomly with a velocity v_i at position x_i

The algorithm used a size of N bats to determine the GMPP, the author states that utilization of high number of N presents slower GMPP convergence time but higher accuracy on finding the GMPP. The vice versa occurs with low number of N bats, thus the balance of "convergence-speed efficiency" as stated by the author is required and thus have set a bat population that falls in line with their requirements.

Moreover, this implementation of the bat algorithm has utilized a method of reflective impedance to calculate the vector (discrete values that make up the solution and a direction) of the initial duty cycles to approximate the initial search space. This method used the impedance values of the load, converter efficiency and the load values. The corresponding power for each of the vectors from a bat is then evaluated and the best bat, d_{best} is stored. An inertia weight factor is applied to the equation of velocity, v_i where each d_i must move towards the best duty cycle, d_{best}. The inertia weight factor is able to determine the speed of a bat, the speed in this case is the movement step of how far a bat is able to move. Basically, it affects the movement of the duty cycle per bat.

In Bat algorithm, each bat has an emission pulse r_i that a random number is competed against after being generated according to uniform distribution. This step occurs after initial search phase. If the random number is greater than r_i, the exploitation stage occurs and local search generates new d_{new} by adding its original value with the velocity. As a result, the new solution is drawn locally by using a random walk around the best current solution. The author in this implementation for GMPPT has utilized a modified generation of the d_{new} using a fixed positive, Φ which is able to limit the generation of the new duty cycle. Each duty cycle is tested for generation of d_{new} and the iteration starts over again.

The convergence criterion is then checked if it has been fulfilled, which is a constraint that limits the amount of times the algorithm should or can run. The condition in the author's bat algorithm implementation pit the two absolute differences in duty cycle, d against each other and fulfills the criteria if this difference is lower than a threshold, ΔD.

The re-initialization technique utilized in this implementation detects the change of the PV panel PSC through a change of the power between an old sample point and a new sample point. A ΔP threshold is set for the requirements, if this threshold is surpassed then the algorithm will reset to its initial state.

The paper in [88] also used a MATLAB/Simulink environment to verify the algorithm performance, then later uses an experimental setup consisting of two series connected SM55 PV panels, oscilloscope, FPGA board and the buck-boost converter. The partial shading on the PV panels are configured in four different shading patterns to be tested with their proposed algorithm. For comparing the algorithm performance, however, it has only compared itself against P&O and PSO methods. Their proposed scheme outperforms the two methods in the field of accuracy and oscillations in PV power at the transient time by obtaining around an average 99% efficiency of the MPPT with a tracking speed of 1.3 s.

3.3.2 Hybrid PSO and P&O Algorithms

In [90], the authors have presented their designed algorithm which is a combination of PSO and P&O search operations within the algorithm framework. The P&O algorithm starts with outputting a particular duty cycle. The P_{pv} at this duty cycle is then measured. Perturbation Δ is applied by increasing or decreasing the duty cycle. The P_{pv} is measured after each perturbation; based on this information, the algorithm decides whether to go to the left or right side of the P-V curve to reach the MPP. The author implements the canonical PSO algorithm in the implementation for the combined PSO and P&O method. The basic framework of PSO is already explained earlier in PSO-VD. The framework of conventional P&O can be given in Fig. 3.1.

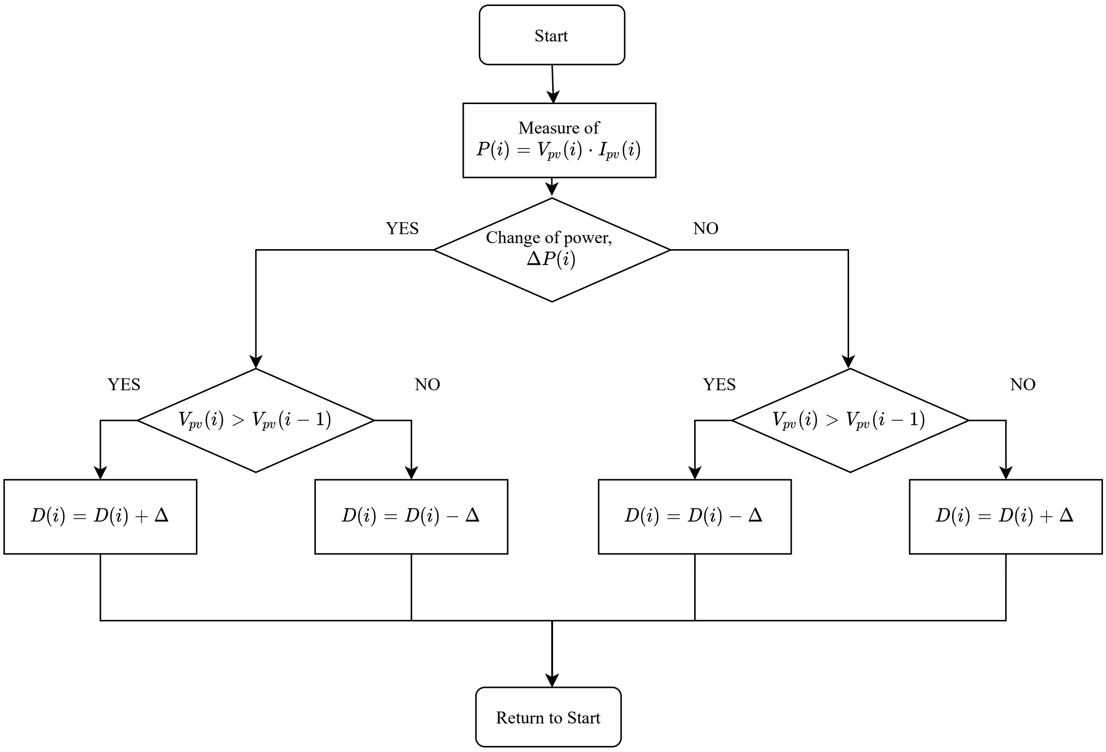
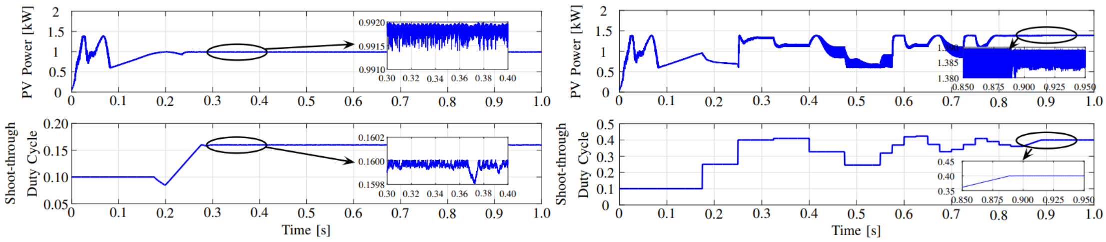


Figure 3.1: Conventional P&O MPPT [90]

Their proposed algorithm functions in two stages, the process starts in PSO algorithm stage and, then continued and maintained at the P&O process. The reasoning given by the author by using PSO first is due to the existence and risk from current ripple of i_{pv}. The converter topology utilized by the author is the quasi-Z source inverter (qZSI) topology which they have stated to cause higher current ripples at higher duty cycles. With this reasoning, the inaccuracy of measurement is possible and hence difficult for PSO to search for GMPP alone.

Thus, the PSO algorithm is used only to reach the vicinity of the GP. It is assumed that the vicinity of the GP has been reached when the convergence criteria is met. In this case when the positions of all particles are close enough from each other. Then the algorithm proceeds to the second stage. When the convergence criteria is met, the controller outputs $d0$ of g_{best}, which is the best position the algorithm has found. This value is subsequently used by the second stage. The second stage used the P&O algorithm. Since the vicinity of the GP has been reached by the previous stage, the P&O algorithm finds the GP with ease. In this case, it is important to have fine steps Δ, in order to avoid undesirable results.



(a) Simulation Results of P&O (b) Simulation Results of PSO-P&O

Figure 3.2: Simulation Results of PSO and P&O [90]

The algorithm particularly does not utilize convergence criteria to stop the search process at the P&O stage, this is common in P&O methods due to the feasibility of constantly perturbing to track its current MPP constantly. The author proposes re-initialization to PSO stage upon the shading pattern change as shown in their framework; however, the details of using power, P threshold or other criteria is undisclosed. To verify the simulation results, MATLAB/Simulink environment is used to implement the algorithm design. The DC-DC qZSI boost converter topology is connected to two undisclosed PV module models. No experimental setup is utilized for verification of real world results.

There are two shading cases in their work, both of these two shading cases retain only two peaks in the P-V curve. The difference of these two can be observed from the placement of the local peaks and GMPP, one case has the GMPP on the left closer to the lower d while vice versa on the other. The author proposes that lower d reduces the current ripple and strain of the inverter.

For comparison of their work against others, canonical PSO and canonical P&O are compared against the proposed combined version. The search speed and accuracy results are observed in Fig. 3.2. The results confirm the viability of the combined method against the conventional GMPPT of PSO and conventional MPPT of P&O in terms of tracking speed and accuracy while obtaining less voltage ripple of 5 W compared to the 30 W voltage ripple of PSO and P&O. The Hybrid PSO and P&O algorithm obtains a tracking speed of 1.3 s at the GMPP with an efficiency of 99.8%. Thus, P&O weakness of local trap is circumvented by the initial global search of PSO and a working GMPPT algorithm is designed.

3.3.3 PSO and Differential Evolution Algorithms

PSO and DE algorithms or known as PSO-VD have been known as popular techniques of EA. Recently, these techniques have been gaining much attention due to their ability in optimizing real-valued nonlinear and multi-modal objective functions. As these techniques are based on search optimization, the GP could be tracked with a reasonable convergence time and a better dynamic response than conventional methods.

PSO is a stochastic optimization method developed by [91]. In PSO, the G_{best} dictates the movement of each particle in the swarm size of N. The particles have a velocity that controls the movement (step size) and direction of each solution, the velocity, V_i^t is usually summed with the particle solution ${x_i}^t$.

DE, a genetic algorithm was introduced by Storn and Price in [92]. The algorithm begins with the initialization of a population called target vectors. Then, a mutation operator produces one mutated vector from the population. Next, crossover operation generates a single trial vector. This new vector replaces the population of target vector in iteration $k + 1$ if the fitness value is higher than it.

The author claims that, the next position of the particle after velocity operator might not be better than the $p_{best}i$. Moreover, in PSO the particles are not eliminated even when they experience the worst fitness. Thus, since the particles remain in the memory of PSO, it wastes the limited computational resources, consequently resulting in a slower speed of convergence. The author in [93] presents the PSO-VD to solve the GMPPT problem. In order to circumvent the above-mentioned weakness of each method, a differential operator, borrowed from DE, in the mutation stage is coupled with the velocity update scheme in PSO. The operator is invoked on the position vectors of two randomly chosen individuals, different from their best fitness. The main characteristic of DE is to keep the competition in the population while the winning particles hardly keep sufficient history. Therefore, the advantage of one method can compensate for the shortcomings of the other technique.

First, a vector y_i which chooses two random particle j_i andk_i and calculates the difference in their duty cycle, D to assign to the vector. The velocity operator of PSO is taken and modified to include this y_i vector in the calculation of a new velocity v_i for P_i particles. The utilization of P_{best} factor in the original PSO velocity operator is removed in favor of differential vector calculation from DE.

The author implements the Trial Vector equation to signify the P_{best} of the population. The trial vector is the resultant sum of the ${v_i}^t$ with ${x_i}^t$. In trial vector fitness evaluation, if the particle reaches a better location or does not change its original position, then the particle is remarked to be at its P_{best}.

After few iterations, particles may turn stagnant in a local search space. To avoid this problem, the particle is shifted by a random mutation to a new location through the mutation operator. This operator used x_{max},x_{min}, maximum and minimum range of the search area which is 0 to 1 and the t_{max} which is the maximum iteration allowable of the algorithm.

The PSO-VD algorithm process for GMPPT continues with differential operator after the initial fitness evaluation of initial population. After the evaluation of the population modified by the differential operator, the particles are assumed for local trap if the ${x_i}^t = {x_i}^(t+1)$ and mutation operator is hence applied to escape the local search area. For convergence criteria of this implementation, the algorithm decides to choose t_{max} as the criteria and thus the algorithm runs fully until the set limit is reached. Much like other algorithms, a re-initialization of the algorithm is implemented upon a set threshold of change in the PV panel's V or I.

MATLAB/Simulink environment is utilized by the authors to verify the algorithm performance of PV system under various PSC. A DC-DC conventional boost converter is applied in the system and a ET-M53695, 95 watt rated solar panel is used. Three particular shading cases are implemented, case 1 maintains a P-V curve of 2 peaks while case 2 and case 3 shading patterns measured the P-V curve with 3 peaks. Moving on to experimental setup, the setup uses two series-connected ET-M53695. For the control unit of the GMPPT, a Texas Instruments TMS320F28335 DSP board is utilized by the authors.

Thus, unlike the conventional PSO, the PSO-VD prohibits the particles from visiting the unnecessary positions by the differential operator borrowed from the DE. In addition, in order to avoid from oscillating around a local optimum, the particle is shifted to a new location by a random mutation when it gets stagnant at local optima. With a sampling time of 100ms per duty cycle, the results observed for the PSO-DE in comparison against PSO and DE show substantial improvement over the other two algorithms. The author's proposed algorithm is shown to be the faster and more accurate algorithm under their waveforms by obtaining 97.5% to 98.2% average MPPT efficiency at around 3 s tracking speed.

3.3.4 Canonical Particle Swarm Optimization Algorithm

In literature for optimization and engineering problems, PSO has always revelled in the spotlight of review and usage due to the simplicity of the algorithm and the relatively good performance for dynamic problems. Even now, modifications and improvement to the canonical PSO framework can be seen in literature. However, review of canonical PSO in GMPPT for PSC is required in order to commence performance verification of the improvements made over them. The authors in [94] present the performance of PSO under cases of PSC. PSO bases itself on the natural phenomenon of bird flock, when applied and mapped to in movement, it is observable that particles move in the search space by following simple mathematical equations which can be called operators. The velocity operator utilized is unmodified from original version of PSO.

The author uses 12 NT R5E3E PV modules, each module rated at 175W. The author also uses MATLAB/Simulink simulation environment to verify the results of PSO under PSC. The results conducted by the author have presented the ability of PSO to track GMPP under PSC. Experimental results are not conducted with experimental setup nor any comparison against other GMPPT methods in literature are made.

Another implementation of PSO was conducted by [95], where the algorithm is implemented on FPGA circuit XC5VLX50-1FFG676 from the Vertex5 family. This circuit is built around an ML501 development board written in VHDL language and compiled through ISE 10.1 from Xilinx. 4 SM55 PV modules are utilized which is rated at 55W each. An experimental setup with current sensor, voltage sensor, isolation and driver for the PWM signal from the FPGA is implemented. The setup also implemented a buck-boost converter where voltage can be stepped up or down. Two shading patterns are tested on their system, one with P-V curve containing 3 peaks and another with 2 peaks. The results of the GMPPT tracking in PSC can be observed in the Fig. 3.3.

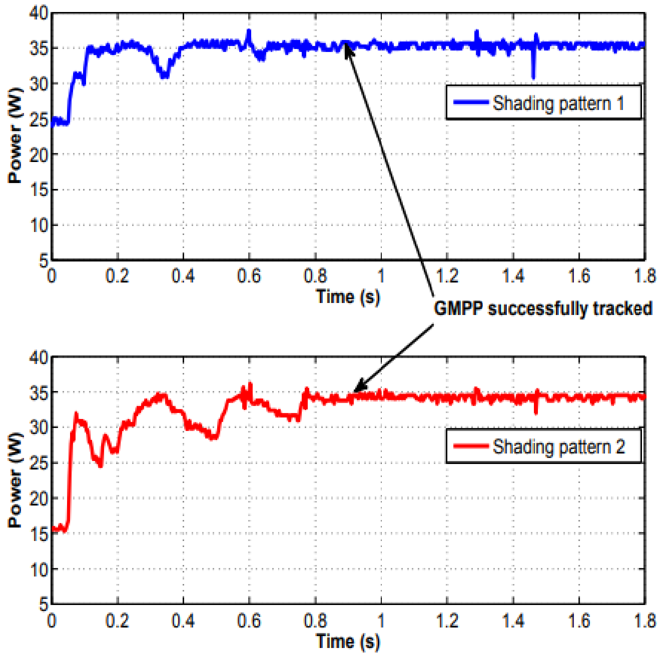


Figure 3.3: PSO Results with FPGA Implementation [95]

In the results observed, the author has concluded that the PSO implementation has successfully handled the GMPPT under PSC. The high accuracy of the proposed scheme to handle the partial shading is stated. The PSO algorithm obtains the GMPP at around 0.9 s and under 99% efficiency in the FPGA implementation across 2 shading patterns.

3.3.5 Leader PSO Algorithm

Leader PSO (L-PSO) is a modified version of PSO by [96] that enhances the global leader for every iteration in a procedure to locate GMPP. Considering the initial count of particles/swarm as five, corresponding five consecutive mutation procedure is applied to the swarm leader. If any of the mutated particle attains better fitness than the global best particle, it will change the solution of current G_{best}, effectively replacing weaker leaders.

The process begins with a random initialization of initial P_i for the duty cycle, D. The fitness evaluation of the population is done, and the velocity and particle update operators of PSO are applied to the population.

The conventional PSO process henceforth ends, mutations are applied to the swarm leader in turns. The implementation by the author has utilized four different mutations in the following procedure; which are, Gaussian normal distribution mutation, Cauchy distribution, elite mutation and scaling mutation. The P_G particle with the global best solution G_{best} generates a new P_{g1} using Gaussian mutation values of "O" mean and "h"-standard deviation. A fitness evaluation is conducted with P_{g1} and if the new fitness is better than P_g, P_{g1} will replace it. Even if the P_g is replaced, the mutation continues with generation of P_{g2} through Cauchy distribution of "s" scaling factor and mean-"O". If $f(P_{g2}) > f(P_g)$, then the P_g will be replaced by P_{g2}. These mutations continue through elite mutation where boundary maximum will sum with the boundary minimum, $X_{max} + X_{min}$ and the new P_{g3} will be generated through the equation, $P_{g3} = (X_{max} + X_{min}) - P_g$. The last mutation is scaling mutation where two random particles $(X_{r1} - X_{r2})$ are multiplied with the scaling factor, F and P_{g4} will sum with the resultant vector sum.

The next step after conducting mutation search, L-PSO algorithm locates the best leader and the possible solution space in which global solution can be found. Algorithm checks for global convergence, and determines that if the particles all converge to each other the criteria has been fulfilled and output the G_{best} solution. For re-initialization condition, the author employs a condition based on the measurement of either voltage in the current k iteration and an older $k-1$ iteration. Through comparison of the voltage V or I, if these values go over a certain threshold (0.2 for voltage and 0.1 for current) the algorithm will reinitialized to detect new MPP.

The proposed L-PSO is experimented in MATLAB environment and experimentally tested using an Intel i7 capable system carrying 4GB ram. As the algorithm is comparing itself against others, the author has denoted that same sampling period of 300ms is given for every duty cycle. Also, the algorithm shared the parameter setup against PSO, a conventional GMPPT against their own improved L-PSO. The experimental setup for the system to test the algorithm consists of PV emulator, a Chroma 62050H and a DC-DC boost converter connected to current and voltage sensors. The gate of their IGBT switch is controlled using the Arduino UNO development platform which also houses the three algorithms used for performance testing.

The author pits its designed and proposed algorithm against conventional P&O and PSO methods. Through the results seen, it is shown that P&O as expected performs slowly in normal shading conditions and gets trapped in local peak upon PSC condition occurrence at the PV panel. PSO is able to perform better than P&O; however, still loses out to their proposed L-PSO algorithm in convergence speed and tracking accuracy. L-PSO algorithm obtains a 99% MPPT efficiency under all shading patterns and is able to obtain the MPP at under 1.86 s.

3.3.6 FWA and P&O Algorithms

FWA is a global optimization method that draws its inspiration from the explosions of fireworks in the sky. The sparks that appear due to the explosion from a firework resemble or are tied to the generation of candidate solutions in a search space. A chosen number N of fireworks are initially chosen to be created. The fitness value of the N fireworks is evaluated, which will control the amount of sparks generated by each individual firework. A higher fitness value will generate more sparks with smaller changes in amplitude or velocity being generated off the individual firework. If the fitness value is lower, then spark generation of the individual firework is reduced and is lower than the higher fitness counterparts, and also reduces the wastage of search times.

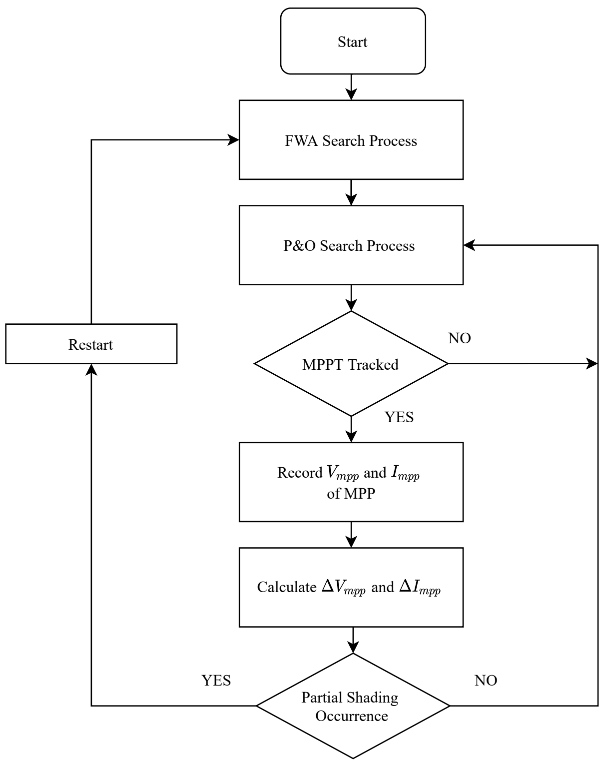


Figure 3.4: The FWA-P&O hybrid for GMPPT [90]

The authors in [97] has proposed the usage of FWA in the GMPPT problem. The framework of their algorithm in implementation is shown in Fig. 3.4. However, they have stated that when there is no partial shading occurrence then the usage of global search is not needed. As such, FWA algorithm is only utilized when the occurrence of partial shading is detected. However, when the controller first starts their proposed algorithm, the FWA must run first due to the lack of initial information about the GMPP location. In step 2 and 3, the P&O process continues after FWA determines a candidate GMPP. The details of determining a candidate GMPP are not given and the convergence criteria of the FWA are also not stated. When the P&O algorithm successfully tracks the MPP in step 3, PV power, P_{pv} has not changed for a certain iteration or time. In step 4, the MPP information of I_{mpp} and V_{mpp} are stored. In step 5, the change in each of these quantities is computed with respect to the most recently stored values (step 5). Upon occurrence of partial shading by the partial shading detection scheme of the authors, if no PSC occurs then the P&O algorithm will continue to perturb at the MPP. Otherwise, FWA algorithm is applied once more to the search range and obtain candidate GMPP, restarting the algorithm search process.

The paper by the authors in [97] also do not utilize MATLAB/Simulink software environment to simulate the code, but only uses experimental verification. The experimental setup employs a DC-DC boost converter to track the GMPP of a PV string containing four series-connected 80W PV modules. This PV string is emulated through an Agilent E4360A modular Solar Array Simulator. A MSP430G2553 micro-controller will control and implement their proposed algorithm. Several PSC cases are presented with unique MPP points on the P-V curve as visible in Fig. 3.5.

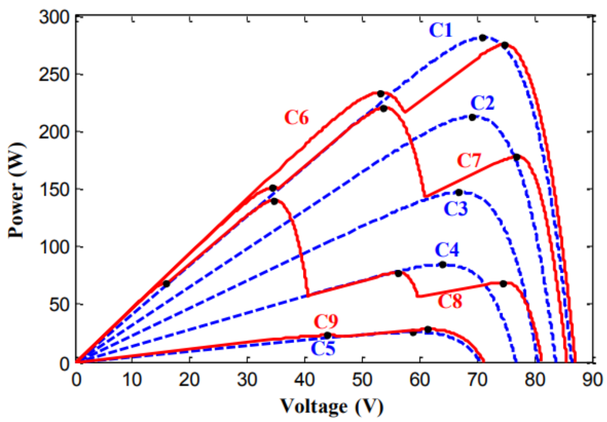
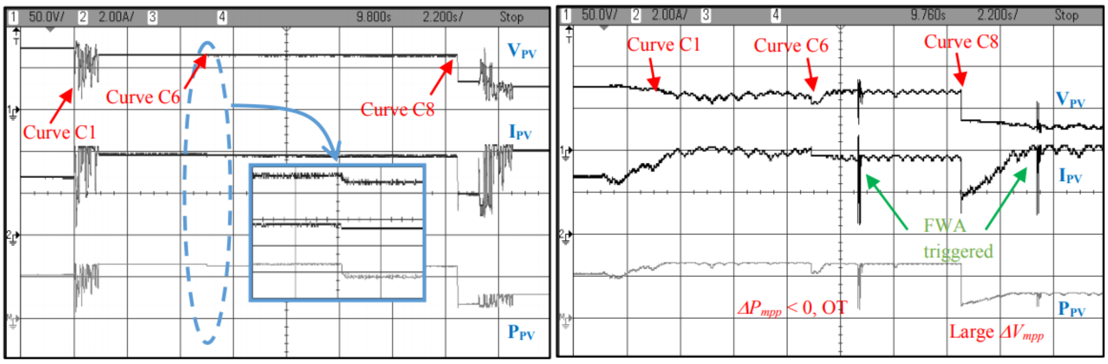


Figure 3.5: Presented cases and their P-V Curves [97]



(a) Simulation Results of PSO (b) Simulation Results of FWA-P&O

Figure 3.6: Dynamic tracking and Power Oscillation of Algorithms [97]

The performance validation of the FWA and P&O GMPPT method is tested in two factors: reduction of power oscillations and dynamic tracking capability. The results of the proposed method in comparison to PSO is described in the Fig. 3.6 where three particular shading patterns are applied to the algorithm of PSO and their proposed FWA and P&O method.

Rather than tracking accuracy and speed. The author presents the two factors as results to their proposed GMPPT algorithm. The results show that the PSO algorithm in Fig. 3.6a oscillate more from the dynamic change of irradiance which causes the change in P-V curve to what is specified in Fig. 3.5. The dynamic tracking capability of their proposed algorithm is also shown in Fig. 3.6b.

The authors in [97] henceforth state that the performance of the proposed GMPPT strategy is compared to that of a conventional PSO based GMPPT control, and has been demonstrated to be superior in terms of power oscillation during tracking, and dynamic tracking capability. To reduce power oscillation in the PV system, the algorithm chooses not to deploy FWA if the shading condition does not produce a high change of irradiation. The algorithm obtains the GMPP under 2.2 seconds after utilizing P&O for the initial search stage. The P&O algorithm is employed under uniform irradiation conditions due to better tracking capability if the GMPP is on a single slope on the P-V curve, and the MPP voltage and current are monitored continuously. FWA is used for its exploration and exploitation capabilities initially in the search of candidate GMPP.

3.3.7 Grey-Wolf Optimization Algorithm

Grey-Wolf Optimization (GWO) is a meta-heuristic algorithm inspired by grey wolves, which prefer to live in a pack and can be used to optimize a function that is difficult to express analytically [98]. In GWO, i represents the wolf number, $P_{best}i$ and G^t_{best} denote the personal and global best values which are to be updated at every iteration during the optimization process. Much like other population based evolutionary algorithms, the grey wolves have a coefficient vector that controls the movement of the population. The grey wolf optimization technique has three coefficient vectors, D, A and C that are all utilized to generate a position vector $(x_i)^t + 1$. D is generated based on the position of the current wolf's duty cycle and coefficient C. It is given with $D = |C \cdot ((x_i)^t) - (x_i)^t|$. Meanwhile, the generation of C is also dependent on coefficient A. They are both given by, $A = |2 \cdot a \cdot r_1 - a|$ and $C = |2 \cdot r_2|$. Where a is a linearly decreasing value from 2 to 0 as iterations progress and $r1$, $r2$ are both random numbers in the range of $[0, 1]$.

Initially, one grey wolf is set to test the fitness of its randomized location. The grey wolf updates itself and saves $P^t_{best} - 1$ of itself as its current P_{best} as it is the start of the algorithm, future iterations must compare to their older iterations of the P_{best}. Then, if any wolf has a duty cycle which global best power, G_{best} is greatest after comparison is recorded. Next, the $i = 1, 2, 3, 4, ...N$ amount of wolves are all evaluated. After evaluation is complete, the algorithm will update x_i, A, C, D and a for the next iteration. The algorithm iterates itself until convergence criteria are completed. The author does not state a detailed method of detecting convergence criteria; thus, it is assumed to be the maximum iterations if this is the case. The author also states a way of re-initialization; however, no further detail is given except it occurs upon change in shading on the PV modules.

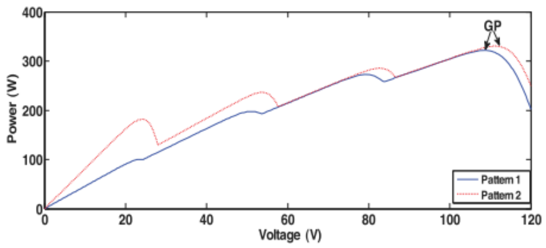


Figure 3.7: P-V Curve of PSC Case from GWO [98]

The results in Fig. 3.7 show the P-V curve of a shading pattern implemented by the author has the most local peaks and also the GMPP tracking results for GWO algorithm in Fig. 3.8. Based on the results shown, the authors present their meta-heuristic GMPPT technique with comparisons made towards P&O and an original Improved PSO. The implemented GMPPT scheme by the author proves itself with results and performance that exceeds the preceding methods introduced in terms of tracking speed and accuracy. GWO obtains the GMPP with an efficiency range of 99.81% to 99.92% at a speed of 3.18 s to the Improved PSO algorithm's speed of 7.9 s in the experimental setup.

For simulation verification, the author utilizes MATLAB/Simulink environment to implement their proposed GWO. To validate the simulation results, Sukam 50 W PV modules were connected in 4S, and 2S2P strings were established. To recreate partial shading effects, the author utilizes man-made efforts through transparent sheets of different shapes shadowing the PV modules. Implementation of the GMPPT is done through a dSPACE1104 controller and their ADC channels are used to measure voltage and current using Hall Effect sensor; hence, DAC channels were used to generate PWM signals and a slave DSP subsystem based on a TMS320F240 DSP. Multiple PSC cases were introduced to the GMPPT to test its performance, the cases can be seen to range from uniform condition to cases where 4 peaks on the P-V curve are caused.

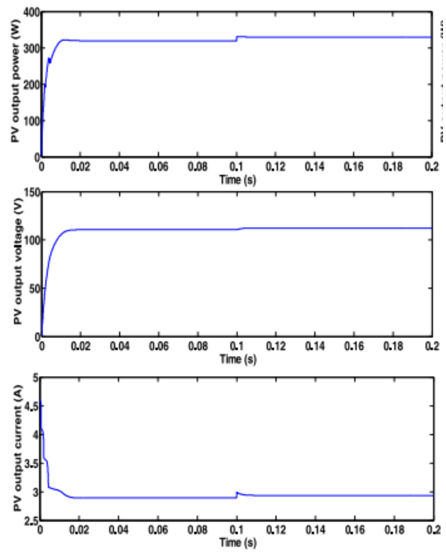


Figure 3.8: Tracking Performance of GWO Algorithm [98]

3.3.8 Earthquake Optimization Algorithm

Earthquake Optimization Algorithm (EA) is a geo-inspired metaheuristic algorithm first introduced in [99]. The application of the algorithm was extended, improved upon in [100]. The authors in [101] have then introduced and adapted the algorithm into an MPPT application. As an example, earthquakes carry two types of waves (P and S) which carry information about the magnitude of the seismic. This principle is used to make the velocity of P-wave and S-waves as an explorer agent providing information from search space to acquire the optimum solution. Two types of wave velocities, P, v_p and S, v_s, are generated through equations. A Lamé parameter is utilized in these equations as well and given to be 1.5. Within the algorithm, the density of the solids is dictated as a random value in a given range of values. A control of operation range for the algorithm to use either the v_p or v_s is dubbed as the S-range. The S-range can be characterized based on the orbiting of solutions around an epicenter (MPP) to ensure optimization behavior. Utilizing this information, their adaptation of this geo-inspired algorithm is presented in Fig. 3.9.

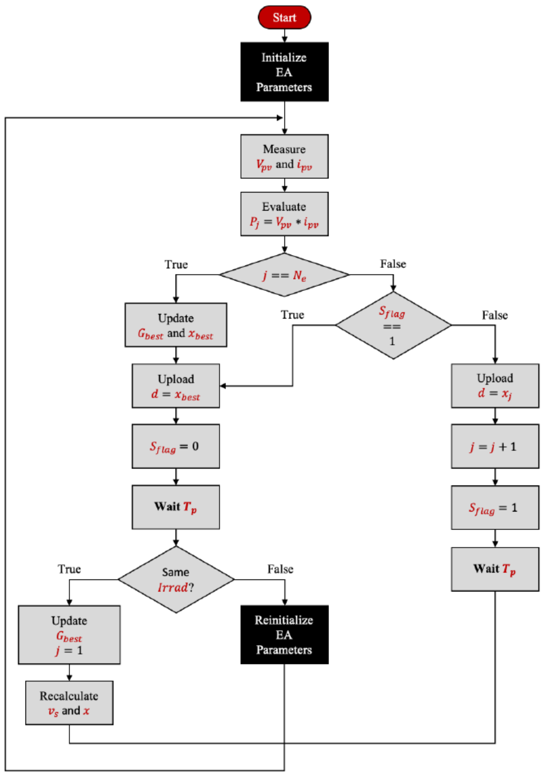
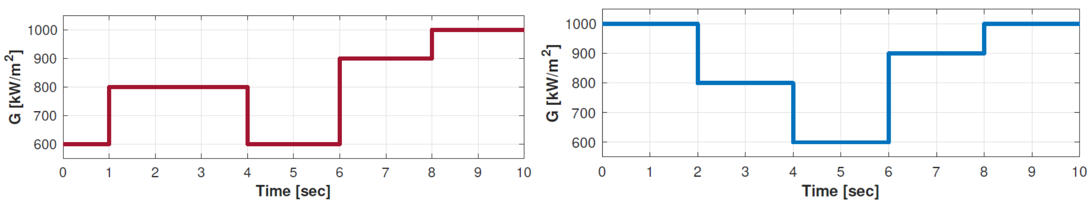


Figure 3.9: Flowchart of EA MPPT Algorithm [101]

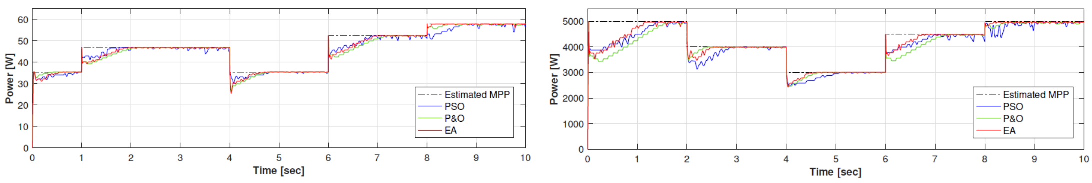
However, it is mention in the adaptation that only the v_s velocity equation is used for this version. The algorithm continuously updates and runs until a stopping criterion is reached. The algorithm demonstrates its search process and is adapted to use in the simulation setup through MATLAB Simulink. The simulation setup uses a conventional DC-DC boost converter with an input of two different PV arrays, a CRM60S125S module and a TP250MBZ module. The CRM60S125S module is arranged as a singular module of 57.96W, while the TP250MBZ module is arranged in a 2P10S string, providing 249W per module. Two test cases can be made with the different PV arrays, a low power case utilizing the singular module and a higher powered case utilizing the array string. The author implements the two cases as presented in Fig. 3.10.



(a) Low power **(b)** Higher power

Figure 3.10: Irradiance profiles of low and high power simulations [101]

Testing in the simulation setup provided the results of power obtained based on the irradiance profiles that change periodically within 10s of testing time are presented in Fig. 3.11. Various algorithm were compared in the test, including PSO, P&O and EA.



(a) Low power **(b)** Higher power

Figure 3.11: Simulation results of low and high power tests [101]

The implemented MPPT scheme by the author proves itself with results and performance that exceeds the preceding methods introduced in terms of energy harvested, MPPT efficiency and total wasted power. In the low power simulation, EA harvests the most energy at 455.6432 W, tracks the MPP with an efficiency of 97.2558% and has the lowest total wasted power at 12.8568 W compared to the PSO and P&O. In the high power simulation, the EA harvests the most energy at 41.388 kW, obtains the highest MPPT efficiency at 96.2512% and has the least amount of total wasted power at 1.6120 kW. However, the proposed algorithm was not tested under shading patterns of more than 1 peak on the P-V curve, further conviction would be required to verify the effectiveness of the algorithm under GMPPT.

3.3.9 Salp Swarm Optimization Algorithm

A new meta-heuristic algorithm, Salp Swarm Optimization Algorithm (SSO) first introduced in [102], has been adapted into MPPT by the authors in [103]. Salps are marine organisms. Their movement is carried out in water through jet action propulsion. In the deep sea, salps are linked into a swarm called a salp chain. The objective of these chains aim for food exploration and better sustainability. A salp chains is made up of a leader and a number of followers. The leader leads the movement, while followers update their positions accordingly. The movement of the salp swarm is attributed towards exploration and exploitation. For MPPT, the position of the salp leader is associated with the output duty cycle. The population is initiated randomly in the search space. Utilizing this information, the flowchart of the proposed implementation for MPPT can be observed in Fig. 3.12.

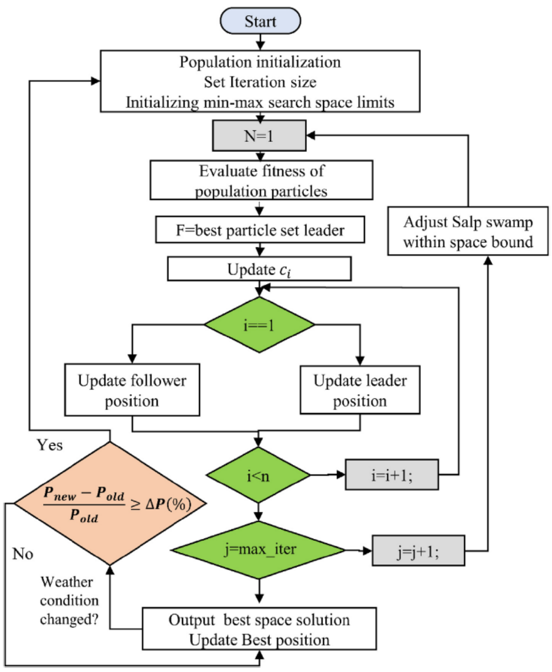


Figure 3.12: Flowchart of SSO [103]

The particles in this adaptation are treated as salps. Similar to PSO, the positions of leader and follower particles are updated using an equation. The equation utilizes information from the swarm leader and food positions to calculate the next iteration position values. These updates to the position values follow Newtonian motion which are given by equations. The equation can be simplified as $(x_j)^i = \frac{1}{2}((x_j)^i) + (x_j)^(i-1)$. A weight c_1 is crucial to balance the exploitation and exploration of the swarm. It is dictated by a calculation of the current iteration and set maximum iterations parameters within the algorithm. Using the equations, when a leading swarm moves towards an optimum solution so does the entire chain of particles. The fittest particle becomes the leader. In each iteration, the distance between the food source and particles is calculated to update position. The closest distance is considered the fittest in this study, and followers' positions are updated accordingly. Particles that exceed a boundary of position update are treated as scouts and randomly initialized to avoid local maxima traps.

The authors also introduced more complex shading patterns to test the SSO. In the author's proposed SSO, a mechanism has been incorporated to make sure the global maxima is guaranteed to be tracked based on a closely relative calibrated technique [104]. The search space is explored through using the search skip jump mechanism and section division point in [105]. In their proposed work, the SSO algorithm was verified in both simulation and experimental setup. Six test cases were applied to the PV systems against all algorithms, including Dragonfly Optimization, P&O, ABC, PSO-gravitational search, PSO, CS and the proposed SSO algorithm. The cases have different shading patterns for the algorithms to solve, which range from a fast varying irradiance, two cases of partial shading, two cases of complex partial shading and one test case imitating real Hong-Kong climate conditions. The irradiance profile and simulation results of case 5, with complex partial shading is presented in Fig. 3.13 and Fig. 3.14.

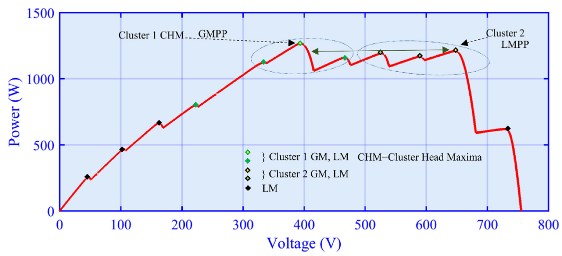


Figure 3.13: Complex Partial Shading condition (2) and cluster formation [103]

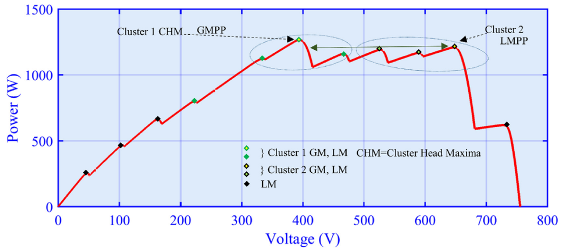


Figure 3.14: Case 5 CPS power zoomed-in comparison [103]

In comparison to the other algorithms, their proposed SSO obtains the highest efficiency and fastest tracking speed at 97.3% and 0.22 s respectively. Overall, the simulation results proved SSO performance exceeded that of all other algorithms tested in comparison. An experimental setup, composed of PV system, boost converter hardware including a designed emulator was utilized for validation. The algorithms are implemented on an Atmel ATMEGA-2560, while the data acquisition is done by an Atmel ATMEGA-328P and MATLAB interfacing. All the tests cases have been replicated and emulated onto the experimental setup, all algorithms were compared under all test cases and the results are provided in 3.15.

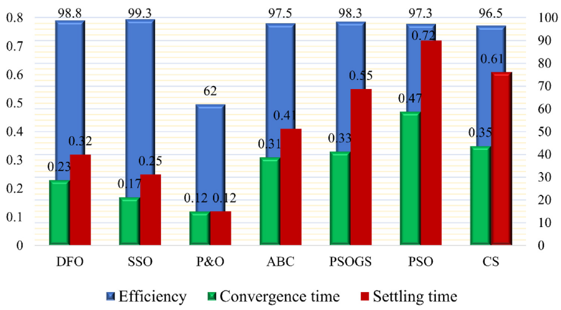


Figure 3.15: Average efficiency, convergence time and settling time of MPPT techniques. [103]

Overall, the experimental results demonstrated that all inferred performance from the SSO in simulation setup was verified. The SSO algorithm, in the experimental setup obtains an average of 99.3% efficiency with a tracking time of 0.25 s. The algorithm, outweighs all other algorithms in the tests in factor of performance in efficiency and in speed except against P&O which is trapped in local minima.

3.3.10 Literature Review Summary

As can be inferred from the review, the methods and techniques in one form or another follow the framework as shown in Chapter 2 of how an algorithm should perform to solve the optimization problem. As shown, GMPPT methods implement themselves in a particular framework where an individual or population of candidate solutions sized N proceed in a step-by-step fashion of searching for GMPP. Mathematical operations that represent the operators in evolutionary algorithm are utilized to modify duty cycle, D. Moreover, the operators assume for the balance of exploration and exploitation of the entire population. Ultimately, there must be a convergence criterion which allows termination of the algorithm search process upon the convergence of the population or, in some cases a maximum iteration has been reached. Dynamic environment of the surrounding may incur a change of PV panel power, P_{pv} through rapidly adjusting irradiance and temperature levels.

The impedance of the circuit must be changed to comply with the change of P_{pv}, thus the algorithm must restart to calculate a new D. Re-initialization is a shared process that the reviewed GMPPT methods typically employ in order to restart the algorithm from a point in the algorithm framework, commonly it is restarted at the beginning. Through re-initialization, algorithms can restart the search for GMPP and obtain new duty cycle that befits the current P-V curve. Moreover, the simulation software utilized for simulation verification is all but guaranteed to be done using MATLAB/Simulink environment as it is the most commonly used simulation tool. Experimental setup of the reviewed GMPPT methods can be divided into real PV panel, emulation through PV emulator or none at all. However, real PSC cases cannot be obtained or simulated accurately in real life without the usage of electronically designation from a PV emulator. Thus, the proposed research believes that the usage of PV emulator is the more accurate tool in simulation of PSC cases where the control of when and what type of P-V curve can be easily controlled.

Table 3.1: General Performance Results of Reviewed GMPPT Techniques

GMPPT	Complexity	Parameters	Peaks	Tracking Speed (s)	Sample Time (s)	Efficiency (%)	Converter Type
Bat Algorithm [88]	Low	5	4	1.3	0.05	98.8	Buck-Boost
Hybrid PSO and P&O [90]	High	11	2	1.3	0.06	99.98	Boost
PSO-VD [93]	High	5	2	~3	0.1	-	Buck-Boost
PSO [94]	Low	5	3	0.9	0.05	99.66	Boost
L-PSO [96]	Medium	5	6	1.86	0.5	99.69	Boost
FWA-P&O [97]	High	8	4	-	-	-	Boost
GWO [98]	High	1	4	-	-	99.92	Boost
EOA [101]	Low	3	1	-	0.1	96.25	Boost
SSO [103]	Low	1	11	0.22	-	97.3	Boost

The Table 3.1 compiled with reference to [5] expresses the performance all the GMPPT techniques reviewed so far. A list of the reviewed algorithms in terms of complexity, general tuning parameter amount usage, highest peak count tested in their PSC, the tracking speed for the respective highest peaks, change in duty cycle per sample time and the overall converter efficiency is demonstrated as results.

The complexity of an optimization algorithm is hard to describe in quantifiable matter for the GMPPT problem as the algorithm faces dynamic environments. Moreover, stochastic optimization methods themselves risk solving the problems by chance and have to rely on convergence time to have a resemblance of finding the time complexity. Based on GMPPT method implementation papers, the term complexity can be split to implementation complexity and mathematical complexity [106]. The time complexity can be resolved to be given from the final tracking speed instead, forgoing mathematical notation as a way to measure it. Implementation complexity is affected by the utilization of complex MPPT algorithms such as PSO, ANN, FLC techniques due to the utilization of micro-controllers, DSP and FPGA to implement them. The mathematical complexity is given by the amount of parameters utilized and the amount of mathematical expressions used [107]. In optimization computation theory, the dimensionality of a problem is given by the amount of variables required to solve the optimization problem which in turn increases the complexity of the problem. But the GMPPT problem only uses P as the input variable, thus the complexity is highly and commonly referred to other aspects. The higher the amount of tunable parameters, the harder it is to balance the algorithm performance for tracking speed and convergence speed due to reasons laid out in Chapter 2. As such, lower parameters are be able to reduce the amount of mathematical computation in an algorithm and in turn reduce the need of high implementation cost as well.

Shading peaks in the results refer to the amount of local peaks and the one GMPP combined. The degree of robustness and accuracy of an algorithm can be given from the tracking speed and efficiency of power conversion obtained. In an increase of peaks, the GMPP becomes harder to find due to the increase of peaks, thus it is possible to evaluate algorithm robustness and search performances based on this amount. The harder the P-V curve is because of the existence of many more peaks, then the longer time it takes to track the GMPP and tracking speed is prolonged. The sampling time in papers refer to, the time taken for the measurement of any V_{pv}, I_{pv}, V_{load} and I_{load}. The measurement of the values after a sampling time has passed is important to the controller unit due to the fact that duty cycles are only modified per sampling period. The system must settle after a duty cycle has been set to allow accurate measurement from either the voltage sensor, current sensor or both. Ample time must be given to avoid inaccuracies in measurement and avoid the mismatch of recording the duty cycle/individual to its measured P_{pv}. The efficiency of power conversion, μ is always given by the percentage of remaining power from the P_{pv} at the P_{load}. Equation (3.1) easily shows the formula of calculating DC-DC conversion efficiency. External factors affect this value easily and the design of the DC-DC converter is typically efficient in simulation however the real-world experimental setup is subject to many uncertainties. The efficiency of a uniform PV array can drop to 5% if the ripple in RMS MPP voltage is approximately 8% [108].

$$\frac{P_{load}}{P_{pv}} \cdot 100\% = \mu(\%). \tag{3.1}$$

In the proposed algorithm, there is a need to balance the complexity of the algorithm, the mathematical operators that improve an individual duty cycle D_i which also implemented an amount of tunable parameters. It is observed in the various improvements made on PSO algorithm that, the algorithms that are modified substantially perform better. For the generation of individual solutions through either combination of new methods or addition of new behavior, the tracking speed substantially changes itself over their non modified versions. The performance of the algorithm's accuracy is also tied to the tracking speed of the algorithm. Moreover, more shading peaks will disrupt GMPP tracking times and in turn reduce tracking speed. We can observe a pattern here where every form of result and expected behavior has to balance itself from the reliance of every other factor. Expected performance comes with expected tradeoff; this ties in to the known fact that one of the major points of tracking speed is reliance on the basis of balancing both exploitation and exploration in the search space evenly.

In conclusion, the ideal form of a GMPPT algorithm can be derived. GMPPT algorithms must be low in implementation complexity, computational complexity with less parameters, able to perform heavily peaked of P-V curves, be as fast as possible with the tracking speed and convergence time, also contain sufficient sampling time to record the P_{pv} while speeding the algorithm and also be as efficient as possible. This is of course an ideal whereas explained before, balance is important and perfection is hard to achieve. However, there is an objective to obtain advantages where ever possible. The proposed research takes a look into the improvement of the GMPPT computational aspects through the modification of solutions in the next section. The modifications to the algorithm can improve its performance without sacrificing too much implementation complexity and are able to make the individual solutions perform as best as possible in high number of peaks P-V curves.

3.4 Performance Enchantment of the GMPPT Algorithms

The chapter aimed to lay out a general framework/structure of normal GMPPT computation behavior that can be mutually exclusive to most evolutionary algorithms, while still showing the example of how programmers design an algorithm under the rules described above. Modern implementations or designs of GMPPT algorithms commonly show improvements over older versions or older ideas through different new or improved methods constantly as evidenced by the development of modified algorithms and hybrid algorithms [5][106][107].

It would be observed from the literature that different operators suit different evolutionary algorithms and their strategies also depend on the application at hand. It is necessary to develop a review of the formerly mentioned operators in MPPT or GMPPT algorithm to aid the design of a GMPPT algorithm in the system through the demonstration of their feasibility in the reviewed papers. The algorithms when containing a same method of PSO for example can be reviewed with the improvements made on it.

The improvements can be classified as adjustment of parameters in the chosen GMPPT technique (e.g population size, coefficient), operators (e.g utilization of coefficient and individual information) and hybridization (e.g addition of other technique methods). The design of the proposed GMPPT technique is improved in understanding these aspects and applying them towards better GMPP search performance under PSC.

3.4.1 Parameter Adjustment or Tuning

As observable from the Table 3.1, the parameters would be dependent on the implementation conducted by the author. The behavior can be seen from the PSO results in Subsection 3.3 where the two different implementations of the same algorithm can have different results due to the parameter usage. Moreover, many improvements were made with PSO as the base and improvements were made to them by applying new methods in PSO-VD, hybrid PSO-P&O. Inside of these reviewed algorithms, comparisons conducted involved the parameter values were shared between canonical and modified forms in order to give contrast to the improvement made from their modification. Thus, not conducting parameter adjustment and tuning is detrimental to the performance of GMPPT.

Moreover, if an implementation of GMPPT were to be made from an optimization technique. What must be considered is the parameter change due to the optimization problem at hand. Obviously, some algorithms in their original versions of testing were tested with benchmarks and multiple different parameters. These different parameters can include N size population, T_{max}, coefficients and weight factor for individuals. The benchmarks provided validation of results to the authors. However, the optimization problem of GMPPT cannot apply the same parameters, as shareable parameters are unfeasible in the time constrained requirement of GMPPT tracking.

An example is derived from PSO as it is reviewed already in this Chapter. Given the PSO algorithm, population size N, inertia weight Ω are the key tunable parameters to decide the overall performance of the algorithm. Maximum iteration limit, T_{max} also decides the time where an algorithm must end. Noticeably, higher iteration limits allow for more search to try and search for better MPP, but stagnancy will be risked to appear. The risk can be seen where a reviewed algorithm implemented an individual solution to shift duty cycles when stagnancy is calculated. However, these risks from T_{max} is circumvented as long as the implementation of good convergence criteria are used where convergence must be detected. After all, stagnancy of population results can basically mean that the algorithm has converged, thus ending the algorithm search process earlier. Thus, in the papers for GMPPT reviewed, the maximum iteration is usually less than 10 and there are also convergence criteria applied. The main reasoning for this is that algorithm that have converged already should achieve the GMPP and thus iteration limit is utilized as fail-safe condition to stop the algorithm. This maximum iteration value is not inherently high for the GMPPT problem, as adaptive mathematical expressions derive their offset of the population's duty cycle off the t_{max}.

Larger N sized swarm would give initial fitness evaluation a good list of candidates for the operators to start their search from. There will be more chances that one individual with good duty cycle, D has found the point on the P-V curve that is closest to a GMPP. The downside of this is of course, each iteration is multiplied with the amount of population. Given high population count and high iteration count, there can be many wasted searches and at the same time prolonged search process due to the need to run through entire N population at fitness evaluation. If a choice is made to select good candidates only, then this wasted time can be instead used for more meaningful searches with a leading individual. In the reviewed GMPPT algorithms, a population size is given dependent on the operators utilized, a method like FWA where more individual candidate solutions are generated off the original population size does not implement as much as 10 or more population size. The sparks from FWA would generate as much as 10 times the amount of minimum spark size allowable per individual, greatly prolonging search times. In L-PSO, mutation of the G_{best} particle is done at a onetime fitness evaluation per mutation hence population size does not affect the performance as much as FWA. However, methods like I&C, P&O, SA and voltage curve tracking utilize only single N sized population, just as conducting individual search. Thus, the population size is determined based on method used.

The previous two parameters were in fact general for most evolutionary algorithms. These parameter values, of course, depend on the type of algorithm framework utilized, but coefficients are unique to the type of algorithm framework instead and are unique to the algorithm chosen. In GWO, the utilization of D,A and C coefficient vectors that contain the numerical values needed to affect the next duty cycle of an individual is observed. In Bat algorithm, the generation of new solutions has the coefficient Ω is a weight factor that limits the speed of their microbats. In terms of GMPPT this means the amount of value change of duty cycle is affected by the Ω. As observable from these coefficients, they are related to the generation of new solutions and hence are the niche of each algorithm framework that must be balanced for GMPPT problem.

As such, parameter tuning is important factor to obtain better GMPPT performances. While parameter tuning itself depends on what parameters are available, the expected behavior in a sense can be changed from changing the parameters such as coefficients to the desire of the designer for the purpose of GMPPT.

3.4.2 Modifications to Generation of the Solutions

Given a general population of N size, the generation of $x_i = 1, 2, 3, 4, ...N$ is determinant on the operators which use tunable parameters,random numbers and coefficients. The three aspects can be seen from the review of implemented GMPPT above, where the parameter tuning adjustment is able to affect the performance of GMPP search greatly in speed and accuracy [5]. Moreover, the usage of the parameters are designed for expected or needed behavior during certain parts of the algorithm framework, e.g slower movement of individuals can be set during higher iterations to maximize local fitness. The following subsections will detail the mathematical expressions and what adjustments are implemented that spawn individual position speed,direction and position.

1. **Variation Operators**

   As explained during Chapter 2, variation operators are different than mutation or selection operators in methodology. The variation operators can be generalized to modify next iteration individual positions, ${x_i}^t$ in local search prioritization in contrast to the mutation operators which generate an offshoot candidate solution from information in the population and are not in the vicinity of G_{best} individual solutions.

   An expected usage of stochastic behavior in implementations of GMPPT algorithms can be seen is large use of random generated numbers. These numbers may be generated in a normal distribution or any other form of probability density of distribution where values are weighed towards the mean, μ. The utilization of distributed number generated to fill the initial population position is more commonplace though. Random number generation is used in many operators including the currently discussed variation operators. For example, random numbers are used in PSO as $r1$ and $r2$ in velocity equation. By using these variables, the mathematical expression becomes stochastic in nature and is able to generate minimal offset if multiplied against, larger offsets can be made from summing original position with randomly generated numbers.

   $$v_i^{t+1} = w_t \cdot v_i^{(t)} + c_1 \cdot r_1[P_{best} - x_i^t] + c_2 \cdot r_2[G_{best} - x_i^t] \tag{3.2}$$

   The influence of coefficients can be seen from acceleration coefficient C_1, it is tied to the cognitive component of the operator expression where it is multiplied with the particle memory, its personal best fitness value P_{best}. The influence of the coefficient can also be observed from acceleration coefficient C_2, it is tied to the social component of the operator expression where it is multiplied with the influence of the G_{best}.

   An observable modification to the canonical PSO velocity operator from (4.15) is seen in PSO-VD implementation for GMPPT in (3.3). The author has removed the influence from P_{best} in the calculation of the velocity. Instead, an influence from the swarm is calculated using information obtained randomly from two random individuals , y.

$$v_i^{t+1} = w_t \cdot v_i^{(t)} + y + c_2 \cdot r_2[G_{best} - x_i^t], \tag{3.3}$$

where y is given from two random chosen particles, x_j and y_k an observable in (3.4).

$$y = x_j - x_k. \tag{3.4}$$

Moreover, in the Bat algorithm GMPPT implementation, modifications are made on the equation of velocity v_i. The parameter ω called "inertia weight factor" is introduced in [109]. This weight factor parameter limits the speeds of their population of microbats. The author presents that weight factor can improve the solution generation from the referenced paper. The calculation of the original velocity generation for a microbat's solution is given in (3.5). In the expression, the social component of the entire swarm is known through information of the current global best solution, G_{best} which will be multiplied with the frequency of each microbat f_i which is a stochastic coefficient.

$$v_i^{t+1} = v_i^{(t)} + (x_i^t - x_{Gbest}) \cdot f_i. \tag{3.5}$$

In the modified expression, an inertia weight factor, Ω is added to the expression as observable in (3.6):

$$v_i^{t+1} = \Omega \cdot v_i^{(t)} + (x_i^t - x_{Gbest}) \cdot f_i. \tag{3.6}$$

As reviewed from implemented versions of their optimization algorithm in GMPPT problem, the modification to operators to fit GMPPT problem is commonplace in order to optimize the search process for PSC. The results from these reviewed GMPPT also present their modifications to be substantial to the problem as they have succeeded other GMPPT in literature with regards to search speed and accuracy.

2. **Mutation Operators**

   Given that there are operators that assist in the generation of better results in term of local search explained in the earlier subsection and in Chapter 2. Operators that are able to look beyond the current solution's search area are needed to escape local trap situations. The mutation operators are equations that generate individual solutions outside the current G_{best} area, thus are able to or should be able to escape local traps and generate global search for the algorithm framework. The behavior of mutation individuals follows one rule in the fitness evaluation of their duty cycles, when the duty cycle of a mutated value does not outperform its original position then it will not replace its original. As such, the weaker individuals do not join the original population to be considered for more searches and wasted searches are prevented or lessened.

An implementation of this is shown in L-PSO as reviewed in the Chapter. L-PSO used multiple mutations on the current G_{best} individual's position. Thus, the best duty cycle of the entire search area is mutated. Various forms of mutation are used, Gaussian normal distribution is utilized and multiplied against as shown in (3.7). In the algorithm, P_g is denoted as the current solution of the G_{best} and it has the same position.

$$P_{g1} = P_g + (X_{max} - Xmin) \cdot Gaussian(o, h) \tag{3.7}$$

where $Gaussian(o, h)$, the Gaussian function which is the normally distributed range of values of the total fitness values of every duty cycle in the population. By modifying mean o and standard deviation h, the degree of generated mutation values can be altered to the user's desire. This allows even some exploitation to occur if parameter values are adjusted properly. The Cauchy distribution of generated mutated value P_{g2} follows the same behavior as the generation of P_{g1}.

Another form of mutation implemented can be observed in elite mutation which is P_{g3} in (3.8)

$$P_{g3} = (x_{max} + xmin) - P_g. \tag{3.8}$$

where x_{max} and x_{min} are respectively the maximum and minimum limit of the generation of duty cycle, which is [1,0]. Observably, the mutation operator here does not utilize any cognitive or social information of the swarm's personal best, P_{best} or global best, G_{best}. The operator is simplest to implement and can guarantee that the mutated position is the opposite of P_g global best solution. There is guaranteed return of a global exploration from this operator.

Scaling mutation is also another mutation that can be observed for implementation. As the name implies, it is able to scale the degree of mutation to a set parameter. The coefficient F controls the multiplication of the sum of position between two randomly chosen individuals, x_j and x_k in the population. The mutation operator in question is shown in (3.9):

$$P_{g4} = P_g + F(x_j - x_k). \tag{3.9}$$

The author states that this mutation is more utilizable for exploitation instead. However, an observation can be made that the value of this mutation can be exploration based from the earlier stages of search process and at early iterations. At the early stage of search process, iteration count can be low and thus the population of duty cycles remains out of convergence. Thus, two randomly chosen individuals from this population at this iteration time could offer more to exploration instead in comparison to late stage randomly chosen individuals which are local based in the area as the population is closer to each other.

As shown, multiple mutation operators have been reviewed and their use can greatly assist in global search or exploration capabilities of the population in the search area. It can be seen that mutation operators can be managed to a certain degree also to control the degree of mutation. The reviewed algorithm that implemented these operators has shown that their algorithm surpasses others in literature in terms of tracking speed and accuracy.

3. **Selection Operators**

From the reviewed GMPPT algorithms, selection operators were not implemented upon an entire population. Selection operators focus on calculating i individuals to bring over into the next iteration for further search. In the reviewed GMPPT techniques; however, entire populations were brought over to the next iteration. While the reviewed techniques did indeed perform adequately for GMPPT and were suitable for GMPP search, a selection operator which can include tournament, elite or random selection of individuals were not implemented. With the basis that weak duty cycles should be pruned from the population, new individuals can rejoin the population swarm after generation from mutation or variation operators. Thus, selection operators can be considered for the design of an algorithm's framework and be tested in comparison to other algorithms that did not implement selection operators.

3.4.3 Hybrid Methods

The main disadvantages of optimization algorithms in PV system applications are their accuracy and speed having low convergence rate when in iterative processes while balancing the exploration and exploitation of the population [110]. The balance of these two factors must be made in order to prove the performance of a GMPPT algorithm. According to an analysis of various GMPPT techniques in [5] and [23], it is concluded that hybrid algorithms are the most interest point in further research for the development of methods in GMPPT. Hybrid GMPPT algorithms have already shown their performance in the reviewed GMPPT algorithm, in the hybrid PSO-VD and FWA-P&O. Other implementations within literature such as hybrid Gaussian process regression-Jaya (GPR-Jaya) algorithm by [111], hybrid whale optimization and pattern search (HWO-PS) algorithm by [112] and hybrid GWO-Fuzzly Logic Controller (GWO-FLC) by [113] have shown the capabilities of hybrid implementations. The hybrid algorithms showcased their combination of two methods to form a new method to search for GMPPT under PSC. The hybrid algorithms are able to follow up or continue the search process after a completion of one counterpart algorithm, delegating certain points of the search process to its other half of the algorithm. The design of their hybrid algorithm were designed with the need of overcoming weaknesses in one method or further improve the performance of the individuals in the population for GMPPT search. Thus, the use of the proposed hybrid algorithms with equations, operators and strategies must be derived from a standpoint that befits the PV system need of GMPPT under dynamic shading conditions through searching for GMPP with fast and accurate speeds while also having good exploitation and exploration of solution search space.

3.5 Research Gap Analysis

Utilizing the information obtained in Subsection 3.3 and 3.4. The research gap analysis of PV systems employing GMPPT algorithms determine the proposed DC-DC converter type and the proposed GMPPT algorithm in this research project.

3.5.1 Proposed DC-DC Converter Type

From the literature review, the PV panels, DC-DC converter and algorithm implemented function as a whole PV system. Validation of the GMPPT algorithms thus require the use and description of a chosen DC-DC converter type. A statement can be made regarding the use of the defined converter types in Chapter 2.2, the literature review has shown that a majority of implementations for GMPPT algorithms under PSC employ the use of boost converters followed by buck-boost converters. To supplement this fact, reviews of GMPPT algorithms also show that the boost converter is a majority in most implementations [5], [23].

The benefit of boost converters in stepping up the output voltage due to lower or unstable voltage levels in the PV system due to PSC can attribute to the decision of most literature is utilizing the design. A buck-boost converter can step down or step up output voltage levels, which give a layer of complexity to the implementation of the algorithm instead. Topology wise, the boost converter is simpler to implement and utilize for the problem of occuring PSC in PV systems. Moreover, improved or modified boost converter design are not utilized in the literature review, the conventional design and its topology would serve to accommodate the algorithm performance only.

In the proposed research, the conventional boost converter design will be adopted in use of simulation and experimental setup to validate the proposed GMPPT algorithm. The design must calculate the component values of the inductor, switch, capacitance and load resistance utilizing formulae in respect of the PV system input and output ranges for voltage and current.

3.5.2 Proposed GMPPT Algorithm

From the literature review, the algorithms have demonstrated their search process and capabilities in seeking GMPP. The GMPPT methods can be categorized into optimization-based algorithms, hybrid approaches combining multiple optimization algorithms. The optimization-based algorithms include swarm intelligence and evolutionary-based algorithms which reiterate upon a set of solutions to find the global best solution. The improvement of algorithm performance and design is also built upon the aforementioned balance of exploration and exploitation in Chapter 2.5. While obtaining the fastest tracking speed and accuracy or efficiency of the GMPPT, the algorithm design considers these two aspects as explained beforehand. Keeping in mind various techniques discussed in Subsection 3.4 based on the reviewed literature, the proposed research aims to resolve the weakness in the algorithms which stem from lack of either exploration or exploitation, while obtaining highest efficiency, most accurate and faster GMPPT results.

Hybrid methods, which consist of combination of two optimization algorithms or optimization method and conventional method have been proposed in the literature. It has been shown that the hybrid methods are able to improve the system performance [23]. However, choosing the right algorithms to be combined is not straightforward. We need to consider several aspects, such as the advantages and disadvantages of each algorithm and the system characteristics, if we want to implement it [26]. Even so, slow convergence rates that could result from improper parameter adjustment and risk of falling into local maxima may still occur when using the enhanced or hybrid algorithms [27]. As a result, the design of GMPPT implementations must aim towards obtaining better GMPPT performance through balance of exploration and exploitation capabilities [114].

Within the literature review, PSO is a well-known evolutionary algorithm which is simple and effective in most general optimization problems. When tracking the GMPP, PSO algorithm outperforms the conventional MPPT algorithms in terms of speed and accuracy [5]. However, the algorithm is hampered by initialization problems where an improper velocity update can severely slow down the convergence rate to the GMPP [29]. Moreover, PSO has a tendency to fall into premature convergence at a local maxima [30]. PSO must consider the resolution of its slow convergence and chance of local trap; thus, the two weaknesses are the main motif of its selection for further research in GMPPT.

Meanwhile, FWA is also a popular optimization algorithm which exploits the local search area for getting high tracking accuracy of the global solution [115]. Two research works have been found for FWA in the literature which are [97] and [28]. The performance results of conventional FWA proved the lack of review of itself as an algorithm in GMPPT due to the performance as a hybrid algorithm. A canonical version of the FWA as a GMPPT and verified against other GMPPT algorithms, is also not implemented or known in current modern literature. Nevertheless, FWA has several issues related to convergence speed [116]. Moreover, FWA has a larger parameter count rendering the parameter adjustment to be difficult for MPPT application in its searching process [117]. Therefore, the weaknesses demonstrated by FWA makes it a solid choice in further research to improve its capabilities for GMPPT and conviction regarding its performance.

To overcome the PSO and FWA weaknesses in solving the GMPPT problems under PSC environment, the research project proposes to use the PS-FW algorithm. The PS-FW algorithm has been introduced in [31] by Chen et. al in order to solve optimization problems. It has been seen in [31] that PS-FW has been bench marked and able to converge rapidly and accurately in 22 global optimization problems. Furthermore, the strong exploitation capabilities of FWA [115] and exploration of the PSO in searching for a potential global solution [118] influences the expected performance in GMPPT under PSC. Thus, a balance of global search and local search can be achieved with the described implementation of PS-FW algorithm, strategies and adaptive spark control. However, the use of PS-FW for solving GMPPT problems in PSC environment is not straightforward due to difference in implementation, thereby more analyses are required. In addition, the use of PS-FW implements the abandonment and supplement strategies, in which, to the best of the conducted review, has not been discussed in the literature for GMPPT problems. The research work also proposes an adaptive control of the PS-FW parameters within spark number generation.

3.6 Chapter Summary

The reviewed GMPPT techniques beforehand described their complexity, parameter usage, tracking speed under PSC and efficiency of power conversion. The review also proves that each GMPPT implementation serves to prove their application scope, meaning performance depends on how the PV system and technique is implemented. As said before, each algorithm has unique methods of approaching the optimization problem, that causes the difference in performance, application, framework design and how the search process determines the GMPP. The parameter adjustment from their implementation into GMPPT, algorithm operators and the concept of hybridization are solutions to enforce GMPPT performance, and both exploration and exploitation in the search area for a GMPPT.

With the reviewed literature, the conventional boost converter topology as explained in Chapter 2 is proven to be a safe choice among other boost converter topology as the implementation is seen commonly in all the reviewed papers. The topology itself is implemented into the PV system in both simulation and experimental setups. MATLAB/Simulink simulation software environment is implemented in the simulation setups of most reviewed GMPPT algorithm implementations. This software will be adopted for use in the research and the methodology is to understood to test the proposed hybrid PS-FW GMPPT algorithm. There are GMPPT implementations that adopt the use of PV emulator and dSPACE RTI unit to create an experimental setup of the PV system by functioning as PV panel and GMPPT controller unit. Thus, the proposed research also adopts the use of these two resources and the methodology is understood. The accessibility of these tools assist in the testing and experimentation of PSC which will be implemented with the proposed GMPPT algorithm.

The proposed GMPPT algorithm in this research is the PS-FW hybrid algorithm. As explained beforehand, the PS-FW algorithm will be implemented for GMPPT application to overcome weaknesses in both PSO and FWA. Thus, the PS-FW algorithm with its abandonment and supplement strategies are implemented for GMPPT application. Alongside the strategy is the proposed adaptive spark control for PS-FW in GMPPT. PSO and FWA are also implemented as GMPPT algorithms to validate obtained performance of the PS-FW hybrid algorithm. The algorithm will be verified under various criteria within the PV system under both simulation and experimental setup.

Out of the criteria laid out in this literature review, emphasis is given to the convergence speed and accuracy in order to prove the hybridization capabilities as a concept to improve future GMPPT algorithms. Parameter count, complexity, hardware costs and the sensor requirement are factors that are to be taken into account with explanation inside the methodology. However, they are not be applied into the results and discussion as a method of comparison as the application of PV system in the proposed implementation focus on the GMPPT algorithms while functioning in fair condition.

Chapter 4

Proposed PV System with Hybrid Algorithm

The completion of the research project objectives requires the validation of the proposed GMPPT algorithm. However, validation to determine the overall performance of the algorithm needs to be done through application into a PV system and tested. To this end, the papers involved in literature review from Chapter 3.3 have implemented simulation and experimental setups to test their algorithm. The reviewed papers have described the setups using the modelling of the PV panel and the DC-DC converter which are connected to any form of device that houses the algorithm. Moreover, the papers describe their proposed GMPPT algorithms in detail of the operators and strategies to be implemented into the PV system. Thus, the PV panel model, boost converter parameters and all involved GMPPT algorithms are explained in this Chapter.

To determine the GMPPT algorithm performance through the PV system, a PV model must be first devised, as the model determines the output current and voltage, based on the irradiance and temperature which allows us to dynamically allocate problems to the PV panel with the partial shading patterns. The PV panel model is only be utilized in simulation setup of the research as resources regarding the PV panel are represented in the experimental setup.

It is important to choose the correct components and values for the design of the boost converter as according to the selection of the boost converter design chosen in Chapter 2.2. The ability of the boost converter to handle the PV system is determined through the calculation of the parameter values. The conventional boost converter design is then implemented into the PV system to be controlled by the GMPPT algorithms that are designed in the research project. The simulation and experimental setups both adopt the calculation of parameter values conducted for the components in the boost converter.

A detailed explanation is given regarding the design of the proposed hybrid PS-FW GMPPT algorithm. First, the introduction of the singular counterparts which are also GMPPT algorithms in literature must be given in the form of PSO algorithm and FWA. Initially, the framework of PSO and FWA was explained briefly in the literature review. However, the implementation must be understood and the design is be properly reflected by elaborating the operators into a flow of processes and equations that can be represented onto mathematical expressions calculated and generated by the GMPPT controller unit. Next, the proposed PS-FW algorithm is described with correlation to both the PSO algorithm and FWA in the aspect that the PS-FW algorithm utilizes strategies and operators in the new search process. The designed GMPPT algorithms of PSO algorithm, FWA and PS-FW algorithm are then applied into the entire PV system that controls the boost converter through the GMPPT controller unit.

In Section 4.1, the PV panel is modelled where it is used in simulation setup with regards to the input of solar irradiance and temperature values. The P-V or I-V curve of the proposed PV model is calculated using the equations given.

In Section 4.2, the conventional DC-DC boost converter specifications are calculated to denote the minimum and maximum values of input power and output power based on the switching frequency specified. The values calculated determine the values used in both simulation and experimental setup.

The singular PSO algorithm is presented in Section 4.3, the modern and canonical form which is used in common GMPPT implementations currently in literature. The operators are denoted and the search process is given.

In Section 4.4, the singular FWA algorithm is presented in the modern and canonical form of which is used in common GMPPT implementations currently in literature. The operators of the FWA are denoted and the search process is presented.

A proposed hybrid algorithm that reintroduces the usage of the operators in both PSO algorithm and FWA is presented in Section 4.5. The proposed PS-FW hybrid algorithm is an algorithm that utilizes these operators and strategies that best fit the GMPPT usage of fast convergence speed and best tracking accuracy.

4.1 PV Panel Modelling

Mathematical-based model of solar cell/module is programmed to obtain desired output data usually, by taking into account of ambient temperature, and solar irradiance level. A mathematical-based model can describe PV cell/module accurately using complicated mathematical algorithm. For the PV system, the equivalent circuit of a solar cell can consist of either single-diode or two-diode models which are the most widely used. The single-diode model has already been proven to be simple as it utilizes less parameters and accurate enough in many cases as applied in [119]. In this section, the implementation for this model of single-diode model of the PV cell is conducted through calculation of the equations and trace of a P-V/I-V curve. The equivalent circuit for a single-diode model PV cell is shown in Fig. 4.1:

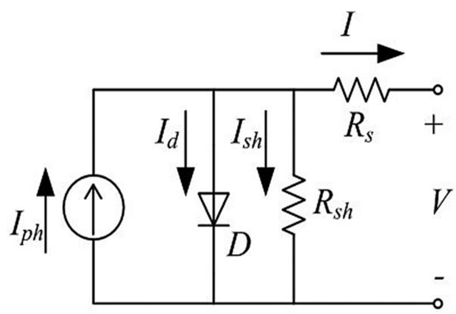


Figure 4.1: The equivalent PV cell with one diode

The I-V curve characteristic of the model is described using (4.1):

$$I = I_{ph} - I_o\{exp^{\frac{q(V+R_sI)}{AKT}} - 1\} - \frac{V + R_sI}{R_{sh}}, \tag{4.1}$$

where V is the panel voltage, I_{pv} is the panel current, I is the output current, I_d is the current of parallel diode, I_{sh} is the shunt current, R_s is the equivalent series resistance, R_{sh} is the equivalent shunt resistance, A is the ideality factor, K is the Boltzmann Constant which is 1.380649×10^{-23}, q is the electron charge (1.602 x $10^{-19}C$) and T is the PV module temperature in °C.

The current I_{ph} at a given temperature is found by the (4.2) which relates it to the irradiation, temperature and those two conditions compared to a reference condition (notably at STC):

$$I_{ph} = I_{scn}(1 + a(T_a - T_n))\frac{G}{G^*}, \tag{4.2}$$

where coefficient I_{scn} is the short-circuit current I_{sc} of the cell at given STC which is usually $(25°C, 1000W/m^2)$, T_a represents a given temperature (°C), a is the temperature coefficient of I_{sc}, G is the irradiance value and G^* is the nominal irradiance at the reference condition (W/m^2).

The reverse saturation current of diode (I_o) at reference temperature of T_n can be given by the (4.3):

$$I_{on} = \frac{I_{scn}}{e^{(qV_{ocn}/(nKT_n))} - 1}. \tag{4.3}$$

The reverse saturation current of the cell at a given temperature (T_a) can be given by the (4.4):

$$I_o = I_{on}(T_a/T_n)^{(3/n)}\ e^{((-qE_g/nK)(1/T_a - 1/T_n))}. \tag{4.4}$$

Using the equations, an I-V or P-V curve characteristic of the determinant PV cell can be traced with different given temperatures and solar irradiance with utilization of manufacturer data regarding the PV cell voltage and current values.

Given this established model of a PV solar cell, the equivalent PV model is able to be simulated into whole PV array or PV strings through theoretical calculations and thus determining the performance of the PV system.

4.2 Conventional DC-DC Boost Converter

A switching mode power supply (SMPS) configuration labelled and configured as a boost converter is used to step down and step up the DC voltage by controlling the duty ratio of the MOSFET and frequency of its switching. If the duty ratio is less than 0.5, the output voltage will be less than the input voltage; while if the duty ratio is greater than 0.5, the output voltage will be greater than the input voltage. Duty ratio is the time at which the MOSFET is on to the total switching time. The conventional boost converter in this research project is implemented into the PV system setup as shown in Fig. 4.2.

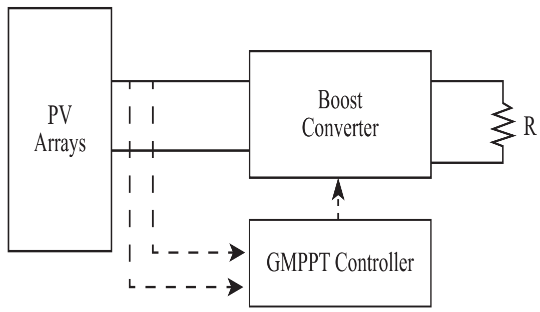


Figure 4.2: A DC-DC Converter with PWM Control from Controller

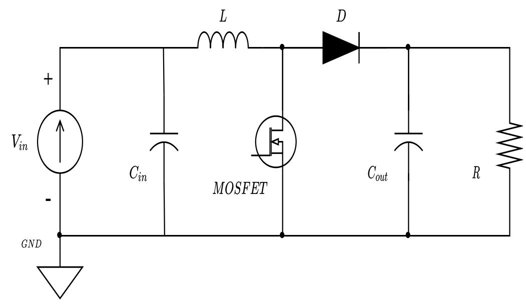


Figure 4.3: Boost Converter Design

Based on Fig. 4.3, the calculation of the boost converter output is to be found, initially a load resistor value is determined from $V_{out} = I_{out} \cdot R$. V_{out} and I_{out} are user defined and desired values of the expected output power from the boost converter and PV system. The PV panels are the V_{in} and I_{in} of the system. The V_{out} is easily pronounced in (4.5).

$$V_{out} = \frac{-D}{1-D} V_{in}, \tag{4.5}$$

where D is the duty cycle of the converter which is given as follows in (4.6):

$$D = 1 - \frac{V_{in}(min) \times \eta}{V_{out}}, \tag{4.6}$$

where η is the efficiency of the converter. Power dissipation is known in the conversion to stem from the temperature and switching loss, an estimated around 90% of efficiency is used in most calculations [120] in a worst case scenario. The efficiency has given it its worst case scenario to facilitate and accommodate the resultant calculations for boost converter component values. V_{in} can be given as the minimum value of the V_{pv}. This value can also be assumed as the V_{mpp} and treated as the V_{in}, due to the fact the boost converter parameter values are calculated to function properly even at the voltage and current given at MPP. Thus, any given calculation of component values for the converter are able to handle the power conversion below rated P_{MPP}. The expected and desired V_{out} must be chosen for the converter and application requirements.

The maximum switch current is calculated, to do this the inductor ripple current, δI_L must be known beforehand in (4.7),

$$\delta I_L = \frac{V_{in}(min) \times D}{f_s \times L}. \tag{4.7}$$

The ripple current present in the boost converter can be given from δI_L. f_s is the desired switching frequency at the switching device. L is given as the inductance value, which if not available, can be calculated at a minimum recommended value from (4.8):

$$L = \frac{V_{in} \times (V_{out} - V_{in})}{\delta I_L \times f_s \times V_{out}}. \tag{4.8}$$

However, the δI_L is typically assumed to be given as 20 to 40% of the output current initially, then the calculation of L can be made. Afterwards, the L can be used in (4.7) to calculate the δI_L to a more accurate degree. The initial assumption of δI_L can be made with the (4.9):

$$\delta I_L = (0.2 \sim 0.4) \times I_{out}. \tag{4.9}$$

A value of 0.3 was assumed for the calculation of δI_L. The $I_{maximum}$ is calculated to find out if the system is able to produce the output current needed. The value of the calculated $I_{maximum}$ must be larger than what is desired from the $I_{out_{max}}$ at the load. If the $I_{maximum}$ is lower than what is needed, a larger inductor inductance is required and calculated using (4.10).

$$I_{maximum} = (I_{lim_{min}} - \frac{\delta I_L}{2}) \times (1 - D), \tag{4.10}$$

where $I_{lim_{min}}$ is the minimum limit of current for the MOSFET or IGBT switch.

Typically, by using a higher inductance, the maximum output current is increased due to reduced ripple current. Lower inductance inductors have the disadvantage of higher ripple current. Regardless, inductors are accompanied with a current rating that must satisfy the maximum output current, $I_{out_{max}}$ in order to avoid high temperatures damaging the inductor. The output current that the switch is able to output, $I_{sw_{max}}$

must be able to be higher than given output current at the $I_{out_{max}}$, this switching current output is provided in (4.11):

$$I_{sw_{max}} = \frac{\delta I_L}{2} + \frac{I_{out}}{1-D}. \tag{4.11}$$

The diode used in the boost converter must be able to handle the rated switching current, and is also required to be higher or equal to the $I_{out_{max}}$, which can be found using (4.12):

$$I_F = I_{out_{max}}, \tag{4.12}$$

where I_F is the average rectifier current limit that is typically available in the data sheet of a given diode. Capacitor specifications are required to determine the selection of input and output capacitor.

In the proposed design of the conventional boost converter, a capacitor at the input side of the boost converter is installed to reduce ripple voltage and stabilize the input side of voltage. The value of the capacitance, C_{min} can be given in (4.13):

$$\delta V = \frac{I_{sw_{max}}}{f_s \times C_{in}}, \tag{4.13}$$

where δV is the desired voltage ripple of the converter. f_s is the switching frequency desired for the system. Typically, δV is also estimated to be around 10-20% of the output voltage, V_{out}.

With the ripple voltage known, it is possible to fulfill the calculation of the C_{in} at (4.13). And the C_{out} minimum required capacitance at the output side can also be calculated in (4.14). Otherwise, the δV can be assumed to be around 10-20%. The lower the voltage ripple, the higher the value of the rated capacitance and the current. Higher value capacitors and inductors combined with the large V_{out} and I_{out} demand a larger physical volume of space to accommodate the size needed to fulfill their power ratings.

$$C_{out} = \frac{I_{out_{max}} \times D}{f_s \times \delta V}. \tag{4.14}$$

Thus, by calculating the component values of inductor, diode, switch and capacitor the desired boost converter is derived. The equations utilized serve to calculate the

Table 4.1: Calculation of Boost Converter Parameters

Parameter	Value	Parameter	Value
$V_{in_{(min)}}$	54.00 V	$I_{maximum}$	40 A
V_{in}	54.00 V	$I_{sw_{max}}$	3.608 A
V_{out}	76.00 V	$I_{lim_{min}}$	22.57 A
I_{out}	1.89 A	I_F	1.89 A
D	0.4315	δV	7.6 V
η	80%	C_{min}	11.868 µF
δI_L	0.567 A	C_{max}	2.682 µF
f_s	40KHz	R_{load}	40 Ω
L	687 µH		

minimum inductance values, minimum capacitance values, maximum possible switching current at the switch and the desired output voltage.

A table that specifies the parameter values for all components has been detailed in a list as shown in Table 4.1. As explained earlier, the converter specifications are calculated at the maximum possible power available, P from the power source. In the following table, the inductor inductance, L and the capacitors capacitance, C_{in},C_{max} are chosen with minimum requirements. Thus, any selection of these two values must be larger than values specified in the table, while also fulfilling I_{out} rating for the inductor and V_{out} rating for the capacitors. The efficiency of the entire system is assumed to be low at 80%; however, the true efficiency of the system can actually be found after experimental validation when the GMPPT algorithm successfully tracks the GMPP where power conversion efficiency is at the highest.

4.3 Particle Swarm Optimization Algorithm

The PSO algorithm is an evolutionary computation technique first proposed by Kennedy and Eberhart in [91]. It assumes a group of birds are looking for food; however, there is only one food in the area. All birds know their own distance to the food, but not the specific location of the food. Thus, the birds move towards flocking around the bird that is closest to the food location, converging towards the best possible location of the food. The algorithm uses particles that each represent a potential individual solution in the function or problem search space, each individual results in an objective fitness value pertaining to the fitness function. The population consists of ith particles that have a velocity and position. The position denotes its objective variable while the velocity of a particle determines its change of position, direction of position at each iteration. Through each iteration, the particle's position and velocity converge to the globally most optimal solution found. Equation (4.15) and (4.16) both determine the new velocity,v_i^{t+1} and position change,$x_i^{(t+1)}$ of the particles respectively:

$$v_i^{t+1} = w_t \cdot v_i^{(t)} + c_1 \cdot r_1[P_{best} - x_i^t] + c_2 \cdot r_2[G_{best} - x_i^t], \tag{4.15}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}, \tag{4.16}$$

where v_i^{t+1} is the velocity for the next iteration, $(t+1)$ of the ith particle, w_t is the inertia weight of the convergence speed for the particles in current iteration, $c_1 c_2$ are cognitive coefficient factors, r_1, r_2 are random real numbers from (0 to 1), $Pbest_i$ is the personal best position of the ith particle, $x_i^{(t+1)}$ is the position of the ith particle at current iteration t, G_{best} is the global best position of the algorithm.

This velocity V_i and coefficients c_1, c_2 are the parameters that affect the speed and searching prowess of PSO. The two coefficients are a factor when multiplied by the r_1, r_2 random numbers, a larger coefficient factor sets the velocity calculations to be higher while the smaller factors offer smaller velocity calculations.

After each iteration, the inertia factor w_t which influences the velocity of the particle reduces linearly. A high inertia factor generates a larger velocity which allows the particle to move in longer steps and search further in exploration, while the smaller inertia factor causes the particle velocity to be smaller and results in shorter steps and enforce a local search exploitation around the current optimal best solution [121]. The inertia weight factor can be calculated per iteration as in (4.17):

$$w_t = w_{max} - \frac{t \cdot (w_{max} - wmin)}{t_{max}}, \tag{4.17}$$

where w_t is the current iteration's inertia, w_{max} is the maximum inertia coefficient, w_{min} is a coefficient that controls the minimum inertia, t_{max} is the maximum iterations that the algorithm can run. Upon reaching the end of one search process, the iteration count is incremented until the maximum iteration limit is reached, enabling the convergence criteria and output the best duty cycle, D.

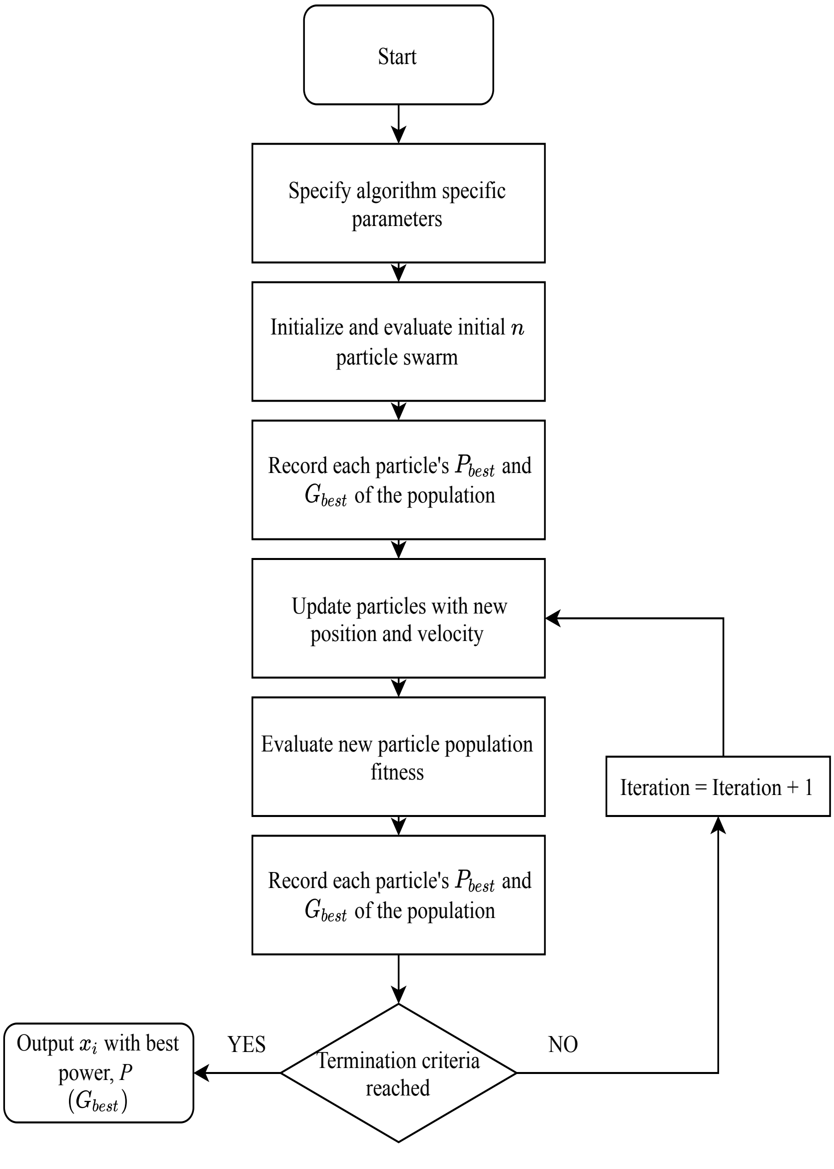


Figure 4.4: PSO Framework

The following Fig. 4.4 describes the flow of process in the PSO algorithm search behavior.

To elaborate on the drawbacks of the canonical singular PSO algorithm that remain in GMPPT implementations currently, a main weakness of the PSO algorithm is that they suffer from from premature converges and slow convergence rate. Following the equation calculation for velocity, a set factor that is innately high causes the velocity to be high even in the beginning of the algorithm's run. The opposite case happens when the factors are set too low, slowing down the change in position or even minimizing it to the point of being redundant in the search. This behavior causes the parameter settings to be difficult to determine correctly as high factors cause premature convergence, low factors cause slow convergence rate. The premature convergence and convergence rate are also affected by the inability of the algorithm to escape local traps. The PSO algorithm lacks a way to explode out their solutions during the algorithm run, if the candidate solution was inadequate then the premature convergence may occur due to lack of the exploration in the algorithm. The third weakness, the lack of good exploration in the algorithm leads to useless searches as an iteration does not improve upon itself with relative change.

4.4 Fireworks Algorithm

The Fireworks Algorithm (FWA) was first proposed by Tan and Zhu in [122]. It sets off a number of n fireworks in a location, which then explode in a number of random locations. The explosions from these fireworks are able to generate sparks which replicate a real firework explosion. Good fireworks produce a higher amount of sparks within a close distance from each other, while the bad fireworks generate only little sparks and further away from each other. In FWA, the individuals are the fireworks and sparks that represent a solution in the search space for the current optimization problem. Much like PSO and other optimization algorithms, fireworks and sparks have their own position and solutions are searched and obtained through successive iterations. Much like PSO which is shown as a population-based kind of evolutionary algorithm, the FWA has already been implemented in problems such as [123] and [124]. Given the age of FWA, it is a relatively new algorithm, improvements and analysis of the algorithm have been conducted in [125] and [126] where the operators are modified or new strategies are introduced. Within this research project, the operators have been derived to best fit the GMPPT problem and are also based on GMPPT implementations of FWA in literature as observable in the Chapter 3.3.

The following Fig. 4.5 describes the flow of process in the FWA search behavior.

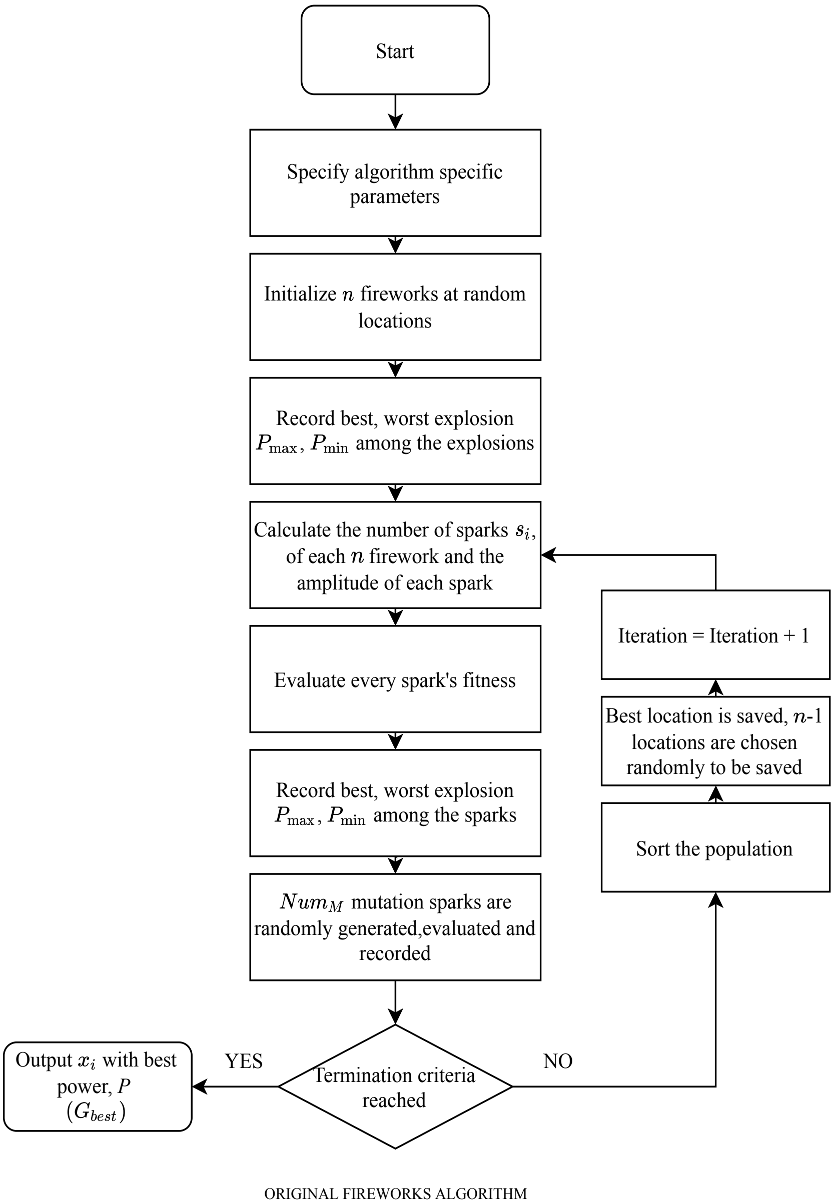


Figure 4.5: FWA Framework

The idea is that a firework represents an individual solution on the search space and each firework may explode into s_i amounts of sparks depending on how well the firework did. The fireworks produce sparks through explosion operator and Gaussian mutation. Sparks position for a firework is determined by explosion amplitude and its amount by the number of explosion sparks. Fireworks with lower fitness values generate lower number of explosion sparks, larger explosion amplitude while better fitness value fireworks generate more sparks and smaller explosion amplitudes. The sparks number can be obtained using (4.18) and the explosion amplitude of generated sparks using (4.19):

$$s_i = m \cdot \frac{f_{max} - f(\dot{x_i}) + \varepsilon}{\sum_{j=1}^{p}(f_{max} - f(\dot{x_i})) + \varepsilon}, \tag{4.18}$$

$$A_i = A \cdot \frac{f(\dot{x_i}) - f_{min} + \varepsilon}{\sum_{j=1}^{p}(f(\dot{x_i}) - f_{min}) + \varepsilon}, \tag{4.19}$$

where s_i is the amount of sparks generated by the ith firework, x_i denotes the current individual firework, m is a variable that controls the amount of sparks generated by a firework, p is the swarm size, f_{max} and f_{min} represent the maximum and minimum objective values among all of the p sized swarm, $f(\dot{x_i}$ is the objective value of the current ith firework in the current iteration, ε is a real number used to avoid zero-division errors, A_i is the amplitude for the generated sparks of the current firework.

A way to control the generated sparks number for a firework can be done through (4.20):

$$S_i = \begin{cases} round(a \cdot m), & S_i < a \cdot m, \\ round(b \cdot m), & S_i > b \cdot m, \\ round(S_i), & \text{otherwise.} \end{cases} \tag{4.20}$$

Parameters a and b represent the bound limits for determining the sparks number. Equation 4.20 is a case determination that controls the s_i number of sparks per explosion generation, the first case would control the minimum value of the sparks, second case would control the maximum value of the sparks and the last case generates the original value otherwise. The generated sparks are evaluated based on their fitness, then a selection process where the fireworks are randomly brought over to the next generation is implemented. This marks the end of one iteration in the search process. Upon reaching the end of one search process, the iteration count is incremented and the algorithm is repeated until the maximum iteration limit is reached, enabling the convergence criteria and output the best duty cycle, D.

The main unbecoming of the conventional FWA would stem from the lack of proof of convergence in its problem solving. The existing literature have proven that the FWA implementations in GMPPT from Chapter 3.6 are also lacking in terms of research and elaboration. Moreover, issues that are commonly shared with the conventional evolutionary algorithms such as convergence speed and slow convergence are also prevalent in the FWA [116]. The algorithm itself also has a problem with a high number of parameters needed to be saved in memory or used as the determinant in the equations during the algorithm process. Thirdly, the behavior of fireworks explosions in the FWA does not share information with each other in the effort of seeking optimal solutions. For example, fireworks explode and the sparks are generated, the generated sparks between each firework do not know the position and fitness value of a group of sparks outside of themselves. So in the case a greater fitness value was found in another firework explosion elsewhere, the sparks generated cannot be altered due to the preexisting generated amplitude and this could lead to useless searches.

4.5 Proposed PS-FW Algorithm

Through the weaknesses mentioned in the previous two subsections, the approach towards GMPPT application can be made. The hybrid PS-FW algorithm for GMPPT is applied to the PV system while under PSC. In the proposed algorithm, the duty cycle, D is represented as position of both particle and explosion spark. While the voltage, V and the current, I are taken as inputs to the algorithm, the duty cycle is an output. In this hybrid method, the FWA fireworks are now represented by the particles from the PSO. The Fig. 4.6 briefly describes the combination of PSO algorithm and FWA, initially in a form of position change due to the explosion and velocity operators.

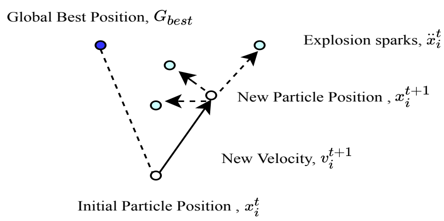


Figure 4.6: The behavior of PS-FW search process

The Fig. 4.7 also describes the step by step process of the proposed hybrid algorithm framework.

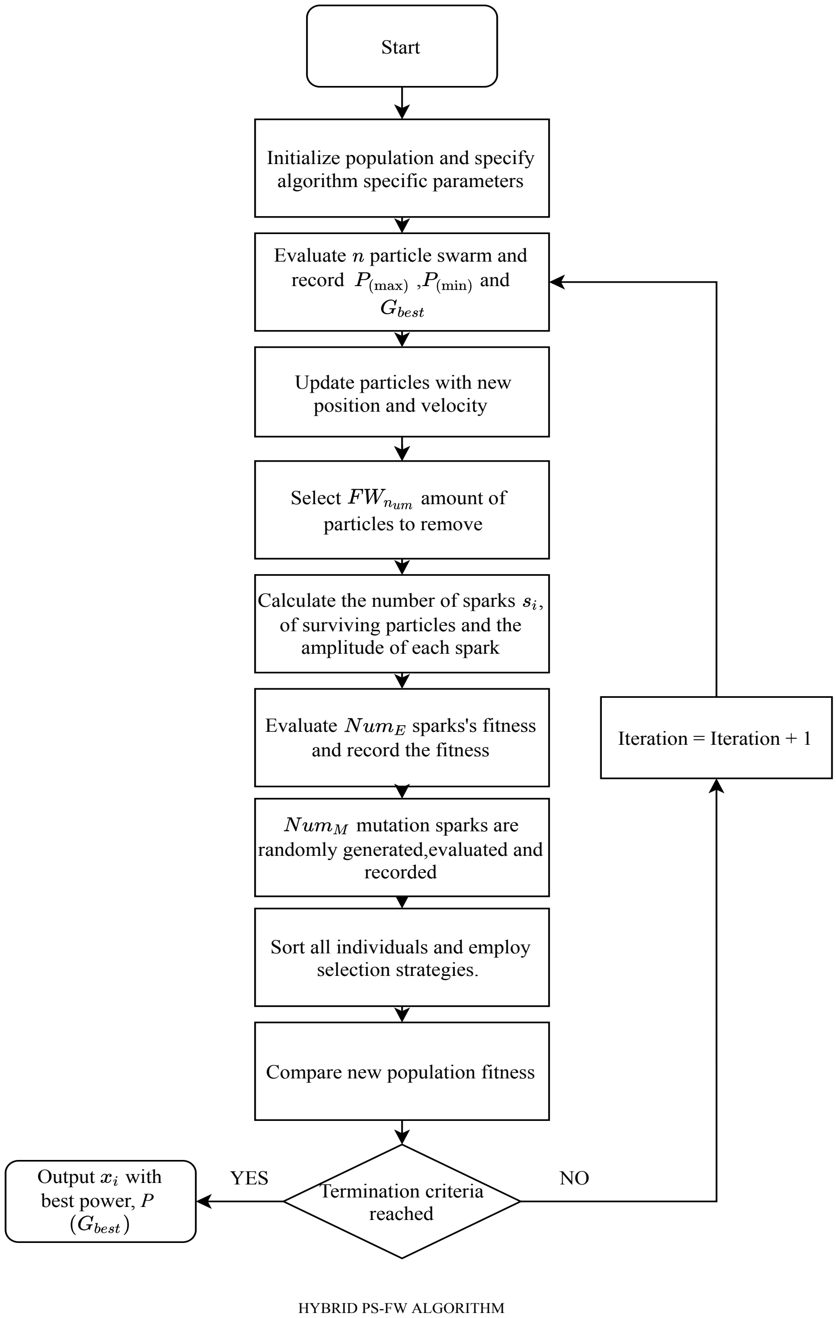


Figure 4.7: PS-FW Algorithm Framework

The PSO algorithm is first applied to obtain the fitness value Power, P of the initial n swarm population size. Initial duty cycle of the n swarm is randomized from a number range from (0,1). After initial fitness evaluation, particles are compared, the global best G_{best} and individual particle personal best P_{best} among the population is updated.

The velocity and position are updated using (4.15) and (4.16). After the update, the inertia factor w is decreased for the next iteration's update, (4.21) shows the equation to decrease the inertia:

$$w_{(t)} = w_{max} - (t \cdot \frac{w_{max} - w_{min}}{t_{max}}). \tag{4.21}$$

The conventional PSO algorithm ends and all particles are sorted in ascending order to their P obtained. P_{num} number of particles are then chosen to have spark explosions, while the FW_{num} number of particles are removed from the original swarm. The equation to determine the FW_{num} is calculated using (4.22):

$$FW_{num} = round[(FW_{max} - FW_{min}) \cdot (\frac{t_{max} - t}{t_{max}})^r + FW_{min}], \tag{4.22}$$

where FW_{max} and FW_{min} are maximum and minimum limits of allowable particles to be abandoned, t_{max} is the maximum iteration count for the algorithm, t is the current iteration count, r represents a real positive integer, the resultant equation is rounded to ensure an integer. From the hybrid PS-FW algorithm, abandonment and supplement strategies are employed to improve search performances. Abandonment strategy refers to the employed behavior of the framework after the initial fitness evaluation to remove individuals from the population, the process aims to cull the weaker individuals from being considered for further search and search time. Supplement strategy refers to a selection scheme conducted after the final evaluation of current iteration individuals, which are the mutation sparks. The importance of the supplement strategy is in repopulating after the abandonment strategy was employed, strong individuals rejoin the population and weaker individuals are removed per iteration. The loop of removal and addition to the population enforces the convergence time while providing local search at candidate solutions.

The remaining P_{num} number of particles are selected to create explosion sparks, $\ddot{x}_i$ where each ith particle has $\ddot{x}_i$ amounts of sparks which are determined by the respective s_i. Each spark has the explosion operators applied to their D. Using (4.18), the number of sparks for each individual P_{num} particle are calculated, their amplitude is calculated using (4.19). Moreover, an adaptive control of the number of sparks that the weaker particles produce is implemented to facilitate the exploration of the method in early runs and providing equal opportunity initially to all particles before converging towards the best solution, while the strong particles remain unchanged and explode with maximum sparks allowed. The adaptive spark number equation is calculated using equation (4.23):

$$S_i = \begin{cases} round(a \cdot m), & S_i < a \cdot m, \\ round(b \cdot m + \frac{t_{max} - m}{t+2}), & S_i > b \cdot m, \\ round(S_i), & \text{otherwise.} \end{cases} \tag{4.23}$$

The duty cycle is finally modified by (4.24):

$$\ddot{x_i}^{t+1} = \dot{x_i} + \Delta x, \tag{4.24}$$

where $\Delta x = A_i \cdot rand(-1, 1)$. After fitness evaluation of the explosion sparks, mutation sparks are used to explore outside the current optima region to avoid trapping inside a local area. The referred mutation operator is defined by the (4.25):

$$\dddot{x}_m = G_{best} + (\beta_1 \cdot \ddot{x}_{rand} - \beta_2 \cdot \ddot{x}_{rand}), \tag{4.25}$$

where $\dddot{x}_m$ is a mutation spark, β_1 and β_2 are random numbers in the range of (0,1), $\ddot{x}_{rand}$ is a random spark with rand being in the range of (1, Num_E), G_{best} is the global best individual.

In the mutation operator, a predefined amount of $\dddot{x}_m = (1, 2, 3 \ldots, Num_m)$ sparks are used to diversify the individual across the current search space to avoid trapping within local search regions. Through this strategy, individuals with greater P are retained over iterations. The explosion sparks which produce greater exploration around the current optimal solution would seek greater P, while the mutation sparks search randomly around the search space for potentially higher P.

The possibility of the algorithm achieving the optimal solution earlier before reaching the maximum iteration count exists, therefore a convergence criterion is needed for the algorithm. The criterion must be checked; thus, the comparison steps after any fitness evaluation is chosen as the checking point. At the end of the algorithm, the GMPP is tracked in lieu of presence of PSCs and the boost converter switches at the best solution of duty cycle, D. The convergence criteria are chosen to be when the process has reached the maximum iteration limit or when the solutions have converged to each other. When the maximum iteration limit has not been reached, the PS-FW algorithm will constantly restart the search process until maximum iteration limit is reached.

The convergence criteria determines the algorithm's performance to search around the solution region. To evaluate if the particles or sparks have converged within a range of each other, the difference of fitness G_{best} and average fitness of the population is within a certain threshold.

Hence, the culmination of proposed hybrid PS-FW GMPPT algorithm implementation in PV system with PSC is described in detailed manner based on the strategy and operators used. The summarized code of the proposed GMPPT algorithm is given in Algorithm 1.

Algorithm 1: PS-FW Summarization

1: Initialize PSO parameters and FW algorithm parameters (w,c_1 , c_2, n…1,2,3) and initialize n population duty cycle, D randomly.
2: Inputs : Voltage, V and Current, I (Power, $P = V \cdot I$)
3: **while** $t < t_{max}$
  4: Obtain P for each n particle.
  5: Comparison of P between each particle in the n size population, G_{best} ,f_{min} P_{best} of population is obtained and updated. Exit and output G_{best} position if convergence criteria are met.
  6: Update particle velocity and position of n size population using Eq (2) and Eq (3).
  7: FW_{num} number of particles are abandoned and removed from the population.
  8: Generate D with offset for each spark based on their respective P_{num} particle. Each spark adds to the total of Num_e.
  9: Fitness evaluation of P for each spark.
  10: Comparison of P between each spark in the Num_e size population, G_{best}, f_{min} of population and P_{best} of explosion sparks is obtained and updated.
  11: Generate Num_m mutation sparks. Each D of the mutation sparks are mutated from the position of random individuals.
  12: Num_m mutation sparks fitness are evaluated and compared, G_{best} of population of mutation sparks is obtained and updated.
  13: Select FW_{num} of individuals from sparks at (8)-(12) to bring into next iteration of process. Selected individuals are combined with P_{num} particles to generate population.
  14: Calculate G_{best} and P_{best} of this new population.
  15: $t = t + 1$
16: end **while**
17: Output G_{best} position, D.

4.6 Chapter Summary

In the Chapter, the work conducted has contributed to the objectives of the research project. As the validation of the proposed GMPPT algorithm requires the implementation of the PV system application under PSC. The designed PV model has been successfully made in Section 4.1 which introduces an implementation of PV panel model for use in the PV system application through simulation software environment.

Next, the conventional DC-DC boost converter or more specifically its minimum and maximum parameters according to the design requirement have been calculated through the equations, is summarized and completed in Section 4.2. With these calculations, the boost converter can be built using the determined parameters of the components in the Simulink environment. Moreover, a selection of components within the experimental setup can be made with regards to the limits of voltage and current rating.

The design of the proposed hybrid PS-FW GMPPT algorithm has been completed. First, the introduction of the singular counterparts, PSO algorithms in Section 4.3 and FWA in Section 4.4 have been explained in detail in terms of the search process. Any operators related to these two algorithms as they are implemented in PV systems within literature have been explained with the equations and explanation regarding their usage. Next, the proposed PS-FW algorithm in Section 4.5 has been described with correlation to both the PSO algorithm and FWA in the aspect that the PS-FW algorithm has based itself upon the continuation of PSO algorithm search process and then into the FWA. The PSO velocity operator begins the first part of the PS-FW algorithm search process. Then, the explosion sparks generation with mutation sparks generation finalizes the FWA process after selection operator. Hence completing the entire PS-FW search process after any of the two convergence criteria is reached which are the convergence of the population or reaching the maximum iteration limit. The designed GMPPT algorithms of PSO algorithm, FWA and PS-FW algorithm are now possible to be implemented within the GMPPT controller unit of both simulation and experimental setups.

In the next chapter, the methodology regarding implementation of the PV system in both simulation and experimental setup will be given. The results of the performance validation in the algorithm framework and search behavior must be determined through finding the accuracy and tracking speed following tests in PV system application under PSC. Hence, the design of the two setups of PV systems need to be detailed and allow the simulation and experimental setup to be constructed properly with different PSC patterns.

Chapter 5

Simulations and Experimental Setup of PV System

In this chapter, the simulation and experimental setups are described which implement and verify the proposed PS-FW hybrid and other algorithms. As chosen in Chapter 3.6, MATLAB/Simulink simulation environment is utilized to verify, test and compare GMPPT algorithms including the proposed PS-FW GMPPT algorithm. The PV model and boost converter specifications obtained in Chapter 4.1 and 4.2 are utilized in this simulation setup to create the PV system application. The boost converter specifications are also shared with the experimental setup; thus, it is through the calculations that selection choice of the boost converter may be done with regards to the voltage and current ratings.

The existence of the dSPACE RTI unit and the Chroma PV emulator within the reviewed literature in Chapter 3.6 proved that the implementations have introduced their capabilities and feasibility of the use in experimental setup of PV system that is able to also control the GMPPT algorithm. In experimental setup, dSPACE RTI interface unit is utilized to measure and record statistical and analytical data for real-world testing and acting as the GMPPT controller by implementing the algorithms. Moreover, the experimental setup utilizes the Chroma PV emulator device to emulate the PV panel output under any shading pattern. The experimental setup is also built with consideration to certain aspects which cannot be replicated like the simulation environment, this includes the voltage offset of the current transducers and settling time considerations for the entire boost converter system. Understanding the tools available can assist in providing required dynamic environments and the necessary control to measure or observe the performance of the entire PV system.

In Section 5.1, the PV system application with PSC is implemented into the MATLAB and Simulink Software environment. The PV panel modules are connected into an array, its specifications at this connection will be summarized. The selected boost converter specifications are chosen also in regards to the calculation made earlier. A frequency time fulfilling the Nyquist Sampling Theorem is chosen for the entire discrete system. Then, the simulation setup as in the software itself will be presented.

The parameters utilized in the boost converter application for simulation setup are completely detailed in Section 5.2. Moreover, the PSC patterns adopted for use to test the GMPPT algorithms are shown in the Simulink environment and their output values will be summarized.

An application of the entire PV system with PSC and GMPPT controller implementation as conducted in the earlier sections for simulation setup is converted for use in the experimental setup in Section 5.3. The experimental setup consists of dSPACE RTI interface unit, Chroma PV emulator and the conventional boost converter. Some considerations will be made in the conversion between simulation and experimental setup as there are factors to account for, which include the settling time of the boost converter, optocoupler and sensor voltage offset.

In Section 5.4, the parameters utilized in the experimental setup for the boost converter are shown. To elaborate, this section provides all necessary component names and values utilized in the experimental setup of the conventional boost converter. Moreover, the respective P-V and I-V curves of the PV arrays arranged in the Chroma PV emulator will be obtained and their output values will be summarized.

5.1 MATLAB and Simulink Software Environment

Verification of the effectiveness of the proposed hybrid PS-FW GMPPT algorithm is required, hence the MATLAB/Simulink simulation software will setup an entire PV system. Systems are easily constructed using blocks from libraries provided and defined personally if needed for custom blocks. Custom blocks were not utilized for this research project and all needed blocks to simulate the PV panel with PSC, conventional boost converter and GMPPT algorithm implementation through a MATLAB function block are readily available through the Simulink libraries.

Table 5.1: PV Module and Array Specifications

PV Panel Parameters	One PV Parameters	3 PV Panel Parameter Settings in Series
Current at MPP, I_{mpp}	2.75A	2.75A
Voltage at MPP, $Vmpp$	18V	54.5V
Power at MPP, P_{mpp}	50W	150W
Open circuit voltage, V_{oc}	21.9V	65.7V
Short circuit current, I_{sc}	3A	3A
Current temperature coefficient, K_I	0.04%°C	0.04%°C
Voltage temperature coefficient, K_V	-0.33%°C	-0.33%°C

The PV system consists of a DC-DC boost converter, a GMPPT control block which is represented by a MATLAB function block and the three 50W PV panels; thus, PV1, PV2 and PV3 connected in series as a PV array in 3 series configuration. By connecting to the 3S configuration in series, the total input current in the system is the same as I_{mpp}, but the voltage is the sum of all V_{mpp}. The specifications of the 50W panel and the panels in 3 series connection used are as follows in Table 5.1

The system is comprised of Simulink blocks that take and measure the input given. An output is provided that is calculated, then generated after a set sampling time has passed in the model's system. The sampling time set in the Simulink environment determines a measurement state where all blocks process their calculations, thus it is required to set the sampling time where the MATLAB code and model's blocks then compute with enough time. The required time is able to found determined based on the slowest time sample output required by a block, in the case of the implemented PV system environment it is the frequency of switching from the PWM generator block.

A calculation of the time sample that is able to process the frequency specified must follow the Nyquist Sampling Theorem. The Nyquist Sampling Theorem states that a band-limited continuous-time signal can be sampled and perfectly reconstructed from its samples if the waveform is sampled over twice as fast as its highest frequency component. The formula for determining this recommended sampling time is found in (5.1):

$$F_s = 2 \times F_n, \tag{5.1}$$

where F_s is the recommended sampling frequency of the system so no information is lost. F_n is the sampling frequency of the subjected signal that is needed to be measured; as such, this is the PWM frequency. Given a 40 KHz PWM signal from the controller, sampling time of at least more or equal than 80 KHz or $1.25^{-}5$ seconds is required for digital signal processing and ensuring no signal loss.

Within the Simulink environment, theoretical calculations of the boost converter are assumed to contain less or no ripple and fast settling times. Depending on the configuration, settling times vary differently and may cause inaccuracies due to the ripple power that fluctuates the reading of a measurement device. However, simulation environments as noticed in literature review where simulation results for GMPPT in switching the DC-DC converter had no trace of the ripple or settling time as describable in [96], more-so that the sampling time applied within simulation environments are typically fast as shown in the Table 3.1.

However, the authors in literature review have presented that a sufficient hold time was required to allow settling of the converter and for accurate measurements in the system. The hold time in question does not refer to the sampling frequency as discussed before but the time where the output duty cycle is allowed to change, which is the time taken per duty cycle change in the entire PV system. Thus, the duty cycle changes every zero order hold time,D_s and at a frequency of 40 KHz. A consideration to take into account is, all algorithms to be tested for both simulation and experimental fall under the same hold time, it is considerable that a sufficient hold time benefits the accuracy of the obtained results. As a result, there is no bias in a faster speed from faster change of duty cycle times when all algorithms output the duty cycle, D with the same D_s. The mentioned hold time to be chosen within Simulink, D_s is set to 100 milliseconds due to the lack of ripple voltage and sufficient sampling time.

Through the MATLAB function block within the Simulink environment, the proposed GMPPT algorithm is implemented. The GMPPT algorithm itself then computes the input and outputs the duty cycle for the MOSFET gate of the boost converter to switch at the specified duty cycle. The system uses a 5μs discrete sampling time. The blocks that consist of the PV panel arrays compute the voltage and current output based on the current irradiance and temperature, while voltage and current measurement blocks obtain the voltage and current within the converter. The zero-order hold block retains the measurement of voltage and current every D_s seconds, after which it outputs the two values into the MATLAB function block as inputs. After one sample period, MATLAB function block outputs the duty cycle. All GMPPT algorithms are also implemented and executed from a MATLAB function block.

The setup of the system within Simulink environment is observable in Fig. 5.1 and the subsystem for the PWM generator block is shown in Fig. 5.2.

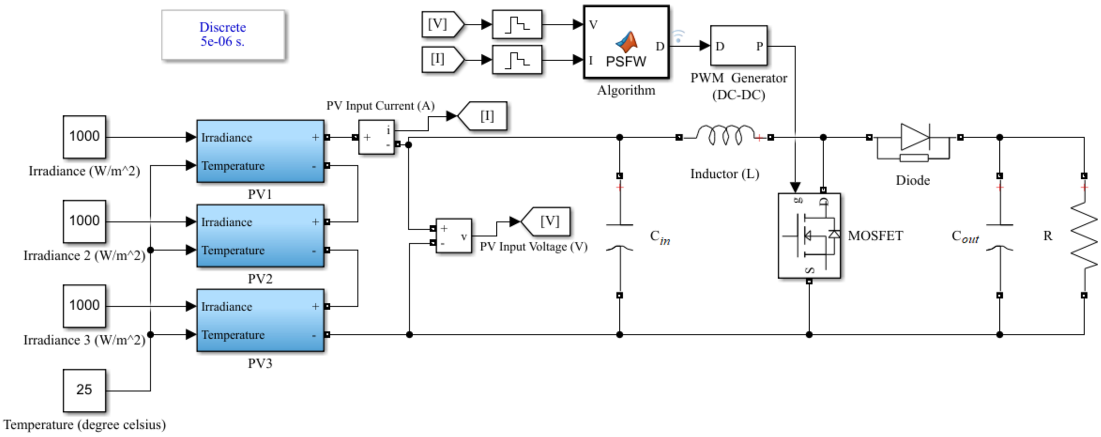


Figure 5.1: Proposed Simulink PV System with Integrated GMPPT Controller

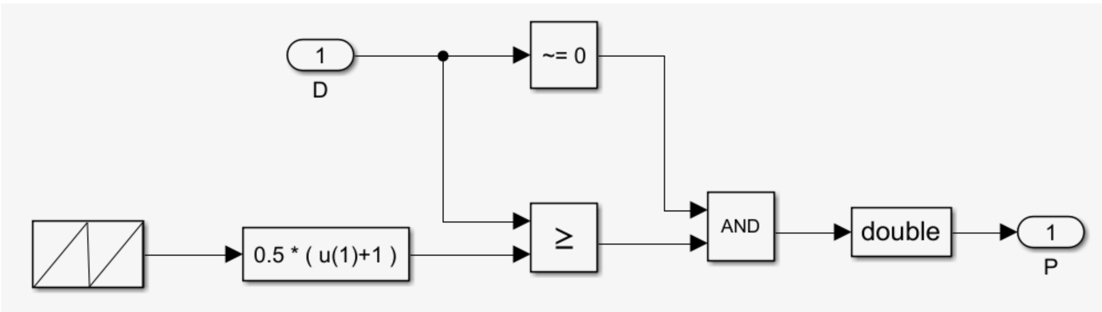
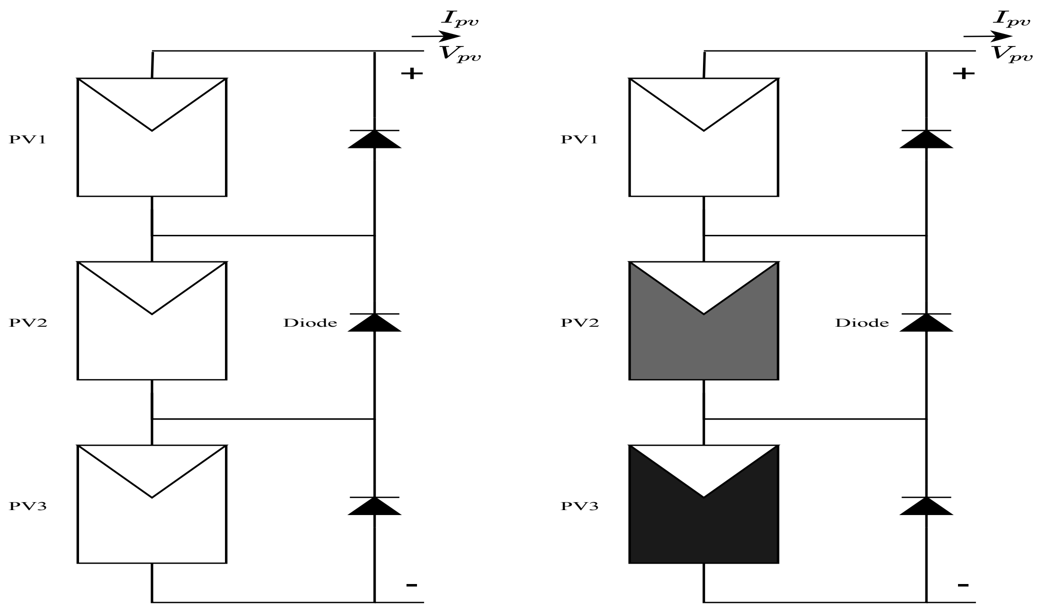


Figure 5.2: PWM Generator Subsystem

The algorithms are tested under 3 different cases of shading on the PV panels. Tests were made under the conditions of constant and partially shaded irradiance and given temperature of 25 degrees Celsius to obtain the P-V or I-V curve. The temperature on the surfaces of PV arrays typically does not experience rapid change compared to the irradiance, thus most literature do not take temperature as a consideration when conducting testing. The rapid change of irradiance with the relatively static temperature are the main causes of the hotspot phenomena and damage to the PV cells. The single diode model PV panel array in 3S configurations is shown in Fig. 5.3.

In conclusion, the popularity of the software in reviewed GMPPT implementations have demonstrated its capabilities and feasibility of the use in simulating a PV system while implementing the GMPPT algorithm. The usage of MATLAB/Simulink software is therefore justified simulation setup while presenting the performance comparisons of all involved GMPPT algorithms. The simulation verification of the results however, must be validated in the results and discussion in experimental setup.



(a) Unshaded **(b)** Shaded

Figure 5.3: 3S PV Panel Arrangement

5.2 Parameters within MATLAB Simulink

The parameters of the simulation setup components are to be detailed. The PV system consists of a DC-DC boost converter, GMPPT control block which is represented by a MATLAB function block and the 3 PV panels connected in the 3S configuration. Initially, the PV panel specifications have been set and chosen in the earlier Section 5.1. This section describes the component values obtained for the boost converter in inductance, capacitance and resistor. Moreover, the shading patterns from the simulation setup of the 3S PV array is given in the form of P-V and I-V curve while also tabling its given power values at MPP, P_{mpp}.

5.2.1 Boost Converter Specifications

The selection of the boost converter's components specifications within the simulation setup are thus listed in Table 5.2. These component values satisfy the minimum requirements of a conventional boost converter as calculated in Table 4.1 of Chapter 4.3.

Table 5.2: Boost converter specifications.

Parameter	Values
Switching Frequency, f_s	40 KHz
Period, s	25 μs
Hold Time, D_s	100 ms
Simulation Sample Time, T_s	5 μs
Resistor Load, R_{load}	40 Ω
Inductance, L	1000 μH
Capacitance, C_{in}, C_{out}	100 μF

where switching frequency, f_s is the switching speed of the MOSFET in the setup. Period, s is determined based on the switching frequency. Simulation sample time, Ts is the sampling time of the discrete system within Simulink that is a logical increment from the chosen frequency. Resistor Load, R_{load} is the load resistor value. inductance, L is the value of the inductance in the inductor coil. Capacitance, C_{in}, C_{out} are the input and output capacitor capacitance values. The values of R_{load}, L and C_{in}, C_{out} are chosen based on the boost converter specifications within Chapter 4 Section 4.2.

5.2.2 PV Shading Patterns

The shading pattern to be tested is important to estimate an occurrence of partial shading in the real world. The shading patterns allow the simulation performance to properly reflect the PV system performance that could occur in real life. Under four different patterns, all PV panels have a given irradiance value and given temperature of 25°C to obtain the P-V or I-V curve. The single NSC pattern and three shading patterns applied for the simulation's PV panel array are as follows:

1. Pattern 1 (Non-shading condition, NSC): All three PV panels receive uniform irradiance of 1000 W/m^2. The P-V characteristic curve of this pattern shows that the maximum power output is at 150 W. The pattern is used as a benchmark and a reference to the power output of the system under STC.

2. Pattern 2 (Partial shading condition 1, PSC1): Both PV1 and PV2 receive uniform irradiance at 1000 W/m^2, however PV3 receives nonuniform irradiance level of 700 W/m^2. This shading pattern produces multiple peaks that are seen on the I-V or P-V characteristic curve where the maximum power output is at 115 W. It is worth mentioning that if the algorithms are trapped in the local peak where power output is lower, we get a significant decrease in power efficiency.

3. Pattern 3 (Partial shading condition 2, PSC2): PV1 receives 1000 W/m^2, PV2 receives 700 W/m^2, and PV3 receives 300 W/m^2. The algorithm's ability to seek out the GMPP is tested in this pattern, as there exists three different peaks on the P-V curve where all power output is different.

4. Pattern 4 (Partial shading condition 3, PSC3): PV1 receives 500 W/m^2, PV2 receives 700 W/m^2, and PV3 receives 300 W/m^2. Middle high points (MHP) exist on this pattern where there are MPP in close proximity between each point [127]. The algorithm's ability to seek out the GMPP when in the presence of MHP will be tested in this pattern.

The PV patterns are applied as NSC, PSC1, PSC2 and PSC3 to the PV panels in Simulink and summarized in the Table 5.3.

Table 5.3: Patterns for NSC, PSC1, PSC2 and PSC3 cases in Simulation

Pattern	Panel	Irradiance(W/m^2)	$P_{mpp}(W)$	$V_{mpp}(V)$	$I_{mpp}(A)$	$V_{load}(V)$	$I_{load}(A)$
1	PV1 PV2 PV3	1000 1000 1000	149.4	54.13	2.76	76.29	1.97
2	PV1 PV2 PV3	1000 1000 700	114.90	56.00	2.05	66.99	1.685
3	PV1 PV2 PV3	1000 700 300	72.44	36.31	1.99	52.97	1.32
4	PV1 PV2 PV3	500 700 300	50.49	35.15	1.43	34.87	1.44

Occurrence of partial shading on a PV string affects the number of local peaks and the single true GMPP that exists on either P-V or I-V curve. A greater number of local peaks on the curves in turn deliberately weaken and cause disadvantageous rate of power

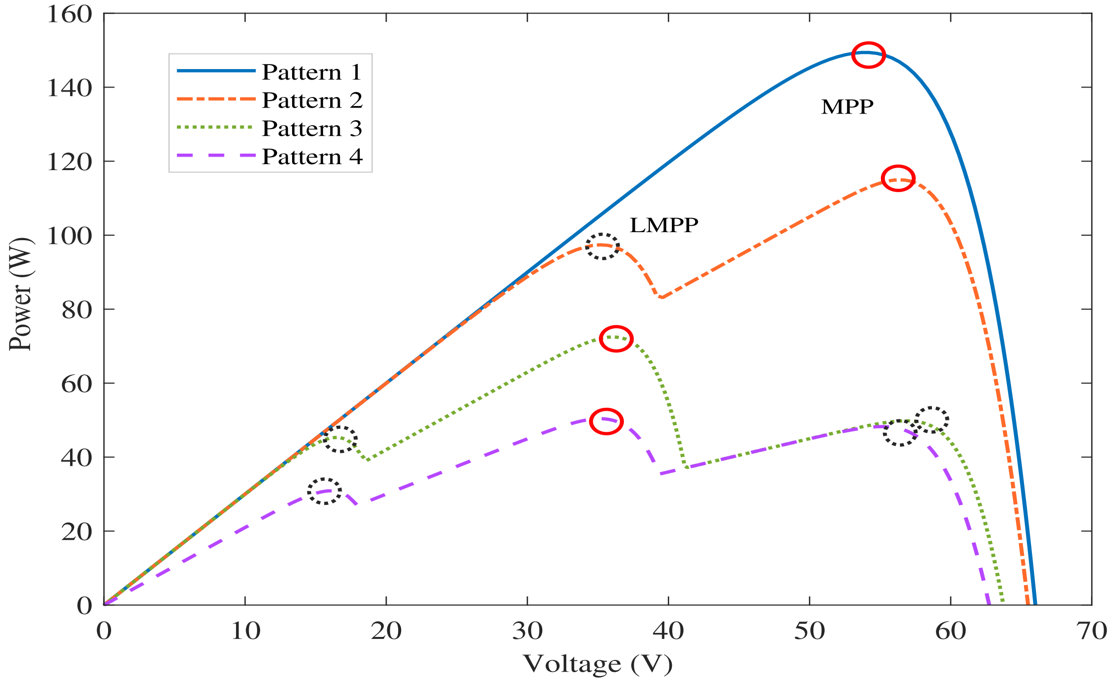


Figure 5.4: P-V characteristic of 4 patterns.

conversion if the chosen GMPP algorithm is unable to search for the correct GMPP and with fast convergence speeds as well. Understanding this, the performance of GMPPT algorithm greatly depends on how well the performance obtained reflects upon the P-V curves with more local peaks. In the patterns applied to the implemented PV system, the performance of all implemented GMPPT algorithms are able to be fairly tested with one to five peaks in the simulation and one to three peaks in the experimental setups through the different shading patterns.

The following P-V and I-V curves observable in Fig. 5.4 and Fig. 5.5 both pin point the MPP on the curve and the expected power output for the array string implemented for the implemented PV system. The P-V curves and I-V curves are traced based on the four proposed respective PV patterns that cause NSC, PSC1, PSC2 and PSC3 on the PV array block. Through the "PV Array" block in Simulink, these curves are obtained and layered upon each pattern in the two subfigures. The local peaks and GMPP are accurately shown on the figures and represent where the implemented GMPPT algorithms must track in order to confirm their accuracy for the power conversion.

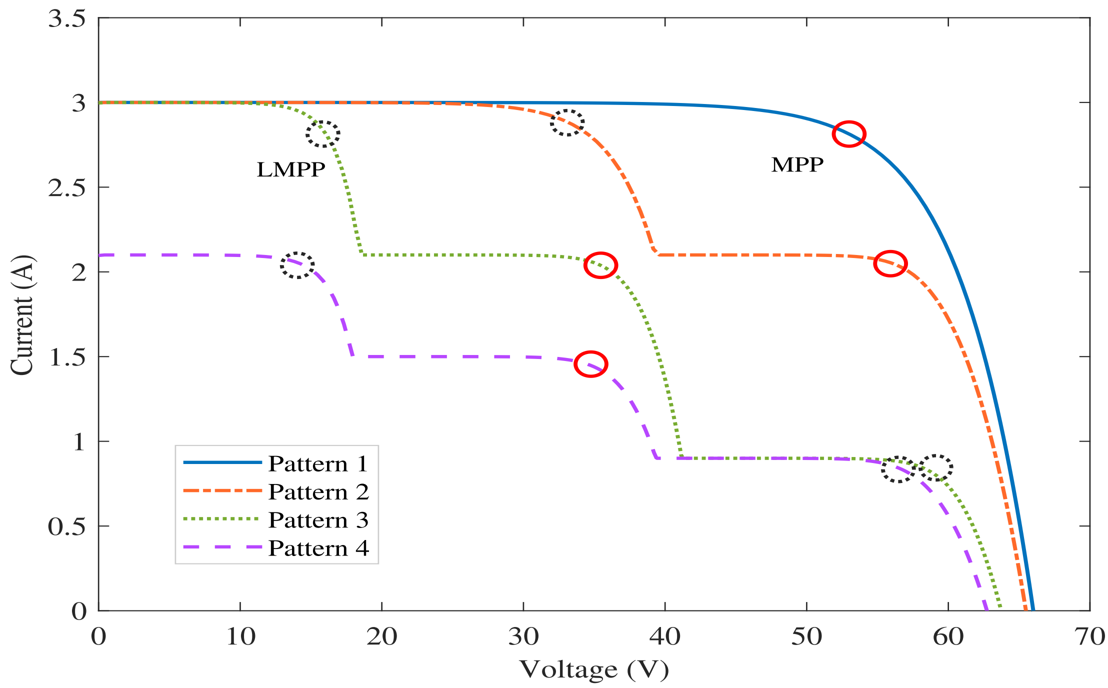


Figure 5.5: I-V characteristic of 4 patterns.

5.2.3 Simulation Expanded Validation

An extended set of tests utilizing more difficult PSC patterns for the P-V curves are proposed to verify the performance of the hybrid PS-FW algorithm within the simulation setups. An increase of peaks will deliberately increase the difficulty of search for the algorithms as a higher possibility of searches falling into local trap is introduced. Two P-V curves, containing four and five peaks patterns satisfying the condition of PSC are introduced to all algorithms. Thus, the PV array setup is expanded from 3 panels to 5 panels in series, allowing the P-V curve to procure 5 total peaks under PSC. The R_{load} is also increased to 100 Ω to satisfy the larger PV array. The PV panels within the array are now specified as PV1, PV2, PV3, PV4 and PV5. Similar to the preceding four patterns, all PV panels have a given irradiance value and given temperature of 25°C to obtain the P-V or I-V curve.

The two PSC patterns, PSC4 and PSC5 are applied for the simulation's PV array as follows:

1. Pattern 5 (Partial shading condition 4, PSC4): PV1 receives 500 W/m^2, PV2 receives 600 W/m^2, and PV3 receives 800 W/m^2, PV4 receives 900 W/m^2 and

PV5 receives 900 W/m^2. In this pattern, 4 peaks exist on the P-V curve.

2. Pattern 6 (Partial shading condition 5, PSC5): PV1 receives 400 W/m^2, PV2 receives 600 W/m^2, and PV3 receives 700 W/m^2, PV4 receives 800 W/m^2 and PV5 receives 1000 W/m^2. In this pattern, 5 peaks exist on the P-V curve.

The expanded PSC P-V patterns applied as PSC4 and PSC5 to the PV panels in Simulink are summarized in the Table 5.4.

Table 5.4: Patterns for PSC4 and PSC5 cases in Simulation

Pattern & Peaks	Panel	Irradiance(W/m^2)	$P_{mpp}(W)$	$V_{mpp}(V)$	$I_{mpp}(A)$	$V_{load}(V)$	$I_{load}(A)$
	PV1	500					
	PV2	600					
5	PV3	800	138.69	94.81	1.463	115.7	1.157
	PV4	900					
	PV5	900					
	PV1	400					
	PV2	600					
6	PV3	700	128.33	73.63	1.742	110.4	1.104
	PV4	800					
	PV5	1000					

The following P-V and I-V curves observable in Fig. 5.6 and Fig. 5.7 both pin point the MPP on the curve for the expanded shading patterns introduced for the simulation setup.

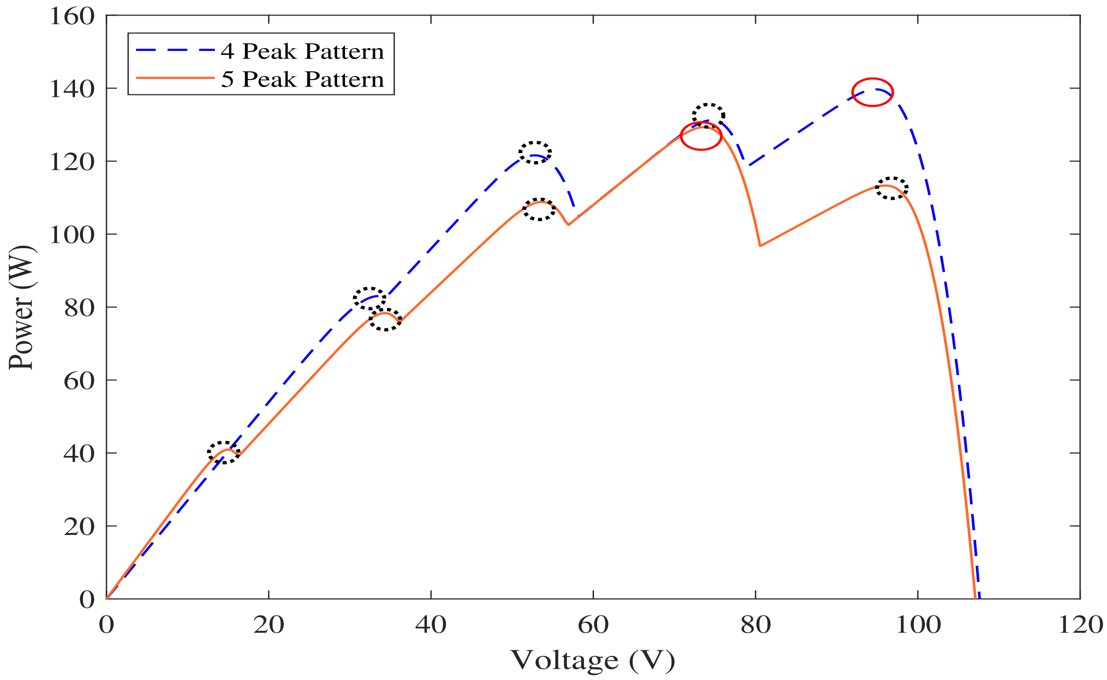


Figure 5.6: P-V characteristic of expanded 2 patterns.

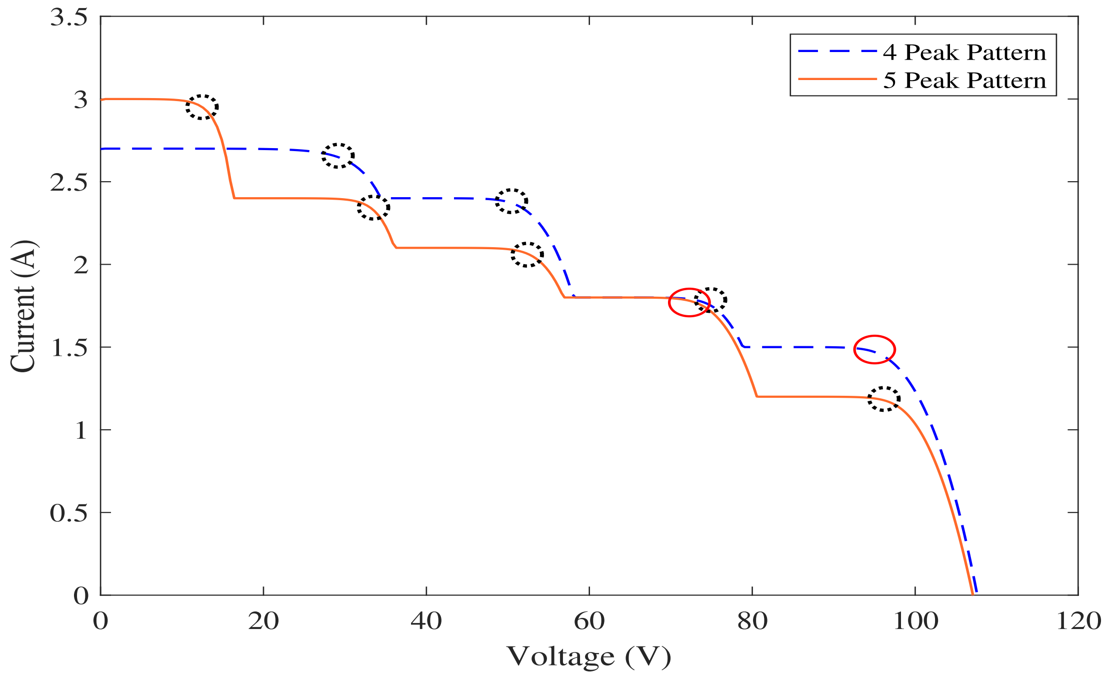


Figure 5.7: I-V characteristic of expanded 2 patterns.

5.3 Experimental Setup and Considerations

The usage of simulation tools greatly understate what is required to be utilized in real life as the experimental setup is not so easily replicated. The experimental setup is able to emulate the performances of an implemented PV system under PSC to a certain degree. Thus, the methodology of the experimental setup is considered in this section.

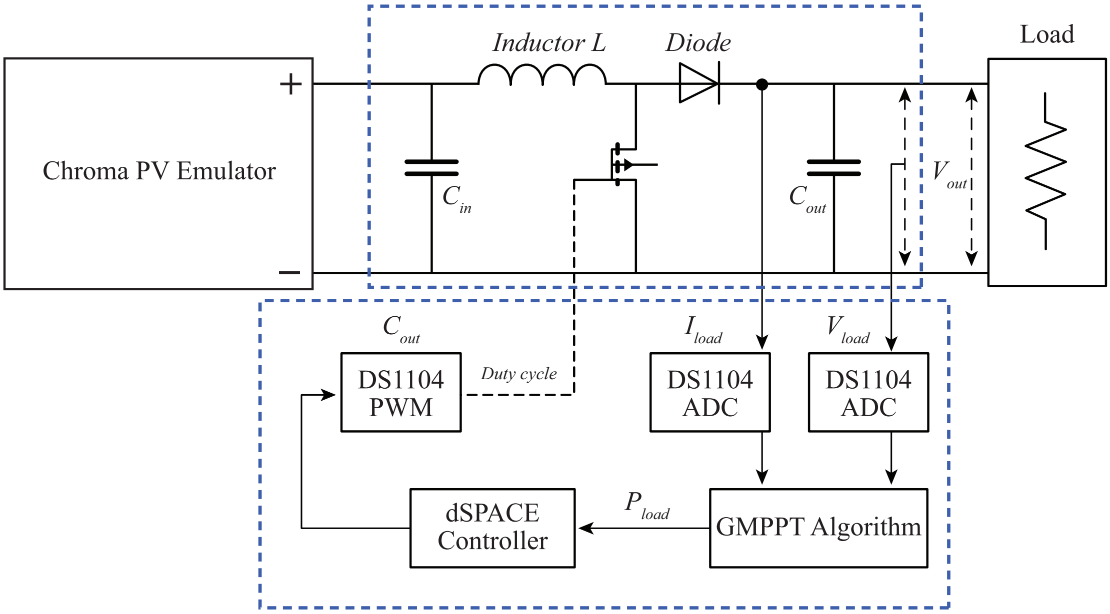


Figure 5.8: Experimental Setup of Proposed PV System

5.3.1 dSPACE Real Time Interface (RTI)

The dSPACE Control Desk software allows integration of MATLAB/Simulink into implementation of the PV system experimental setup. This process was done through installing the RTI platform support that links the Simulation software to the dSPACE RTI interface unit which acts as the controller of the physical board. This particular link was established by the installation of proprietary software by dSPACE and after executing the MATLAB program. The main program consists of a graphical user interface (GUI) which, with the use of libraries allowed the integration of the physical hardware with the control of variables or measurement of signal data.

The following Fig. 5.9 shows the connections between the PV system and the GMPPT controller, the dSPACE RTI unit. In this implementation, analog-to-digital converters (ADC) are required, which are voltage and current sensors to read the information from the output power. An implementation utilizing the digital-to-analog converters (DAC) in the form of PWM channel to send the duty cycle at a specified frequency is also required.

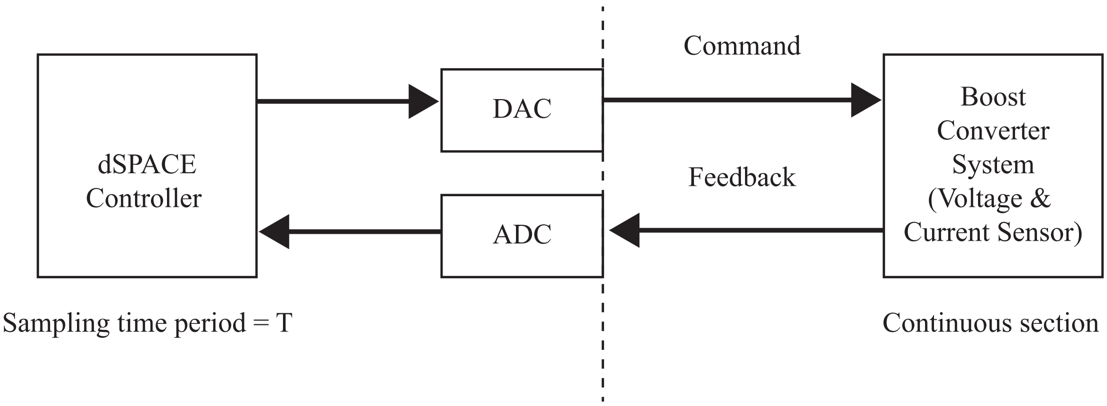


Figure 5.9: Real-time control structure

The CP1104 connector board is the interface that links the software from physical hardware to the computer. The connector board is seen in the Fig. 5.10. From the boost converter configuration, the gate of the MOSFET are attached to the PWM pin, voltage sensors are attached to the ADC channels.

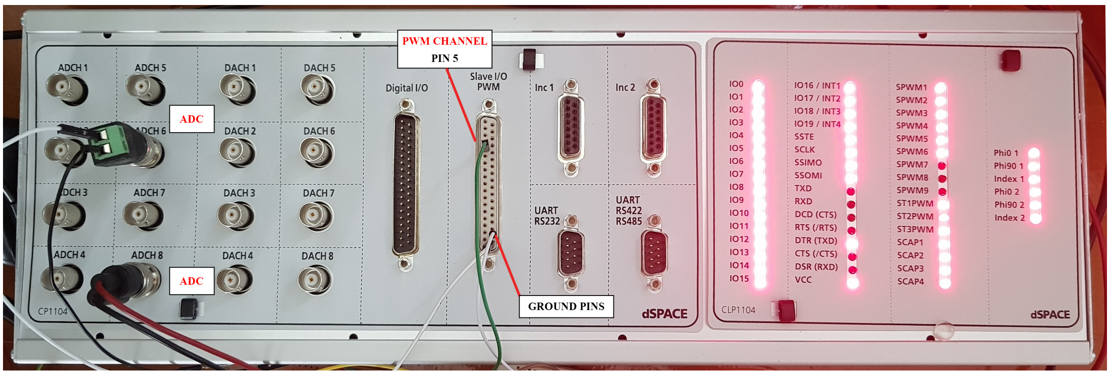


Figure 5.10: Physical CP1104 Board and Connections

The software is observed in the following Fig. 5.11. Within the Simulink environment which has already been linked to the dSPACE RTI, models must be created using the libraries provided by dSPACE to link the software interface to physical interface in real time manner. The physical interface includes the two ADC channels related to both current and voltage sensors and one DAC PWM channel. The pins of the ADC utilized are the ADC5 and ADC6 respectively, while the PWM output is located on Pin 17. The physical input signal input range is from –10V to +10V. dSPACE RTI scales this by a factor of 0.1 to place the value on a range of – 1V to +1V initially. The ADC signal is multiplied by 10 to remove the scale factor.

Meanwhile, the PWM is set to a starting voltage and in either symmetric or asymmetric wave-forms in the specified frequency. The frequency specified for the experimental setup is equal to the desired value from simulation and the design, which is 40 KHz while the starting voltage is $0V$ and in symmetric mode. Symmetric waves start the wave-form signal immediately to the specified duty cycle value in the beginning of the period, in comparison to the asymmetric mode where signal activates when time passes half the period. The settling time of the system requires that symmetric mode is utilized to prevent delays in the boost converter so that it may settle faster in the first change of duty cycle in accordance to the recording of the time taken for convergence.

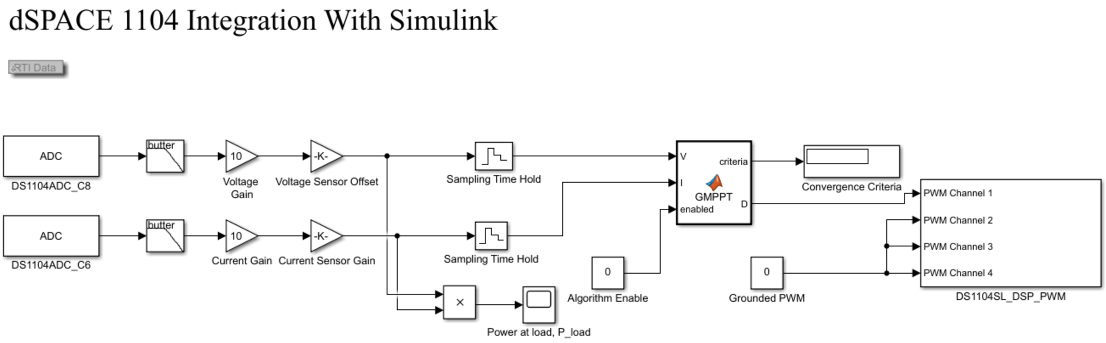


Figure 5.11: Model Built with Target to dSPACE RTI

Measurement and recording is available from the Control Desk, the data obtained in this experimental setup are exported to MATLAB compatible database. The database thus consists of; power at the input P_{input}, voltage at the load V_{load}, current at the load I_{load} and current time t of the experimental recording which is set to start at the enable condition of the algorithm that ends upon the achievement of convergence criteria. The data, which is easily presented in MATLAB are the main basis of how the recording and measurement of data is conducted in the research project.

The software described has explained the link between the physical components of the CP1104 board, computer, sensors and the duty control of the boost converter through PWM pin. The control of the physical components is possible, measurement values are obtainable and the GMPPT algorithm is able to be implemented through the entire controller system. With this, the data required to express the experimental results exactly the same as the simulation results is possible.

With the implementation of PV emulator as the power source, the proposed research will be able to fulfill the experimental setup requirements of a PV panel or array. The experimental PV system will be able to reflect the simulation settings. Moreover, the shading patterns that are proposed are easily emulated so that the PV array under no shading pattern and three shading patterns. are applicable in the experimental tests. The experimental setup is therefore built upon the connection of the input of the boost converter as the Chroma PV emulator, the control of the duty cycle switching of the MOSFET gate through dSPACE RTI and the measurement of voltage and current at the input of the boost converter. However, certain considerations must be taken into account that are not shared between the simulation conditions. These factors can affect the results that must be compensated or resolved through implementation of other components.

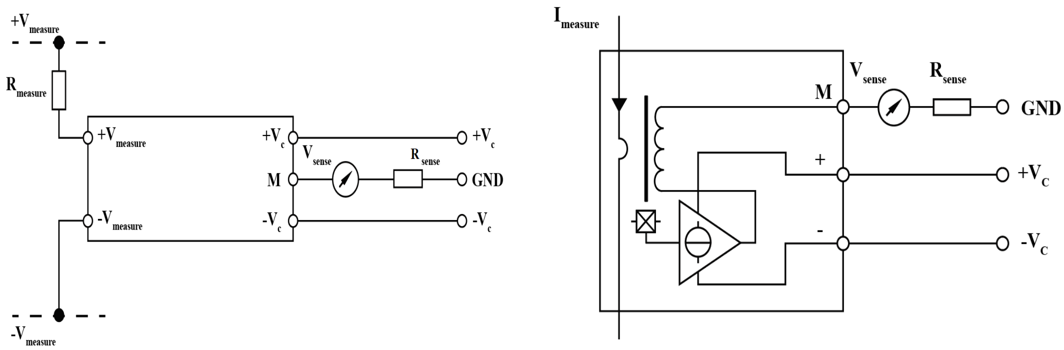
5.3.2 Voltage and Current Sensors

With the discussion of the simulation and experimental setup disclosed beforehand, the two setups aim to implement the GMPPT algorithms for testing and validation of their performance. However, considerations in the form of hardware must be taken into account to ensure the performance of the implemented experimental setup. To begin with, the inclusion of real current transducers requires calculations to ensure that the offset of the R_{output} which is a derivation of the sensed voltage or current is calculated. The voltage and current sensors are current transducers which must be powered by a positive and negative rail voltage source.

For the aspect of current sensing, through-hole current sensors have an empty volume of space in the transformer loop of the component, which allow the insertion or pass by of the wire to be sensed. The transformer loop is charged and current flows through the R_{output}, allowing voltage to be output to the ADC channel and hence sense the current in the circuit after the transformation ratio.

$$V_{sense} = R_{sense} \times I_{sense} \tag{5.2}$$

Hence, the V_{sense} output at the resistor to the ADC channel is obtained. However, most current transducers have an offset that must be compensated. The overall accuracy is given by a percentage in the manufacturer data sheet, thus it is more practical to calculate the offset manually with a multi-meter on a powered transducer with zero power load. With current sensor and voltage sensor, utilization of a multi-meter to measure the R_{sense} in parallel to obtain the offset. Within the Simulink software, this offset is easily applied into the Simulink and dSPACE linked model to compensate for this value. The diagram of the voltage and current sensor circuit connection utilized in the experimental setup can be found in Fig. 5.12. In the LV25-P voltage sensor circuit, the $V_{measure}$ represents the parallel connection at either the input side of the boost converter towards the PV or the load, the V_c is the positive and negative 15V power rails used to power the sensor and M is our sensor output which connects to the dSPACE ADC channel. In the LA25-P current sensor circuit, the $I_{measure}$ is sensed through a through-hole connection at the input side of the boost converter towards the PV or the load.



(a) LV25-P Voltage Sensor (b) LA-25P Current Sensor

Figure 5.12: Voltage and Current Sensor Circuits

5.3.3 Signal Measurement and MOSFET Driver

Another aspect to consider when converting to experimental setup is the settling time of the entire boost converter system. The boost converter in real life must consider settling time of the components in the conventional boost converter. Much unlike the simulation setup where 100 millisecond sample time was given before a change in duty cycle, the change in the duty cycle, sampling time is chosen to be 1 second for the experimental setup. This is shown in the Fig. 5.13. The X-axis is given in seconds.

While the Y-axis precedes the amplitude of a signal, which are the measurements from the LV25-P voltage sensor and LA-25P current sensor. Within the dSPACE software environment, the measurement of settling time required for accurate measurement is shown.

Figure 5.13: Settling Time For Measurement.

The PWM channel of the dSPACE retains a voltage limit output of $\pm 10V$ at the channel. If the voltage at this channel bypasses the set voltage, then there is a considerable risk that damage to the PWM channel will occur. The protection of the experimental equipment must be considered to prevent permanent damage and loss of assets.

The voltage at the PWM channel can overflow or leak due to the reverse current flow at the boost converter system from the MOSFET switch. In the case that the MOSFET is damaged from power dissipation or heat, then the MOSFET may melt internally and cause the power overflow. With the high power in the system with V_{mpp} at $76V$, the value is 7.6 times higher than the voltage limit at the PWM channel.

Moreover, with the value of the voltage output of the PWM channel only outputting around $\pm 10V$, the MOSFET switch depending on the model is unable to switch fully. V_{gs} is the threshold required to open and close the switch fully at the specified frequency. The frequency is dependent on the model and typically also provided by manufacturer data sheet. The V_{gs} of the implemented model IRF3710Z requires $15V$ to fully switch on, thus the PWM channel is unable to drive sufficient voltage to power the switch. To alleviate the lack of voltage, a MOSFET driver or commonly called optocoupler which is commonly an 8-pin IC must be implemented. The optocoupler has a primary goal of propagating the PWM signal at the input side, then outputting the PWM signal at the output side. The PWM signal retains its duty cycle range, the frequency and most importantly is able to output voltage at boosted levels according to the level of boost provided by the manufacturer data sheet. The device isolates the dSPACE board's PWM channel from the boost converter and PV system, completely negating the chance of damage which may be incurred. The optocoupler used in this proposed research is the TLP250(H) by Toshiba which is powered by an external DC-DC power supply.

In conclusion, these considerations are taken into account to prevent asset damage, the risk of harm to the persons involved in the experimental setup and also supplement the voltage required to power the MOSFET in the complete PV system with GMPPT algorithm controller. The connection of the physical components and software interfacing hence completes the experimental setup. As such, the real experimental setup is connected and any considerations are also taken into account since the ideal simulation conditions cannot be replicated in real life.

5.4 Parameters for Experimental Setup

The parameters of the experimental setup components are to be detailed. The entire PV system consists of the Chroma PV emulator, DC-DC boost converter and GMPPT controller unit which is represented by the dSPACE interface unit. This section describes the component part models chosen for the boost converter. With regards to the simulation setup and work conducted in Chapter 4.2, the selection of boost converter components is made and chosen with consideration towards the power ratings not prevalent in simulation environment.

Initially, the PV panel specifications within simulation setup have been set and chosen in the earlier Section 5.1, thus the Chroma PV emulator follows the same specifications from the simulation setup. Thus, the use of Chroma PV emulator to substitute for the PV panel is detailed in this section. Moreover, the shading patterns from the experimental setup of the 3 series PV array is given in the form of P-V and I-V curve while also tabling its given power values at MPP, P_{mpp}.

Table 5.5: Component Summary

Component	Model	Description
C_{in}	EEUEE2C101	- 100 µF , 160V rating, Aluminium Electrolytic Capacitor
C_{ou}	EEUEE2C101	- 100 µF , 160V rating, Aluminium Electrolytic Capacitor
Inductor	Wurth 7447075	- 1000µH Torodial, Leaded , 3A maximmum rating
MOSFET	IRF3710	- N-Channel MOSFET which satisfy specified 40 KHz - MOSFET higher efficiency over IGBT [128] - Drain to Source Voltage V_{dss} of 100V, Drain Current at I_D, 57A - Handles maximum I_{out} and V_{out}limit ratings.
Diode	IN5408 Rectifier Diode	- Average Rectified Current of 3A , satisfies maximum I_{out} - Maximum RMS Voltage of 700V, satisfies maximum V_{out}
Resistive Load	Tubular Rheostat	- 40Ω - Withstand high temperatures at 500W

5.4.1 Boost Converter Specifications

The section closely details all utilized parts within this proposed research for the boost converter in the experimental setup. The component names and the reasoning of selecting these components which satisfy the requirement of minimum requirements from the calculations conducted in Chapter 3 for the design of a conventional boost converter. With consideration of the minimum specifications required, the components are assembled into a conventional boost converter, connected to the PV emulator and controlled at the switch with the GMPPT algorithms.

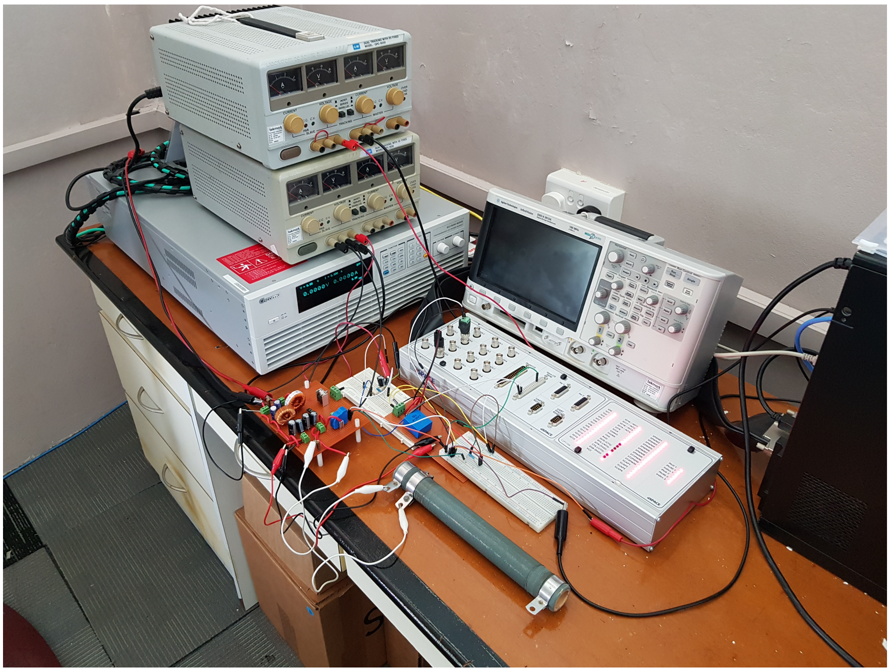


Figure 5.14: Experimental PV System Setup

A completed working experimental setup is described in the image Fig. 5.14. The system is connected as per described in this chapter. The utilization of the setup during testing must consider the safety of the individual in mind and partake in proper safety measures. All tests and proper experimentation are conducted in the utilization of this experimental setup.

5.4.2 Chroma PV Emulator

The Chroma PV emulator is an electrical device that is able to simulate the properties of a PV panel with multiple settings possible. The particular model utilized in this proposed research is the 62100-H which is connected to a 3-phase AC power source due to the high power output possible. As such, the settings for the specified PV panel must be set accordingly to prevent harm to the user and damage to any connected components, which in the implementation are the boost converter and the load.

The relevant requirements of the emulator is that it must include configuring the PV array into 3 PV panels in series as according to the $50W$ PV panel specification. Also, the NSC, PSC1, PSC2 and PSC3 patterns must be emulated in the specified patterns 1, 2, 3 and 4. Through the emulation, the device functions as the PV panel with positive and negative leads as the output to be connected at the boost converter. Other than an analog interface with digital display, the device is interfaced with a computer in multiple communication modes available including RJ45, USB-B to USB-A and RS232. The communication mode utilized in the experimental setup is the USB-B to USB-A mode. The method of control is done through the National Instruments(NI) Lab View based proprietary software included by the manufacturers. Relevant drivers from NI are installed that is compatible with the software to execute the program.

The communication scan button detects the communication mode used, by pressing the OK button then proceeds into the main menu of the software. Through this menu, the Dynamic MPPT button must be pressed which allows configuration in a new menu for the PV array settings. The PSC patterns are able to be specified with desired irradiance and temperature which allow configuration to the PSC.

Moreover, the PV panel configuration used for these arrays are configured easily and in series or parallel with amount of panels connected per string. Following the simulation setting parameters in Section 5.2.2, all four patterns are applied into the 3S PV array. A compilation of the four proposed shading patterns under the emulator's specifications are shown in Fig. 5.15, Fig. 5.16 and Fig. 5.17. The patterns validate that the P-V curve and I-V curve of the affected PV panels are obtained accurately for the experimental testing of the proposed GMPPT algorithms.

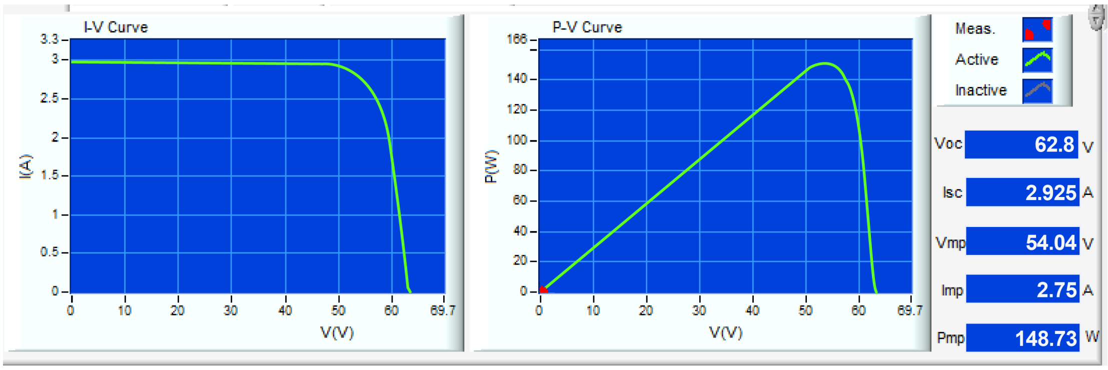


Figure 5.15: Pattern 1 at Emulator

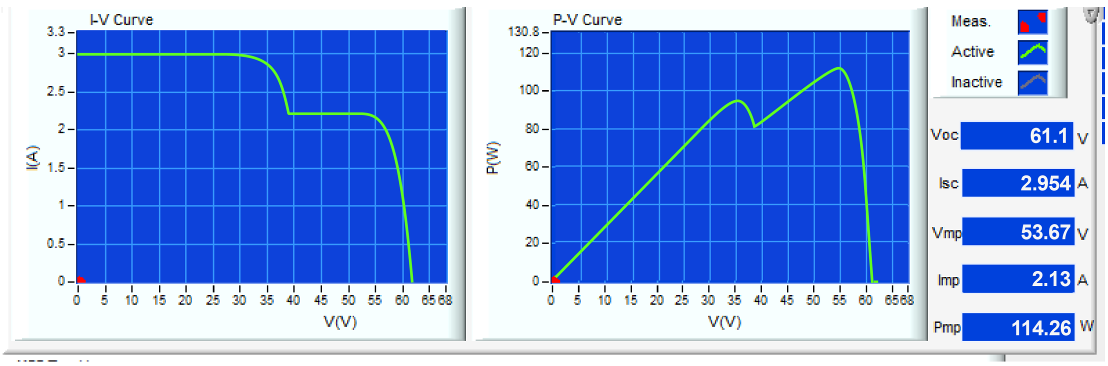


Figure 5.16: Pattern 2 at Emulator

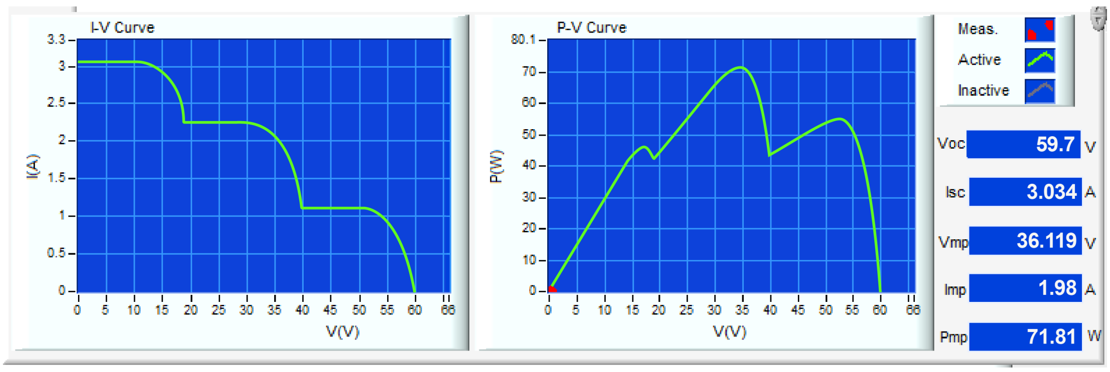


Figure 5.17: Pattern 3 at Emulator

With the new curves of all shading patterns detailed by the emulator, the PV array

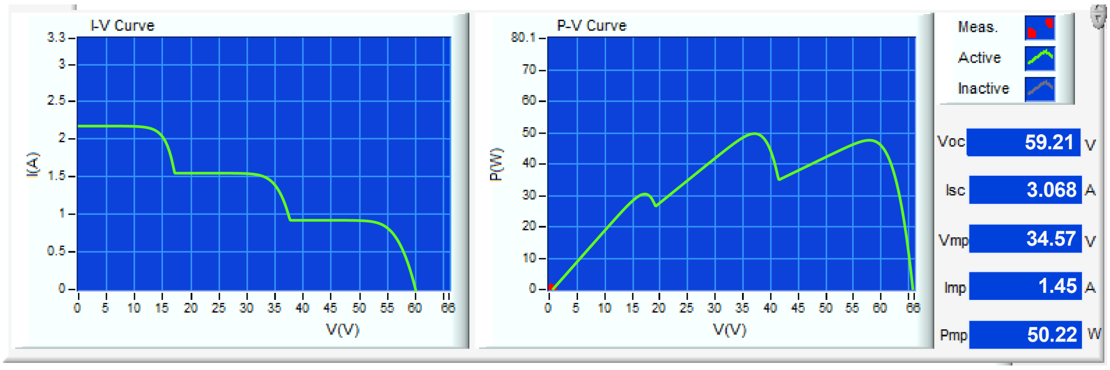


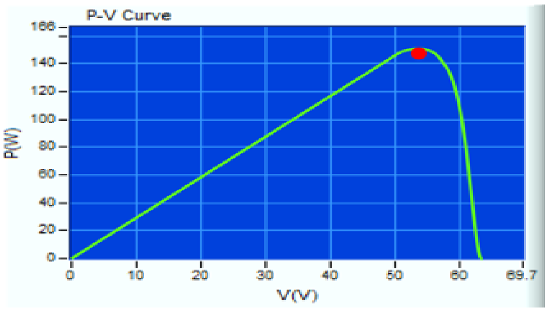
Figure 5.18: Pattern 4 at Emulator

performances under the emulator setup are presented with minimal differences. The Table 5.6 details four pattern cases and their respective power, P_{mpp} on the curve from the Chroma PV emulator. The performance values of these patterns under the experimental setup must be obtained in the results section due to the numerous uncertainties in inaccuracies through tolerance across each possible component which include diode, MOSFET, resistor and the voltage/current sensors. The exact value of the P_{input} are to be presented in the results and discussion upon testing the GMPPT algorithms.

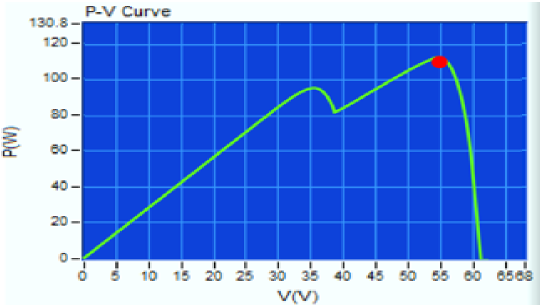
Table 5.6: Patterns for NSC, PSC1, PSC2 and PSC3 cases in PV Emulator

Pattern & Peaks	Panel	Irradiance(W/m^2)	$P_{mpp}(W)$	$V_{mpp}(V)$	$I_{mpp}(A)$
1	PV1 PV2 PV3	1000 1000 1000	148.73	54.04	2.75
2	PV1 PV2 PV3	1000 1000 700	114.26	53.67	2.13
3	PV1 PV2 PV3	1000 700 300	71.81	36.19	1.98
4	PV1 PV2 PV3	500 700 300	50.22	34.57	1.45

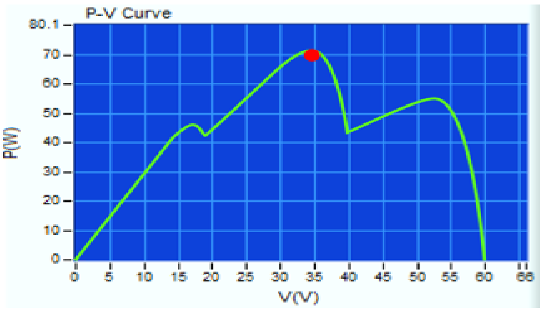
Within the experimental setup, the tracked GMPP on the proposed P-V curves to be tested are observed from the software of the Chroma PV Emulator in the following Fig. 5.20. The main objective of all the GMPPT algorithms are to reach this point and achieve the highest conversion efficiency.



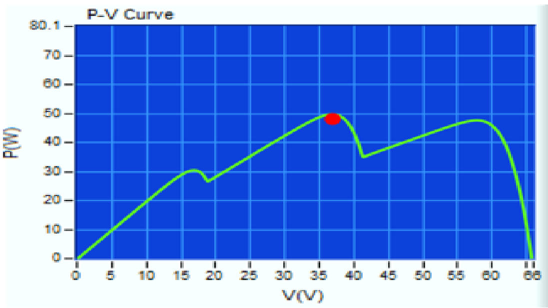
(a) Pattern 1 Tracked GMPP)



(b) Pattern 2 Tracked GMPP



(c) Pattern 3 Tracked GMPP



(d) Pattern 4 Tracked GMPP

Figure 5.20: Tracked GMPP under the Chroma Emulator

5.5 Chapter Summary

In this Chapter, the work conducted has contributed to the objectives of the research project. To validate the performance of GMPPT algorithms involved in this work, the design, the methodology and setup of both simulation and experimental setups were first required. The designed simulation setup within MATLAB/Simulink simulation software environment has been successfully made in Section5.1 with detail regarding the parameter specifications summarized in Section 5.2. Moreover, the shading patterns in the simulation setup, shading patterns for the expanded simulation and for the rest of the proposed research were disclosed for use in the experimental setup as well.

Next, the experimental setup has been detailed and given considerations to the conversion between simulation and experimental conditions. First, the dSPACE RTI unit has had substantial exposition regarding its usage and the placement as the controller unit in the entire PV system in 5.3. The considerations in aspects of settling time, optocoupler and the voltage offset from the experimental setup are also described.

Finally, the parameter specifications as shown in the earlier simulation setup are also conducted for the experimental setup in 5.4. The difference between the setups are the specifications regarding each boost converter component model selected. The utilization of these models have been selected and summarized in terms of the original converter specifications required from Table 5.2. Each component has been successfully constructed into the conventional boost converter for the experimental setup.

The simulation and experimental setups are the required applications of methodology to simulate then verify the PV system under NSC, PSC1, PSC2 and PSC3 cases with GMPPT algorithm control. The simulation setup in particular applies the PSC4 and PSC5 in the setup additionally. This Chapter has successfully complemented the literature review in Chapter 3 where the selection of simulation tool to verify GMPPT and PV system was made, while the experimental devices are presented in their feasibility to provide the research data required to validate GMPPT algorithm performances.

In the next chapter, the performance comparisons of all algorithms with no shading and partial shading patterns are to be made. The verification of all methodology and results are also obtained in the simulation and experimental testing based on the discussion that will be made.

Chapter 6

Results and Discussion

The PV system application is created from the results of the methodology. Hence, the results of implemented GMPPT algorithms are obtained in this Chapter using the simulation and experimental setups. A discussion regarding each result and observations on the wave-forms provided through compiling, testing and analyzing the behavior of the effects of the GMPPT operators, equations and strategies is conducted.

In the Section 6.1, the degree of performance validation needed to prove the proposed GMPPT algorithm implemented in the application is described. Certain test conditions are applied in order to assume the performance of all given algorithms. Moreover, the parameter settings in the test are set according to the summary given.

The wave-forms and results discussion from the testing of all implemented GMPPT algorithms in the simulation implementation of the PV system application is obtained and labelled in Section 6.2.

In Section 6.3, the wave-forms and results discussion from the testing of all implemented GMPPT algorithms in the proposed experimental implementation of the PV system application are obtained and labelled.

The case study and discussion is made in Section 6.4, the discussion are made based on the obtained wave-forms and observing the patterns while deriving expected results from them. The discussion is made upon all implemented GMPPT algorithms and contrast is made based on each algorithm's performances. The tracking of the GMPP is explained in terms of accuracy and convergence speed; then, the speed of the convergence is through the different operators. The power threshold is finally used as a method to control convergence and discussed. Through the discussion, future considerations and improvements of a GMPPT algorithm can be known and expanded upon in the next chapter.

The proposed PS-FW GMPPT algorithm performance will be described in summary in its capabilities for the PV system application under PSC within Section 6.5. The summary itself compiles the discussion in order to prove the PS-FW GMPPT algorithm as a viable alternative and improvement to the other implemented GMPPT algorithms.

6.1 Simulation Validation

In this section, the simulation performance will test the validity of the implemented GMPPT algorithms. The culmination of all involved components has been calculated in value and expected to function as a whole PV system that is able to emulate and produce required results. The PV system in the simulation setup is reliant on the methodology proven using PV panel with the accurate P-V/I-V curves under any proposed PV patterns containing NSC or PSC, boost converter that is able to switch properly, accurate voltage and current sensors at the input side of the converter and finally a controller that can track the GMPP by implementing GMPPT algorithm.

In this proposed research, the chosen GMPPT algorithms to compare the algorithm performance must be relevant to the context. With the use of hybridization, PS-FW is composed from the operators, strategies and techniques introduced from PSO and FWA algorithms. Thus, the two algorithms are required to be introduced to the PV system and applied with testing validation to also prove the proposed GMPPT algorithm in sections of the performance criteria. The algorithms chosen must be able to contrast and provide information from the improvement of the proposed PS-FW GMPPT algorithm. The algorithms performance validation thus consist of singular PSO algorithm and FWA, which are the counterparts of the proposed PS-FW hybrid algorithm. Moreover, another hybrid algorithm, DE-PSO optimization algorithm by [93] is implemented to provide contrast between our proposed hybrid and one established in the literature.

The conventional MPPT methods such as P&O or Hill Climbing, are relatively weak in global search functionality and do not perform well in PV systems that face any PSC. The explanation of the P&O algorithm's real life performance in GMPPT has already been presented in the literature review of Chapter 3. P&O works like a form of hill-climbing on the P-V curve, its framework and search behavior will stop perturbing itself once the previous obtained MPP is better than the new MPP. Thus, P&O will be invalidated from testing as it will fail to track GMPP if the slope on the P-V curve is not the first one.

Out of the factors that relate to the performance of GMPPT algorithms described and proven in the literature review and summarized in Chapter 3.6, the research project introduces operators, shading peaks, tracking speed and the efficiency of the power conversion to determine the simulation and experimental results. These criteria will pronounce and describe the performance of the GMPPT algorithm implementation. In the proposed research, these criteria will be proven from the implemented GMPPT algorithms in the simulation and experimental setup. Moreover, the criteria will be appended with the guarantee of pseudo-random number generation for the initialization of starting population. Another criterion introduced will be the threshold of power as a convergence criterion; which are undisclosed or unpopular as a subject of review or performance criteria when evaluating algorithms from the given literature review conducted, both the new criteria will be implemented to test performance results of the GMPPT implementations.

6.1.1 Seed and Algorithm Parameter Setting

MATLAB or Simulink in particular handle the aspect of RNG manipulation. Within the MATLAB function block, the function ”rng(seed)” dictates the seed for the MATLAB random number generator. Given a seed value of 5, utilizng the function ”rng(5)” initializes the Mersenne Twister generator using a seed of 5. This ’rng’ function allows control of the global stream which determines the sequence of random numbers generated from functions such as ”rand”, ”randi”, ”randn”. The function is particularly most useful in guaranteeing the generation of initial starting population within both simulation and experimental setups as they both implement and house the GMPPT algorithm through MATLAB. Moreover, setting a random seed for algorithm operators with the same initial population would allow us to contrast the performance of new operators brought in through hybridization through shared operators between PS-FW, DE-PSO, PSO and FWA. Through this contrast, evaluation of performance is more viable as a measure and the research results are further enriched from understanding the improvements brought about from implementation of various operators. All seeds provided in the initial population do not generate a GMPP. Table 6.1 denotes how the settings are set for this simulation test.

Table 6.1: Same seed value test parameters.

Seed Values	PS-FW	DE-PSO	PSO	FWA
Initialization	18	18	18	18
Velocity Operator	Randomized	Randomize	Randomized	N/A
Fireworks Operator	Randomized	N/A	N/A	Randomized
Selection Operator	Randomized	N/A	N/A	Randomized

For PSO, the algorithm is used as is from the Chapter 3 discussion, the operators derived from there are from the canonical implementation of current algorithms, its implementation is commonly shared among all currently implemented GMPPT applications. The parameters for the PSO are maximum inertia parameter w_{max}, minimum inertia parameter w_{min}, velocity modification parameter c_1 and c_2.

The parameters for the FWA are maximum amplitude modifier A, maximum sparks count m, maximum mutation sparks Num_M, zero-error division parameter ϵ, spark number calculation modifier r, maximum spark count comparison modifiers a and b.

One consideration for the FWA is that GMPPT implementations of the algorithm are not widespread or heavily reviewed in literature. The operators in GMPPT implementations for canonical FWA retain the same operator equations from the canonical version. However, the selection operator is highly contested for specific reasoning of how the implementation is conducted. A general behavior adopted by authors are that uniform randomly chosen fireworks in the population would be brought over into the next iteration. This is implemented into the FWA operator as a random selection of fireworks to be brought over to the next generation.

Within the DE-PSO algorithm, PSO side parameters will be c_1, c_2, w_{max} and w_{min}. The DE side parameters implemented are crossover rate CR, scaling factor K and combination factor F. This research project the same value of PSO parameters from above, while the value of crossover rate, scaling and combination factors are adopted from the implementation in literature.

In PS-FW hybrid algorithm, the implemented operators adopt all previous parameters from the two singular GMPPT algorithms. The additions introduced via the abandonment strategy introduced 2 more parameters that control the amount maximum and minimum number of particles/fireworks dropped; which are the abandonment control parameters, F_{max},F_{min}. Otherwise, the parameter values are equal to the previous two algorithms.

The parameter value of all involved algorithms is stated in the Table 6.2. The parameters of the singular algorithms will be shared into the hybrid PS-FW algorithm, PSO and FWA parameters are adopted by the PS-FW algorithm. Thus, the behavior of the operators can be explained easily and the performance of each operator is presented within each GMPPT used. More importantly, the contrast of each singular counterpart can be made. However, in the case of PSO, larger iteration count t_{max} was provided as the PSO algorithm could not converge to the candidate GMPP in allocated time frame, thus the reasoning for the increased iteration limit.

Since the algorithm parameters are shared, there is an assumption of performance being equal across the board. However, explanation regarding the performance of the algorithm under the same parameters is reasoned with in the discussion at the experimental results section in this chapter.

Table 6.2: Parameter Usage in all GMPPT algorithms

Algorithm	Parameter Values
PS-FW	$w_{max} = 0.95$, $w_{min} = 0.45$, $c_1 = 1.45$, $c_2 = 1.45$, $A = 0.5$ m=4, $Num_m = 4$, $\epsilon = 1e^{-100}$, $F_{max} = 4$, F_{min} =2 , $r = 2$, $a = 0.04$, $b = 0.9$, n=8, t_{max}=4
PSO	$w_{max} = 0.95$, $w_{min} = 0.45$, $c_1 = 1.45$, $c_2 = 1.45$ $t_{max} = 10$, $n = 8$
FWA	$A = 0.5$, m=4, $Num_m = 4$, $\epsilon = 1e^{-100}$, $r = 2$ $a = 0.04$, $b = 0.9$, $t_{max} = 4$, $n = 8$
DE-PSO	$w_{max} = 0.95$, $w_{min} = 0.45$, $c_1 = 1.45$, $c_2 = 1.45$ $F = 0.7$,$CR = 0.8$, $K = 0.5$

The performance criteria of respective GMPPT implements that have already described in Chapter 3 are utilized as performance validation measurements of the implemented GMPPT algorithms in this research project. Also, the convergence criteria of the PSO, FWA, DE-PSO and PS-FW algorithms maintain that the population converges to the optimal solution rather than ending the algorithm upon obtaining MPP. This factor is supplemented by explanations in the literature review, a convergence of all N individuals should prove that the algorithm has finished searching.

The difference of power threshold as a convergence criterion is the strategy of a

MPPT algorithm using the difference of measured fitness value power, P_{pv} of the entire population to control the ending of the GMPPT search process. This threshold, when surpassed, will denote the state of convergence for a population as the process has successfully searched and converged into one MPP. This was disclosed more in Chapter 2, where the value of this threshold was not proven or given and at times the algorithms are stated only upon convergence of the entire population. The statement is unacceptable as a large threshold can easily cause the system to believe it has converged and a small threshold can cause further meaningless searches. Given that this threshold value is seldom modified as a way to control when the algorithm ends, the experimental testing phase of this research proposes an argument that the threshold value is to be analyzed to determine that the threshold is set properly while maintaining balanced exploration and exploitation characteristics of any GMPPT algorithm. The threshold ultimately also balances the time local search consumes.

Moreover, the research project proposes that validation of results are taken one step further with the including of pseudo-random number generation manipulation to guarantee initial population solution duty cycles and also any relevant functions that call for random number generation. Hopefully the effects of implemented techniques can be isolated from the chances that lucky scenarios occurred in favor of any of the GMPPT algorithms, which include the proposed PS-FW algorithm. Furthermore, the analysis of all parameters and in particular the P threshold is proposed that can potentially alter the algorithm search behavior time and accuracy. Through obtaining all these results, the PV system methodology can be proven to be implemented correctly. The implementation of the threshold criteria and random seed test are conducted in experimental methodology as the results will be proven further than in the simulation tests.

6.2 Simulation Performance

The simulation performance of chosen GMPPT and under the implementation of the PV system is conducted and compared. As mentioned beforehand, the system is implemented with use of the calculated values in 4.1. Thus, the converter uses values for the components as shown in 5.2. All GMPPT algorithms are tested with 1 no shading and 3 different shading patterns, the produced results describe the performance of the PSO, FWA, DE-PSO and PS-FW algorithms for use in GMPPT under PSC. The peaks range of difficulty begin with 1 power point peak as the easiest and 3 power point peaks as the hardest, the results observed are based off this fact. Further validation of the simulation performance is provided through 2 more shading patterns, which will be expanded in the next subsection.

Within MATLAB/Simulink simulation environment, a scope block has provided the performance results in terms of power, voltage, current and the applied duty cycles at sampling times. All the values have been recorded and accumulated into suitable format for accessibility.

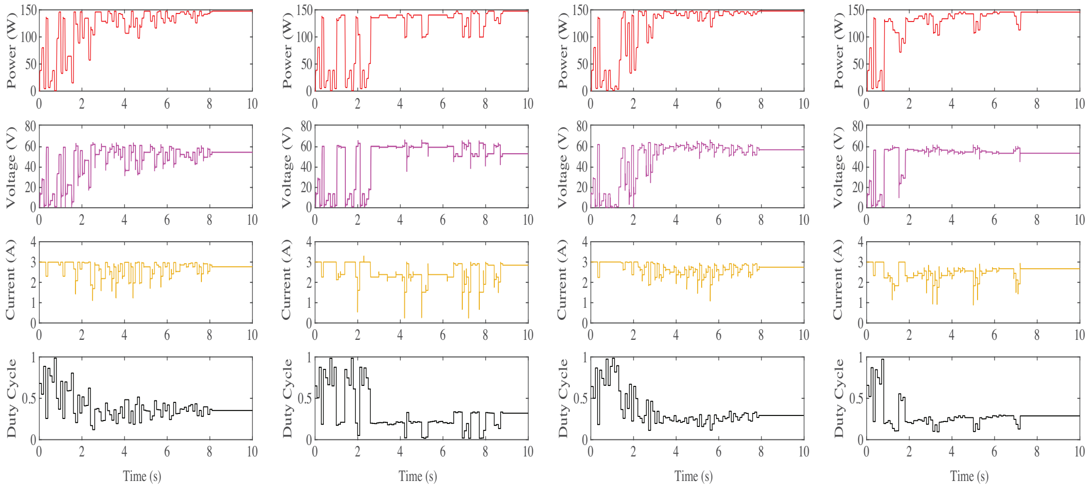
In literature review, the results are defined from tracking speed and accuracy. Typically, the GMPPT efficiency is defined as the difference of the power obtained from the defined P-V curve and the power sensed from sensors attached at the start of the boost converter configuration, which essentially detects the PV array's voltage and current and derive the PV power, P_{pv}. Thus, three power values are taken into account when measuring the converted power efficiency, which are maximum power obtained from the PV panels as seen in the curves, P_{mpp}, the maximum power obtained or sensed at the input side of the boost converter, P_{pv}, and, the maximum power obtained at the load, P_{load}. When evaluating the power of the P_{pv} against the P_{mpp} from the curve, the η_{gmpp}, GMPPT efficiency can be calculated by using [129]

$$\eta_{gmpp} = \frac{\int_0^t P_{(pv)t} dt}{\int_0^t P_{(mpp)t} dt}. \tag{6.1}$$

The total conversion efficiency is derived from percentage difference of the P_{load} against the P_{mpp}, providing η_{load}, the system's conversion efficiency when under GMPP which can be calculated using [129]

$$\eta_{load} = \frac{\int_0^t P_{(load)t} dt}{\int_0^t P_{(mpp)t} dt}. \tag{6.2}$$

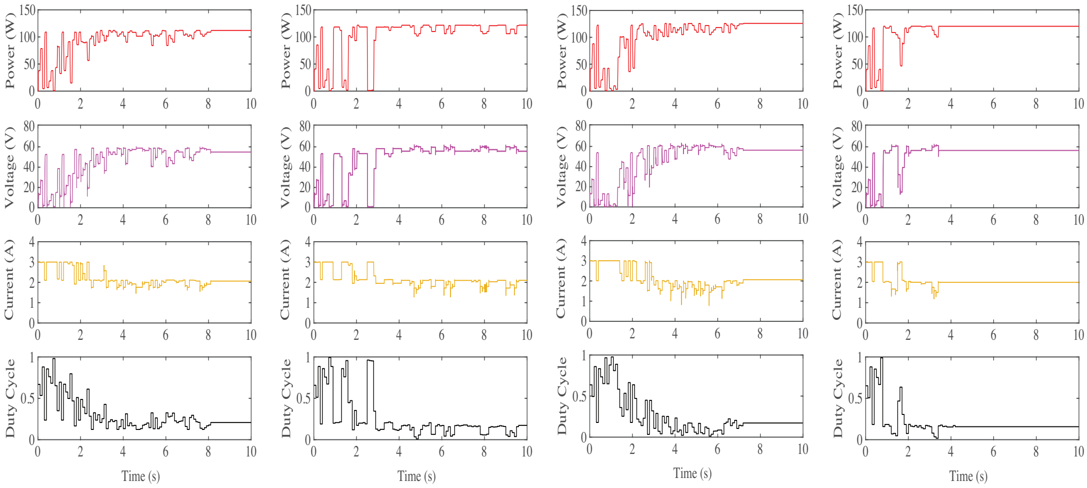
A compilation of the performance of the different algorithms under Pattern 1 to Pattern 4 non-shading and shading case patterns is presented in Fig. 6.1, Fig. 6.2, Fig. 6.3 and Fig. 6.4.



(a) PSO Pattern 1 **(b)** FWA Pattern 1 **(c)** DE-PSO Pattern 1 **(d)** PS-FW Pattern 1

Figure 6.1: Simulated Pattern 1 results.

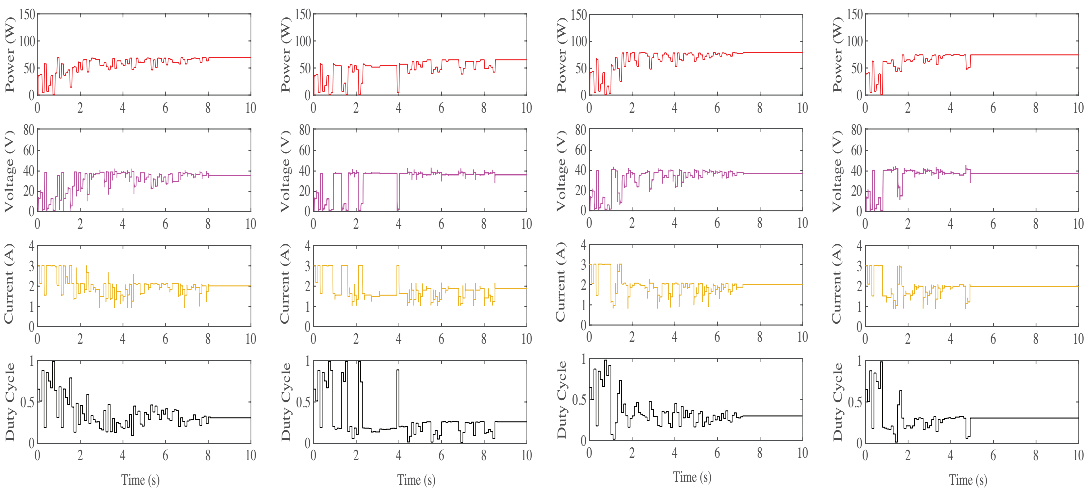
The GMPPT algorithms performances under the Pattern 1 non-shading case can be observed in the Fig. 6.1. The PSO algorithm obtains the GMPP at 8.1 seconds with an efficiency of 100%. The FWA obtains the GMPP at 8.9 seconds with an efficiency of 99.06%. The DE-PSO algorithm obtains the GMPP at 7.9 seconds with an efficiency of 100%. The PS-FW algorithm obtains the GMPP at 7.3 seconds with an efficiency of 100%.



(a) PSO Pattern 2 **(b)** FWA Pattern 2 **(c)** DE-PSO Pattern 2 **(d)** PS-FW Pattern 2

Figure 6.2: Simulated Pattern 2 results.

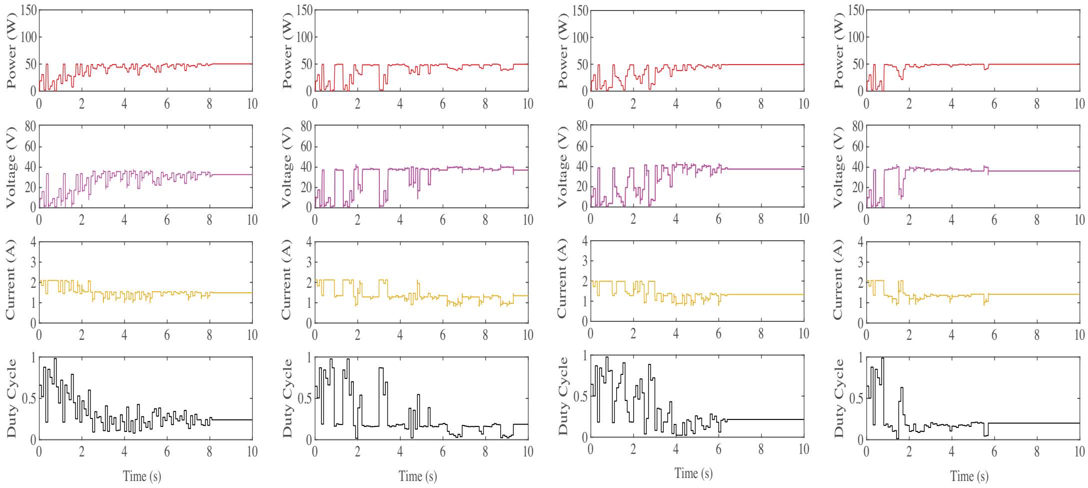
The GMPPT algorithms performances under the Pattern 2 shading case 1 can be observed in the Fig. 6.2. The PSO algorithm obtains the GMPP at 8.1 seconds with an efficiency of 100%. The FWA obtains the GMPP at 9.6 seconds with an efficiency of 100%. The DE-PSO algorithm obtains the GMPP at 7.2 seconds with an efficiency of 100%. The PS-FW algorithm obtains the GMPP at 4.2 seconds with an efficiency of 100%.



(a) PSO Pattern 3 **(b)** FWA Pattern 3 **(c)** DE-PSO Pattern 3 **(d)** PS-FW Pattern 3

Figure 6.3: Simulated Pattern 3 results.

The GMPPT algorithms performances under the Pattern 3 shading case 2 are observed in the Fig. 6.3. The PSO algorithm obtains the GMPP at 8.1 seconds with an efficiency of 100%. The FWA obtains the GMPP at 8.5 seconds with an efficiency of 100%. The DE-PSO algorithm obtains the GMPP at 7.1 seconds with an efficiency of 100%. The PS-FW algorithm obtains the GMPP at 4.9 seconds with an efficiency of 100%.



(a) PSO Pattern 4 **(b)** FWA Pattern 4 **(c)** DE-PSO Pattern 4 **(d)** PS-FW Pattern 4

Figure 6.4: Simulated Pattern 4 results.

The GMPPT algorithms performances under the Pattern 4 shading case 3 are observed in the Fig. 6.4. The PSO algorithm obtains the GMPP at 8.1 seconds with an efficiency of 100%. The FWA obtains the GMPP at 9.3 seconds with an efficiency of 99.48%. The DE-PSO algorithm obtains the GMPP at 6.3 seconds with an efficiency of 100%. The PS-FW algorithm obtains the GMPP at 5.7 seconds with an efficiency of 100%.

The tracking speed, PV power output, efficiency is obtained from the simulations and compared. A compilation of the performance of the different algorithms under Pattern 1 to Pattern 4 non-shading and shading case is presented in Fig. 6.1, Fig. 6.2, Fig. 6.4 and Fig. 6.3. The simulation results are extracted and presented in the Table 6.3. They are separated by all applied GMPPT algorithms in the test. The algorithms begin from the left with PSO algorithm, to FWA, to DE-PSO and end at the right with PS-FW algorithm.

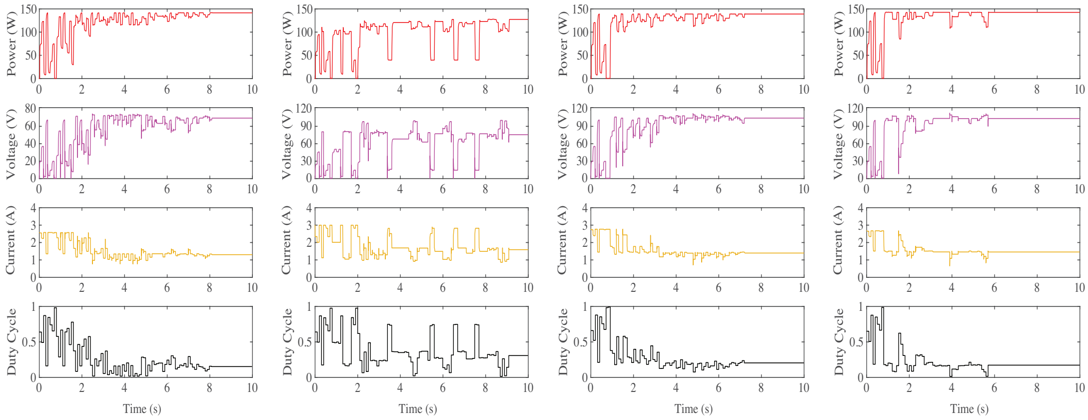
Table 6.3: Simulated Performance of GMPPT algorithms.

Pattern	Algorithm	P_{mpp} (W)	P_{pv} (W)	P_{load} (W)	Tracking Speed (s)	MPPT Efficiency (%)	Converter Efficiency (%)
1	PSO	149.4012	149.4012	145.1084	8.1	100.00	97.12
	FWA	149.4012	148.0025	143.6075	8.9	99.06	96.12
	DE-PSO	149.4012	149.4012	145.1084	7.9	100.00	97.12
	PS-FW	149.4012	149.4012	145.1084	7.3	100.00	97.12
2	PSO	114.9045	114.9045	112.0012	8.1	100.00	97.47
	FWA	114.9045	114.9045	112.0012	9.6	100.00	97.47
	DE-PSO	114.9045	114.9045	112.0012	7.2	100.00	97.47
	PS-FW	114.9045	114.9045	112.0012	4.2	100.00	97.47
3	PSO	72.4427	72.4427	69.6887	8.1	100.00	96.19
	FWA	72.4427	72.4427	69.6887	8.5	100.00	96.19
	DE-PSO	72.4427	72.4427	69.6887	7.1	100.00	96.19
	PS-FW	72.4427	72.4427	69.6887	4.9	100.00	96.19
4	PSO	50.4533	50.4533	48.7954	8.1	100.00	96.71
	FWA	50.4533	50.1912	48.6031	9.3	99.48	96.33
	DE-PSO	50.4533	50.4533	48.7954	6.3	100.00	96.71
	PS-FW	50.4533	50.4533	48.7931	5.7	100.00	96.71

It can be inferred that PS-FW algorithm easily converges and tracks the GMPPT fastest among the four tested algorithms and under Pattern 1 to Pattern 4. In particular, the PS-FW algorithm ranges from a minimum of 7.59% to a maximum of 56.25% faster than the PSO, FWA and DE-PSO algorithms to converge to the GMPP in Pattern 1 to Pattern 4 patterns. It is also noticed that the PSO, DE-PSO and PS-FW algorithms have accurately tracked the GMPP in Pattern 1 to Pattern 4 while the FWA algorithm loses out in exploitation in Pattern 1 and Pattern 4.

6.2.1 Expanded Validation Performance

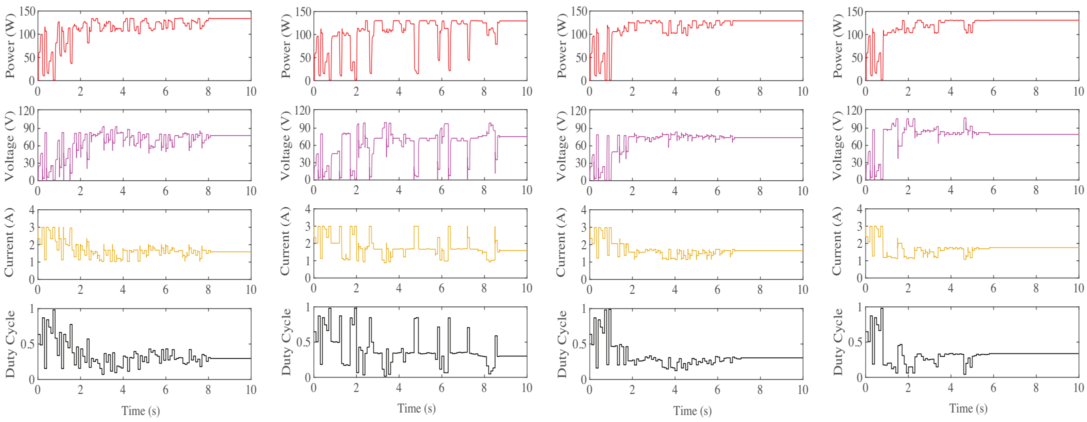
The expanded simulation performance of the PSO, FWA, DE-PSO and PS-FW algorithms under the shading Pattern 5 and Pattern 6 are presented in Fig. 6.5 and Fig. 6.6.



(a) PSO Pattern 5 **(b)** FWA Pattern 5 **(c)** DE-PSO Pattern 5 **(d)** PS-FW Pattern 5

Figure 6.5: Simulated Pattern 5 results.

The GMPPT algorithms performances under the Pattern 5 shading case 4 are observed in the Fig. 6.5. The PSO algorithm obtains the GMPP at 8.1 seconds with an efficiency of 100%. The FWA obtains the GMPP at 8.9 seconds with an efficiency of 91.96%. The DE-PSO algorithm obtains the GMPP at 7.3 seconds with an efficiency of 100%. The PS-FW algorithm obtains the GMPP at 5.7 seconds with an efficiency of 100%.



(a) PSO Pattern 6 **(b)** FWA Pattern 6 **(c)** DE-PSO Pattern 6 **(d)** PS-FW Pattern 6

Figure 6.6: Simulated Pattern 6 results.

The GMPPT algorithms performances under the Pattern 6 shading case 5 are shown in the Fig. 6.6. The PSO algorithm obtains the GMPP at 8.1 seconds with an efficiency of 100%. The FWA obtains the GMPP at 8.6 seconds with an efficiency of 100%. The DE-PSO algorithm obtains the GMPP at 7.1 seconds with an efficiency of 100%. The PS-FW algorithm obtains the GMPP at 5.9 seconds with an efficiency of 100%.

The tracking speed, PV power output, efficiency is obtained from the expanded simulations and compared. A compilation of the performance of the different algorithms under the Pattern 5 and Pattern 6 shading case is presented in Fig. 6.5 and Fig. 6.6. The simulation results are extracted and presented in the Table 6.4.

Table 6.4: Expanded Simulated Performance of GMPPT algorithms.

Pattern	Algorithm	P_{mpp} (W)	P_{pv} (W)	P_{load} (W)	Tracking Speed (s)	MPPT Efficiency (%)	Converter Efficiency (%)
5	PSO	138.6943	138.6943	133.6917	8.1	100.00	96.39
	FWA	138.6943	127.5411	122.5451	8.9	91.96	88.35
	DE-PSO	138.6943	138.6943	133.6917	7.3	100.00	96.39
	PS-FW	138.6943	138.6943	133.6917	5.7	100.00	96.39
6	PSO	128.3374	128.3374	121.8325	8.1	100.00	94.93
	FWA	128.3374	128.3374	121.8325	8.6	100.00	94.93
	DE-PSO	128.3374	128.3374	121.8325	7.1	100.00	94.93
	PS-FW	128.3374	128.3374	121.8325	5.9	100.00	94.93

It can be inferred that PS-FW algorithm easily converges and tracks the GMPPT fastest among the four tested algorithms under Pattern 5 and Pattern 6 shading cases. In particular, the PS-FW algorithm ranges from a minimum of 16.90% to a maximum of 35.96% faster than the PSO, FWA and DE-PSO algorithms to converge to the GMPP in Pattern 5 and Pattern 6 shading cases. It is also noticed that the PSO, DE-PSO and PS-FW algorithms have accurately tracked the GMPP in Pattern 5 and Pattern 6 while the FWA algorithm loses out in exploitation in Pattern 5.

Based on initial and expanded simulation results, the advantage of PS-FW algorithm can be seen where the solutions will converge at maximum point with fast speeds and great accuracy compared to the slow convergence of PSO. The duty cycle as seen in the wave-form describes the abandonment and supplement strategy of PS-FW algorithm. Particles in the initial population which did not provide a good power output were subsequently removed and explosion sparks generated are only from the surviving population. The duty cycles in later iterations were not from the initial population as observed from the lack of any searches conducted there, the supplement strategy successfully selects good particles for the next iteration. Meanwhile, the PSO convergence presents its weakness of slow convergence through the long search required to converge its population. The curve of the wave-form for duty cycle slowly flattens itself proving its slow convergence speeds. However, the extensive search of the duty cycles proves the good exploration capabilities of PSO as the entire search area is found.

FWA adopts the same behavior of PS-FW in local convergence capabilities through the explosion spark generation; however, the selection strategy implemented is not suitable and the chance of explosion for good fireworks is less. The abandonment strategy is not used; thus, the initial weakness of bad exploration is not supplemented. The local search capabilities, however, are prevalent in the sparks generation as the explosions are made at good fireworks; duty cycles that provide greater power have slight changes in their values to search for better MPP around its area with the use of amplitude operator. The waveform of duty cycle in FWA results describe the bad selection strategy where even weaker fireworks were able to explode, the curve is irregular which signifies the explosions of varying duty cycles. Convergence of the duty cycles in the waveform is shown to be slow due to the prevalent weaker explosion sparks being able to join the population from a lack of good selection scheme.

The DE-PSO algorithm performance validates its capability in achieving faster tracking speed through the hybridization of PSO and DE algorithm. Moreover, it is able to achieve the speeds while tracking the GMPP. The DE side of the hybrid algorithm in retaining particles every iteration that do not achieve greater results and only replacing particles with better obtained power benefits the convergence speed of the overall algorithm. In the results, it is shown that the convergence speed of DE-PSO is faster than PSO and FWA. However, the weakness of slow convergence from the PSO aspect is still prevalent as the population fails to converge in time compared to PS-FW algorithm. Still, the benefits of DE-PSO is able circumvent the convergence weakness slightly. .

As the PS-FW algorithm has an aggressive abandonment and selection strategy, the population maintains healthy individual solutions that can be exploited further in the next iteration and can obtain the state of convergence in the population fast and easily. In PS-FW, the waveform of the duty cycle curve proves that the convergence is faster to obtain than the PSO, FWA and DE-PSO convergence speeds.

The initial population size, the number of particles to be dropped, and the number of sparks that a particle may produce are important to determine the optimal solution. A large initial population size is required to find a good potential solution and start the exploitation process from there. In this application, the PV system employs 8 particles as the population which allows ample chances of a potential solution. If the initial population size is small, the convergence time will be faster as there are less particles to explode sparks from, but the solution may not be accurate and diverge further from the GMPP. Given that many particles will be abandoned after the initial fitness evaluation; the adaptive spark number operator ensures that each particle can have at least one spark and as such the chances of trapping into a local search region will be decreased as every one of the particles can explode at least once. Further on, the chances to explode are relegated only to the current most optimal solution, the tracking speed for the MPP is greatly increased; however, there is a greater risk of falling into local search region as there is less searching in the process. In contrast, the mutation operator and velocity operator after the explosion spark generation step will focus on global search.

For the application of this PS-FW algorithm, a PV system which requires the tracking of GMPP to be as fast and accurate as possible, the algorithm will be limited in steps or amount of iteration cycles given to extract the GMPP. The speed of the PS-FW thus proves to be faster than PSO and FWA, with equal or better accuracy in GMPPT performance from the power obtained.

At the crux of it, the algorithms must therefore be tested in a real-life setup to ensure that its behavior and waveform curves can be replicated as the simulation results have shown. From the simulation results, it can be inferred that PS-FW can be used as an alternative to conventional GMPPT algorithms in PSC due to the results and discussion made above.

6.3 Experimental Validation

The simulation results have presented the feasibility of the proposed GMPPT hybrid algorithm with the PSC cases in terms of accuracy and speed. However, the proposed results must be validated under real experimental setup in order to prove the observations first, then discussion can be given to the proposed PS-FW algorithm, PSO and FWA. Within this section, the experimental results for the algorithms must be similar to the simulation or better than, in terms of speed, accuracy and with the behavior and waveform curves of the algorithm framework in its search patterns.

To this end, the specified conventional boost converter, its current transducers, Chroma PV emulator and the dSPACE RTI control unit are interlinked together to form the setup needed to test the various GMPPT algorithms in all shading patterns of PSC. Through utilization of the Chroma PV emulator, accurate shading cases can be also implemented much like the simulation environment of MATLAB/Simulink. The boost converter is implemented with the calculations of component values conducted at the Chapter 4. The dSPACE board houses all the GMPPT implementations. The board will also measure LV-25P and LA-25P current transducer values which are the voltage and current sensing components, they are connected through ADC channels available. The PWM channel on board of the dSPACE is able to output duty cycle at desired frequency settings. Thus, the board is able to measure all relevant information available that is needed for the input of a GMPPT algorithm and output of duty cycle.

Also, another test vector is introduced to prove the GMPPT algorithms by supplying a random seed of all involved function calls. The random seed is given to all experimental test cases, this means initial population will always be different and any random function call is not the same as another test case. The Table 6.5 denotes how the settings are set for the tests involving the GMPPT algorithms.

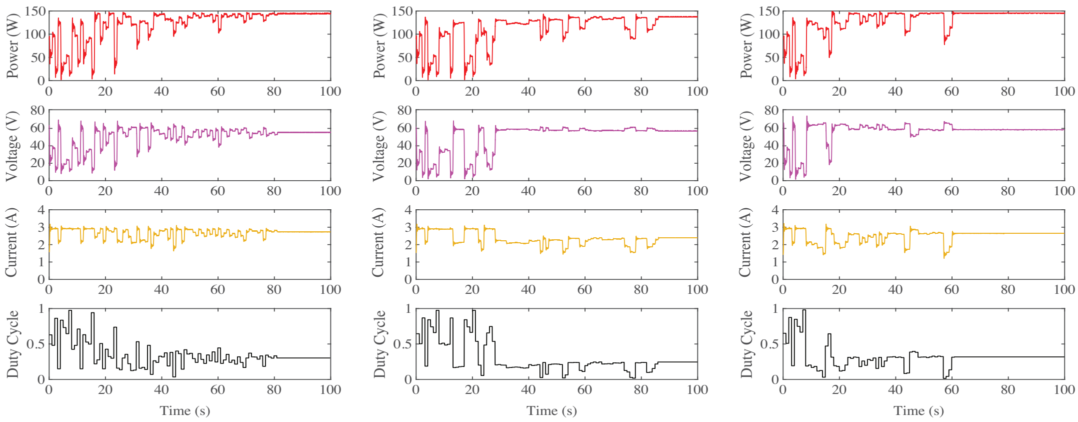
Table 6.5: Random seed value test parameters.

Seed Values	PS-FW	PSO	FWA
Initialization	Randomized	Randomized	Randomized
Velocity Operator	Randomized	Randomized	N/A
Fireworks Operator	Randomized	N/A	Randomized
Selection Operator	Randomized	N/A	Randomized

Thus, results are split into same seeded and random seeded test settings without change to other parameters. The next two subsections detail each setting and their results; which are observable in wave-forms much like the simulation results.

6.3.1 Same Seed Test

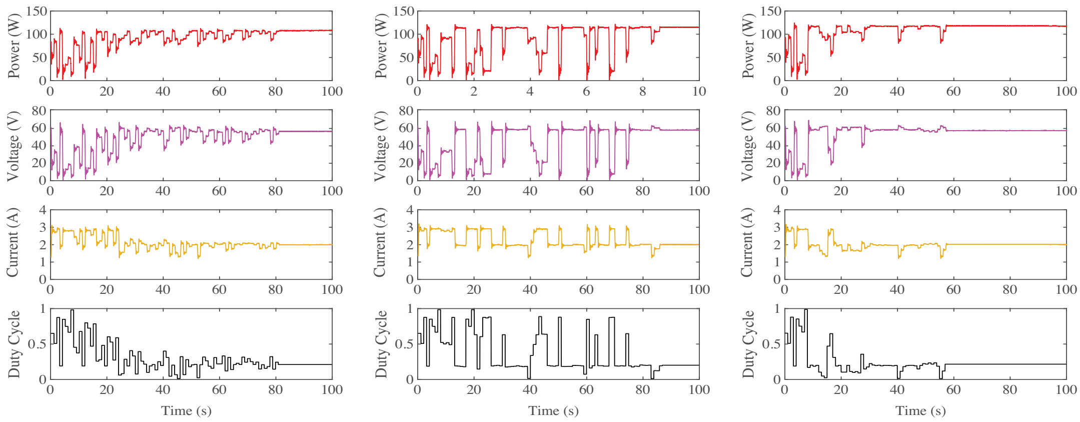
The following Figures and sub-figures describe the experimental results of proposed hybrid PS-FW algorithm, and implemented GMPPT algorithms; utilized to compare and discuss the GMPPT process. In Fig. 6.7, Fig. 6.8 and Fig. 6.9, the GMPPT algorithms in all patterns (NSC, PSC1, PSC2, PSC3) shading patterns are presented. The results are presented from PSO to FWA and finally into PS-FW algorithm. They are separated by the three applied GMPPT algorithms in the test. The algorithms begin from the left with PSO algorithm, to FWA and end at the right with PS-FW algorithm. The results are formed from the condition that all GMPPT algorithms retain the same seed in population initialization with random seed to the operators to observe the changes made to the initial population by each of the algorithms.



(a) PSO Pattern 1 **(b)** FWA Pattern 1 **(c)** PS-FW Pattern 1

Figure 6.7: Experimental seeded Pattern 1 results.

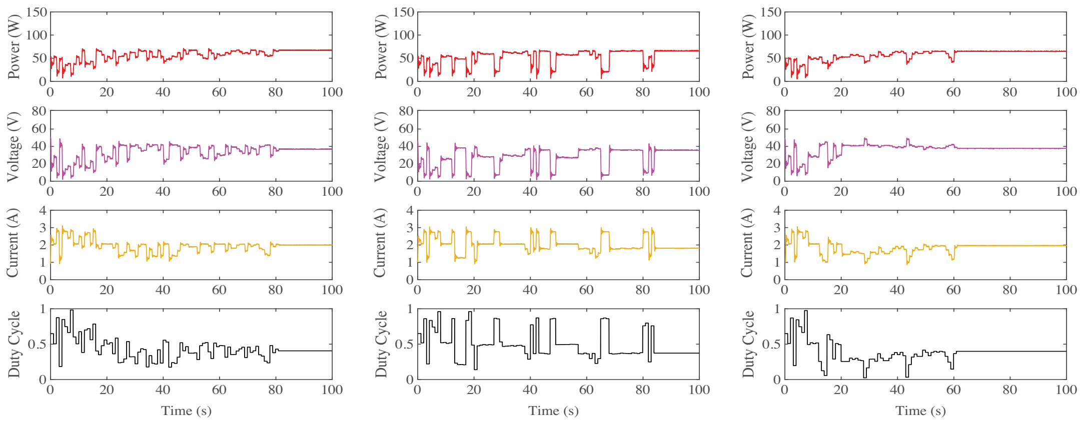
The GMPPT algorithms performances under the Pattern 1 shading case are shown in the Fig. 6.7. The PSO algorithm obtains the GMPP at 81 seconds with an accuracy of 99.12% efficiency. The FWA obtains the GMPP at 87 seconds with an accuracy of 92.92% efficiency. The PS-FW algorithm obtains the GMPP at 61 seconds with an accuracy of 99.19% efficiency.



(a) PSO Pattern 2 **(b)** FWA Pattern 2 **(c)** PS-FW Pattern 2

Figure 6.8: Experimental seeded Pattern 2 results.

The GMPPT algorithms performances under the Pattern 2 shading case 1 is shown in the Fig. 6.8. The PSO algorithm obtains the GMPP at 81 seconds with an accuracy of 99.39% efficiency. The FWA obtains the GMPP at 87 seconds with an accuracy of 99.27% efficiency. The PS-FW algorithm obtains the GMPP at 56 seconds with an accuracy of 99.43% efficiency.

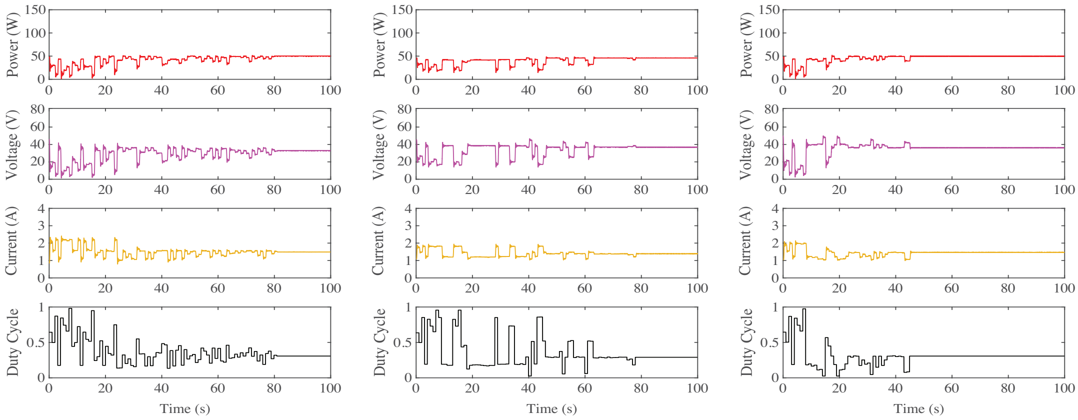


(a) PSO Pattern 3 **(b)** FWA Pattern 3 **(c)** PS-FW Pattern 3

Figure 6.9: Experimental seeded Pattern 3 results.

The GMPPT algorithms performances under the Pattern 3 shading case 2 is seen in the Fig. 6.9. The PSO algorithm obtains the GMPP at 81 seconds with an accuracy of 99.03% efficiency. The FWA obtains the GMPP at 84 seconds with an accuracy of

98.89% efficiency. The PS-FW algorithm obtains the GMPP at 61 seconds with an accuracy of 99.08% efficiency.



(a) PSO Pattern 4 **(b)** FWA Pattern 4 **(c)** PS-FW Pattern 4

Figure 6.10: Experimental seeded Pattern 4 results.

The GMPPT algorithms performances under the Pattern 4 shading case 3 can be observed in the Fig. 6.10. The PSO algorithm obtains the GMPP at 81 seconds with an accuracy of 98.24% efficiency. The FWA obtains the GMPP at 77 seconds with an accuracy of 96.23% efficiency. The PS-FW algorithm obtains the GMPP at 45 seconds with an accuracy of 98.39% efficiency.

In the respective set of results shown, PS-FW hybrid algorithm has successfully exceeded the performances of its singular counterparts in terms of speed and similar accuracy. It can be observed that PS-FW algorithm easily converges and tracks the GMPPT fastest among the three tested algorithms and under all shading patterns. In all patterns, the PS-FW algorithm successfully exceeds the singular counterparts in speed. Among the accuracy results compared, it is shown that the PSO, FWA and PS-FW algorithms have successfully tracked GMPP in all patterns except FWA that has lower accuracy in Pattern 1. In this test setting, the PSO and FWA algorithms are unable to converge in time before the iteration limit, the given threshold of 1W proves to be hard to fulfill for these two algorithms. However, the PS-FW algorithm is able to converge easily while tracking GMPP as observable in the faster speeds with varying range.

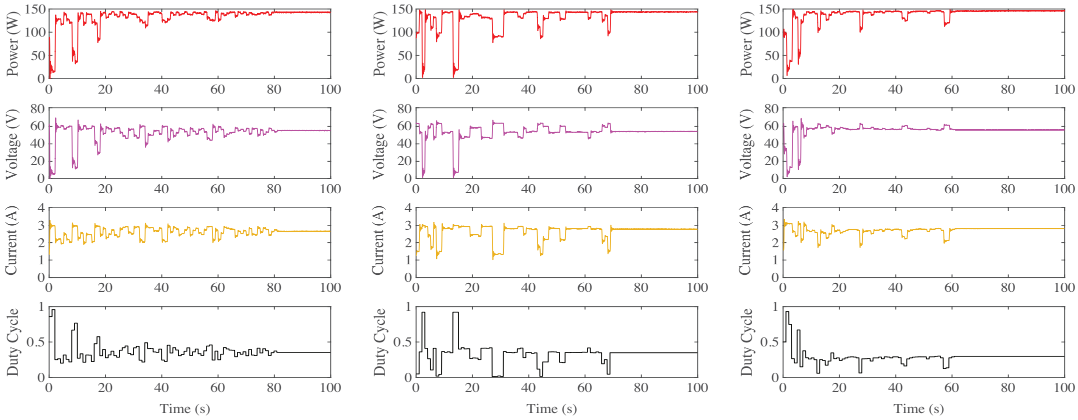
Table 6.6: Same seed experimental performance of GMPPT algorithms.

Pattern	Algorithm	P_{mpp} (W)	P_{pv} (W)	P_{load} (W)	Tracking Speed	MPPT Efficiency (%)	Converter Efficiency (%)
1	PSO	148.73	147.43	143.34	81.00	99.12	96.37
	FWA	148.73	138.21	134.11	87.00	92.92	90.17
	PS-FW	148.73	147.53	143.42	61.00	99.19	96.43
2	PSO	114.26	113.57	109.46	81.00	99.39	95.79
	FWA	114.26	113.43	109.35	87.00	99.27	95.70
	PS-FW	114.26	113.61	109.47	56.00	99.43	95.81
3	PSO	71.81	71.12	65.61	81.00	99.03	91.36
	FWA	71.81	70.99	65.54	84.00	98.89	91.26
	PS-FW	71.81	71.15	65.63	61.00	99.08	91.39
	PSO	50.22	49.34	45.21	81.00	98.24	90.02
4	FWA	50.22	48.33	44.16	77.00	96.23	87.93
	PS-FW	50.22	49.41	45.29	45.00	98.39	90.18

The results from the test are detailed in Table 6.6. The average MPPT efficiency is around 96.23% to 99.43%, while the converted power efficiency is given to range from 90.02% to 96.43%. Under all the patterns evaluated, the PS-FW algorithm achieves a minimum improvement of 24.69% to a maximum of 41.55% at converging tracking speed relative to PSO and FWA in all shading patterns. FWA also demonstrates inaccuracy in tracking as the power conversion from P_{pv} is worse than the PS-FW hybrid and PSO algorithms. The PSO and PS-FW GMPPT accuracy are in close proximity due to the great exploration from velocity operator, the values are similar and the mismatch could be caused by tolerance or inaccuracies in the experimental system. Thus, PS-FW provides faster tracking speed, better ability to converge, and better tracking accuracy in the same seed test settings.

6.3.2 Random Seed Test

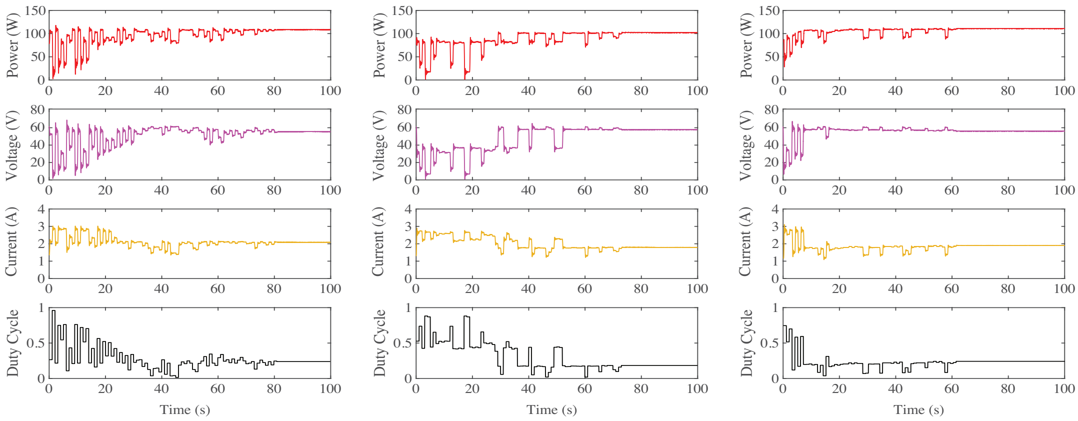
The following Figures and sub-figures describe the experimental results of proposed hybrid PS-FW algorithm and implemented GMPPT algorithms utilized to compare and discuss the GMPPT process. The experimental results of random seed initial population of the proposed hybrid PS-FW algorithm, and implemented GMPPT algorithms are shown in Fig. 6.11, Fig. 6.12, Fig. 6.13 and Fig. 6.14. The algorithms begin from the left with PSO algorithm, to FWA and end at the right with PS-FW algorithm. The results are formed from the condition that all GMPPT algorithms retain the random seed in population initialization and random seed to the operators to observe the changes made to the initial population by each of the algorithms.



(a) PSO Pattern 1 **(b)** FWA Pattern 1 **(c)** PS-FW Pattern 1

Figure 6.11: Experimental random seed Pattern 1 results.

The GMPPT algorithms performances under the Pattern 1 shading case is observed in the Fig. 6.11. The PSO algorithm obtains the GMPP at 81 seconds with an accuracy of 99.11% efficiency. The FWA obtains the GMPP at 69 seconds with an accuracy of 98.97% efficiency. The PS-FW algorithm obtains the GMPP at 61 seconds with an accuracy of 99.11% efficiency.

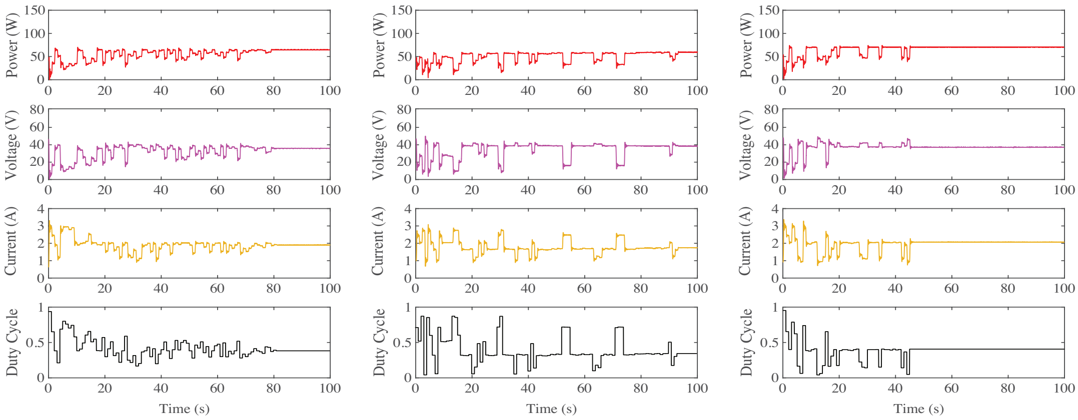


(a) PSO Pattern 2 **(b)** FWA Pattern 2 **(c)** PS-FW Pattern 2

Figure 6.12: Experimental random seed Pattern 2 results.

The GMPPT algorithms performances under the Pattern 2 shading case 1 is observed in the Fig. 6.12. The PSO algorithm obtains the GMPP at 81 seconds with an accuracy of 99.36% efficiency. The FWA obtains the GMPP at 75 seconds with an accuracy of

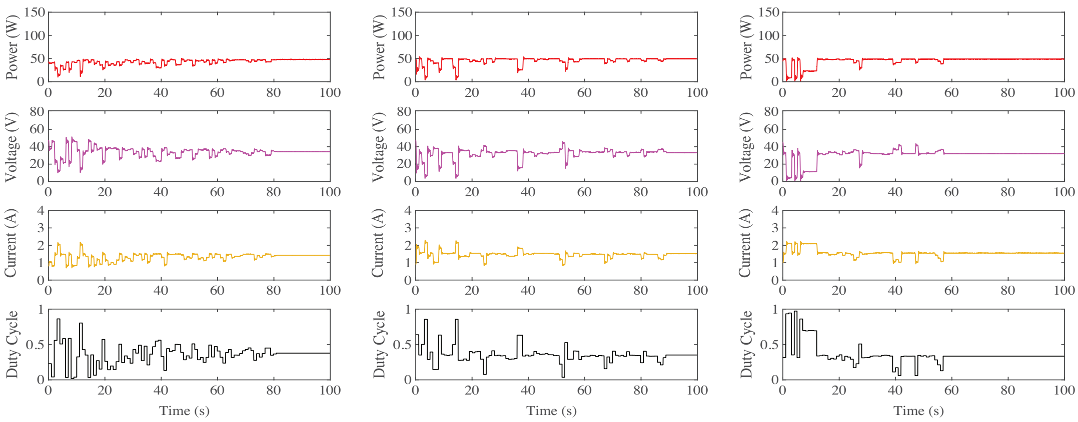
90.46% efficiency. The PS-FW algorithm obtains the GMPP at 62 seconds with an accuracy of 99.38% efficiency.



(a) PSO Pattern 3 **(b)** FWA Pattern 3 **(c)** PS-FW Pattern 3

Figure 6.13: Experimental random seed Pattern 3 results.

The GMPPT algorithms performances under the Pattern 3 shading case 2 is observed in the Fig. 6.13. The PSO algorithm obtains the GMPP at 81 seconds with an accuracy of 98.99% efficiency. The FWA obtains the GMPP at 93 seconds with an accuracy of 84.61% efficiency. The PS-FW algorithm obtains the GMPP at 45 seconds with an accuracy of 99.11% efficiency.



(a) PSO Pattern 4 **(b)** FWA Pattern 4 **(c)** PS-FW Pattern 4

Figure 6.14: Experimental random Pattern 4 results.

The GMPPT algorithms performances under the Pattern 4 shading case 3 is observed in the Fig. 6.14. The PSO algorithm obtains the GMPP at 81 seconds with an accuracy of 97.92% efficiency. The FWA obtains the GMPP at 93 seconds with an accuracy of 98.07% efficiency. The PS-FW algorithm obtains the GMPP at 58 seconds with an accuracy of 98.12% efficiency.

The results demonstrate that PS-FW hybrid algorithm outperforms the performances of its singular counterparts. It is obvious that PS-FW algorithm easily converges and tracks the GMPPT fastest and under all shading patterns. In all shading patterns, the PS-FW algorithm successfully exceeds the singular counterparts in speed. With regards to the accuracy, it is shown that the PSO, FWA and PS-FW algorithms have successfully tracked GMPP in all patterns except FWA that has inaccuracy in Pattern 2 and Pattern 3. In comparison to the same seed setting, FWA is capable of achieving convergence in time before the iteration limit completes. However, PSO is still unable to fulfill convergence as expected due to slow convergence rates from the velocity operator. Thus, PS-FW provides faster tracking speed, better ability to converge, and better tracking accuracy in the random seed test settings.

Table 6.7: Random seed performance summary of GMPPT algorithms.

Pattern	Algorithm	P_{mpp} (W)	P_{pv} (W)	P_{load} (W)	Tracking Speed	MPPT Efficiency (%)	Converter Efficiency (%)
1	PSO	148.73	147.41	143.31	81.00	99.11	96.35
	FWA	148.73	147.21	143.07	69.00	98.97	96.19
	PS-FW	148.73	147.42	143.33	61.00	99.11	96.36
2	PSO	114.26	113.53	109.49	81.00	99.36	95.82
	FWA	114.26	103.31	99.21	75.00	90.46	86.83
	PS-FW	114.26	113.56	109.52	62.00	99.38	95.85
3	PSO	71.81	71.09	65.61	81.00	98.99	91.36
	FWA	71.81	60.76	55.38	93.00	84.61	77.12
	PS-FW	71.81	71.17	65.78	45.00	99.11	91.60
	PSO	50.22	49.18	44.98	81.00	97.92	89.56
4	FWA	50.22	49.25	45.08	93.00	98.07	89.76
	PS-FW	50.22	49.28	45.11	58.00	98.12	89.82

The results from the test are detailed in Table 6.7. The measurement takes into account the power obtained, tracking speed and MPPT efficiency as they are the primary values as deciding factors of a chosen GMPPT algorithm. The given MPPT efficiency averages from around 84.61% to 99.38%, while converted power efficiency ranges from 77.12% to 96.36%. The speed of convergence in the PS-FW hybrid can be observed to be even faster than the tracked speed of the GMPP in PSO and FWA within the same seed testing. The PS-FW algorithm ranges from a minimum of 17.44% to a maximum of 51.72% faster than the PSO and FWA algorithms to converge to the GMPP in all patterns. FWA obtained a lower tracking accuracy as the power conversion from P_{pv} is less than PS-FW hybrid and PSO algorithms in the Pattern 2 and Pattern 3. As mentioned before in the previous test setting, the PSO and PS-FW GMPPT accuracy is comparable due to the great exploration of a candidate region from PSO. Thus, the random seed setting results are concluded with PS-FW as the victor through faster tracking speed, ability to converge and good tracking accuracy.

6.4 Performance Discussion

Within this section, the experimental results for the algorithms must be similar to the simulation or better than, in terms of speed, accuracy and with the behavior and waveform curves of the algorithm framework in its search patterns.

With the completion of summary of the results in the experimental testing, discussion can be built upon the findings and how the proposed hybrid PS-FW outweighs the singular canonical versions in tracking speed while maintaining good accuracy.

In the experimental testing, the initial claims of GMPPT performance are proven. The PS-FW algorithm has exceeded the performance of singular PSO and FWA counterparts in aspects of speed and accuracy under the multiple test conditions of seeded and non-seeded settings. While the PS-FW algorithm does indeed perform adequately enough to replace the non hybridized forms, there is a need to explain the performance from the algorithms and how they achieve the GMPPT searching under their own frameworks. We begin this discussion by explanation in the subsections below which will prove to be the criteria or aspects of an algorithm's performance.

The performance can be categorized into the following sections that describe the operators, search framework and threshold value of power to justify parameters chosen and applied to the algorithms involved in the experimental testing for GMPPT under PSC. The parameters are shared also for simulation environment; however, it was important to evaluate them under experimental setup and in real life. In the case of a possible parameter combination containing better performances in GMPPT, then it is justified that the bias is irrelevant as all algorithms chosen will share the parameter values. If not stated, any parameter values and testing conditions are all same if applicable in the case of the singular versions of PS-FW compared to its hybrid.

6.4.1 Tracking GMPP Accuracy

The qualitative assumption of accuracy in a GMPPT algorithm is tied to the degree of local search around the candidate solutions performed by the population. Given a larger population, the local search or exploitation of the candidate solution can potentially be easier. A good candidate solution is derived from large initial population and with greater chances. However, a larger population of solutions directly affects the difficulty of proving convergence of the population. Moreover, the large population may lead to many useless searches when the GMPP was already found.

Within the experimental results, it can be seen from canonical PSO algorithm that the convergence speed is inadequate when compared with the proposed PS-FW algorithm, but the accuracy of the particle to find GMPP is high. The operator applied within the PSO algorithms consists of the velocity operator that moves the individual solutions. The velocity of an individual solution is too slow to converge when a potential candidate MPP is found. The PSO particles have slow search and slow convergence as the duty cycle can be seen to slowly flatten itself over time towards the candidate MPP.

The PSO has a good exploration, but lacks the necessary speed to benefit from this balance as the convergence speed is slow from lack of exploitation.

The singular FWA has adequate GMPP accuracy in the sense of local search as its operator is adopted straight into PS-FW. But, the exploration of the FWA with only the original mutation operator is proven lacking with the weaker results obtained with minimum of more than 10% mismatch to the GMPP. FWA has missed the trajectory of its individuals to the candidate MPP in regards to the other two. The exploitation of FWA is proven with the better local search capabilities in the exploitation of current candidate MPP; however, it did not manage to find better duty cycles even with ample chance given to all explosion sparks generated. The selection strategy chooses the fireworks to carry over into the next generation randomly; thus there is a chance in the search that a firework that is not around the current candidate MPP is chosen. Its presence in the population harms the convergence speed as the average fitness is skewed by the weaker solutions.

The proposed PS-FW hybrid has supplemented the behavior and benefits from the focus on local search. This behavior is clearly observed in all Figures where in the PS-FW, particles succeed in choosing candidate MPP and start local search of candidate MPP immediately with the explosion sparks generation. The same behavior is also seen but with a chance of wasted search with the FWA algorithm as it explodes on every firework regardless of its position for global best MPP. PSO's balance is skewed towards exploration as the exploitation is weak from slow convergence around the candidate area.

PS-FW hybrid which makes use of the tournament selection strategy is able to randomly obtain solutions to bring over to the next iteration. The abandonment strategy removes weaker solutions after velocity operator is applied and thus the population remains healthy. Observable from the wave-forms of the duty cycle is that the velocity operator and mutation operators succeed in global exploration while a sufficient chunk and population is conducting local search with the amplitude operator that generates movement of the explosion sparks from the fireworks or particles. The mutation operator in question does not apply Gaussian distribution, Elite mutation or the like but a type of mutation which relies on the global best fitness value. The population of duty cycles with the greatest power, P will ultimately stagnate within a small difference between each other and signify convergence. In conclusion, the PS-FW hybrid successfully exploits more from local search than PSO while obtaining a better solution even under the same initial population set of duty cycles.

But, the PS-FW has equal accuracy to the PSO algorithm in terms of GMPPT as the power conversion is the same. Since PSO algorithm is proven to be able to find the GMPP due to great exploration, then it can be assumed that the PS-FW successfully adopted the PSO algorithm's exploration capabilities.

6.4.2 Speed of Convergence Rate from Operators

The convergence rate of the velocity operator in PSO algorithm as described beforehand situates itself as having slow convergence; however, the convergence rate itself for velocity can be controlled from its variables c_1,c_2 and w. The change in duty cycle value is the sum of velocity and original duty cycle, thus the desired movement for faster convergence can be controlled from a decrease of all the variables. Even in its stochastic nature, the change of a solution can be made lower or higher with certain degree of magnitude through the modification of those values. Originally, the canonical PSO algorithm framework utilizes only the velocity operator as the strategy of both global and local search for the solutions. However, modern canonical versions typically adopt the inertia weight parameter as a way to control the global and local search during early and later stages of the search process. These versions are as observed in both literature review and in the first half of the proposed PS-FW hybrid. Given the inertia weight, the PSO algorithm is introduced with an algorithm of controlling exploration and exploitation. However, it is seen that this balance is inefficient due to the time taken to reach convergence, as well as wasted search time in the time to reach a candidate MPP's solution. When favouritism towards exploitation is given instead to speed up the convergence through reducing all parameter values, then the exploration of the system will be proven lacking.

The PSO algorithm particles contain solutions that fluctuate greatly from the velocity operator applied where less exploitation of the candidate MPP is conducted. The fluctuation of the velocity operator imitates the convergence of an entire solutions, in a sense the stagnation of the entire population resembles and builds upon the convergence of all solutions. This proves that the PSO algorithm is slow to converge upon a candidate MPP as the particles exploit the areas around itself due to the inertia weight factor at the late stages of search. The convergence from requiring the average fitness to be less in the population becomes hard to fulfill due to this.

The singular FWA retains superb exploitation capabilities around a candidate MPP; its convergence rate would be just as fast as PS-FW algorithm if it had an abandonment strategy or better selection strategy as the population sometimes retains the weaker fireworks due to the inadequate and random selection strategy. The abandonment strategy would partake in removing the weak fireworks. The process does supplement a sort of exploration, but the amplitude of the sparks generated off the weak fireworks lacks any momentum to explore far enough to be relevant to the FWA. The result of the behavior delays the convergence time as there are weaker solutions in the population with no competitive selection strategy to cull the weaker fireworks. In short, the exploitation capabilities are strong, but another method of exploration would need to be introduced if the FWA needs to perform as adequately as PSO algorithm in accuracy while retaining faster speed from its own fast convergence.

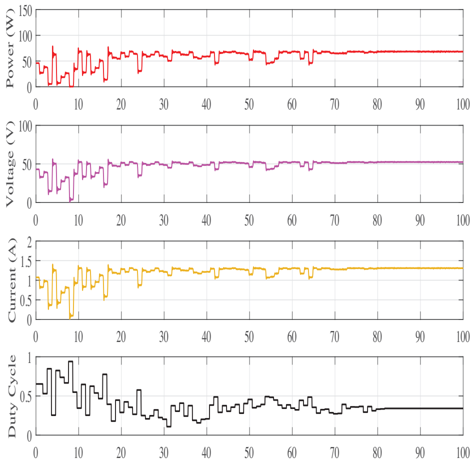
Our proposed PS-FW hybrid algorithm aimed to succeed its singular counterpart in exploitation and has done so without sacrificing the balance towards exploration. It is observable in the wave-form from the results obtained in both non-seeded and seeded case that the local search capability of the PS-FW hybrid algorithm is sufficient in finding the GMPP. The mutation and velocity operators both also work in twine to prevent any case of local trap. Moreover, the initial stage of searching allows all explosion sparks to explore the region once. The result of the strategy allowed the strong convergence through local search of an already good candidate for the GMPP, while preventing any case of local trap. It is evident in the seeded case that a perfect location is not found and more searching is required for the GMPP, it is observable in the wave-form that the correct GMPP is only found after local search of the candidate GMPP.

As the algorithm attempts to also search the candidate GMPP which is done by exploding into the sparks for better solutions, it converges its population to the area while also keeping mutated sparks and particles searching outside the current region. These mutated sparks and particles do not rejoin the population, while the normal explosion sparks begin to rejoin the population randomly through tournament selection strategy but still keeping one leader particle in the population memory. Thus a great balance of exploration and exploitation is achieved. Regardless of non-seeded or seeded case, the operators will be able to perform in the same behavior as evident in the two cases of wave-forms. With the comparison made between experimental and simulation setup, the discussion conducted beforehand regarding the convergence rate can be verified and proven.

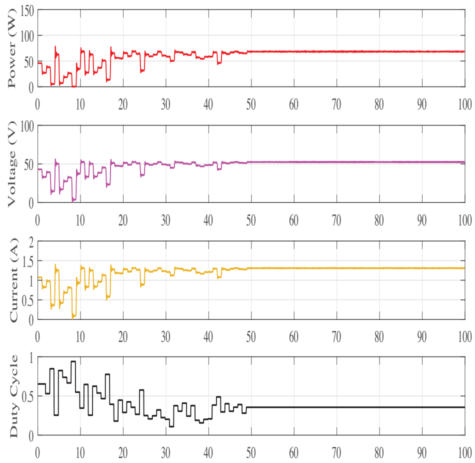
6.4.3 Power Threshold to Modify Convergence Rate

The power threshold and maximum iteration limit are the de-facto utilization of a convergence criteria for GMPPT algorithms. The algorithm must not end before any one of these criterion is fulfilled. The design of a GMPPT algorithm may find it desirable and more profitable to end the search processes when the GMPP is reached, but the question in response can be asked with the credibility of the solution and the GMPP. First of all, the problem with setting the convergence criteria as reaching the GMPP requires the algorithm to know the value of power at GMPP, P_{mpp}. This factor requires precognition of knowledge regarding all possible power points on the P-V curve and at which combination of irradiance and temperature. As such, the use of a set value of power for the GMPP is unsuitable and costly to implement which was one of the main basis of using stochastic optimization algorithms to solve the GMPPT problem. Moreover, dynamic environments which cause PSC will undoubtedly dislodge the area of GMPP in the P-V curve, setting the P_{mpp} value off track and failing the search properly. The reasons given above stress the need of searching for a solution space properly with balance of exploration and exploitation that are very much affected by a convergence criterion in tandem with reasons stated before from the operators and population.

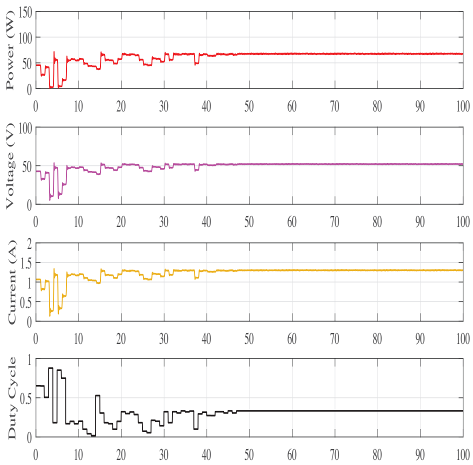
In the proposed PS-FW algorithm, the algorithm was explained to be able to balance exploration and exploitation adequately in comparison to PSO algorithm and FWA. However, the power threshold convergence criteria can be observed to alter time spent to converge on a potential GMPP. A given threshold which is too high will result in too fast of a convergence speed as not all solutions were able to perform exploitation properly given the inadequate time as the algorithm has thus ended. A given threshold that is too low can potentially forever cause the algorithm to search iteratively until the maximum iteration limit is reached. This is a prevalent issue on the population based search algorithms PS-FW, PSO and FWA. The smaller threshold, if in tandem with a larger population size, can weaken the convergence time needed to converge entire population into a candidate MPP, as the entire population must stagnate as close as possible between every N individual. A larger threshold with a larger population size is able to somewhat alleviate this solution, the balance of threshold is thus required.



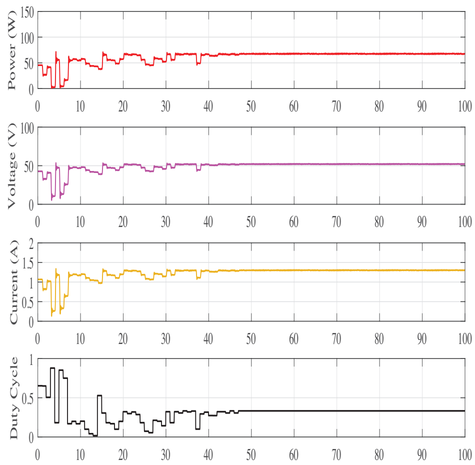
(a) PSO (Low Threshold)



(b) PSO (High Threshold)



(c) PS-FW (Low Threshold)



(d) PS-FW (High Threshold)

Figure 6.15: Threshold Comparison of PSO and PS-FW

Testing has been conducted on two algorithms, the PS-FW algorithm and the PSO algorithm. PSO algorithm has troubling issues regarding convergence as explained and shown in the results so a larger threshold is given to test the performance. PS-FW algorithm is used to promote the proposed algorithm's performance. The Table 6.8 describes the algorithm's test conditions, first of all the testing parameters, which are the parameters involved in operators will be unchanged between both threshold tests of 1W and 2W.

Table 6.8: Thresholds Applied for Testing

Testing Parameters	Power Threshold (W)	Convergence Time	
		PSO	PS-FW
Same	1	Slow	Same
Same	2	Fast	Same

For example, Fig. 6.15 shows the proposed PS-FW algorithm with a high threshold value, along with describing PSO algorithm with high threshold values. In Fig. 6.15a, the lower threshold, 1W is used which shows a prolonged speed of convergence and tracking time of the PSO algorithm. When modified to a larger threshold of 2, the Fig. 6.15b describes a much faster tracking speed of PSO algorithm. In PS-FW algorithm, the threshold value does not affect the PS-FW search process much and it is able to perform in equal behavior between both threshold values.

It can be observed that threshold value is able to influence the ending time that determines the tracking speed of an algorithm. All GMPPT algorithms have successfully tracked the GMPP adequately under both threshold values of 1W and 2W. Thus, given that the 1W power threshold is harder for entire N population to converge in, the threshold is proposed to be utilized and justified for all previous wave-forms shown except in this subsection.

An evidence to the performance of the proposed hybrid is that in the due time given, PS-FW is able to converge faster than PSO algorithm even under equal threshold parameter, equal starting population and all shading patterns. The exploitation of the explosion sparks in the PS-FW algorithm is able to sufficiently maintain the population in convergence range between each other while searching for even better GMPP on the P-V curve. The abandonment and selection strategy successfully circumvents the aspect of slow convergence and instead opts towards the local search and global search immediately instead of slow converging populations.

The population does not remain in stagnation though, as mutation sparks are always searching outside the current candidates, with velocity operator particles searching initially at earlier iterations as well. This behavior in the algorithm framework always maintains a healthy population of good solutions so that the convergence is easier, but this difficulty in converging to the threshold can be affected from a large population as mentioned before as well. While the threshold is indeed possible to be set higher to achieve a faster convergence rate, a lower threshold tests the capability of local search for an algorithm. In conclusion, the threshold rate is set to 1W and shared between all algorithms for fair assessment and testing to prove local search capabilities.

This section reviews the threshold as a factor to balance for the convergence of the GMPPT algorithms. The testing is conducted in the experimental setup due to power ripple in the converter system, sensor measurement and the dSPACE RTI may alter the accuracy of the measurement. These elements are not present in the implemented Simulink simulation of the PV system. Thus, the experimental setup had the best conditions to test the power threshold as a convergence criterion for all involved GMPPT algorithms; since, when the error tolerance of the entire GMPPT system is expected to have minute inaccuracies, the threshold check is much harder to achieve. In conclusion, the threshold proved a substantial influence that is able to inadvertently control convergence criteria in the GMPPT algorithm. If the proper threshold is not set, then in essence, the results from all GMPPT algorithms always end in a set maximum iteration times the amount of population chosen as the parameter. The behavior is unsuitable for the GMPPT as it is required for the GMPPT to actually end before the iteration limit is reached to enforce robustness of the algorithm through balance of the exploitation and exploration with the fastest time and pinpoint accuracy.

6.5 Validity of Proposed Hybrid

Within simulation and experimental validation conducted, the methodology is proven correct and applied properly; which are the measured values of boost converter, emulation of PV system using the Simulink environment, and experimental setup of PV system using Chroma PV emulator and dSPACE RTI system. The results present themselves according to the theoretical explanations conducted within the literature as well as the objective of each operator is proven from the discussion regarding the proposed PS-FW hybrid in Chapter 3. The canonical versions of PSO algorithm and FWA are inefficient when compared to the hybrid algorithm in terms of speed and accuracy under various factors. The factors includes guarantee of both seeded population and completely randomized RNG test and then a threshold that is small enough to ensure all algorithms do not converge as easily as possible.

Ultimately, the proposed PS-FW hybrid GMPPT algorithm has thus proven its balance of exploration and exploitation capabilities by being able to conduct great local search with explosion sparks generation while good exploration is obtained from mutation and velocity operator. The abandonment and supplement strategy would circumvent otherwise disadvantageous solutions in the population that would slow down convergence. The singular PSO algorithm lacked the mutation needed for global search if it changed inertia weight in favor of faster exploitation. Meanwhile, the singular FWA lacks the exploration needed and thus explosion sparks do not retain good global search capabilities.

The strategies in tandem and combination with each other for PS-FW algorithm have overcome the weaknesses of PSO and FWA described. With the hybridization, PS-FW algorithm proves its capability as a new GMPPT algorithm that is able to perform as an alternative GMPPT solution to others in the literature. The hybridization is also proven successful to the extent that, the utilization of hybrid algorithms has directly improved performance of GMPPT algorithms.

6.6 Chapter Summary

In this Chapter, the culmination of work conducted has completed the objectives of the research project. The proposed PS-FW GMPPT algorithm has been tested under the methodology designed in the simulation and experimental setup. The results have been successfully obtained and discussion regarding all implemented GMPPT algorithms conducted in terms of tracking speed and accuracy. Moreover, the validity of the proposed hybrid is successfully proven in the midst of the comparisons made. The concept of hybridization is also proven slightly in favor of the performance to PV systems under PSC.

In Section 6.1, the criteria of how performance validation is conducted is further detailed and appended from the given selection in Chapter 3.6. The suggested criteria to test the algorithms are introduced, both the seed and algorithm parameter settings have demonstrated the GMPPT algorithm capabilities in modifying the population to track GMPP. Moreover, threshold of power has been introduced as the test setting that is able to control convergence rate and final tracking time.

Next, the wave-forms and results discussion from the testing of all implemented GMPPT algorithms in the simulation implementation of the PV system application has been obtained in Section 6.2. With the proposed PS-FW GMPPT algorithm exceeding the performance of the two singular counterparts of PSO and FWA as well as the hybrid DE-PSO algorithm in tracking speed and best accuracy in all 5 shading patterns; an assumption can be made on the performance of all implemented algorithms. The simulation results successfully prove the initial assumptions and allow the algorithm to be implemented into an experimental setup for further validation.

Section 6.3 has provided the discussion built upon the simulation results, by implementing the GMPPT algorithms tested into the PV system application using experimental setup. Both same seed and random seed tests are made to test the algorithms performance in the operator to modify populations until a GMPP is reached. In a starting population condition where the initial population is replicated for each test and GMPPT algorithm, the PS-FW algorithm has successfully tracked GMPPT than other algorithms with best accuracy and fastest speed in all 3 shading patterns. In another test, the experimental testing has applied random initial population to test conventional performance in real world scenarios as each operator and population are not guaranteed. In the tests for the PS-FW algorithm, the experimental results conducted mimic the findings obtained in the simulations. The PS-FW algorithm successfully obtains the fastest tracking speed and best accuracy.

Regarding the discussion on the singular counterparts, Section 6.5 explains that PSO algorithm and FWA both are characterized by the weaknesses that motivate the implementation of PS-FW hybrid algorithm into GMPPT for PV systems under PSC. The PSO algorithm has weaknesses in exploitation or local search as denoted by the slow convergence in the results wave-forms, which more than likely result in slow convergence times and thus slow tracking speed. The weakness is observed to be caused by the velocity operator and the inertia weight. In FWA, the weakness is given by the lack of global search or exploration which reduces tracking accuracy and proven in the lower power conversion efficiency and GMPPT efficiency observed in simulation and experimental results. The weakness is caused by lack of mutation or movement of fireworks to enforce global search.

The hybrid PS-FW algorithm then demonstrates that the combination of these two algorithms and strategy is able to successfully balance exploration and exploitation by obtaining the results proven before. The PS-FW algorithm uses the velocity operator for use in exploration, while the convergence issue in PSO is successfully subsided with explosion sparks generation for better fireworks with greater fitness values. Its framework is proven with the results obtained, the hybridized algorithm is able to be utilized in the GMPPT algorithm with no qualms based on its superior performances.

The research project hence concludes with all research objectives completed; since, the GMPPT algorithm that is able to track local and global maxima respectively is completed. A simulation and experimental setup of the boost converter topology accompanied with the PV array under any PSC that is controllable with the GMPPT algorithm is validated with the obtained results. Finally, the implemented GMPPT algorithms under our PV system application in terms of performances based on the balance of exploration and exploitation is fully disclosed in terms of results and discussion.

Chapter 7

Conclusions and Future Works

The research project concludes with the simulation and experimentation verification of the GMPPT methods. The design of a whole PV system and the review of some certain modern implementations of GMPPT are conducted and tested for simulation setup within the MATLAB / Simulink environment. Meanwhile, the experimental setup validates the design of the simulation setup of PV system with GMPPT controller with the utilization of dSPACE RTI and the PV panel under multiple cases of PSC is emulated with Chroma PV Emulator. The experimental design is accompanied with the use of suitable hardware components that complete the conventional boost converter design which had calculated parameters in the literature, that are able to handle the power load in the system when the PV panels are in GMPP.

7.1 Conclusions

In Chapter 1, the discussion regarding the requirement to implement GMPPT over MPPT methods and the application into PV systems under PSC is given. The reasoning towards GMPPT is given by the appearance of multiple MPP on the P-V curve that an MPPT method may or may not be able to track efficiently, hence there is a need of GMPPT. Our aim, problem statements and research scope are presented in this chapter.

A review of the occurrence of PSC on PV panels has been conducted in Chapter 2. The DC-DC converters are responsible to implement the entire PV system, thus the types of boost converters utilized in the PV systems are reviewed as they are the main components responsible for switching the duty cycle from the GMPPT method to maximize power conversion efficiency. The P-V curve representing a problem that requires the use of meta-heuristics is also explained in regards to its contrast to a multi-modal problem, the meta-heuristics must be used to track the GMPP properly with good performance.

In Chapter 3, the GMPPT methods utilized in modern literature that are involved and related with the proposed GMPPT algorithm in the research project have been reviewed. The performance criteria that evaluates these modern implementations are observed, how the algorithms enable the search of their populations with the use of variation operators in order to track the GMPP are introduced. Furthermore, the concept of hybridization between multiple meta-heuristic methods in order to form a GMPPT method is introduced.

The PV panel model proposed has been used to construct the PV array in the simulation environment to conduct simulation validation in Chapter 4. The DC-DC conventional boost converter design is then calculated in terms of all parameters of the electrical components in the circuit so that the simulation and experimental setup are able to obtain component and component values to construct the setup. The rest of the chapter proposes the hybrid PS-FW GMPPT algorithm that is not implemented for use in GMPPT application under PSC. The algorithm abandons the disadvantages and utilizes the good concepts from its singular counterparts to provide better performance in tracking speed and accuracy through balance of exploration and exploitation.

In Chapter 5, the methodology of the simulation and experimental setup is described in detail. The simulation software utilized in the project is the MATLAB/Simulink simulation software environment that is able to procure the theoretical results of the PV system under PSC correctly while controlling the GMPPT through functions. The shading patterns introduced in the project possesses 1, 2 and 3 power points on their P-V or I-V curves which describe where the MPP is. The simulation setup introduced two more shading patterns with 4 and 5 power points on their P-V or I-V curves. The total of 5 shading patterns are used to test the simulation setup while 3 are used in the experimental setup. The experimental setup, consists of the dSPACE 1104 RTI that acts as a controller board used to record and output signals through ADC or PWM output and the Chroma PV emulator that outputs the designed PV panel at specified irradiance levels, essentially allowing us to emulate the shading patterns as well. The voltage and current sensors record the DC-DC boost converter output values, while the GMPPT receives these two values as input to produce and generate duty cycles for the converter to switch at a specified frequency. Considerations for the experimental setup are of course taken in measure due to the switch over from simulation setup. The components required for the boost converter are also described, presented with the reasoning of the choice made while still fulfilling the calculated minimum requirements.

In Chapter 6, the GMPPT results and discussion are procured and given. How the proposed research chooses to validate the results is given in the criteria specified in the literature review. The speed of the algorithm, tracking accuracy of the algorithm and convergence rate of the algorithm are the criteria. Moreover, other criteria have been introduced which include the power threshold to determine convergence and convergence rate. Another criterion is the seeded result which does not contain a population with result fulfilling the GMPP immediately to observe operator performance for exploration and exploitation. The recorded tracking speed and accuracy of the proposed PS-FW GMPPT algorithm has proved itself to be faster than its singular counterparts and has excelled in terms of the aforementioned criteria. The hybrid algorithm itself has proved the concept of hybridization briefly, through the adoption of good concepts in meta-heuristic methods shown from using exploration from PSO and exploitation from FWA. The velocity operator of PSO provides the global search necessary to disregard local traps, while the amplitude and sparks generation operator performs the local search to increase accuracy of tracking. Moreover, the hybrid itself introduced other niche strategies, such as, abandonment and removal of weaker particles, adaptive reduction of sparks in further iterations and a better selection strategy that is more competitive in the survival of better fitness duty cycles.

To reiterate on the designed hybrid PS-FW GMPPT in this project, the hybrid PS-FW was proposed in respect to the stated weaknesses of the canonical singular PSO in exploitation and the canonical singular FWA in exploration. A design choice of hybridization method which combines the strategies or operators which modify individual solutions utilizing both swarm information and personal information. The two GMPPT algorithms are hybridized into a singular GMPPT algorithm through retention of velocity operator from PSO for exploration while keeping explosion spark operator and mutation operator from the FWA.

Moreover, the canonical FWA introduced the selection operator which is a randomized retention of individuals of the solution. In the hybrid algorithm, a tournament selection operator scheme is introduced in order to retain the good individuals with greater MPP. The selection scheme introduced has shown its capabilities in improving convergence and exploitation by being able to select good candidates among a tournament style ranking where fitness is used to evaluate them. The greatest difference between the performance of FWA and PS-FW algorithm was proven to be the exploration capabilities as the PSO's velocity operator was not present to improve exploration of the population; thus, the weakness is supplemented by the difference of modification towards the mutation operator used. The two factors were used in PS-FW algorithm to improve GMPPT and prove that FWA had lower accuracy than that of PS-FW from the lower power conversion efficiency at GMPP. In PS-FW algorithm, an abandonment strategy was introduced where weaker individuals with worse MPP are always dropped in favour of the healthier individuals, maximizing the convergence chance and exploitation of current candidate GMPP. Of course, the trade off for this was weaker exploration chance from explosion of the other individuals. However, the utilization of mutation operator and velocity operator modifies individuals which do not rejoin the population unless a greater candidate GMPP was found. The GMPPT algorithm is modified to include adaptive qualities where chances to explode for weaker individuals are nullified and the amount of individuals to be abandoned lessen with increasing iteration counts. The measures are taken to enforce the convergence speed of the algorithm. All involved strategies with the parameters established have successfully balanced the exploitation and exploration of the PS-FW GMPPT algorithm, its results are validated from the increased tracking and convergence speed with highest accuracy to the GMPP. The proposed algorithm successfully obtains a minimum of 7.59% better tracking speed of the GMPP under simulation verification at one initial population setting compared to the PSO, FWA and DE-PSO. The PS-FW under experimental verification is able to achieve at least a minimum of 24.69% better tracking speed of the GMPP in two initial population settings compared to the PSO and FWA.

The meta-heuristics optimization methods which can directly translate to being implemented into GMPPT problem, as GMPPT methods were conducted in order to understand the framework of the basic methodology where the method iteratively improves its solution(s) with natural, genetic, generational and physics based modelling of the operators, terms and strategies. The PV system which was to be directly controlled by the GMPPT method that is housed inside a controller is understood and the design of the system is proven with various methodologies. For example, the usage of PV models in simulation to the utilization of hardware PV emulator, the conventional boost converter design parameter calculations and the partial shading cases replicated on the

P-V or I-V curves. These were substantial in order to derive the entire PV system under cases of PSC which were fortuitous in the validation of the performance for all involved GMPPT methods: PSO, FWA proposed hybridized PS-FW.

The key contributions of this research as have been set out to be accomplished can be concluded:

- The PS-FW algorithm with abandonment and supplement strategies successfully solved GMPPT problems under PSC environment as evidenced by the wave-form obtained from the results.

- The proposed adaptive spark control in the PS-FW algorithm to accelerate the convergence time in later stages of the search process, which is a common weakness of most GMPPT.

- In simulation setup, the performance of our proposed algorithm against PSO, FWA and DE-PSO is demonstrated while the experimental setup demonstrated the performance of our proposed algorithm with PSO and FWA. The PS-FW algorithm accomplishes the best results in both simulation and experimental setups among the implemented algorithms.

In turn, the research project is successfully fulfilled, with minor delay due to external circumstances, the milestones and time-line are completed with a modicum of respect to the reasons stated. While the understanding of new concepts to the researcher has taken some effort, the understanding of various concepts have proved impeccable to the design of the GMPPT algorithm from this research project.

Nevertheless, the proposed PS-FW GMPPT algorithm showcases its merit as a liable alternative to PSO and FWA. The increased speed and accuracy puts PS-FW at a pedestal against its counterparts, which already exist in implementations of PV systems. The algorithm choice in designing future PV systems is further exemplified with the use of our proposed algorithm with its good performance using the abandonment and supplement, and adaptive spark control strategies. The strategies employed present their merit in rallying convergence of individuals in a population with the emphasis on speed and accuracy, future designs of GMPPT algorithms may employ similar strategies to obtain the desired performance. Furthermore, the future work of PV system design may specifically utilize the proposed research work as their GMPPT algorithm with the guaranteed performance quality. With regards to the future developed PV systems, the conducted work regarding the methodology of PV system development in the form of the simulation and experimental setup are concise enough to be replicated for further development.

7.2 Future Works and Considerations

In the future work, the completed research work will strive to improve concepts unexplored or not fully developed in this research project. It includes aspects from the experimental methodology, as well as all the GMPPT algorithms involved. As the proposed research seeks to commercialize the research work in the future, the discussion made below must be considered in the future plans.

Within the boost converter design, steady state oscillation is a real condition seen in the settling time of the DC-DC boost converter during experimental testing. It is not observed in the simulation setup due to theoretical conditions. The transient response, in electrical engineering specifically, is the circuit's temporary response that dies out with time. Following closely is the steady state response, which is the behavior of the circuit a long time after an external excitation is applied. The oscillations are observable during the settling time of the converter observed from the measurement of the wave-forms in the dSPACE software, moreover the results show the settling time of the power, voltage and current sensed. Research must be done regarding the steady state oscillation, it should be related to the step sizes of switching as large gaps in the duty cycle may cause ripple power. The transient response may be improved using a proportional–integral–derivative controller through controlling the feedback of the system. The controller is subsequently used in industrial grade control systems that require continuously modulated control. In our PV system, the boost converter configuration only provided basic capability of obtaining GMPP and showed low converted efficiency at the load resistance of around 91% to 94% . The PV system configuration itself should implement transient stability improvement to facilitate the steady state oscillations while obtaining better final conversion efficiency.

An apparent downside to the hybrid PS-FW GMPPT algorithm however, would reside in the number of parameters used in its search process. A small scale PV system which aims for low cost implementations may be unable to implement the PS-FW algorithm due to the size or computation capability required. The lower cost microcontroller devices or other GMPPT controller units will be hampered from using the algorithm.This limitation must be addressed by reducing the parameter dependency in the framework and have the PS-FW GMPPT algorithm be tested under commercially popular controller units.

1. In the experimental methodology, another criterion that is able to influence the validity or give value to the GMPPT algorithms performances would be the feature to restart itself under dynamic PSC. The feature if implemented inside the GMPPT code, restarts the algorithm search framework upon determining the occurrence of PSC, by which it means that the irradiance has changed to a significant degree that warrants the restart of the algorithm. The idea is novel, but could be a moot point as all involved GMPPT methods may just implement it. It does not detract from value of a singular method, but it does not allow us to draw comparison through discussion. But, the occurrence of a changing PSC is always possible and thus the future work can be considered.

2. Within the GMPPT method's parameters, the results section has assumed same value in the parameters of all shared operators. The assumption was to give contrast of the changes made in the operators and search strategies newly introduced so that the research work does not need to constantly explain the parameter choice. However, the future consideration that should be performed will be the introduction of parameters tuned to the point that it may draw out the maximum performance possible from a method. The choice of the initial parameters can not be concluded as final. Thus, further changes to all GMPPT methods performances of the operators due to the internal parameters including the hybrid PS-FW GMPPT algorithm are possible for better or worse. With optimization done on the internal parameters, the optimized PS-FW algorithm can benefit from further validation and performance results obtained for GMPPT problem through comparison of each algorithm at their peak performance.

3. Furthermore, more GMPPT algorithms should be introduced to contest with the hybrid PS-FW GMPPT algorithm. The concept of hybridization should be further considered in another design of the GMPPT algorithm in order to improve the performances as proven in literature and in the research results. While the PSO is already an industrially utilized GMPPT method, the FWA method is relatively unused in literature which warranted the research into its performance

in the research work. The two methods should be supplemented with the modified versions of it present in literature and implemented within the experimental methodology.

4. With the completion and success of the PV system implementation, the research project innovations can attribute towards the development of whole solar inverters or PV inverters which can feed into commercial electrical grid, local, and off-grid electrical networks. The inverters themselves implement GMPPT algorithms as well and are the next step of further research for the commercial systems. Moreover, besides bench marking the energy efficiency of the hybrid algorithm and PV system with those in the research reports, the life span of the newly designed hybrid system can be assessed or appraised in relation to the devices that are available commercially. This future work can be considered as the algorithm enters the stage at which commercial distribution is viable, which further exposes the research work conducted.

In conclusion, the future work and considerations specified detail the further plan of research work for endeavors beyond the scope of this thesis. The future plans of research work will base the improvement of overall PV system implementation based on the boost converter design, GMPPT algorithm design along with its parameters, the GMPPT performance validation and the commercial plans possible.

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