Maximum power point tracking for a photovoltaic power system

Nguyen, Tat Luat

2010

Nguyen, T. L. (2010). Maximum power point tracking for a photovoltaic power system. Master's thesis, Nanyang Technological University, Singapore.

<https://hdl.handle.net/10356/46769>

<https://doi.org/10.32657/10356/46769>

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MAXIMUM POWER POINT TRACKING FOR A PHOTOVOLTAIC POWER SYSTEM

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School of Electrical and Electronic Engineering

A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Master of Engineering

2010

Acknowledgements

My heartfelt appreciation and gratitude goes to my supervisor, Professor Low Kay Soon, for his guidance, supports and advices over the past two years. Without his supports and invaluable advices, I would not have been able to fulfill the dissertation.

My best appreciation also goes to DSO National Laboratory, especially Dr. Goh Cher Hiang and Ms. Goh Lily, for the financial support and research materials throughout the course of this research.

Special thanks to Mr. Zheng Chao for his helpful advices in developing Labview programs for the solar simulator and valuable research materials provided. Thanks to all the lab technicians in control engineering lab for their precious help in providing equipments and set up the systems.

Last but not least, I am sincerely thankful to my family and friends for their understanding, encouragement and support through all these times.

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Summary

This dissertation proposes a novel maximum power point tracking (MPPT) algorithm that works optimally for a photovoltaic system under fast changing temperature and irradiation conditions. The new approach can effectively improve the tracking speed and accuracy simultaneously, which is the contradiction in conventional methods such as P&O or INC. This is particularly important for photovoltaic systems that frequently experience rapidly changing environmental conditions. This dissertation also presents a global MPPT algorithm based on the DIRECT algorithm to successfully track the true global maximum power point when the solar panels are under partial shading conditions. This is achieved without the use of costly components and can be easily implemented in a low cost microcontroller. The algorithm increases substantially the efficiency of the solar power conversion by allowing the solar cells to operate at their ideal operating point regardless of changes in the load and illumination. The converter switches between local search and global search to ensure that the converter is operating at the true global maximum. To validate the performance of the proposed schemes, experimental and simulation studies have been conducted. The results have shown that the proposed approaches are robust and possess a fast tracking speed

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Chapter 1

Introduction

1.1 Motivation and overview

The conventional way of generating energy by burning fossil fuels has contributed over the years to pollution, environmental issues and global warming effect. They are not renewable and estimated to run out in decades. Therefore, it is increasingly important to look for other renewable energy resources. Among them, solar energy is the largest [1] and practically unlimited. In one ambitious scenario [2], the solar energy is projected to cover 20% of the global electricity consumption by 2040. In the plan, the solar energy may contribute to the reduction of CO₂ emissions by the equivalent of 75 average-sized coal-fired power plants or 45 million cars by 2020. The solar energy is also very well suited to provide energy access in rural areas. This will lead to the improvement in healthcare, education and economic opportunities. In some applications, especially in the space, the solar energy is also the only primary power source available. The photovoltaic (PV) modules still have relatively low conversion efficiency until today, typically 6%-17% for normal cell and 20-40% for special cell [2]. The solar arrays' I - V characteristic curves are also highly nonlinear. They vary with the environmental conditions such as temperature and insolation level [3]-[11]. As a result, a solar array has an optimum operating point known as the maximum power point (MPP) that also varies with the cell temperature and the insolation level. Any change in one of these factors results in a

change of the array's MPP. To achieve maximum efficiency, it is necessary to constantly adjust the solar arrays' operating point depending on its current state of operation.

Over the past decades, many maximum power point tracking (MPPT) techniques have been developed and implemented [12]-[80]. They vary in implementation hardware [12]-[19], complexity, convergent speed and range of effectiveness [20]-[80]. Among the developed methods, "Perturb and Observe" (P&O) [20]-[29] and Incremental Conductance (INC) [30]-[35] are the most commonly used due to their simplicity and ease of implementation. While the P&O method involves a perturbation in the operating voltage or duty cycle of the power converter, the INC method bases on the fact that the slope of the solar array power versus voltage curve is zero at the MPP. Theoretically, the steady state oscillations in INC method would be eliminated. In practice, this will not happen as the null value of the slope seldom occurs due to sensor and quantization errors. Thus, the INC method also experiences steady state oscillations like the P&O scheme. By using small perturbation step, the accuracy can be increased and the power loss due to the steady state oscillations is reduced. But it also results in slower tracking speed. Therefore, a few methods have been proposed to overcome this contradiction [23]-[24], [30]-[31] by introducing variable step-size approach. If the operating point is far from MPP, the step size is increased to enable fast tracking. If the operating point is near the MPP, the step size is made small so that the oscillation is well reduced. This contributes to a higher efficiency. However, the theoretical essence of the variable step size is lacking [23]-[24], while the performances of these algorithms are largely obtained by the trial and error tuning of these parameters [30]-[31]. The results are also sensitive to the accuracy of

sensors. Fuzzy and neural network methods [36]-[45] that focus on the nonlinear characteristics of PV array provide an alternative for the MPPT control. The versatility of these methods is limited since the output characteristics of the PV array should be well ascertained to create the MPPT control rules.

Most of the MPPT algorithms assume that the insolation remains constant or changes insignificantly during the sampling period. This is not true in rapidly changing insolation cases. To cope with this issue, dP-P&O method is proposed by some authors to perform an additional measurement in the middle of the MPPT sampling period [20]. Then it can separate the power change due to a perturbation step from the change due to both the perturbation step and the irradiation. This approach provides the MPPT a correct tracking direction during rapidly changing environmental conditions. However, it also reduces the tracking speed by almost half as compared to the conventional method.

The comparative study of the few methods, such as P&O, INC etc., has been reported in [12]. Most of the methods reviewed in [12] perform well in the uniform insolation conditions. However, the main drawback of these methods is that they can only track a single maximum, which is absent when the solar panels are partially shaded. The reason is that these methods are based on the “hill-climbing” principle of moving the next operating point (OP) in the direction that power increases. If the P - V (or P - I) characteristic is not unimodal, these methods could only successfully reach a local maximum.

To overcome this limitation, a few novel MPPT methods have been developed [75]-[80]. Kobayashi etc. [75] and Irisawa etc. [76] have proposed a two-stage method to track the global peak (GP). In the first stage, the operating point of the PV system moves into the vicinity of the global peak power point. In the second stage, it converges to this global peak power point. However, this method may not track the real MPP for some non-uniform insolation conditions. For this reason, it requires additional control process to track the real MPP. Miyatake etc. [77] employed a line search algorithm with improved Fibonacci search to find the global MPP when the PV array is partially shaded. This approach too cannot guarantee to find the global MPP under all conditions. In [78], a fractional open-circuited voltage method that periodically sweeps the PV array voltage from open-circuit to short-circuit is proposed. It updates the fraction that gives the relationship between MPP voltage and open-circuited voltage to find the optimal operating point. Consequently, this causes more power losses. In [79], a voltage based power compensation method that deactivates shaded PV modules by forward biasing the corresponding bypass diodes according to the shaded level of the PV module is proposed. This method is suitable for system that consists of multi-modules in series and parallel. However, knowledge of the system is essential for successful tracking. Hiren and Vivek [80] also proposed a two-stage method that consists of a global stage and a local stage to track the GP. A global stage is used to find the region of local MPPs while the local stage employs P&O to fine track the local MPPs. At first the method finds the nearest local MPP. It then searches on its neighborhood to find other local MPPs. The decision to search in the same or reverse direction depends on the comparison of local MPPs and other criteria. The search is stopped when the algorithm finds the highest local MPP.

Thus, the tracking speed is limited as almost all local MPP are searched and compared to find the GP.

In this thesis, a new search algorithm that has the same ease of implementation as the P&O and INC schemes is proposed. The proposed approach is based on the DIRECT (DIviding RECTangles) algorithm [82] which is a general optimization scheme. The new approach shows a better steady state performance and faster tracking speed, especially in the presence of multiple maximum power points and rapid changing of insolation level. Under partially shaded conditions, the algorithm can successfully track the global MPP within 11 sampling cycles. Experimental results show that its tracking efficiency can be 10% higher than some of the recent methods under the rapidly changing environmental conditions.

1.2 Objectives

The objectives of this dissertation are as follows:

- Develop a robust maximum power point tracking algorithm that can outperform the conventional methods in terms of tracking speed and efficiency. The new algorithm should have the same ease of implementation as the conventional methods, but still can overcome their limitations, especially in a rapidly changing environment.

- Develop a robust MPPT algorithm that is optimized for the partially shaded insolation conditions. The algorithm must be able to differentiate the partially shaded condition and the uniform insolation condition. Thus, it can switch to a suitable tracking strategy to increase the tracking speed and the efficiency. The algorithm should also be easily implemented using a low cost micro-controller.
- Develop a simulation model of a PV system that can simulate the system's behavior with different MPPT control methods. The components of the PV system should include the environmental effect, the PV panel, the power processing system and the electrical load in modular form. Thus, a module can be substituted with a more comprehensive module later if required.
- Design and implement a prototype solar energy system that can be used to validate the performance of the proposed algorithms in terms of tracking speed, robustness and tracking efficiency.

1.3 Main contributions

The main contributions of this thesis are summarized as follows:

- A novel MPPT algorithm that outperforms the conventional approaches has been developed. The new approach can effectively improve the tracking speed and the accuracy simultaneously, which is the contradiction in conventional methods such as P&O or INC. This is particularly important for systems that operate in rapidly

changing environmental conditions. Furthermore, the new algorithm can be implemented using a low cost microcontroller.

- A technique to identify the partially shaded condition of solar panels has been developed. A new global MPPT algorithm has also been developed to successfully track the global MPP of solar panels that are under partially shaded conditions. Simulation and experimental studies have shown that the new technique can significantly increase the tracking efficiency as compared to the conventional global MPPT techniques in literature.
- A system-level simulation model of a PV system based on MatLab/Simulink has been developed. The developed model is versatile and can be used to simulate the dynamic behavior of PV system with different controllers or operating conditions. The optimized parameters obtained from the simulation models can be used in a real system design with minimum modification.
- An integrated PV test system has been developed using a virtual instrument environment. The system can emulate different test scenarios to evaluate the MPPT algorithms. Experimental results show that the system provides useful information and is a valuable tool for the testing and development of the PV system.

1.4 Organization of the thesis

The thesis is organized as follows:

Chapter 1 introduces the background of the topics, motivation, objective and main contribution of the thesis.

Chapter 2 reviews the maximum power point tracking algorithms developed in literature. A wide variety of techniques have been described with a brief discussion and categorized.

Chapter 3 presents a novel photovoltaic MPPT algorithm that is optimized for rapidly changing atmospheric conditions. The new approach can effectively improve the speed and the accuracy simultaneously. A new approach for tracking PV's global MPP has also been proposed based on the DIRECT algorithm. The proposed approach overcomes the weaknesses of several existing methods as it is capable of searching for the global maximum under partial shading conditions.

Chapter 4 presents a system-level simulation model of the PV system. All PV power system components, e.g. environmental conditions, the PV arrays, the power processing system and the electrical load, have been modeled modularly to the required level of complexity. The experimental verification of the simulation models are also discussed in the chapter. The tuning of the algorithms' parameters and various simulation results are also presented.

Chapter 5 discusses the PV system's prototype design for evaluating the MPPT algorithms. The chapter also describes the development of a virtual instrument test system to generate the system operation under various atmospheric conditions. The experimental results of the proposed algorithms have been compared with other published algorithms. Details of the comparison have been discussed to justify the performance and robustness of the proposed algorithms.

Finally, the conclusions are presented in Chapter 6. Possible plans and directions for future research work are also included.

Chapter 2

A Review of Maximum Power Point Tracking Algorithms

2.1 Introduction

A typical solar cell consists of a p-n junction fabricated in a thin layer of semiconductor with its electrons located in either the conduction band or the valence band. Initially, all the electrons in the semiconductor fill up the valence band. When the photons strike the electrons in the semiconductor, some of the electrons will acquire enough energy to leave the valence band and enter into the conduction band [73]. These electrons can then move freely and create electricity. The other source aiding to the current flow is from the positively charged holes that are left behind when the electrons depart from the valence band. By reducing the required energy for the electron to move from the valence band to the conduction band, more electron-hole pairs will be created. This can be done by doping the solar cells [74]. The more photons absorbed by a solar cell, the more electron-hole pairs are formed and this results in higher energy conversion efficiency.

The energy conversion efficiency and cost of the solar cell are affected by the approaches to manufacture the solar cells, such as the type of semiconductor used for the cell or the crystal structure employed. They play as internal factors controlling the solar cell's output. The solar cell's output is also affected by other external factors such as the

ambient weather conditions like temperature, illumination, shading, etc. In this chapter, the characteristic of a solar cell will first be discussed. Different tracking algorithms to obtain the solar arrays' maximum power point will then be reviewed.

2.2 The I - V characteristic of a solar cell

The current-voltage characteristic of a solar cell is nonlinear and is a function of the environmental conditions such as temperature and irradiance [3]-[4]. As a result, a PV array has an optimum operating point (OOP) known as the MPP locating around the 'bend' or 'knee' of the I - V characteristic curve. A typical I - V characteristic of a solar cell is shown in Fig. 2.1

Fig. 2.1 Typical I - V characteristic of a solar cell

From Fig. 2.1, it is observed that the I - V characteristic of a solar cell can be divided into two regions: the current source region and the voltage source region. The internal impedance of a solar cell is high in the current source region locating on the left side of MPP, while it is low in the voltage source region locating on the right side of MPP. In the current source region, the output current remains almost constant when the terminal voltage changes. On the other hand, the terminal voltage varies minimally over a wide

range of the output current in the voltage source region. The maximum current that a solar cell can provide is the short-circuited current I_{sc} . This is the PV cell's current when the output terminals are short-circuited. If there is no current flow, the solar cell is operating at its maximum available voltage known as the open-circuited voltage V_{oc} .

One of the environmental conditions that strongly affects the output of a solar cell is the irradiance that measures the amount of sunlight energy reaching the cell. The average irradiance reaching the earth in ideal condition is about 1000W/m^2 . This value varies according to the geographical locations, the sun's angle, atmosphere, and weather conditions. Because the generated current of a solar cell is proportional to the flux of incoming photons, the irradiance has a great impact on the output current of a solar cell. On the other hand, the voltage of a solar cell is hardly affected by the change in irradiance; since the open-circuited voltage depends only logarithmically on the irradiance. In most of the applications, this relationship is considered negligible. Fig. 2.2 shows the typical dependence of I - V curves on changing irradiation level which is normalized in Suns unit. One "Suns" is equivalent to 1000W/m^2 .

Fig. 2.2 The dependence of I - V curve on irradiation level at 30 °C

Another important factor that affects the I - V characteristic is the cell's temperature. As shown in Fig. 2.3, the output voltage of the PV array increases as temperature falls.

Fig. 2.3 The dependence of I - V characteristics on temperature at 1 Sun.

The main reason of this behavior is the temperature dependence of the electron's and the hole's mobility in the semiconductor material. For a silicon semiconductor, the electron's mobility will decrease from $1700 \text{ cm}^2/\text{volt-sec}$ at 27°C to $440 \text{ cm}^2/\text{volt-sec}$ at 227°C while the hole's mobility will decrease from $600 \text{ cm}^2/\text{volt-sec}$ at 27°C to $200 \text{ cm}^2/\text{volt-sec}$ at 227°C [96]. The increasing temperature also causes an increase in the band gap energy of the semiconductor material. This results in a less efficient solar cell.

Since the change of I - V characteristic caused by the temperature and irradiance is difficult to predict, it is essential to control the solar cell's operating point (OP) close to the MPP to extract the maximum power from the solar cell. It is also necessary to adjust the OP in real time as the solar panels always operate in a dynamic environment.

2.3 A review of the MPPT techniques

From the I - V characteristic curve of the solar cell as shown in Fig. 2.3, the power curve of the solar cell can be determined. Fig. 2.4 shows the typical characteristic power curve of a PV array under uniform insolation condition.

Fig. 2.4 The P - V characteristic power curve of a PV array under uniform condition

The objective of the MPPT techniques is to automatically find the V_{MPP} or I_{MPP} at which a PV array generates the maximum power P_{MPP} under a given temperature and irradiance. Fig. 2.5 illustrates the typical block diagram of a MPPT system. In this case, the PV array is connected to a power converter that varies the PV array's current through the control of converter's duty cycle according to a specific MPPT technique. Over the past decades, many MPPT techniques have been developed and implemented [12]-[80]. They vary in implementation hardware [12]-[19], complexity, convergent speed and range of effectiveness [20]-[36]. Among the developed methods, the "Perturb and Observe" (P&O) [20]-[29] and the Incremental Conductance (INC) [30]-[35] are the most commonly used due to their simplicity and ease of implementation. The details of various MPPT techniques will be reviewed in the following sections.

Fig. 2.5 Typical block diagram of a MPPT system

2.3.1 Perturb and observe (P&O) method

The P&O method involves the use of a perturbation in the PV array's operating voltage. If the PV array is connected to a power converter, it can be achieved by perturbing the converter's duty cycle. The P-V curve in Fig. 2.4 shows that incrementing (decrementing) the voltage increases (decreases) the power if it is operating on the left of the MPP. It decreases (increases) the power if it is operating on the right of the MPP. Therefore, the subsequent perturbation should remain in the same direction to reach the MPP if the power increases. Otherwise, the perturbation should be reversed. The process is repeated periodically until the MPP is reached. Fig. 2.6 shows the simplified flow chart for realizing the P&O technique.

Fig. 2.6 Flow chart of the P&O method

In the steady state, the system oscillates about the MPP. To improve the tracking accuracy and reduce the power loss due to steady state oscillations, a small perturbation step can be used. However, this will result in slower tracking speed. A solution to this conflicting situation is to have a variable perturbation size that becomes smaller towards the MPP [25]–[27]. In [25], the fuzzy logic control is used to optimize the magnitude of the next perturbation. [26] proposes a two-stage algorithm that offers a fast tracking in the first stage and then a fine tracking in the second stage. On the other hand, [27] bypasses the first stage by using a nonlinear equation to estimate an initial OP that is close to the MPP.

Fig. 2.7 Divergence of P&O from MPP

Another weakness of the P&O method is that it may fail under rapidly changing atmospheric conditions as illustrated in Fig. 2.7. Assume that the operating point starts from point A, an increase in the PV voltage ΔV will bring the OP to point B if the atmospheric conditions changes slowly during the sampling time. The perturbation will be reversed in the next cycle due to the fall in tracking power. In the fast changing atmospheric conditions, an increase in irradiance may shift the power curve from P_1 to P_2 within one sampling period. The operating point then moves from A to C, which represents an increase in tracking power. Thus, the perturbation will be kept in the same direction in the next sampling period. Consequently, the operating point diverges from the MPP and will remain so if the irradiance steadily increases. To ensure that the MPP is tracked even under large changes in irradiance, dP-P&O method performs an additional measurement in the middle of the MPPT sampling period [20]. This allows it to differentiate the change in tracking power due to the perturbation step of MPPT from the change due to both the perturbation and the irradiation change. However, the method requires the sampling rate to be double.

In practice, the implementation of P&O method requires two sensors for measuring the PV array voltage and current to compute the power. In [28], a method of estimating the array current from the array voltage is proposed to eliminate the current sensor.

2.3.2 Incremental conductance (INC) Method

The incremental conductance (INC) method [30]-[35] is based on the characteristic of the slope of the PV array power curve. From Fig. 2.4, it is observed that

$$\begin{aligned}\frac{\partial p}{\partial v} &= 0, & \text{at MPP} \\ \frac{\partial p}{\partial v} &> 0, & \text{left of MPP} \\ \frac{\partial p}{\partial v} &< 0, & \text{right of MPP}\end{aligned}\tag{2.1}$$

Substituting $p = vi$ into (2.1) and rearranging the equations, we have

$$\begin{aligned}\frac{\partial i}{\partial v} &= -\frac{i}{v}, & \text{at MPP} \\ \frac{\partial i}{\partial v} &> -\frac{i}{v}, & \text{left of MPP} \\ \frac{\partial i}{\partial v} &< -\frac{i}{v}, & \text{right of MPP}\end{aligned}\tag{2.2}$$

From (2.2), the MPP can be tracked by comparing the instantaneous conductance $\frac{i}{v}$ to the incremental conductance $\frac{\partial i}{\partial v}$. The flowchart is shown in Fig. 2.8. In the flow chart, V_{ref} is the reference voltage for the PV array. At the MPP, V_{ref} equals to V_{MPP} .

Fig. 2.8 The flowchart of INC algorithm as shown in [32]

Once the system is operating at the MPP, the PV array's OP is maintained unless a change in ΔI is noted, indicating a change in the atmospheric conditions and hence the MPP. Theoretically, the steady state oscillations in INC method would be eliminated. In practice, the null value of the slope of Fig. 2.4 is seldom observed due to the sensor and the quantization errors. Thus, the INC method also experiences the steady state oscillation like the P&O method. To increase the tracking speed and reduce the oscillation, the variable step size method has been proposed [30]-[31].

Besides using (2.2) to find the MPP, the other effective way to perform the INC technique is to sum the instantaneous conductance and the incremental conductance to generate an error signal as follows [34]-[35]

$$e = \frac{i}{v} + \frac{\partial i}{\partial v} \quad (2.3)$$

Since e becomes zero at the MPP, a simple proportional and integral (PI) control can be used to drive the error signal to zero.

2.3.3 Fuzzy logic control

Fuzzy logic controllers have the advantages of working with imprecise inputs. They do not need an accurate mathematical model and can handle nonlinearity [36]-[42]. The control generally consists of three stages: the fuzzification, the rule base lookup table and the defuzzification. During the fuzzification stage, numerical input variables are converted into linguistic variables based on a membership function similar to Fig. 2.9

Fig. 2.9 Membership function for inputs and output of fuzzy logic controller

In Fig. 2.9, there are five fuzzy levels: NB (negative big), NS (negative small), ZE (zero), PS (positive small), and PB (positive big). Moreover, a and b are input variables to the MPPT fuzzy logic controller. They are usually the error E and the change in error ΔE as follows [40]

$$E(n) = \frac{P(n) - P(n-1)}{V(n) - V(n-1)} \quad (2.4)$$

$$\Delta E(n) = E(n) - E(n-1) \quad (2.5)$$

where P and V are the power and voltage of the solar cells.

Once E and ΔE have been calculated and converted to the linguistic variables, the change in the power converter's duty cycle can be obtained from the rule Table 2.1.

Table 2.1 Fuzzy rule base table as shown in [40]

ΔE E	NB	NS	ZE	PS	PB
NB	PB	PB	PS	PB	PB
NS	PB	PS	PS	PS	PB
ZE	NS	NS	ZE	PS	PS
PS	NB	NS	NS	NS	NB
PB	NB	NB	NS	NB	NB

As shown in Table 2.1, when the OP is far to the right of the MPP, E is NB and ΔE is PB. To largely increase the duty ratio, ΔD should be PB to reach the MPP. In the defuzzification stage, ΔD is converted from a linguistic variable (NS) to a numerical variable b using a membership function as in Fig. 2.9. This provides the signal that will control the power converter to reach the MPP. For better accuracy, seven fuzzy levels are used in [37]-[38]. To give more weight on some specific fuzzy levels, the membership function is sometimes made less symmetric [36], [39]-[40].

Though MPPT fuzzy logic controllers have been shown to perform better than P&O method under varying atmospheric conditions, their effectiveness strongly depends on the knowledge of the control engineer in choosing the right error computation and coming up with the rule base table. To achieve the optimum performance, an adaptive fuzzy logic control could be applied to tune the membership functions and the rule base table [42]. The other effective MPPT method is the neural network method [43]-[45] that focuses on the nonlinear characteristics of the PV arrays. This will be discussed in the next section.

2.3.4 Neural network method

In [43]-[45], the neural network is proposed to perform MPPT. It is commonly designed to have three layers: input, hidden and output layers as illustrated in Fig. 2.10. In each layer, the number of nodes varies and depends on the designers' choice.

Fig. 2.10 Example of a neural network

The input to the network can be irradiance, temperature, PV array parameters such as V_{OC} and I_{SC} , or any combination of these variables. The output is usually the duty cycle signal that drives the power converter. How close the operating point gets to the MPP depends on the algorithms used by the hidden layer and how well the neural network has been trained [43]-[45].

The links between the nodes i and j in the network are all weighted and labeled as w_{ij} as shown in Fig. 2.10. These weights have to be carefully determined through a training process to accurately identify the MPP. In the training, different patterns describing the relationship between input(s) and output(s) are tested over months or even years to find the best patterns. Since each PV array has different characteristics, it is necessary to specifically train the neural network used for each PV array. Besides, the training process also needs to be conducted periodically to account for the changing characteristic of the PV array. Thus, the versatility of the method is limited, especially for low cost PV system.

2.3.5 The sliding mode control method

Different from the fuzzy logic or neural network method, the sliding mode control method is based on the nonlinear control approach. It has fast tracking performance and can converge to the MPP in several tens of milliseconds [46]. A sliding mode control method uses a buck-boost converter to achieve MPPT. Based on the fact that $dP/dV > 0$ when OP is on the left of the MPP and $dP/dV < 0$ when OP is on the right of the MPP, the switching function u of the converter is expressed as

$$\begin{cases} u = 0, & S \geq 0 \\ u = 1, & S < 0 \end{cases} \quad (2.6)$$

where $u = 0$ means the switch is open and $u = 1$ means the switch is close. The sliding surface S is given by

$$S = \frac{dP}{dV} = I + V \frac{dI}{dV} \quad (2.7)$$

Simulation and experimental results [46] showed that the algorithm's tracking speed is much faster than the P&O method. However, the method often requires the use of larger capacitor and inductor components than the conventional methods.

2.3.6 Fractional open-circuited voltage & short-circuited current methods

The fractional V_{OC} method is one of the easiest and cheapest MPPT methods. It is based on the nearly linear relationship between V_{MPP} and V_{OC} of the PV array under varying irradiance and temperature conditions [47] – [51], i.e.

$$V_{MPP} \approx k_I V_{OC} \quad (2.8)$$

where k_I is a constant of proportionality.

In (2.8), V_{MPP} and V_{OC} for the specific PV array can be empirically determined at different irradiance and temperature levels. k_I can then be computed using (2.8). k_I has been reported to be between 0.71 and 0.78 depending on the characteristics of the PV array. Once k_I is known, V_{MPP} can be computed using (2.8) with V_{OC} measured periodically by momentarily shutting down the power converter. The method incurs some disadvantages such as temporary loss of power. To prevent this problem, [47] proposed the use of a pilot cell that must be chosen to represent closely the PV array's characteristics to obtain V_{OC} .

Similar to the fractional V_{OC} method, the fractional I_{SC} is formulated based on the approximately linear relationship between I_{MPP} and I_{SC} [52]-[54] as follows

$$I_{MPP} \approx k_2 I_{SC} \quad (2.9)$$

where k_2 is a proportionality constant and also has to be determined accordingly to the PV array in use. k_2 generally ranges from 0.78 to 0.92. To measure I_{SC} , an additional switch has to be added to the power converter to periodically short the PV array. Then I_{MPP} can be estimated using (2.9).

The fractional V_{OC} and I_{SC} methods cannot locate the true MPP since (2.8) and (2.9) are only approximation. Another disadvantage is that the proportionality factors k_1 and k_2 are not valid in the presence of partial shading of the PV array. To update these factors, the method needs to be modified with additional complexity and incurs more power loss [50].

2.3.7 Load current or load voltage maximization

Most of the MPPT techniques require two sensors to sense the current and voltage. To further reduce the hardware cost, the load current or load voltage maximization method that requires only one sensor has been proposed. To maximize the PV array power, the method maximizes the converter's output power [55]-[59]. Some linear load examples, i.e. voltage source, pure resistive, series combination of a voltage source and a resistor,

current source types are described in Fig. 2.11. Hyperboles representing lines of constant power are also plotted. The loads might operate at any point, drawing power that is not greater than PV array maximum power P_M .

Fig. 2.11 Different load types 1: voltage source, 2: resistive, 3: resistive and voltage source, 4: current source [55]

To reach the maximum output power P_M , the load current i_{out} should be maximized for a voltage-source type load (line 1) as shown in Fig. 2.11. For the current-source load (line 2), the load voltage v_{out} should be maximized to reach P_M . For the other load types, either i_{out} or v_{out} can be used for tracking maximum power. This is also true for nonlinear loads as long as they do not exhibit negative impedance characteristics [55]. Thus, it is sufficient to maximize either the load current or the load voltage to maximize the load power for almost all loads of interest. In other words, only one sensor is needed. When the load current (or voltage) is used as the control variable, the positive feedback can be implemented to control the power converter such that the load current is maximized and

the PV array operates close to the MPP [57]-[59]. Since the method assumes that the power converter is lossless, the exact operation at the MPP will not be achieved.

2.3.8 The ripple correlation control (RCC) techniques

The RCC technique [60] approaches an alternative way to reduce the hardware cost. The method can be implemented with simple and inexpensive analog circuits. The RCC uses the ripple of the PV array power (current or voltage) caused by the power converter's switching action. To perform MPPT, the RCC correlates the time derivative of PV array power $\frac{\partial p}{\partial t}$ with the time derivative of PV array current $\frac{\partial i}{\partial t}$ or voltage $\frac{\partial v}{\partial t}$ to drive the power gradient to zero and reach the MPP. Since the prior information about the PV array characteristics is not required, the method can adapt to different PV systems.

There are also other methods that perform MPPT resemble the RCC. The method in [61] disturbs the duty ratio to generate a power disturbance. In [62]-[63], a hysteresis-based version of RCC is used. In [64], a low frequency dithering signal is employed to disturb the power. Then a 90° phase shift in the current (or voltage) with respect to power at the MPP is used just like in RCC. The difference in [64] is that the injection is an extra, low frequency signal and not an inherent converter ripple.

2.3.9 Other MPPT techniques

The current sweep [65] method uses a sweep waveform to obtain the PV array current and update the I - V characteristic at fixed time intervals. Then the V_{MPP} can be computed from the characteristic curve in the same intervals. The method is implemented through

analog computation and is only feasible if the power consumption of the tracking unit is lower than the increase in power brought to the entire PV system.

DC-link capacitor droop control [66]-[67] is specifically designed to work with a PV system that is connected in parallel with an ac system line. The method does not require the computation of the PV array power, but its response deteriorates when compared to the method that detects the power directly [67]. This control scheme can be easily implemented with analog operational amplifiers and decision-making logic units.

dP/dV or dP/dI feedback control performs MPPT by computing the slope (dP/dV or dP/dI) of the PV power curve and feeds it back to the power converter with some control to drive it to zero [68]-[72]. In [68], dP/dV is computed with its sign and is stored for the past few cycles. Based on these signs, the duty cycle of the power converter is either incremented or decremented to reach the MPP. A dynamic step size is also used to improve the transient response of the system. In [69], a linearization based method is used to compute dP/dV . To approximate dP/dV , sampling and data conversion are used with subsequent digital division of power and voltage [70]-[72]. In [71], dP/dI is integrated together with an adaptive gain to improve the transient response. In [72], the PV array voltage is periodically incremented or decremented and dP/dV is compared to a reference error until the MPP is reached.

2.3.10 MPPT techniques specialized for partial shading conditions

In practice, the PV arrays may experience partial shading conditions due to the passage of clouds or the shadows from surrounding obstacles, etc. Under this condition, the I - V curve has a multi-steps characteristics and the P - V (or P - I) curve has multiple local maxima [11], [73]-[78]. Fig. 2.12 shows some examples of the I - V characteristic curve under partially shaded conditions.

Fig. 2.12 PV array's characteristic curves under partially shaded conditions

The conventional MPPT techniques reviewed in sections 2.3.1 – 2.3.9 can only track the single local maxima that may not be the true peak power point of the system. This would result in a major lost in tracking power. In [80], it was demonstrated that losses due to shading could lead up to 70% of tracking loss.

To overcome the conventional MPPT limitations under partially shaded conditions, several methods have been reported. In [75]-[76], a two-stage method to track the global peak (GP) is proposed. In the first stage, the OP of the PV system moves into the vicinity

of the real peak power point. Then it converges to the peak power point in the second stage. However, this method may not track the real MPP for some non-uniform insolation conditions. For this reason, it requires additional control process to track the real MPP. In [77], a line search algorithm with improved Fibonacci search is used to find the global MPP when the PV array is partially shaded. This approach too cannot guarantee the finding of the global MPP under all conditions [77]. In [78], a fractional open-circuited voltage method that periodically sweeps the PV array voltage from open-circuit to short-circuit is proposed. It updates the fraction that gives the relationship between MPP voltage and open-circuited voltage to find the optimal operating point. Consequently, this causes more power losses. In [79], a voltage based power compensation method that deactivates shaded PV modules by forward biasing the corresponding bypass diodes according to the shaded level of the PV module is proposed. This method is suitable for system that consists of multiple modules in series and parallel. However, knowledge of the system is essential for successful tracking. In [80], a global stage is used to find the region of local MPPs while the local stage employs P&O to fine track the local MPPs. The searching is stopped when the algorithm finds the highest local MPP. Thus, the tracking speed is limited as almost all local MPP may be found and compared to find the GP.

2.4 Conclusion

This chapter reviews a wide variety of MPPT methods. For brevity, slight modifications of existing methods as distinct methods are not presented. Each technique has its own advantages and disadvantages depending on the context of application. Table 2.2

summarizes a comparison of the commonly used MPPT techniques. This comparison gives a guideline for selecting a suitable scheme for a specific application.

Table 2.2 The comparison of the commonly used MPPT schemes

MPPT scheme	Recommended implementation (digital/analog)	Implementation Complexity	Conversion Speed	Performance during partial shading
Perturb& Observe	Both	Low	Slow- medium, depending on the methods as discussed in section 2.3.1	Local maximum
Incremental conductance	Both	Low	Slow- medium, depending on the methods as discussed in section 2.3.2	Local maximum
Fuzzy logic method	Digital	High	Fast	Complexity in rule base forming for tracking GP
Neural network method	Digital	High	Fast	Suitable network selection is required
Sliding mode control	Digital	Medium	Fast	Local maximum
Fractional V_{OC} or I_{SC}	Both	Low	Medium	Not even local maximum
Load current or load voltage maximization	Analog	Low	Fast	Local maximum
RCC	Analog	Low	Fast	Local maximum
dP/dV or dP/dI feedback control	Digital	Medium	Fast	Local maximum
Search based methods	Digital	Varies depending on the methods as discussed in section 2.3.10	Varies depending on the methods as discussed in section 2.3.10	Tracking of GP is possible

Chapter 3

A Novel Maximum Power Point Tracking Algorithm

3.1 Introduction

In this chapter, a new search algorithm that has the same ease of implementation as P&O and INC schemes is proposed. The proposed approach is developed based on the DIRECT (DIviding RECTangles) algorithm that was developed in [82] for searching the global extreme of a Lipschitz function in an interval where the Lipschitz constant is unknown. In section 3.2, it is shown that the function describing the Power/Voltage relationship of PV cells is a Lipschitz function. Therefore, the DIRECT algorithm can be employed in tracking global maximum power of a PV system. The new approach shows a better performance and faster tracking speed, especially in the presence of multiple maximum power points and sudden high level change of insolation.

3.2 Lipschitz characteristics of P - V function

Over the past decades, different models have been proposed to characterize the solar cells [3]-[11]. For a group of solar cells (a module) that consists of n_s solar cells connected in series and n_p solar strings connected in parallel operating under the same environmental conditions, the current-voltage output characteristics can be described as

$$i = n_p I_{ph} - n_p I_{rs} \left\{ \exp \left[\frac{q}{kTAn_s} \left(v + i \frac{n_s}{n_p} R_s \right) \right] - 1 \right\} - \frac{v + i \frac{n_s}{n_p} R_s}{\frac{n_s}{n_p} R_{SH}} \quad (3.1)$$

where the variables in (3.1) are defined in Table. 3.1

Table 3.1 Symbol definition

Symbol	Definition	Unit
I_{ph}	Photo current generated by solar cells	A
I_{rs}	Reversed saturation current of diode.	A
A	Ideal factor with value from 1 to 2	-
k	Boltzman's constant. (1.38×10^{-23})	JK ⁻¹
q	Electron charge (1.602×10^{-19})	C
R_s	Series resistance.	Ω
R_{SH}	Shunt resistance.	Ω
i	Solar cell current.	A
v	Solar cell voltage	V

Multiply (3.1) by v yields the power p and then perform partial differentiation with respect to v yields the following

$$\frac{\partial p}{\partial v} = i + v \frac{\partial i}{\partial v} \quad (3.2)$$

where

$$\frac{\partial i}{\partial v} = - \frac{\frac{qn_p}{kTAn_s} I_{rs} e^{K(v+i\frac{n_s}{n_p}R_s)} + \frac{n_p}{n_s R_{SH}}}{1 + \frac{qn_p}{kTAn_s} I_{rs} R_s e^{K(v+i\frac{n_s}{n_p}R_s)} + \frac{R_s}{R_{SH}}} \quad (3.3)$$

When the PV array is under partially shaded condition, the PV cells under the same insolation condition can be regrouped to form new modules [10]-[11]. These modules can be considered to be connected in series and/or parallel to form a new PV array according to the shading pattern. Fig. 3.1(a) shows an example of grouping a PV array that consists of two branches in parallel. In each branch, the two unshaded modules are grouped as the sub-assembly 1 while the two shaded modules are grouped as the sub-assembly 2. Thus, each branch can be considered as a series of two sub-assemblies that have different I - V characteristics. Fig. 3.1(b) illustrates a PV array with shaded modules. In the figures, the shaded modules are illustrated with gray color. Based on the shading pattern, the PV array can be considered as a parallel of five groups.

(a) An example of grouping the shaded PV modules (b) A PV array consists of 5 groups of PV modules

Fig. 3.1 Grouping a PV array with shaded modules

Assuming that the new configuration consists of N_p branches in parallel and a maximum of N_s modules in series in a branch, the output current i_a and voltage v_a can be described as

$$i_{ar} = \sum_{br=1}^{N_p} i_{br} \quad (3.4)$$

$$v_{ar} = \sum_{j=1}^{N_s} v_j \quad (3.5)$$

where i_{br} is the current in b^{th} branch, v_j is the voltage across j^{th} module in a branch.

Multiply (3.4) by (3.5) yields the power p_{ar}

$$p_{ar} = \sum_{br=1}^{N_p} i_{br} \sum_{j=1}^{N_s} v_j \quad (3.6)$$

Perform partial differentiation of (3.6) with respect to v_{ar} , we have

$$\frac{\partial p_{ar}}{\partial v_{ar}} = i_{ar} + v_{ar} \frac{\partial i_{ar}}{\partial v_{ar}}, \quad \forall v_{ar} \in [a, b] \quad (3.7)$$

where

$$\frac{\partial i_{ar}}{\partial v_{ar}} = \sum_{br=1}^{N_p} \left(\sum_{j=1}^{N_s} \frac{\partial v_j}{\partial i_{br}} \right)^{-1}, \quad \forall v_{ar} \in [a, b] \quad (3.8)$$

Consider j^{th} module in b^{th} branch, it can be verified that

$$\frac{\partial v_j}{\partial i_{br}} = - \frac{1 + \frac{q}{kTA} I_{RS} R_S e^{K(v_{bj} + i_{bj} \frac{n_{S\_bj}}{n_{P\_bj}} R_S)} + \frac{R_S}{R_{SH}}}{\frac{qn_{P\_bj}}{kTAn_{S\_bj}} I_{RS} e^{K(v_{bj} + i_{bj} \frac{n_{S\_bj}}{n_{P\_bj}} R_S)} + \frac{n_{P\_bj}}{n_{S\_bj} R_{SH}}} \quad (3.9)$$

From (3.7)-(3.9), $\partial p_a / \partial v_a$ exists in the interval $[a, b]$ and thus is bounded by the real value M in that interval. By the mean value theorem, for every $v_1, v_2 \in [a, b]$, there exists $c \in [v_1, v_2]$ such that

$$\frac{|p(v_1) - p(v_2)|}{|v_1 - v_2|} = \left. \frac{\partial p}{\partial v_a} \right|_c, \quad c \in (v_1, v_2) \quad (3.10)$$

As $\left. \frac{\partial p}{\partial v_a} \right|_c$ is bounded by M , (3.10) becomes

$$|p(v_1) - p(v_2)| \leq M |v_1 - v_2|, \quad \forall v_1, v_2 \in [a, b] \quad (3.11)$$

Equation (3.11) is known as the Lipschitz condition [82]. Since the function $p(v)$ satisfies the condition, it is known as a Lipschitz function with Lipschitz constant M .

Assuming v_l is a sample point and v is a variable, the Lipschitz inequality (3.11) gives both the upper and lower bounds for $p(v)$ in an interval (a, b) as [81]

$$p(v_l) - M |v - v_l| \leq p(v) \leq \max_{v \in [a, b]} p(v) \leq p(v_l) + M |v - v_l| \quad (3.12)$$

If v_l is at the center of $[a, b]$, it can be shown from (3.12) that

$$p(v_l) - M \frac{b-a}{2} \leq p(v) \leq \max_{v \in [a, b]} p(v) \leq p(v_l) + M \frac{b-a}{2} \quad (3.13)$$

The bounds (3.12) and (3.13) are illustrated in Fig. 3.2(a) and Fig. 3.3(a) for the case that the solar arrays are operating under uniform insolation and partially shaded condition, respectively. In the figures, the typical P - V characteristic curves of the solar arrays have been illustrated by the blue lines. In an interval $[a, b]$, these P - V curves are confined in the boundary area (the gray areas in the figures) which are defined by (3.12). The maximum (or minimum values) of “the boundary areas” can be verified to be the intersection points of $p(v_l) + M|v-v_l|$ (or $p(v_l) - M|v-v_l|$) with the boundary lines. When the boundary intervals become smaller, the boundary areas also get smaller as illustrated in Fig. 3.2(b) and Fig. 3.3(b). In these figures, the lower bounds in (3.12) and (3.13) are not illustrated for clarity.

Fig. 3.2 Lipschitz function and bounds for a PV array under uniform insolation condition

(b) – Bounds observed from 1st sample (b) Bounds observed from 3rd sample

Fig. 3.3 Lipschitz function and bounds for a PV array under partially shaded condition

(b) – Bounds observed from 1st sample (b) Bounds observed from 3rd sample

From (3.13), an estimate for the closeness of $p(v_1)$ to P_{MPP} is:

$$\max_{v \in [a, b]} p(v) - p(v_1) = P_{MPP} - p(v_1) \leq \frac{b-a}{2} \quad (3.14)$$

Thus, (3.14) gives a bound on how far the global peak is from the observed sample with just one sample. Both the maximum slope in the sampling interval and the interval $[a, b]$ might be quite large initially as shown in Fig. 3.2(a) and Fig. 3.3(a). By taking further samples, $(b-a)$ can be replaced by the length of successively smaller subintervals as shown in Fig. 3.2(b) and Fig. 3.3(b). In this manner, an efficient algorithm can be developed to find a solution within a pre-specified tolerance of an optimal solution in a finite number of iterations [81]-[84]. The DIRECT search-algorithm is one of them and it is especially effective where Lipchitz constant M is unknown or difficult to be estimated [82].

3.3 Overview of DIRECT algorithm

The DIRECT optimization algorithm was first introduced in [82] and was motivated by a modification to the Lipschitzian optimization. It was developed in order to solve difficult global optimization problems with bound constraints and a real-valued objective function. The name DIRECT comes from the shortening of the phrase "Dividing RECTangles", which describes the way the algorithm moves towards the optimum. DIRECT is a sampling algorithm and requires no knowledge of the objective function gradient. Instead, the algorithm samples points in the domain and uses the obtained information to decide the next search.

The DIRECT algorithm will converge to the global optimum value of the objective function [82]. The strengths of DIRECT lie in the balanced effort it gives to local and global searches and the few parameters it requires to run. It has been shown to be very competitive with the existing algorithms in its class [82]. DIRECT has been used to solve the gas transmission pipeline optimization [85].

In this section, two main ideas of DIRECT algorithm, namely the Area-Dividing Strategies and Potentially Optimal Intervals will be reviewed. Subsequently, its development to track the MPP of a PV array will be presented in the following sections.

3.3.1 Area-dividing strategies

Fig. 3.4(a) illustrates the area-dividing strategy of DIRECT algorithm when a sampling interval $[a, b]$ has been specified.

Fig. 3.4 (a) Dividing Strategy (b) Potentially Optimal Intervals

As shown in Fig. 3.4(a), a sample V_1 is initially taken at the center of $[a, b]$. This interval is subsequently divided into three equal parts. The samples V_2 and V_3 are then taken as the center points of the left and the right intervals, respectively. The sample V_1 simply becomes the center of the new middle interval. After evaluating these three samples, the next sampling interval is decided. Once an interval is chosen for further exploration, it will be triply divided with two new samples, i.e. V_{32} and V_{33} in Fig. 3.4(a) will be sampled. This results in 5 samples at the end of 2^{nd} dividing cycle as shown in Fig. 3.4(a).

3.3.2 Potentially optimal interval (POI)

When an interval is to be divided for further sampling, the interval is termed as *potentially optimal*. Let $\varepsilon > 0$ be a positive constant and $f_{\max}$ be the current best sampled value. The interval J is said to be *potentially optimal* if there exists a rate of change constant $\tilde{K} > 0$ such that [82]:

$$f(c_j) + \tilde{K} \frac{(a_j - b_j)}{2} \geq f(c_i) + \tilde{K} \frac{(a_i - b_i)}{2}, \text{ for } i \neq j \quad (3.15)$$

$$f(c_j) + \tilde{K} \frac{(a_j - b_j)}{2} \geq f_{\max} + \varepsilon |f_{\max}| \quad (3.16)$$

where a_i , b_i and c_i are the upper bound, lower bound and center of the interval I . a_j , b_j and c_j are the upper bound, lower bound and center of the potentially optimal interval J .

The inequality (3.15) expresses the decision only to choose the intervals that would promise the best improvement in the function value. For intervals with the same length, it

implies that only the interval with the highest function value at its center is potentially optimal. The parameter ε in (3.16) ensures that the POIs would yield better improvement than f_{max} by at least an amount $\varepsilon|f_{max}|$. As reported in [82], the algorithm becomes more local in its searching when the value of ε gets smaller. For the PV system under investigation, the maximum percentage error of the measured power can be used as a guideline for the choice of ε . In our design, the maximum errors of the current and voltage sensors are 1.5%. Thus, the maximum measurement error of the power is less than 3%. When the proposed algorithm is performing global search, ε is chosen as 0.03. When the algorithm is performing the local search, ε is set to zero to allow the GP to be reached. Fig. 3.4(b) plots the function value versus the length of the interval. Among all the intervals, only those satisfy (3.15) and (3.16) are considered potentially optimal [82]. The original DIRECT algorithm divides all POIs to search for the GP globally and locally at the same time. For the proposed algorithm, the dividing strategy is different. This will be explained in the corresponding sections.

3.4 A novel MPPT algorithm for a PV array under uniform conditions

3.4.1 DIRECT algorithm for PV system

The area-dividing strategy of DIRECT algorithm has been adopted for searching the MPP. Originally, DIRECT was developed to solve global optimization problem for function with multiple local extremes. Since the P - V curve only presents a single MPP under uniform insolation condition, the definition of the POI can be redefined as

Definition 1: From several equal intervals, only the interval with highest function value at its middle point is the only potentially optimal interval.

The inequality (3.15) expresses that only the interval with the highest function value at its middle point has the highest upper bound among several equal intervals. Therefore, the definition expresses the decision only to choose the interval that would promise the best improvement in the power value. Thus, the MPP would fall in the POI or be close to the interval's boundaries. When the size of the POI gets smaller, the MPP will be reached within a small tolerance.

3.4.2 Development for sudden insolation change

Under uniform insolation condition, the I - V characteristic of a solar cell can be divided into two regions: the current source region and the voltage source region as illustrated in Fig. 2.1. As a result, a PV array has an optimum operating point known as the MPP that locates around the 'knee' of the I - V characteristic curve. In the current source region, the output current remains almost constant when the terminal voltage changes. On the other hand, the terminal voltage varies minimally over a wide range of the output current in the voltage source region. The maximum current and voltage that the PV array can generate are the short-circuited current I_{SC} and the open-circuited voltage V_{OC} respectively. As discussed in chapter 2, the changing atmospheric conditions will affect I_{SC} and V_{OC} . Thus, by combining all the increase/decrease scenarios of I_{SC} and V_{OC} on the I - V characteristic curve, all possible changing scenarios of the I - V curve can be studied. Fig. 3.5 shows those scenarios when the I - V curve changes from (I_{sc1}, V_{oc1}) to (I_{sc2}, V_{oc2}) .

Fig. 3.5 Operating point changing scenarios

(a)-Scenario 1, (b)-Scenario 2, (c)-Scenario 3, (d)-Scenario 4, (e)-Scenario 5, (f)-Scenario 6

In Fig. 3.5, it is assumed that the system is operating at the MPP in the previous step, i.e. the reflected equivalent load R_{pv} at the PV array output matched the PV output resistance R_{MPP} at the MPP. Initially, the load line D_{m1} passes through point 1 of (I_{sc1}, V_{oc1}) curve. Any change in temperature or insolation would move the OP from 1 to 2' on the new $I-V$ curve (I_{sc2}, V_{oc2}) . This results in a change ΔP in the tracking power. Thus, a predefined ΔP_{cr} can be used to detect a change in $I-V$ curve as discussed in [80].

The new OP 2' is not at the optimum OP. This implies that the tracker needs to shift the OP from 2' to 2 that is the new MPP. This can be done by increasing (e.g. Fig. 3.5 (b, d, f)), or decreasing (e.g. Fig. 3.5 (a, c, e)) the slope of the load line, i.e. increasing or decreasing the duty cycle D of the buck-boost converter. The location of the OP 2' on (I_{sc2}, V_{oc2}) curve can be identified by using a small increment in the duty cycle D . If $\frac{\Delta P}{\Delta D} < 0$, the system is operating in “the current source region” as shown in Fig. 3.5(a), 3.5(c), 3.5(e). Otherwise, it is in “the voltage source region” as shown in Fig. 3.5(b), 3.5(d), 3.5(f).

(a) D_{max} estimation method

In the case that the new OP 2' is in “the voltage source region” (e.g. Fig. 3.5(b), 3.5(d), 3.5(f)), it needs to be shifted from 2' ($D_2=D_{m1}$) to 2 (D_{m2}). In other words, the duty cycle needs to be increased due to the inverse relationship between the duty cycle and the voltage in the buck-boost topology. To find the new optimum duty cycle D_{m2} , the algorithm needs to take samples in the segment (D_2, D_{max}) , where $D_{max} > D_2$. Fig. 3.6(a) illustrates this sampling segment and the method to estimate the upper bound D_{max} . In the figures, there are four known parameters namely the maximum short-circuited current I_{sc_max} , the PV array's current $I_{D2'}$, voltage $V_{D2'}$ at the load line D_2 and the equivalent resistive load R_{load} at the DC-DC converter output. The methodology is based on the I - V curve characteristic that V_{m2} at the new MPP is close to $V_{D2'}$ since the OP 2' is in “the voltage source region”.

Fig. 3.6 D_{max} estimation method with buck-boost topology

(a) – Segment estimation , (b) - Interval estimation

When the PV array's load line is at the upper bound D_{max} (green line), the equivalent load at the PV array output can be estimated as

$$\tilde{R}_{pv} = \frac{\tilde{V}_{pv}}{\tilde{I}_{pv}} \quad (3.17)$$

where the estimated voltage $\tilde{V}_{pv}$ and current $\tilde{I}_{pv}$ can be calculated as follows

$$\tilde{V}_{pv} = \alpha \times V_{D2'} \quad (3.18)$$

$$\tilde{I}_{pv} = I_{sc\_max} \quad (3.19)$$

In (3.18), α is a scaling factor that is less than 1 since $\tilde{V}_{pv}$ must be less than $V_{D2'}$ for $D_{max} > D_{2'}$. The value of α decides the range of the estimated interval. A smaller value leads to

larger estimated interval. In (3.19), $\tilde{I}_{pv}$ is chosen as I_{sc_max} since I_{sc2} is unknown and could range from 0A to I_{sc_max} depending on the atmospheric condition.

For the buck – boost topology, the relationship between R_{pv} and R_{load} is [86]

$$R_{load} = \frac{1}{\eta} \times \frac{1}{R_{pv}} \times \left(\frac{D}{1-D} \right)^2 \quad (3.20)$$

where η is the converter's efficiency and D is the operating duty cycle of the converter.

Rewriting (3.20), we have

$$D = \frac{\sqrt{\eta R_{load}}}{\sqrt{R_{pv}} + \sqrt{\eta R_{load}}} \quad (3.21)$$

Assuming η is constant in (3.21), the maximum duty cycle D_{max} that the DC-DC converter can be adjusted to get the R_{pv}^o in (3.17) can be verified as (Appendix A.2)

$$D_{max} = \frac{\sqrt{\eta R_{load\_max}}}{\sqrt{R_{pv}^o} + \sqrt{\eta R_{load\_max}}} \quad (3.22)$$

where R_{load_max} is the maximum value of R_{load} .

In application whereby the load changes insignificantly during tracking, R_{load} can be assumed to be constant. Thus, substituting R_{load} for R_{load_max} , (3.22) becomes

$$D_{\max}^{\circ} = \frac{\sqrt{\eta R_{load}}}{\sqrt{R_{pv}^{\circ} + \sqrt{\eta R_{load}}}} \quad (3.23)$$

By evaluating (3.20) at $D_{2'}$, R_{load} can be calculated as follows

$$R_{load} = \frac{1}{\eta} \times \frac{I_{D_{2'}}}{V_{D_{2'}}} \times \left(\frac{D_{2'}}{1 - D_{2'}} \right)^2 \quad (3.24)$$

As discussed in the 1st paragraph of this section, the algorithm only needs to take samples in the interval $(D_{2'}, D_{max})$ to find the MPP. Since the sample at $D_{2'}$ has already been known, the interval $(D_{2'}, D_{max})$ is extended to become a larger interval (D_{min}, D_{max}) such that the $D_{2'}$ is the first sample of (D_{min}, D_{max}) as shown in Fig 3.6(b). D_{min} can be calculated as follows

$$D_{min} = D_{2'} - \frac{D_{max} - D_{2'}}{5} \quad (3.25)$$

The algorithm then only need to take two more samples S_2 , S_3 as illustrated in Fig 3.6(b) to find the optimum subinterval among the 3 subintervals.

(b) D_{min} estimation method

In the case that the new OP 2' is in “the current source region” (e.g. Fig. 3.5(a), 3.5(c), 3.5(e)), it needs to be shifted from 2' ($D_{2'} = D_{m1}$) to the new optimum OP 2 (D_{m2}). Hence, the duty cycle should be decreased and the algorithm only needs to consider the segment ($D_{min}, D_{2'}$), where $D_{min} < D_{2'}$. Fig. 3.7(a) illustrates this sampling segment and the method to estimate the lower bound D_{min} . There are four known parameters namely V_{oc_max} , $I_{D2'}$, $V_{D2'}$ and R_{load} . The methodology is based on the I - V curve characteristic that I_{m2} at new MPP is close to $I_{D2'}$ since OP 2' is in “the current source region”.

Fig. 3.7 D_{min} estimation method with the buck-boost topology

(a) – Segment estimation, (b) - Interval estimation

When the PV array's load line is at the lower bound D_{min} (green line), the equivalent load at PV array output can be estimated as in (3.17) with $\tilde{V}_{pv}$ and $\tilde{I}_{pv}$ can be calculated as follows

$$\tilde{V}_{pv} = V_{oc\_max} \quad (3.26)$$

$$\tilde{I}_{pv} = \beta \times I_{pv2'} \quad (3.27)$$

In (3.27), β is a scaling factor that is less than 1 since $\tilde{I}_{pv}$ must be less than I_{pv2} for $D_{min} < D_2$. The value of β decides the range of estimated interval. A smaller value leads to larger estimated interval. In (3.26), $\tilde{V}_{pv}$ is chosen as V_{oc_max} since V_{oc2} is unknown and could range from any values up to V_{oc_max} depending on the atmospheric condition.

Assuming η is constant in (3.21), the minimum duty cycle D_{min} that the DC-DC converter can be adjusted to get $\tilde{R}_{pv}$ is

$$D_{min} = \frac{\sqrt{\eta R_{load\_min}}}{\sqrt{\tilde{R}_{pv}} + \sqrt{\eta R_{load\_min}}} \quad (3.28)$$

where R_{load_min} is minimum value of R_{load} .

In application whereby the load changes insignificantly during tracking, R_{load} can be assumed to be constant. Thus, substituting R_{load} for R_{load_min} , (3.28) becomes

$$D_{min} = \frac{\sqrt{\eta R_{load}}}{\sqrt{\tilde{R}_{pv}} + \sqrt{\eta R_{load}}} \quad (3.29)$$

where R_{load} is calculated as in (3.24).

As discussed in the beginning paragraph of this section, the algorithm only needs to consider the interval (D_{min}, D_2) to find the MPP. Since the sample at D_2 has already been

known, the interval (D_{min}, D_2) is extended to a larger interval (D_{min}, D_{max}) such that D_2 is the first sample of (D_{min}, D_{max}) as shown in Fig 3.7(b). Hence, D_{max} can be calculated as follows

$$D_{max} = D_2 + \frac{D_2 - D_{min}}{5} \quad (3.30)$$

Subsequently, the algorithm only need to take two more samples S_2, S_3 as shown in Fig. 3.7(b) in order to find the optimum subinterval among the 3 subintervals.

(c) Stopping criteria and tracking speed

The algorithm reduces the sampling interval to one third in each iteration if the stopping criterion is not met. The search is terminated when the change in duty cycle is less than a predefined value Δd_{cr} . It is then assumed that the maximum power point has been reached. This critical value Δd_{cr} could be chosen as the step perturbation Δd of the duty cycle in the P&O or the INC algorithm. For example, Δd_{cr} can be evaluated as proposed in [21]. Let n be the number of iterations when the search is terminated, the interval length Δd_n at the n^{th} iteration must be less than Δd_{cr} , i.e.

$$\Delta d_n = \frac{D_{max} - D_{min}}{3^n} \leq \Delta d_{cr} \quad (3.31)$$

Let τ_s be the sampling time for the system, the tracking speed of the algorithm can be evaluated as follows (Appendix A.3)

$$t_{abs} \cong 2n \times \tau_s \cong \frac{2}{\ln 3} \times \ln \left(\frac{D_{\max} - D_{\min}}{\Delta d_{cr}} \right) \times \tau_s \quad (3.32)$$

3.4.3 Algorithm for tracking in slow changing condition (small range extension)

During slowly changing atmospheric conditions, the optimum OP changes slowly. In other words, the subsequent MPP is close to the previous MPP and a small variation in the duty cycle will lead to a successful tracking. To follow the MPP in the steady state, the searching range is extended towards both sides of the current MPP D_m by a small amount as follows

$$D_{\max} = D_m + \frac{3}{2} \Delta d \quad (3.33)$$

$$D_{\min} = D_m - \frac{3}{2} \Delta d \quad (3.34)$$

By extending the range as described in (3.33) and (3.34), the next sampling points (at the center of the 3rd and 1st subintervals) will be away from D_m (at the centre of the 2nd subinterval) with an amount Δd . In other words, the next sampling points will be on both sides of the found MPP D_m and separated from D_m with an amount Δd . By continuously extending the searching range with a small amount from the optimum OP, small steady state oscillations will occur. However, the algorithm has the ability to track the new optimum OP when the environmental conditions change slowly.

3.4.4 Algorithm for tracking in rapidly changing insolation condition

In section 3.4.2, the algorithm requires 3 samples to narrow the searching range by one third. In the rapidly changing insolation, the changing insolation level could make the P - V characteristic curve vary significantly during the sampling as illustrated in Fig. 3.8. In the figure, it is assumed that the insolation keeps increasing during the consecutive sampling cycles, i.e $(k-1)T$, kT , $(k+1)T$ and $(k+2)T$. Since the P - V curve changes significantly during the sampling, the three samples (P_{D1} , P_{D2} and P_{D3}) are obtained from the different P - V curves. Thus, the identification of the next sampling interval based on these samples would be wrong. To cope with the issue, the 3rd sample D_3 is sampled again in 4th sampling cycle as shown in Fig. 3.8.

Fig. 3.8 Measurement of power between sampling points

Based on the samples from the 3rd and 4th cycles, the change in the sampled power caused by insolation change in one sampling period can be calculated as

$$\Delta P = P'_{D3} - P_{D3} \quad (3.35)$$

Assuming that the changing rate of the insolation is approximately constant during the 3 consecutive samplings, the previous sampled power can be then compensated as

$$P'_{D2} = P_{D2} + 2 \times \Delta P \quad (3.36)$$

$$P'_{D1} = P_{D1} + 3 \times \Delta P \quad (3.37)$$

Thus, the comparison between 3 samples can give the correct decision. As DIRECT only takes 2 new samples for iteration, it is possible that the same sample is the maximum in three consecutive iterations. In this case, the compensation in the 3rd iteration is inaccurate since the 1st sample point that is also the maximum sample in the previous two iterations has been compensated for too many times. If the 1st sample is the maximum for 2 consecutive iterations, it will be taken again with other two samples (D_2 and D_3) in the next iteration to prevent the compensation error.

Fig. 3.9 shows the flow chart of the proposed algorithm operating in the uniform insolation condition. Depending on the new OP location on the I-V curve, “ D_{max} Estimation” or “ D_{min} Estimation” function will be called and the new sampling interval can be estimated. The algorithm then divides and takes samples in the new interval to search for the MPP. When the MPP has been found, the algorithm calls the “Small Range Extension” function as described in section 3.4.3 to follow the MPP. If the algorithm

detects a large change in environmental conditions, it will be reset to estimate the new sampling interval and to search for the new MPP.

Fig. 3.9 Flow chart of DIRECT algorithm for uniform insolation level cases

3.5 A novel MPPT algorithm for solar array under partially shaded insolation condition

In practice, the PV array may experience partial shading condition due to the passage of clouds or the shadows from surrounding obstacles, etc. Under this condition, the $I-V$ curve has a multi-steps characteristics and the $P-V$ (or $P-I$) curve has multiple local maxima as shown in Fig. 2.12. Since the previous proposed algorithm in section 3.4 assumes that there is

only one MPP in the P - V curve, its searching strategy only focuses on searching the nearby local MPP. This local MPP may not be the true MPP in the presence of multiple local MPPs. The wrong tracking can lead up to 70% of tracking loss [87]. To overcome this problem, the proposed algorithm has been further developed in this section for successful tracking of the global MPP under partial shading conditions.

3.5.1 Identification of sampling interval for PV system

In the following discussion, the range that the duty cycle will not exceed is termed as the “absolute sampling interval”. Theoretically, V_{MPP} is between 0V and V_{oc_max} . In the case that a DC/DC converter is used to vary the OP of a PV system, the duty cycle is in the range of [0, 1]. However, this range $[D_{min\_abs}, D_{max\_abs}]$, where $D_{min\_abs} > 0$ and $D_{max\_abs} < 1$, can be constrained much smaller in practice. Fig. 3.10 shows a method to systematically estimate D_{min_abs} and D_{max_abs} with the known boundary parameters: I_{sc_max} , I_{sc_min} , V_{oc_max} , V_{oc_min} , R_{load_max} , R_{load_min} . From Fig. 3.10, the maximum and minimum reflected equivalent load at the PV array output can be estimated as

$$R_{pv\_min} = \frac{\tilde{V}_{oc\_min}}{I_{sc\_max}} = \frac{\alpha \times V_{oc\_min}}{I_{sc\_max}} \quad (3.38)$$

$$R_{pv\_max} = \frac{V_{oc\_max}}{\tilde{I}_{sc\_min}} = \frac{V_{oc\_max}}{\beta \times I_{sc\_min}} \quad (3.39)$$

where α and β are scaling factors for estimating V_{oc_min} and I_{sc_min} respectively. Their values are less than 1 and determine the range of the estimated interval.

Fig. 3.10 Absolute sampling interval estimation method

Depending on the DC-DC converter topology, the duty cycle bound D_{min_abs} and D_{max_abs} can be estimated accordingly. For the buck – boost topology used in this study, it can be deducted from (3.21) as

$$D_{min\_abs} = \frac{\sqrt{\eta R_{load\_min}}}{\sqrt{R_{pv\_max}} + \sqrt{\eta R_{load\_min}}} \quad (3.40)$$

$$D_{max\_abs} = \frac{\sqrt{\eta R_{load\_max}}}{\sqrt{R_{pv\_min}} + \sqrt{\eta R_{load\_max}}} \quad (3.41)$$

During the initial tracking, there is insufficient information obtained from the present I - V characteristic curve and the absolute sampling interval is used for tracking the GP. However, in most cases, much information can be obtained from the previous sample points and the V_{oc} or I_{sc} can be estimated. Thus, by replacing V_{oc_max} , V_{oc_min} with V_{oc} and I_{sc_max} , I_{sc_min} with I_{sc} in (3.38) and (3.39), the specific sampling interval (D_{min} , D_{max}) can

be estimated smaller than $(D_{min\_abs}, D_{max\_abs})$. The smaller sampling interval will lead to an increase in convergent speed.

3.5.2 Identification of the partially shaded condition

Under partially shaded condition, it is observed that the $I-V$ curves have multiple stairs [11]. One such example is shown in Fig. 3.11. Assuming that DIRECT has successfully moved the OP to the MPP with D_{m1} in the previous step. When the partial shaded condition occurs and causes a change in the $I-V$ curve, the OP moves from A to B as shown in Fig. 3.11(a). Since the duty cycle remains the same, there is a reduction of the solar power. To track the new MPP, the proposed DIRECT algorithm takes 3 new samples D_i ($i=1, 2, 3$). Based on the information obtained from the samples, it is possible to identify if the PV array operates under uniform or partially shaded conditions. This is discussed in the following section.

Fig. 3.11 (a) OP movement (b) First 3 samples illustration

(a) I - V curve has 3 stairs

As illustrated by the gray area in Fig. 3.11(a), a single stair in multi-stairs I - V curve can always be considered as part of an I - V curve under uniform condition. Assuming that the sampling interval is estimated properly, the three samples (D_1 , D_2 and D_3) that are the intersection of the three load lines D_i ($i=1, 2, 3$) and the I - V curve would fall in different local stairs as shown in Fig. 3.11(a). Let I_{Di} and V_{Di} ($i=1, 2, 3$) be the PV array's current and voltage with the converter operates at the duty cycle D_i ($i=1, 2, 3$). Let I_{MPP_1st} be the PV array's current at the MPP of the 1st stair of the I - V curve and V_{oc_2nd} be the open-circuited voltage of the middle stair of the I - V curve as shown in Fig. 3.11(a). Then it can be observed that I_{D1} is smaller than I_{MPP_1st} while I_{D3} is close to I_{MPP_1st} . Moreover, V_{D2} is larger than V_{oc_2nd} and V_{oc_2nd} is larger than V_{D1} . Thus, I_{Di} ($i=1, 3$) and V_{Di} ($i=1, 2$) are well separated and we have the following conditions

$$\frac{\Delta I_{D3,1}}{I_{D3}} = \frac{I_{D3} - I_{D1}}{I_{D3}} \geq 0.1 \quad (3.42)$$

$$\frac{\Delta V_{D1,2}}{V_{D2}} = \frac{V_{D2} - V_{D1}}{V_{D2}} \geq 0.2 \quad (3.43)$$

In (3.42)-(3.43), the boundary criteria “0.1” and “0.2” are chosen based on the observation that I_{MPP} and V_{MPP} is about 90% and 80% of I_{sc} and V_{oc} of single I - V curve, respectively [75].

(b) I - V curve has more than 3 stairs

If the I - V curve has more than 3 stairs, any 2 consecutive stairs can always be grouped and considered as one larger stair. For example, the 2nd and 3rd stair in Fig. 3.12 can be grouped as one stair (the dotted green curve). In the figure, the two-arrow green lines measure the value of $\Delta I_{D3,1}$ (the difference between I_{D3} and I_{D1} as shown in (3.42)) and $\Delta V_{D1,2}$ (the difference between V_{D2} and V_{D1} as shown in (3.43)) in the 3-stair I - V curve. The two-arrow pink lines measure the value of $\Delta I_{D3,1}$ and $\Delta V_{D1,2}$ in the 4-stair I - V curve. As shown in Fig. 3.12, the two-arrow pink lines' lengths are larger than the two-arrow green lines' lengths. Thus, the first 3 samples D_i ($i=1, 2, 3$) in the I - V curve that has more than 3 stairs are more separated from each other than the 3 stairs cases. In other words, (3.42) and (3.43) easily hold true in those cases.

Fig. 3.12 Partially shaded condition identification in more than 3-stair I - V curves

(c) I - V curve has 2 stairs

Fig. 3.13 illustrates the scenario that (3.42) and (3.43) also hold true in the two-stair I - V curve cases. As shown in the figure, even though there are two samples D_i ($i=1, 2$) in the

same big stair, (3.43) is still satisfied. Moreover, D_i ($i=1, 3$) are in different stairs and (3.42) holds true.

Fig. 3.13 Partially shaded condition identification in 2-stair I - V curves

In the case that only (3.42) or (3.43) is satisfied, further samples are required to identify the insolation condition. Fig. 3.14(a) illustrates cases when inequality (3.42) is not satisfied. In other words, I_{D3} is close to I_{D1} . Since both samples D_3 and D_1 are in the “current source region” of the 1st I - V stair, I_{D3} and I_{D1} are both equal to I_{sc2} as shown in Fig. 3.14(a). As V_{D3} is much smaller than V_{D1} , P_{D3} is smaller than P_{D1} . Therefore either sample at D_1 or D_2 is the maximum among the first three samples. Assuming that sample at D_1 is the maximum, DIRECT would divide interval D_1 into 3 subintervals. Then two new samples $D_{1,2}$ and $D_{1,3}$ are taken as shown in Fig. 3.14(a). By checking the information obtained by $D_{1,3}$, $D_{1,2}$ and D_2 , the insolation condition can be identified properly. Similar process is applied for cases when only (3.43) is not satisfied as shown in Fig. 3.14(b). In this case, the insolation condition can be identified by checking information obtained by $D_{3,3}$, $D_{3,2}$ and D_2 .

(a) Cases when (3.42) is not satisfied

(b) Cases when (3.43) is not satisfied

Fig. 3.14 Five samples taken to identify partially shaded conditions

(a) Cases when (3.42) is not satisfied, (b) Cases when (3.43) is not satisfied

(d) Discussions

In general, DIRECT has high success rate to identify partially shaded condition if at least one of the first 3 samples D_i ($i=1, 2, 3$), such as sample D_2 in Fig. 3.14(a) and sample D_3 in Fig. 3.14(b), is taken in a different stair from the other two samples. This condition

always happens if the initial sampling interval is sufficiently large. However, in the event that the first 3 samples are located in the same stair as illustrated in Fig. 3.15, DIRECT would identify the condition as uniform case. It will switch to the locally-biased strategy. Since the first 3 samples are located separately across the sampling interval, the stair that contains all the first 3 samples should have the largest area as illustrated in Fig. 3.15. In other words, this stair contains the maximum power point. Thus, DIRECT still can reach the global MPP.

Fig. 3.15 Cases when partially shaded condition identified as uniform.

In Fig. 3.16, the flow chart of the algorithm for identifying the partial shading condition is presented. In the flow chart, the variable “global” is used to store the state of partial shading condition. It is set to 1 if partial shading condition is identified. Otherwise, it is set to 2. The other variable “flag” is set to 1 if (3.42) is not satisfied and is set to 2 if (3.43) is not satisfied. If either (3.42) or (3.43) is not satisfied, the algorithm divides and takes samples in the interval that has the maximum power. Then the “Identify D_j ” block that is marked by red color in the flow chart will identify the suitable samples for new evaluation in (3.42) and (3.43). Thus, the algorithm can identify the presence of the

partial shading condition. Depending on the identified insolation condition, the algorithm will proceed to either “local biased strategy” or “global biased strategy” to search for the MPP. These strategies will be discussed in the following sections.

Fig. 3.16 Flow chart of the algorithm to indentify partial shading condition

3.5.3 Global strategy of DIRECT algorithm

When the PV arrays are under partially shaded condition, a global strategy that focuses on exploring the larger potential optimum interval (POI) is proposed. Fig. 3.17 illustrates the first four iterations. As described earlier, the 1st iteration is used to identify the

insolation condition. In the 2nd iteration, DIRECT first triply divides POI D_j ($j=1$ in the case illustrated in Fig. 3.17(a)). Then two new samples D_{j3} and D_{j2} are taken as marked by “cross” in Fig. 3.17(c). At the end of the 2nd iteration, there are a total of 5 intervals that can be categorized into two types of interval length: one third and one ninth of original interval length as shown in Fig. 3.17(d). In Fig. 3.17, the arrows indicate the movement of D_j when it changes from the old interval that has been triply divided to the new and smaller interval.

According to (3.15) and (3.16), both intervals D_2 and $D_{1,2}$ are the POIs. However, the globally-biased strategy only chooses the one with the largest interval length, D_2 , for further sampling in the 3rd iteration as shown in Fig. 3.17(e). This results in 6 small intervals and one larger interval (interval D_3) whose length is one third of the original length as illustrated in Fig. 3.17(f).

Fig. 3.17 Iterations of DIRECT in globally-biased form

(a), (c), (e), (f) – PV curve illustration for 1st, 2nd, 3rd, 4th iteration respectively. (b), (d), (f), (h) – Interval illustration for 1st, 2nd, 3rd, 4th iteration respectively.

In the 4th iteration, there are two “potentially optimal intervals” theoretically. But DIRECT still divides the one with larger length, interval D_3 , as shown in Fig. 3.17(g).

The dividing results in 9 intervals whose lengths are all equal to one ninth of the original length. Depending on the available known parameters, the initial sampling interval's length that can be estimated as shown in section 3.5.2 ranges from 0.3 to 0.5. Hence, the length of those 9 intervals ranges from 0.03 – 0.05. In most applications, this value is small enough that some sample points are close to the global MPP. In other words, the intervals that they represent contain the global MPP. At this stage, if two samples that have the highest powers are close to each other, such as $D_{l,1}$ and $D_{l,2}$ in Fig. 3.17(g), the GP's region is considered to be found and falls in the POI. To reach the global MPP, DIRECT switches to locally-biased strategy. However, if those two sampling points are not consecutive, this indicates that the system may have two GPs or one local MPP whose value is close to the GP. In this case, globally – biased DIRECT would continue for two more cycles. This means that DIRECT will further divide and sample the single POI, interval $D_{l,2}$, in the 5th iteration. As a result, there are two type of interval's length again: 1/9 and 1/27 of initial sampling interval's length. DIRECT further samples the larger POI (1/9 of the initial sampling interval's length) to explore the searching range in the 6th iteration. Then, DIRECT changes to locally-biased strategy to focus on reaching the global MPP.

In general, DIRECT takes a total of 9 samples to explore the searching region in the first 3 iterations. To prevent DIRECT from exploring unpromising regions, the number of samples can be reduced if the first 3 sampling points, D_i ($i=1, 2$, and 3), give the following information:

1. V_{D3} is less than V_{min} ($V_{min} = 1/3 V_{oc}$ in our experiments), which means D_{33} falls in a region that the global MPP can not appear. Then the sampling point $D_{3,3}$ will not be taken.
2. $I_{D2} < I_{min}$, ($I_{min} = 1/3 I_{sc}$), or $V_{D2} > V_{max}$ ($V_{max} = 0.9V_{oc}$) which means D_{22} falls in a region that the global MPP can not appear. Then the sampling point $D_{2,2}$ will not be used.
3. Inequality (3.42) is not satisfied, which means D_3 and D_1 fall in the constant current region of the same peak. Then $D_{3,3}$, $D_{3,2}$, will not be taken.
4. Inequality (3.43) is not satisfied, which means D_2 and D_1 fall in the voltage source region of the same peak. Then $D_{2,2}$, $D_{2,3}$ will not be considered.

3.5.4 Locally-biased strategy of DIRECT algorithm.

Under uniform insolation condition, the I - V curve is a single step and the P - V curve has a unique MPP as shown in Fig. 3.18.

Fig. 3.18 PV characteristic curve under uniform insolation.

(a) – IV curve. (b) – PV curve

In this case, the unique MPP will be in the POI D_j (or very close to the interval boundary) that has the maximum power P_{Dj} . In Fig 3.18(b), this is the center subinterval D_I . This means that DIRECT does not need to explore other intervals D_i ($i \neq j$) in later iterations, even though they can be potentially optimal if they satisfy inequality (3.15) and (3.16). In the locally – biased strategy, the interval that has the largest sampling power at the center is the only potentially optimal interval. In this strategy, DIRECT reduces the sampling interval to one third after each iteration if the stopping criterion is not met. The search is terminated when the change in duty cycle is less than a predefined value Δd_{cr} . It is then assumed that the maximum point has been reached. This critical value Δd_{cr} can be chosen to be the duty cycle perturbation Δd in P&O or INC algorithm similar to those proposed in [21].

In Fig. 3.19, the simplified flow chart of DIRECT algorithm is presented. For clarity, the “partial shading condition identification algorithm” illustrated in Fig. 3.16 is presented as a “partial shading condition?” block in the flow chart. Depending on the state of insolation condition, the value of “global” is set accordingly as discussed in section 3.5.2. Then “local biased strategy” or “global biased strategy” will be used to search for the MPP. When the MPP has been found, the algorithm can call the “Small Range Extension” function as described in section 3.4.3 or use the P&O method to follow the MPP. If the algorithm detects a large change in environmental conditions as indicated by $\Delta P > \Delta P_{cr}$ in the flow chart, it will reset to estimate the new sampling interval and search for the new MPP.

Fig. 3.19 Flow chart of DIRECT algorithm

3.6 Conclusion

In this chapter, a novel photovoltaic MPPT algorithm optimized for rapidly changing atmospheric conditions has been presented. The proposed approach employs the dividing strategy of DIRECT algorithm. It is also further developed to track the MPP of the PV system under uniform environmental conditions. The proposed approach can effectively improve the tracking speed and the accuracy simultaneously, which is particularly important for systems that frequently experience rapidly changing atmospheric conditions.

A new approach for tracking PV's global maximum power point has also been proposed based on the DIRECT algorithm. The new approach has the same ease of implementation as the P&O and INC schemes. But it can overcome their weaknesses as it is capable of searching for the global maximum power point. This is paramount for the systems that are partially shaded.

The simulation results in chapter 4 and the experimental results in chapter 5 will show that the proposed approaches could outperform the existing methods in terms of the tracking performance and robustness, especially in fast changing environmental conditions. Furthermore, the algorithms can be implemented quite easily using a low cost microcontroller.

Chapter 4

Modeling and Simulation of Photovoltaic System

4.1 Introduction

The design of a PV system includes many areas, such as the PV cells, the converter circuits, the control system, the operating environment etc. To speed up the design process, the availability of a computer-aided simulation tool is desirable. This chapter presents a system-level simulation model of a PV system that is based on MatLab and Simulink. All the PV power system components such as the environment, the PV arrays, the power processing system and the electrical load will be modeled modularly to the required level of complexity. For this work, only a moderate complexity model is developed. This is sufficient to evaluate the new control algorithms before building a prototype. The model can simulate the dynamic behavior of the PV system with different controllers and operating conditions. The optimized design obtained from the simulation can also be implemented in a real system with minimum modifications. As the models are developed in modules, any model developed in the early stage can be easily substituted with more accurate models in the later stage if required. Fig. 4.1 shows the PV system model developed in this work.

Fig. 4.1 The simulation model of a PV system

As shown in Fig. 4.1, the environmental conditions, the PV arrays, the dc/dc converter, the electrical load and the DSP are modeled as subsystems. The detail modeling of each subsystem will be discussed in the following sections. To ensure the integrity during data transfer between the environmental blocks and the PV array block, the “rate transition” blocks are inserted in the signal paths. The values of I_{pv} , V_{pv} and the simulation time can also be probed to the workspace for the online analysis if required.

4.2 Model’s construction of a PV array

4.2.1 A single diode model of a typical PV array

A typical solar cell consists of a p-n junction fabricated in a thin wafer or layer of semiconductor. In the dark, the I - V characteristic of a solar cell has an exponential characteristic that is similar to that of a diode. When exposed to light, the absorption of photons with energy greater than the band gap energy of the semiconductor creates the

electron-hole pairs. These carriers are swept apart under the influence of the internal electric fields of the p-n junction. This creates a current proportional to the incident irradiation. This current flows in the external circuit that the cell is connected to, or shunted internally by the intrinsic p-n junction diode when the output of the solar cell is opened. Hence, the open-circuited voltage characteristic of the solar cell is set by the characteristic of equivalent parallel diodes. Thus, the simplest equivalent circuit of a solar cell is a current source in parallel with a diode. Over the years, more complex models have been proposed to characterize the solar cells [3]-[11]. In our work, only a moderate model is needed for the control purpose and this leads to the adoption of a single diode PV model [6] as shown in Fig. 4.2.

Fig. 4.2 The circuit diagram of a single diode PV model
(a)- R_{SH} is included in the model. (b) $-R_{SH}$ is negligible

The current-voltage output characteristic of a solar cell can be described by the following mathematical equation

$$i = I_{ph} - I_{rs} \left[\exp \left(\frac{q(v + iR_s)}{kTA} \right) - 1 \right] - \frac{v + iR_s}{R_{SH}} \quad (4.1)$$

where the symbols in (4.1) are defined in Table. 3.1

For a PV array consists of n_s solar cells connected in series and n_p solar strings connected in parallel, (4.1) can be modified as

$$i = n_p I_{ph} - n_p I_{rs} \left\{ \exp \left[K \left(v + i \frac{n_s}{n_p} R_s \right) \right] - 1 \right\} - \frac{v + i \frac{n_s}{n_p} R_s}{\frac{n_s}{n_p} R_{SH}} \quad (4.2)$$

$$\text{where } K = \frac{q}{kTAn_s} \quad (4.3)$$

The effect of non-ideal factors (R_s , R_{SH} in (4.2) and A in (4.3)) on the ideal I - V curve has been investigated and the results are illustrated in Fig. 4.3.

Fig. 4.3 The effect of non-ideal factor on the ideal I - V curve.

(a) The effect of R_s and R_{SH} . (b) The effect of non-ideal factor A

As seen in Fig. 4.3(a), the series resistance R_s affects the slope of the I - V curve at V_{oc} while the shunt resistance R_{SH} varies the slope of the I - V curve at I_{sc} . To evaluate the effect of A on the I - V curve, its value is changed gradually from 1 to 2 while R_{SH} and R_s

are kept constant. As shown in Fig. 4.3(b), the “ideality factor” A more likely decides the bend shape of I - V curve. A value near to one results in the MPP located at higher current comparing to the case when A value is near to two.

In practice, the manufacturers produce cells that have sufficient large value of R_{SH} . Thus, the impact of R_{SH} is negligible. However, the value of R_S is not small enough to be negligible. Neglecting R_{SH} in the model and (4.2) yields

$$i = n_p I_{ph} - n_p I_{rs} \left\{ \exp \left[K \left(v + i \frac{n_s}{n_p} R_S \right) \right] - 1 \right\} \quad (4.4)$$

Applying curve fitting with the manufacturer’s experimental data, the value of A and R_S can be estimated by the method of parameter extraction and model evaluation in MatLab [4]. The relationship of R_S and the slope of I - V curve at V_{oc} can be found by differentiating (4.4) and then evaluating at $V=V_{oc}$:

$$R_S = -\frac{dV}{dI_{V_{oc}}} - \frac{1}{X_V} \quad (4.5)$$

$$\text{where } X_V = I_{rs(T_1)} \times \frac{q}{AkT_1} \times \exp \left(\frac{qV_{oc(T_1)}}{AkT_1} \right) \quad (4.6)$$

Equations (4.4) - (4.6) only describe the behavior of PV array output under static environmental conditions. To model the dynamic behavior of PV arrays according to the changing environmental conditions, the dependency of I_{ph} and I_{rs} on the working

temperature and insolation level proposed in [5] have been included in the modeling as follows

$$I_{ph} = I_{ph(T_1)} [1 + K_0 (T - T_1)] \quad (4.7)$$

$$I_{ph(T_1)} = G \times \frac{I_{SC(T_1, 1000)}}{1000} \quad (4.8)$$

$$I_{rs} = I_{rs(T_1)} \times \left(\frac{T}{T_1}\right)^{\left(\frac{3}{A}\right)} \times \exp\left[\frac{-qV_g}{Ak} \left(\frac{1}{T} - \frac{1}{T_1}\right)\right] \quad (4.9)$$

$$I_{rs(T_1)} = \frac{I_{SC(T_1)}}{\exp\left(\frac{qV_{OC(T_1)}}{AkT_1} - 1\right)} \quad (4.10)$$

where $I_{ph(T_1)}$, $I_{rs(T_1)}$ are the photo current and the reversed saturation current at the standard temperature T_1 , respectively. G is the operating irradiation level (W/m^2). K_0 is the temperature coefficient of I_{ph} .

4.2.2 Mathematical model of triple junction solar cell

The multi-junction solar cells consist of InGaP, (In)GaAs and Ge as the substrates. They are known to have ultra high conversion efficiency and can reach 31% due to the lattice-matched configuration [56]-[57]. The production cost of multi-junction solar cells composed of III–V materials is higher than that of typical Si solar cells. Thus, they are mainly used in high concentrator systems such as in terrestrial applications [58]-[59]. In low concentration applications, multi-junction solar cells have also been studied for space

satellite uses [60]–[62]. Fig. 4.4 shows a schematic of the triple-junction solar cell evaluated in this work.

Fig. 4.4 Schematic of an InGaP/InGaAs/Ge triple-junction solar cell

The triple-junction solar cells could be viewed simply as the cascading of three main semiconductor layers. Thus, the solar cell can be decomposed as a series of three different solar cells as shown in Fig. 4.5 [51].

Fig. 4.5 Schematic of an equivalent circuit model for a triple-junction solar cell

As only a moderate PV model is needed, the model is further simplified into one equivalent solar cell. However, the ideal factor A in the original mathematical model is replaced by the product Am_s , where m_s is the triple-junction model factor and has the value ranges from 2 to 4. From the data sheet provided by the manufacturer, some useful specifications have been extracted for the modeling process as shown in Table 4.1.

Table 4.1 The key specification of the triple junction solar cell

At Temperature (@AMO)	T	28	°C	Temperature Coefficients
Open-circuited voltage	V_{OC}	2.593	V	-5.11 mV/°C
Short-circuited current	I_{SC}	0.465	mA	3.03715e-4 A/°C
Voltage, max power	V_m	2.327	V	- 6.2 mV/°C
Current, max power	I_m	0.451	mA	1.928e-4 A/°C
Maximum power	P_m	1050	mW	2.245e-4 W/°C

To obtain the best fitting I - V curve, the values of A , m_s , $dV/dI_{V_{OC}}$ and the equivalent band gap energy V_g could be estimated based on the method of parameter extraction and model evaluation proposed in [5]. For the solar cells used in the modeling, these values have been estimated as: $A=1$, $m_s=2.6$, $V_g=1.6$ eV and $\frac{dV}{dI_{V_{OC}}}=-0.217V/A$. Fig. 4.6 shows that

there is very close matching between the model and the manufacturer I - V curves under the test condition.

Fig. 4.6 PV model vs Manufacturer I - V curves for a single PV cell.

If the cell’s temperature changes from 30°C to 60 °C, the new I_{SC} and V_{OC} of the solar cell can be calculated as

$$I_{SC(60^{\circ}C)} = I_{SC(30^{\circ}C)} + K_o(60-30) = 0.465 + 3.037 \times 10^{-4} \times 30 = 0.474 \text{ A} \tag{4.11}$$

$$V_{OC(60^{\circ}C)} = V_{OC(30^{\circ}C)} + K_{o,v}(60-30) = 2.593 - 5.11 \times 10^{-3} \times 30 = 2.440 \text{ V} \tag{4.12}$$

Fig. 4.7 shows that the model’s simulation result matches closely with (4.11) and (4.12). The mismatch error is about 0.2%.

Fig. 4.7 Changing of I_{sc} and V_{oc} meets the manufacturer specifications

4.2.3 Theoretical maximum power point

From the mathematical PV model derived in (4.3), Appendix A.1 verifies that the PV array's current, voltage and power at the MPP are as follows

$$I_{MPP} = n_p I_{ph} - n_p I_{rs} \left[e^{\frac{1 + 2K \frac{n_s}{n_p} R_s [n_p I_{ph} + n_p I_{rs} - I_{MPP}]}{n_p I_{ph} + n_p I_{rs} - I_{MPP}}} I_{MPP} - 1 \right] \quad (4.13)$$

$$V_{MPP} = \left[\frac{1}{K(n_p I_{ph} + n_p I_{rs} - I_{MPP})} + \frac{n_s}{n_p} R_s \right] \times I_{MPP} \quad (4.14)$$

$$P_{MPP} = V_{MPP} I_{MPP} \quad (4.15)$$

Based on (4.13)-(4.15), a sub-model in PV model could be developed to find the MPP according to the variance of the environment.

4.2.4 Simulink model of PV array

Considering the temperature T_{ac} , the irradiation level $Suns$, the number of PV cells in series N_s , the number of PV cells in parallel N_p and the operating voltage V_a as inputs, a PV array model can be built in Simulink by using the mathematical descriptions (4.4)-(4.10). First, a subroutine " $I_a = \text{arrayI}(V_a, Suns, T_{ac}, N_s, N_p)$ " based on (4.4) – (4.10) has been developed to describe the behavior of the PV array as shown in Appendix B.1. The subroutine receives T_{ac} , $Suns$ as the environmental conditions and N_s , N_p as the array's configuration. Depending on the PV array's operating voltage V_a , the appropriate operating current I_a will be calculated by (4.4)-(4.10). Figure 4.8(a) presents the building blocks of the PV array model. As shown in the figure, the *arrayI_sf* block described in

Appendix B.2 has been used as a mechanism to fetch the inputs to “ $I_a = \text{arrayI}(V_a, \text{Suns}, T_{aC}, N_s, N_p)$ ” subroutine and to output the result I_a back to the Simulink environment.

Fig. 4.8 Modeling of a PV module.

(a) PV array model. (b) PV array model for evaluating MPP

Since maximizing the output power from the PV system according to the changing environment is always an essential issue, the analysis and the simulation of a PV system often evolve in comparing the current arrays' OP with the optimum OP. The optimum OP as given in (4.13)–(4.15) can be employed to calculate the optimum operating condition of the PV array at a specific atmospheric condition. The building of this MPP subsystem is similar to the building of a normal PV subsystem as shown in Fig. 4.8(b). However, the MPP subsystem has only 4 inputs (T_{aC} , Suns , N_s and N_p). The outputs are I_{MPP} , V_{MPP} and P_{MPP} .

Though the developed model only describes the behavior of a PV array under uniform insolation condition, a more complex model that simulates the behavior of multiple modules under various environmental conditions could be easily built based on the developed model. When the PV array is under partially shaded condition, the PV cells under the same insolation condition can be regrouped to form new modules [10]-[11]. Then these modules can be considered to be in series and/or parallel to form a new PV array according to the shading pattern [10]-[11]. Assuming that the new configuration consists of N_p branches in parallel and a maximum of N_s modules in series in a branch, the output current i_a and voltage v_a can be described as

$$i_a = \sum_{b=1}^{N_p} i_b \quad (4.16)$$

$$v_a = \sum_{j=1}^{N_s} v_j \quad (4.17)$$

where i_b is the current in b^{th} branch, V_j is the voltage across j^{th} module in a branch.

To simulate the behavior of the PV array under partially shaded conditions, a more complex PV model can be built based on (4.16)-(4.17), i.e. the series and/or parallel connection of the PV subsystems. In the model, each PV subsystem has its own temperature T_{ac} and irradiation level $Suns$ depending on the shading patterns. Fig. 4.9 illustrates the modeling of a PV array under the partially shaded condition.

(a) PV array under partially shaded condition

(b) Modeling of the PV array

Fig. 4.9 Example of building PV array model under partially shaded condition

(a) PV array under partially shaded condition. (b) Modeling of the PV array

The PV array consists of two branches where the 2nd branch is under partially shaded condition. According to the method described in section 3.2, the PV array can be considered as a combination of three sub-assemblies as illustrated in Fig. 4.9(a). Each sub-assembly has its own environmental condition and configuration, i.e. the number of

solar cells in series and parallel. The developed PV array model can be used to model these sub-assemblies as illustrated in Fig. 4.9(b). For clarity, the environmental conditions and the configuration of each sub-assembly model are not shown in the figure. Since the 2nd branch is a series of two sub-assemblies, the “IO branch 2” block is used to regulate the branch’s output current.

4.2.5 Simulink model of the environmental conditions

Since the PV array’s output characteristics largely depend on the temperature and insolation level, the environmental conditions have been modeled separately and applied as inputs to the PV array model. For a simple changing scenario of the environmental conditions such as a step change in insolation condition, the “signal builder” blocks in Simulink could be used. Fig. 4.10 shows one of the “signal builder” blocks available in Simulink and its generated signal as a changing irradiation level.

Fig. 4.10 Signal Builder block as a changing irradiation level source

To evaluate the PV model in the real environment, the actual temperature and insolation level are measured at a fixed sampling time. The data are then stored in the file server that will be accessed during the simulation. Appendix B.3 shows the MatLab sub-function that outputs the stored temperature data from file server at each simulation step. Since the simulation step size is much smaller than the sampling time of the environmental data, interpolation is used to obtain the values between the sampling times. Fig. 4.11(a) and Fig. 4.11(b) show the temperature and insolation model respectively.

Fig. 4.11 Model of the environmental condition
(a) Temperature Modeling. (b) Insolation Modeling

As shown in Fig. 4.11, the s_function (Temp_sf and Sun_sf) has been used to output the calculated data from sub-functions to the PV model module. The sampling time of the

environmental data is set as 1s in the figure. The $10\mu\text{s}$ simulation step size is fetched to the models by “the clock”.

4.3 Model’s construction of the buck-boost converter

DC/DC converters are used to connect the PV generators to the DC loads. They can be classified as boost converters, buck converters and buck-boost converters. In this thesis, the buck-boost converter has been chosen due to its versatile control ability as explained later in chapter 5.

The mathematical model of the DC/DC converter has been well studied [41]-[46]. Among the developed models, the state-space model is used to simulate DC/DC converter at system level [41]-[42]. Fig. 4.8 shows the circuit model of the buck-boost converter. The switching devices (diodes and switch) are modeled as ideal components (zero ON voltages, zero OFF currents and zero switching times). For the passive components such as the inductors and the capacitors, they are modeled as ideal components in series with their ESR.

By applying the Kirchhoff’s voltage law on the loop that contains the inductor and the Kirchhoff’s current law on the node that the capacitor branch connected to, the dynamics of the converter operating in continuous conduction mode (CCM) can be obtained [41]-[42]. Fig. 4.12(a) and Fig. 4.12(b) show the system’s states when the switch is on and off, respectively. In the figures, the circuits that have the currents flowing through in each

state are illustrated with the bold lines. The arrows indicate the current's flow directions and the voltage's drop direction.

(a) The switch is ON

(b) The switch is OFF

Fig. 4.12 Buck-boost topology. (a) The switch is ON. (b) The switch is OFF

As shown in Fig. 4.12, the voltage V_{Cout} across the ideal output capacitor and the output voltage V_{out} are related via the following equation

$$v_{out} = v_{Cout} + R_C C_{out} \frac{dv_{Cout}}{dt} \quad (4.18)$$

If x is defined as a control signal as

$$x = \begin{cases} 1, & \text{switch on} \\ 0, & \text{switch off} \end{cases} \quad (4.19)$$

Then the dynamic of the circuit can be described by combining the dynamics of the inductor current I_L , the output capacitor voltage V_{Cout} and the input voltage V_{in} in both ON/OFF states as follows

$$\frac{di_L}{dt} = \frac{1}{L} [xv_{in} + (1-x)v_{out} - i_L R_L] \quad (4.20)$$

$$\frac{dv_{Cout}}{dt} = -\frac{1}{C_{out}} \left[\frac{v_{out}}{R_{out}} - (1-x)i_L \right] = -\frac{1}{C_{out}} [i_{load} - (1-x)i_L] \quad (4.21)$$

$$\frac{dv_{Cin}}{dt} = \frac{1}{C_{in}} [i_{in} - xi_L] \quad (4.22)$$

Representing (4.18)-(4.22) by the mathematical and signal blocks in Simulink, the buck-boost converter model can be built as shown in Fig. 4.13.

Fig. 4.13 Buck-boost SIMULINK Model

For modularity, all the model's building blocks are masked together as a subsystem with the values of the capacitors, inductor and resistors as the system's parameters. Hence, the model's characteristics can be easily varied by changing the model's parameters. As shown in Fig. 4.13, the inputs to the model are chosen as the pulse-width-modulation (PWM) signal from the controller block and the current I_{in} from the PV array's model.

The outputs are chosen to be the inductor current I_L , the output capacitor voltage V_{Cout} , the output voltage V_{out} and the PV array operating voltage V_{in} .

4.4 Model's construction of a DSP

Control of the PV systems is normally digitally implemented in DSP (or microcontroller). This results in fewer components, no hardware adjustments, less aging effects and smaller temperature drifts. The control parameters adjustment for adapting to different environments is also easy and flexible. To facilitate the conversion from the developed control methods in the simulation model to the digital control in DSP, the Simulink model has been built to emulate the DSP.

In practice, the control algorithms are usually developed in C language. After compilation, the source code is downloaded to the DSP memory that allocates the program's variables in the data section and the control steps in the program section. Fig. 4.14 shows the main control block in the DSP model that simulates the interaction between the program section and data section.

Fig. 4.14 Main control block in the DSP model

In the simulation model as shown in Fig. 4.14, the program sections are actually the allocated memories for the MatLab functions that are stored in the workspace and are accessed during the simulation. The address of each program section is the function name that the program section refers to such as `main_sf` in Fig. 4.14.

Since each function has its own variable, each program section also has its own data section. If the number of variables is small, the memory blocks in Simulink as shown in Fig. 4.14 are used as the data sections for fast accessing. In this case, the passing of variables and calculated results to/from a program section (a MatLab function) are all executed by the `s_function` block, such as “`main_sf`” as shown in Fig. 4.14. On the other hand, if the number of variables is large, the variables’ names and values are also

organized and stored in a file by the MatLab “*dlmwrite function*”. The MatLab “*dlmread function*” then accesses to the file to get the appropriate variable if it is required.

Since the required memory size in the main control block shown in Fig. 4.14 is large, it has been divided into two sections. One is used for the high accessing time variables and modeled by the memory blocks as shown in Fig. 4.14. The other is stored in the text files. In our model, “the main control block” receives two filtered inputs I_{ref} and V_{ref} . The output is the digital PWM duty cycle and the interrupt flag that enables the timer interrupt in the “input block” of the DSP model. Fig. 4.15 shows the complete model of the DSP system.

Fig. 4.15 Simulink model of the DSP

(a) Full System Model. (b) Input Block Model. (c) PWM Block Model.

As illustrated in Fig. 4.15(a) and Fig. 4.15(b), the timer interrupt routine is modeled by a sub-function in the “input block”. The interrupt ensures that the sampled I_{pv} and V_{pv} only be processed by the digital filter when the whole system has reached the steady state from the last applied control signal. After being filtered, I_{pv} and V_{pv} are fed into the main control block. Depending on the requirements, different digital filter types can be implemented in the timer interrupt routine.

To ensure the integrity during data transfer between each block in the model, the “rate transition blocks” are inserted in the signal data paths as shown in Fig. 4.15(a). Since the “rate transition block” can change the sampling rate of the incoming signal, they can be used to model the ADC peripheral of the DSP if they are put in front of the “input block” as marked by the red rectangle in Fig. 4.15(a). The other DSP peripheral that has been modeled is the PWM block. The built-in Simulink blocks model this peripheral as shown in Fig. 4.15(c). The input to the PWM block is the digital duty cycle received from the main control block. The output is the analog PWM signal.

The presented DSP model only simulates the moderate behavior of the CPU core and two peripherals at the system-level. The other parts of the DSP are not required and are not modeled. However, they could be incorporated into the current model later with the appropriate interaction descriptions if required. Since the control programs in the DSP model are first developed in MatLab text programming, they can be easily converted into C program after the simulation study has been completed.

4.5 Simulation results

4.5.1 Evaluation of the PV model

To verify the effectiveness of the developed PV model, various simulation studies have been conducted and the results are compared with the actual I - V data collected from a 20W solar panel under actual sunlight. In the experiment, a temperature sensor (LM35) and an insolation meter (APRS6567) are used to measure the panel's surface temperature and insolation level. To record the I - V characteristic curves at the test conditions, the buck-boost converter's duty cycle is increased from 0.2 to 0.8 with a 0.02 step-size. At each step, the measured values of I_{pv} and V_{pv} are stored for later use. These values can then be plotted in MatLab to build back the actual I - V characteristic curves at the test conditions.

Since the 20W solar panel is the mono-crystalline type consisting of 36 cells in series, the single diode solar model is used for the evaluation. In the simulation, the temperature and insolation level are set to be the same as in the actual experiments. Fig. 4.16 plots the simulation and experimental results under three different operating conditions. In the figures, the solid lines are the I - V characteristic curves while the dotted lines are the corresponding P - V curves. The red color lines represent the experimental data while the blue color lines represent the simulation data.

(a) At environmental condition: ($1000 \text{ W/m}^2 - 50^\circ\text{C}$)

(b) At environmental condition: ($950 \text{ W/m}^2 - 39^\circ\text{C}$)

(c) At environmental condition: ($300 \text{ W/m}^2 - 33^\circ\text{C}$)

Fig. 4.16 The experimental versus the simulated I - V and P - V characteristic curves.

(a) At environmental condition: ($1000 \text{ W/m}^2 - 50^\circ\text{C}$). (b) At environmental condition: ($950 \text{ W/m}^2 - 39^\circ\text{C}$). (c) At environmental condition: ($300 \text{ W/m}^2 - 33^\circ\text{C}$).

As shown in Fig. 4.16, the simulation results of the PV model closely resemble that of the real PV system under the same working conditions. In the simulation results, the I - V curves at the “voltage source region” are flatter comparing to those in the experimental results. The reason is that the effect of R_{SH} is neglected in the modeling.

4.5.2 Evaluation of the buck-boost converter model

To verify the developed circuit model and its suitability in the system studies, the step response experiments have been conducted with different duty cycles under the same irradiation level and temperature. To ensure that the PV array’s I - V characteristics are the same as in the simulation and the experiment, the solar array simulator (Agilent E4350B) has been used as the PV array source. The SAS is capable of simulating the I - V curve of different arrays under various environmental conditions as long as the I - V curve’s data points are available for inputting to the SAS. In the table mode, the user could provide a maximum of 4000 data points of a real I - V curve. In the experiments that are set up as shown later in Fig. 5.5, the current sensor converts the sensed current into voltage. Fig. 4.17-4.19 show the current and voltage step response in the prototype PV system and in the simulation model when the duty cycle of 0.55, 0.65 and 0.75 are applied, respectively.

Fig. 4.17 Time response of PV array voltage and current with 0.55 duty cycle
a) Experimental data. (b) Simulation data

Fig. 4.18 Time response of PV array voltage and current with 0.65 duty cycle
(a) Experimental data. (b) Simulation data

Fig. 4.19 Time response of PV array voltage and current with 0.75 duty cycle
(a) Experimental data. (b) Simulation data.

As can be observed from the figures, the simulation results agree well with the experimental data in both the dynamic and steady state value of V_{pv} and I_{pv} . Maximum errors of 8% in the current and 5% in the voltage overshoot during the switching transition are observed. This is due to the fact that the switching components are modeled as ideal switches. Other sources of error are: 1) the use of built-in equation solvers and the step size of the simulator, 2) the mismatch of the temperature and insolation used in the simulation model and the actual test conditions, 3) the errors in the measuring instruments.

4.6 Model's implementation for evaluating the MPPT algorithms

The developed simulation models are useful for evaluating the MPPT algorithms' performance. By predicting the algorithm's behavior with different tuning parameters, a suitable set of tuning parameters can be selected for the implementation of the algorithm

in the real system. In this section, the effect of different algorithm's parameters on the system performance is investigated. Simulations are also conducted to evaluate the effectiveness and the performance of the proposed algorithm and the variable step sized dP-P&O algorithm [22, 28].

4.6.1 The algorithm's parameters effect on its performance

As discussed in sections 3.4 and 3.5, the proposed algorithm samples an interval to find the MPP. Thus, the interval's length that is determined by the value of α in (3.18) or β in (3.27) strongly affects the algorithms' tracking performance. If the algorithms are in the steady state, the Δd value in (3.34) and (3.35) determines the amplitude of the steady state oscillation.

(a) The effect of α

As illustrated previously in Fig. 3.6, α decides the upper bound of the sampling interval when the new OP is in "the voltage source region". To simulate this scenario, a simulation with a step change in the insolation level has been conducted. Initially, the insolation level begins with 1000 W/m^2 . Subsequently, it changes from 1000 W/m^2 to 500 W/m^2 and remains there for 3s. It then changes from 500 W/m^2 to 1000 W/m^2 and remains there for another 3s before the simulation ends. Thus, the operating point changing scenario illustrated in Fig. 3.5(f) can be created as shown again in Fig. 4.20(a).

Fig. 4.20 Changing scenario to evaluate α on algorithm performance
(a) I - V curve changing. (b) P_{MPP} changing

In Fig. 4.20(a), the blue curve denotes the I - V curve at lower insolation level while the red curve denotes the I - V curve at higher insolation level. The increase in insolation level in the experiment makes the new OP 2' falls in the voltage source region of the red I - V curve. Fig. 4.20(b) demonstrates the changing of the maximum power point during the simulation. The blue line represents the maximum PV array's power at the 500 W/m² insolation level while the red lines represent the maximum power at 1000 W/m² insolation level.

Fig. 4.21 shows the simulation results at different α for the same changing scenario illustrated in Fig. 4.20(b). The red rectangles indicate the early tracking state while the MPP has not been found. In Fig. 4.21(a) and Fig. 4.21(b), they also denote the state after that the algorithm switches to “the range extension strategy” to search for the changing MPP.

Fig. 4.21 The effect of α on the algorithm's tracking performance

(a)- $\alpha=0.3$. (b)- $\alpha=0.5$. (c)- $\alpha=0.8$. (d)- $\alpha=0.95$.

As shown in Fig. 4.21(a) and Fig. 4.21(b), smaller α results in more fluctuation of the tracking power in the early stage. This is because a smaller α leads to a larger estimated sampling interval. Thus, α cannot be chosen too small. On the other hand, Fig. 4.21(c)-4.21(d) show the effect of choosing a large α on the algorithm's tracking performance. In Fig. 4.21(a) and Fig. 4.21(b), the green rectangles denote the tracking state while the algorithm searches for the MPP in the estimated interval. After finding that MPP, the algorithm switches to “the range extension strategy” to follow the MPP. Since α is large, the estimated interval is small and does not contain the actual PV array's MPP. Thus, the MPP in the estimated interval is not the PV array's MPP. By extending the searching

range in the later stage, the algorithm can eventually track the MPP but the tracking time will be longer.

To choose a suitable range of α so that the algorithm has the best tracking performance, Fig. 4.22 shows the plot of the algorithm's tracking efficiency in the early stage versus different α . The tracking efficiency is calculated as the ratio of the average tracking power versus the maximum power (60W in the simulation) in the early stage. Since the early stage duration depends on the α as presented by the red rectangles' length in Fig. 4.21(a) – 4.21(d), a 0.8s duration is fixed in all the calculation.

Fig. 4.22 Evaluation of α on algorithm's performance at 50% increase in insolation level

Fig. 4.22 reveals that there is an optimum value of α at a given changing environmental condition. In the case shown in Fig. 4.20(b), this optimum α value is about 0.5. Another observation is that the optimum region of α , i.e. region (0.35, 0.55) in Fig. 4.22, is quite

wide and flat. Thus, a moderate variation of α from its optimum value does not significantly reduce the tracking efficiency.

To study the characteristic of α during the dynamic changing environmental conditions, various simulations under different changing insolation level have been conducted. Fig. 4.23 shows the simulation results.

Fig. 4.23 Evaluation of optimum α at different increase amount in insolation level

From Fig. 4.23, it is observed that the optimum α reduces almost linearly with the increase in insolation level. It can be deducted from Fig. 4.20(a) that the new OP 2' is further away from the new MPP 2 with a larger increase in insolation level. Thus, the optimum α should be smaller to estimate a larger sampling interval. In practice, the change in insolation level can be estimated from the change in measured current without using an insolation sensor. Based on this change in insolation level and the study in Fig. 4.23, the optimum α can be estimated. Other observation from Fig. 4.23 is that the

tracking efficiencies under various change in insolation levels is acceptable with a fixed α of 0.35-0.45. This fixed α can be chosen to simplify the algorithm.

(b) The effect of β

As illustrated previously in Fig. 3.7, the β value decides the lower bound of the sampling interval when the new OP is in “the current source region”. This scenario happens in the first stage of the simulation described previously in Fig. 4.20(b). In this stage, the insolation level changes from 1000 W/m² to 500 W/m² and remains there for 3s. Thus, the varying operating point scenario illustrated in Fig. 3.5(a) can be created. Fig. 4.24 shows the simulation results at different β values. The red rectangles indicate the early tracking state while the MPP has not been reached. In Fig. 4.24(a) – 4.24(c), they also indicate the state after that the algorithm switches to “the range extension strategy” to follow the MPP.

Fig. 4.24 The effect of β on the algorithm’s tracking performance

(a)- $\beta=0.3$. (b)- $\beta=0.5$. (c)- $\beta=0.7$. (d)- $\beta=0.95$.

As shown in Fig. 4.24, smaller β causes larger fluctuations in the tracking power in the early stage. This is because smaller β results in a larger estimated sampling interval. Thus, β cannot be chosen too small. On the other hand, Fig. 4.24(d) shows the effect of large β on the algorithm's tracking performance. In the figure, the green rectangles denote the tracking state while the algorithm searches for the MPP in the estimated interval. After finding this MPP, the algorithm switches to "the range extension strategy". Since β is large, the estimated interval is small and does not contain the PV array's MPP. Thus, the MPP in the estimated interval is not the PV array's MPP. By extending the searching range in the later stage, the algorithm can eventually track the MPP but the tracking time will be longer.

Similar to the selection of α discussed in previous section, there is also an optimum range of β at a given changing environmental scenario so that the algorithm has the best tracking efficiency. To evaluate the characteristic of the optimum β , various simulations have been conducted with different β at different variations in insolation level. Fig. 4.25 shows the dependence of the algorithm's tracking efficiency in the early stage on β at various reduction amount of insolation level.

Fig. 4.25 Evaluation of optimum β at different reduction amount in insolation level

From Fig. 4.25, it is observed that the optimum β reduces almost linearly with the reduction in insolation level. As mentioned earlier in the previous section, the change in insolation level can be estimated from the change in the measured current. Based on this change in insolation level and the study in Fig. 4.25, the optimum β can be estimated. Moreover, the tracking efficiencies under various insolation levels are acceptable with a fixed β of 0.5-0.6. This fixed β can be chosen to simplify the algorithm.

(c) The effect of Δd

In the steady state, Δd determines the extended sampling interval's length. Thus, it decides how far the next sampling point is away from the MPP. Fig. 4.26 shows the simulation results conducted with various Δd under the same environmental variation that

reduces the insolation level from $1000 \text{ W/m}^2 \rightarrow 800 \text{ W/m}^2 \rightarrow 600 \text{ W/m}^2 \rightarrow 400 \text{ W/m}^2 \rightarrow 300 \text{ W/m}^2$.

Fig. 4.26 The effect of Δd value on the algorithm's tracking performance.

(a)- $\Delta d=0.0005$. (b)- $\Delta d=0.001$. (c)- $\Delta d=0.003$. (d)- $\Delta d=0.015$.

Similar to the perturbation step size in the P&O method, large Δd results in large steady state oscillation as shown in Fig. 4.26. However, a small Δd results in insignificant change in the tracking power as shown in Fig. 4.26(a). Thus, the algorithm may fail to follow the change in the MPP. Fig. 4.27 plots the steady state tracking efficiency versus the size of Δd .

Fig. 4.27 Steady tracking efficiency versus the Δd size

As seen from Fig. 4.27, the tracking efficiency that is decided by the steady state oscillation reduces as step size Δd increases. From various simulation evaluations, the suitable Δd value has been found to be in the range of (0.001, 0.0025) as marked by the cycle in Fig. 4.27. If Δd is in this range, the algorithm would give good steady state performance across various insolation levels.

4.6.2 Evaluation of the MPPT algorithms' performance

The simulation model is useful for evaluating the performance of the proposed algorithm as well as benchmarking with other algorithms. To evaluate the effectiveness of the proposed approach, its performance is compared with the variable step size dP-P&O algorithm [22, 28] under different environmental conditions.

(a) Rapidly changing insolation conditions

To evaluate the performance of the MPPT algorithms under rapidly changing environmental conditions, the insolation ramps together with the sudden step changes are used as in [22, 28]. As shown in Fig. 4.28, the insolation is initially set at 900W/m^2 (equivalent tracking power of 54W). After 3s , it suddenly falls to 750W/m^2 . Then it increases linearly to 900W/m^2 and remains at this level for another 3s before decreasing linearly to 750W/m^2 . The 3s period for the increasing and decreasing ramps was selected for a short simulation time. At the end of the period, the insolation suddenly jumps to 1000W/m^2 and remains at this level until the end of the simulation. Fig. 4.28 shows the simulation results when DIRECT and dP-P&O are implemented.

Fig. 4.28 Tracking Power during rapidly changing irradiation
(a) – DIRECT. (b) – dP-P&O

As seen in Fig. 4.28(a), DIRECT shows good tracking of the MPP. Similarly, dP-P&O can also follow the MPP as shown in Fig. 4.28(b). However, it sometimes loses the MPP for few cycles during the rapidly increasing and decreasing insolation level. Furthermore, the DIRECT algorithm has a smaller oscillation than the dP-P&O algorithm

in the steady state. Overall, the P&O tracking efficiency is 95.7 % while the DIRECT's is 99%.

Fig. 4.29 shows the simulation results in another changing scenario of the environmental conditions. In this scenario, the changing rate of the insolation level has been changed.

Fig. 4.29 Tracking Power during rapidly changing irradiation
(a) – DIRECT. (b) – dP-P&O

Similar to the observation in the previous simulation, the proposed algorithm shows a much better tracking performance as compared to the dP-P&O approach. The overall P&O tracking efficiency is 96% while DIRECT is 99.1 %.

(b) Sudden and high level change in insolation

To evaluate the tracking speed of the algorithms, a step change in insolation level at a rate of 3s has been conducted. Fig. 4.30-4.32 show the simulation results conducted at various step changes in insolation level.

Fig. 4.30 Tracking Power with insolation: $1000\text{ W/m}^2 \rightarrow 800\text{ W/m}^2 \rightarrow 1000\text{ W/m}^2$
(a) – DIRECT. (b) – dP-P&O

Fig. 4.31 Tracking Power with insolation: $1000\text{ W/m}^2 \rightarrow 600\text{ W/m}^2 \rightarrow 1000\text{ W/m}^2$
(a) – DIRECT. (b) – dP-P&O

Fig. 4.32 Tracking Power with insolation: $1000\text{ W/m}^2 \rightarrow 300\text{ W/m}^2 \rightarrow 1000\text{ W/m}^2$
(a) – DIRECT. (b) – dP-P&O

As seen in Fig. 4.30 – 4.32, the P&O tracking speed is at least two times slower than the DIRECT algorithm’s tracking speed. The larger the change in insolation level, the further the new OP is from the new MPP. Thus, the variable step sized dP-P&O will need longer

time to track the new MPP. Since the DIRECT algorithm does not base on the sequential tracking strategy, its tracking time is less affected by the distance between the new OP and the new MPP. Thus, the difference between the tracking efficiency of the variable step size dP-P&O and the DIRECT algorithm will increase for rapid and large change in insolation level. Fig. 4.33 shows the tracking efficiency of two algorithms versus the amount of sudden change (both decrease and increase) in insolation level. In the figure, the amount of change in insolation level is quantified by percentage of reduction (or increase) in the insolation level.

Fig. 4.33 Efficiency versus amount of sudden change in insolation level

From Fig. 4.33, it is observed that the tracking efficiency reduces dramatically in the dP-P&O case but not in the DIRECT case when the amount of sudden change in insolation level increases. This has verified the high tracking speed of the DIRECT algorithm especially under rapid and high-level changing insolation conditions.

4.7 Conclusion

This chapter presents a simulation model of a PV system. All PV power system components such as the environment, the PV arrays, the power processing system and the electrical load have been modeled modularly to the required level of complexity. This provides ease of substituting a more accurate but complex model in the later stage if the needs arise. The model can simulate the dynamic behavior of the PV system in different control algorithms or operating conditions. It has been developed so that the optimized designs obtained by the simulation model can be easily implemented in the real system design with minimum modifications.

To study the proposed algorithm's behavior, various simulations have been conducted. Based on the simulation results, a suitable range of the algorithms' parameters has been proposed. These values can be used as a guide when designing the algorithm in real system.

To evaluate the effectiveness of the proposed approach, its performance is also compared with the variable step size dP-P&O algorithm. Simulation results show that the proposed algorithm yields a faster tracking speed and a better steady state performance as compared to the variable step size dP-P&O algorithm.

Chapter 5

Prototype System Design and Experimental Results

5.1 Introduction

Various tests need to be conducted to evaluate the MPPT algorithms' performance under different operating conditions. To conduct these tests, a PV test system that is able to emulate the real environmental conditions is developed. Besides using the real solar panels as the power source, the test system is required to emulate the PV array to provide the same operating environment for different tracking schemes. Fig. 5.1 shows the block diagram of the test system. As shown in this figure, both the real solar arrays and solar array simulator (SAS) can be used as the power source for the PV power processing system (i.e. the buck-boost converter and the power control module). The design of the PV power processing system will be discussed in section 5.3. The electronic load (HP E6050B) is connected to the output of the buck-boost converter to provide the loading. The voltage and current sensing circuits incorporated in the system are used for continuously monitoring the PV arrays' operating point. These sensing signals are displayed in real time using a Lecroy scope (Waverunner Xi-A) that can also function as a data logger. The logged data can be accessed by the PC through the transmission control protocol/internet protocol (TCP/IP).

Fig. 5.1 Block diagram of PV Test System

5.2 PV power source design

For real panel test, two branches of the solar arrays have been connected in parallel with each branch uses two 20W solar panels (i.e SPSM-20D) connected in series. To reduce the effect of shading, by-pass diodes are used across each panel and blocking diodes have been installed in each branch. The key specifications of a solar panel are shown in Table 5.1.

Table 5.1 Specifications of the 20W PV panel

At Temperature	T	25	$^{\circ}\text{C}$
Open-circuited voltage	V_{oc}	21.5	V
Short-circuited current	I_{sc}	1.386	A
Voltage at max power	V_m	17	V
Current at max power	I_m	1.178	A
Maximum Power	P_m	20	W

In the laboratory, the solar array simulator is used as the power source to provide the same operating environment for different tracking schemes. The SAS is capable of simulating the I - V curve of different arrays under various environmental conditions as long as the I - V curve's data points are available for the SAS. In its curve mode, the SAS could approximate an I - V curve when four parameters, namely V_{oc} , I_{sc} , I_{mp} and V_{mp} are inputted to the system. In the table mode, the user could provide a maximum of 4000 data points of a real I - V curve. To set the SAS's parameters for different test scenarios, the virtual instrument (VI) platform is programmed to support a graphical user interface. The virtual instrument platform implemented in the PC controls the SAS using the GPIB interfaces as illustrated in Fig. 5.1.

The concept of virtual instrument (VI) has demonstrated its usefulness in various industrial applications [88]-[92]. VIs are different from the traditional instrument both outwardly and inwardly. Outwardly, VIs are computer-based instruments that consists of computer and instrument I/O devices. Inwardly, the functionality of VIs are written in software programs while the traditional instruments are built almost exclusively into hardware and dedicated firmware [93]-[95]. Currently, LabVIEW from National Instrument and VEE from Hewlett Packard are the most widely used VI languages. In

this thesis, LabVIEW has been used to develop the VI platform. In the program, the user interface that is called the front panel is built by a set of tools and objects provided. Fig. 5.2 shows the front panel control of the SAS.

Fig. 5.2 Front panel control of SAS

The front panel can be categorized into the following functions:

- “System initialization & control” provides virtual tool (Reset Device) to reset all the hardware and software status. Instruments address, SAS’s operating mode and the test scenarios can be selected and changed using “SAS Address in”,

“Operating Mode” and “Operating Scenario Selection” tools as shown in Fig. 5.2.

When the operating scenario of the PV arrays is selected, the appropriate I - V curve’s data will be downloaded to the VI platform from the file server as shown in Fig. 5.1. The information is then used to program the SAS to emulate the PV array under the selected test scenario. The changing speed of the I - V curves can be set by the “Interval Timing” tool. In other words, the fast or slow changing environmental conditions can be emulated to evaluate the algorithms’ performance. The control panel also provides the option (“Start from row no.” and “End Row” as shown in Fig. 5.2) to build back only a selected portion of the whole operating scenario. This is to shorten the test period if only a portion of a long operating scenario is needed for evaluation.

- “System display” provides various virtual tools to display the status of the SAS such as: the on-going operating scenario, the number of I - V curve in the scenario, the current generated I - V curve (i.e. I_{sc} , I_{MPP} , V_{MPP} , V_{oc}) and the current operating point (i.e. I_{pv} and V_{pv}).

Through this study, the VI platform has demonstrated its usefulness for setting different test scenarios and monitoring the status of the PV system easily. The VI platform becomes very important for controlling the SAS to produce the same scenario in multiple experiments for benchmarking the proposed algorithm with other established approaches.

5.3 PV power processing system design

As discussed in chapter 2, the current-voltage (I - V) output characteristic of a PV generator is nonlinear. It has an optimum operating point (OP) that gives the maximum power for a given temperature and insolation condition. To maximize the energy transfer, the load I - V characteristics must intercept the PV generator's optimum OP as close as possible. In general, the matching of the electrical load and the PV generator's optimum OP seldom occurs during the operation of a PV system. Thus, the power processing systems is often installed between the PV generators and the electrical load to transfer the power to the load and/or to the grid. Among them, the DC/DC converters are widely used. Fig. 5.3 shows a typical block diagram of a PV power system that implements a dc/dc converter as a power processing system.

Fig. 5.3 Typical block diagram of a MPPT system

In Fig. 5.3, the dc/dc converter conditions the energy generated by the PV array following a specific MPPT algorithm. Depending on the MPPT techniques, the algorithm can be implemented by using the analog circuits or digitally by the microcontroller. The inputs to the control block are usually the sensed current and voltage from the PV array

or from the load. The output of the MPPT block is the PWM signal with a controlled duty cycle. By changing the duty cycle, the converters are used as the impedance transformer to eventually match the electrical load with the PV array's optimum OP. Consequently, the reachable range of the input impedance and the output voltage level depends on the converter topology in used.

5.3.1 The selection of DC/DC converter topology

Fig. 5.4 shows the block diagram of a solar panel connected to a DC/DC converter and its corresponding $I-V$ curve. In the figure, R_i is the equivalent input resistance of the converter as well as the load resistance for the solar panel. R_L is the equivalent load resistance of the converter.

Fig. 5.4 Panel-converter connection

(a) – PV system block diagram. (b) – Impedance matching illustration

For a given operating condition, the dc/dc converter regulates the array's voltage V_A such that $R_i = R_{MPP}$ as shown in Fig. 5.4(b) to operate at the MPP. Depending on the converter topology, the variable range of R_i is different. By varying the duty cycle, the buck converter can regulate R_i in the range $[R_L, \infty)$ while the boost converter can only regulate R_i in the range $[0, R_L]$ [15]. For a given converter topology, the MPP cannot be reached if

R_{MPP} is not belong to the allowable values for R_i . Therefore, the buck topology can only track the MPP if $R_{MPP} \geq R_L$ while the boost topology can only track the MPP if $R_{MPP} \leq R_L$.

For the buck-boost topology, R_i can take any values from 0 to ∞ by varying the converter's duty cycle [15]. Thus, it can successfully match R_i to R_{MPP} regardless of the atmospheric conditions and the value of R_L . Hence, the buck-boost converter has the most flexibility. In our work, the prototype is developed for general study and the buck-boost topology is selected.

5.3.2 Buck-boost converter design

Fig. 5.5 shows an 80W prototype buck-boost converter designed for a PV system with the operating ranges shown in Table 5.2.

Fig. 5.5 System block diagram of a PV system with buck-boost converter

Table 5.2 Operating ranges for PV power system

Symbol	Operating Ranges	Unit
PV cells temperature (T)	(0, 60)	$^{\circ}C$
Insolation level (G)	(0, 1000)	W/m^2
Equivalent Resistive Load (R_L)	(10, 20)	Ω
PV array's short-circuited current (I_{SC})	(1, 4)	A
PV array's open-circuited voltage (V_{OC})	(15, 30)	V
Switching frequency (f)	20	kHz
dsPIC30F1010A I/O voltage range	(0, 5)	V
10-bits A/D sampling rate used	400	$ksps$

Based on Table 5.2, the selection of the buck-boost converter's circuit elements are discussed in Appendix C. From the calculation, the output capacitor C_o , the input capacitor C_{in} , and the inductor L have been chosen as: $C_{in}=470\mu F$, $C_o=220\mu F$, $L=1.5mH$.

5.3.3 Snubber circuit design

For the dc/dc converter, the switch is exposed to a high stress during the “hard switching” because the maximum voltage and the maximum current must be supported simultaneously. This leads to a high switching loss. In practice, the stress will be even higher due to the presence of the parasitic inductance (L_p) and the capacitance (C_p) that causes the ringing during transitions. C_p includes the switch junction capacitance and the stray capacitance due to the circuit layout and mounting. L_p depends on the finite size of

the circuit layout and the lead inductance. To reduce the circuit’s stress during switching, the use of a snubber network is essential. The snubbers are the small networks that control the effects of the circuit reactance. The basic intent of a snubber is to absorb energy from the reactive elements in the circuit. By controlling the changing rate in voltage (or current) or the clamping of the overshoot, a snubber circuit limits the amount of stress that the switch must endure. Thus, it increases the reliability of the switch. Snubbers may be passive or active networks. In this section, the design of the polarized dissipative current snubber and voltage snubber networks are discussed. Fig. 5.6 shows the waveform of the inductor current, the PV array current, the diode current and the voltage across the IGBT switch of the circuit in Fig. 5.5. In the measurement, the inductor and the diode currents have been scaled down 100 times by a 0.1Ω sensing resistor and the differential probe. The switching current I_{SW} is only scaled down 5 times by a 0.2Ω sensing resistor.

Fig. 5.6 Circuit behavior before adding all snubber networks

It is observed from Fig. 5.6 that the currents flowing through the inductor and the diode have about 19 MHz maximum ringing frequency and a peak spike of 30A. Thus, this

results in a high stress on the switch and the diode during switching. To reduce the stress, a current snubber circuit that controls the rising rate of the switch's current and the decreasing rate of the output diode's current should be added.

(a) The polarized dissipative current snubbers

Fig. 5.7 shows the implementation of the polarized current snubber network in a buck-boost converter.

Fig. 5.7 The implementation of current snubber network in buck-boost converter

As shown in Fig. 5.7, the snubber inductor L_{snub} in series with the switch presents the switch with an inductive load so that it reduces the rising rate of the switch's current (and also the decreasing rate of diode's current) when the switch turns on. A diode is added in series with the snubber resistor R_{snub} to prevent the switching current flowing directly through R_{snub} . Thus, only the energy stored in L_{snub} during switching is dissipated in R_{snub} and the converter's efficiency can be increased.

The selection of the snubber network's circuit elements are discussed in Appendix D. From the calculation, R_{snub} and L_{snub} have been chosen as: $R_{snub} = 20\Omega$, $L_{snub} = 10\mu H$. Fig. 5.8 shows the circuit behavior after adding the current snubber network.

Fig. 5.8 Waveform after adding current snubber

As shown by the red rectangle area in Fig. 5.8, the current snubber has significantly reduced the 30A peak of the output diode reversed current (also the peak of the switching current) to about 5A. However, when the switch turns off, the discharge of the energy stored in the snubber inductor has contributed to a higher spike in the switching voltage V_{SW} (about 100V in addition). Adding a resistor-capacitor-diode (RCD) snubber across the switching can reduce this spike's amplitude.

(b) The RCD voltage snubbers

The RCD snubber is used to control the voltage's rising rate on the drain or on the collector of a switching transistor. The snubber increases the switch reliability by reducing the switch's peak power dissipation. Fig. 5.9 shows the implementation of the RCD snubber in a buck-boost converter.

Fig. 5.9 The implementation of voltage snubber network in buck-boost converter

As illustrated in Fig. 5.9, the RCD voltage snubber network is added in parallel with the switch. The snubber circuit is only active during the switching transition. When the switch turns off, the current from the inductor is diverted through the snubber diode to the snubber capacitor C_{RCD} . This current charges C_{RCD} to the rail voltage until the main diode turns on to carry the inductor current. When the switch turns on, C_{RCD} discharges through the resistor R_{RCD} and the switch. The switch's power dissipation during turning off is transferred into the snubber. Besides, the rising rate of the voltage is also reduced.

The selection of the RCD snubber network's circuit elements is discussed in Appendix D. From the calculation, R_{RCD} and C_{RCD} have been chosen as: $R_{RCD} = 75\Omega$, $C_{RCD} = 0.22\mu\text{F}$. Fig. 5.10 shows the circuit behavior after adding both the current snubber network and the voltage snubber network.

Fig. 5.10 Currents and voltage waveform after adding voltage snubber

It is observed from Fig. 5.10 that the voltage snubber has significantly reduced the spikes' amplitude presented in the switch's voltage by almost 70% as compared to the value shown in Fig. 5.8.

5.3.4 Interfacing circuit design

(a) Sensor circuit

As shown in Table 5.2, the PV array's voltage may range from 0V to 30V. To feedback this voltage for MPPT controller, a voltage divider in parallel with the solar panels is used to scale this voltage to (0V, 5V) before inputting to the microcontroller.

To sense the current, a high-side unipolar current shunt monitors INA139 has been used. It has a wide input common-mode voltage range from 2.7V to 40V. Moreover, its low quiescent current (60μA) permits the connection to either side of the power supply with a minimal error. Fig. 5.11 shows the schematic diagram.

Fig. 5.11 Description of INA139 current sensor

As shown in Fig. 5.11, a small precision resistance R_S (0.1Ω) connected in series with the load is used in the circuit. The voltage drop across the resistor is directly proportional to the current flowing to the load. The device converts a differential input voltage to a current output. This current is converted back to a voltage with an external load resistor R_L as follows

$$V_o = \frac{I_S R_S R_L}{1k\Omega} \quad (5.1)$$

Thus if $R_S=0.1\Omega$ and $R_L=12.5k\Omega$, the current/voltage conversion gain of the sensor is 1.25.

(b) Anti-aliasing filter

Filters are used to remove the high frequency noises and interferences from the signal path prior to the analog-to-digital (A/D) conversion. Since the sampling frequency (f_s) of dsPIC is about 400 kHz, the corner frequency should be lower than 200 kHz ($f_s/2$)

according to the Nyquist theory. Furthermore, the minimum gain of the filter at $f_s/2$ should be less than the signal-to-noise ratio (SNR) of the sampling system. For instance, if a 10-bit A/D converter is used, the ideal SNR is 60 dB. The filter is designed such that its attenuation at 200 kHz is at least 60 dB.

For the filter, the Bessel filter is used as it has a flat magnitude response in the pass-band and no ringing in the stop band. Fig. 5.12 shows the circuit diagram of the designed filter.

Fig. 5.12 The circuit layout of the 4th order low pass filter

Fig. 5.13 shows the overall photovoltaic power processing circuit. In the figure, the PV array is shown as a current source I_{pv} for simplicity. Furthermore, the IGBT driving circuit and the sensor circuits' connection to the DSP are not included in the figure.

Fig. 5.13 The photovoltaic power processing circuit layout

5.4 Experimental results and discussion

Various experiments have been conducted with the developed prototype based on both the proposed MPPT and other MPPT schemes. To ensure that the system reaches the steady state in each MPPT cycle before another begins, the sampling interval of the algorithms is chosen as 0.05s by using a timer interrupt.

5.3.1 Evaluation of the proposed algorithm under uniform insolation condition

To evaluate the effectiveness of the proposed MPPT algorithm under uniform insolation conditions, its performance is compared with the dP-P&O scheme [20]. Moreover, the variable step sized method as proposed in [31] has also been implemented to increase the tracking speed of the dP-P&O scheme.

(a) Rapidly changing insolation conditions

To evaluate the performance of the proposed algorithm with the dP-P&O algorithm during rapidly changing environmental conditions, the insolation ramps and sudden step changes are used. The experimental results are shown in Fig. 5.14 and 5.15. For these experiments, the initial insolation is 900W/m^2 . After 10s, the insolation falls to 300W/m^2 . Subsequently it increases linearly to 900W/m^2 and remains at this level for another 10s before decreasing linearly to 300W/m^2 . At the end of the period, the insolation surges to 900W/m^2 and remains at this level until the end of the experiment. The aforementioned time durations are selected to shorten the experimental time to demonstrate the tracking behaviors of the algorithms. Fig. 5.14 and 5.15 show the tracking voltage, current and power with the proposed algorithm and the dP-P&O approach, respectively.

Fig. 5.14 Experimental tracking characteristic of DIRECT during rapidly changing irradiation

Fig. 5.15 Experimental tracking characteristic of dP-P&O during rapidly changing irradiation

From the results, it is observed that the experimental data match well with the simulation study in Fig. 4.28. While DIRECT shows good tracking of the MPP (the red line) as in Fig. 5.14, dP-P&O sometimes can not track the MPP as illustrated by the dotted blue lines in Fig. 5.15. Furthermore, when there is a large increase in the insolation level (marked by the dotted blue rectangle in Fig. 5.15), the dP-P&O takes a longer time to reach the new MPP. It takes almost 6s for the dP-P&O to track new MPP while it takes less than 1s for the proposed algorithm.

Comparing to the simulation result in Fig. 4.28(b), the dP-P&O takes a longer time to track the new MPP as shown in Fig. 5.15. The main reason is that dP-P&O is more sensitive to the sensor error. This error is at its maximum when the OP falls in the low current and high voltage region. This scenario often occurs when there is a large change from a low to a high insolation level as illustrated in Fig. 3.5(d) and Fig. 3.5(f).

Fig. 5.16 and 5.17 show the tracking power with both MPPT approaches in other changing environmental scenarios. The scenarios are based on I-V curve changing profile of an X-SAT satellite [97, 98].

Fig. 5.16 Power tracking during 2nd scenario
(a)-DIRECT. (b) P&O.

Fig. 5.17 Power tracking during 3rd scenario

(a)-DIRECT. (b) P&O.

As shown in these figures, while the variable step size dP-P&O algorithm failed to track the MPP during the fast changing of insolation, the proposed algorithm successfully follows closely the MPP. During the slower changing patterns, both algorithms have successfully tracked the MPP. Overall, the tracking efficiency of the proposed algorithm is about 3% higher than the variable step size dP-P&O algorithm.

(b) Evaluation for sudden and high level change in insolation

To evaluate the tracking speed of the algorithms, experiments were conducted with different step changes in the insolation levels at the rate of 3s and 1s. Fig. 5.18 and Fig. 5.19 show the typical experimental results using DIRECT and dP-P&O respectively.

Fig. 5.18 Voltage, current and power tracking of DIRECT with step changes in insolation

Fig. 5.19 Voltage, current and power tracking of dP-P&O with step changes in insolation

Fig. 5.18 shows that the proposed algorithm takes less than 0.5s to track the new MPP. On the other hand, its tracking speed varies slightly with different starting points when the environmental conditions change. As for the dP-P&O method, Fig. 5.19 shows that it takes about 2s to track the new MPP. Moreover, its tracking speed varies largely depending on the new OP's location on the I - V curve. In the first stage of the experiment

when there is a drop in insolation level, the dP-P&O takes about 2.5s to track the MPP. In the second stage of the experiment when there is an increase in the insolation level, it takes about 1.8s to track the new MPP.

As discussed in the simulation studies in section 4.6.2, a larger change in the insolation level causes the new OP to be farther away from the new MPP. Thus, the variable step sized dP-P&O will need a longer time to track the new MPP. Since the localized DIRECT algorithm is not based on the sequential tracking strategy, its tracking time is less affected by the distance between the new OP and the MPP. Thus, during rapid and large changes in the insolation level, the difference between the tracking speed of the variable step sized dP-P&O and the DIRECT algorithm will increase. Fig. 5.20 shows the tracking efficiency of the two algorithms versus the amount of the insolation level change (both decrease and increase) at the rate of 3s and 1.5s. In the figure, the amount of change in insolation level is quantified by the percentage of reduction (or increase) in the insolation level. The tracking efficiency is calculated as the ratio of the average tracking power versus the maximum power at the same environmental condition. At each step of the insolation level reduction (or increase), the tracking efficiency is calculated and is then plotted as shown in Fig. 5.20.

Fig. 5.20 Efficiency versus amount of suddenly changing insolation level
(a) Increase in insolation level. (b) Reduction in insolation level.

As shown in Fig. 5.20, when the amount of changing insolation level increases, the tracking efficiency reduces dramatically in dP-P&O but not DIRECT. With 60% of reduction in the insolation level at a changing rate of 1.5s, the tracking efficiency of the proposed algorithm is 25% higher than the variable step size dP-P&O algorithm. This has verified the high tracking speed of DIRECT algorithm especially during the rapidly changing insolation conditions.

5.3.2 Evaluation of DIRECT algorithm for partially shaded condition

(a) Experiments conducted using solar array simulator

To evaluate the effectiveness of the proposed approach under partially shaded condition, its performance is compared with the algorithm in [80] which is also developed for partially shaded condition. To ensure that both the schemes are benchmarked under the same operating environment, the experiments are conducted with 3 Agilent E4360B solar array simulators (SAS) connected in parallel as a power source. The experiments were conducted with 3 consecutive scenarios. In the first scenario, the SAS generates the I - V curve of the PV array under the uniform insolation condition. This condition is maintained for 1.5s before it is changed to partially shaded condition. For this partially shaded condition 2, the I - V curve is programmed to have two local MPPs. After another 1.5s, the partially shaded condition is changed such that the I - V curve is having 3 local MPPs. The experimental results in Fig. 5.21 and Fig. 5.22 show the tracking voltage, current and power when the DIRECT and the algorithm in [80] are implemented respectively.

Fig. 5.21 Tracking voltage, current and power of the proposed algorithm

Fig. 5.22 Tracking voltage, current and power of the algorithm developed in [80]

As shown on the top left of Fig. 5.21, the proposed algorithm first samples three points in the initial sampling interval to identify the insolation state. From (3.42)-(3.43), the

information obtained from these samples is used to confirm the presence of uniform insolation condition. Subsequently, the proposed algorithm switches to the locally biased mode in the 4th sampling cycle as indicated by the vertical arrow in Fig. 5.21. In Fig. 5.22, the algorithm in [80] first tracks the nearest local MPP. It then searches on the left of this local MPP to find others. This is illustrated by the gradual increase and then decrease in the tracking voltage (and power). Since the solar panels are under uniform insolation, the tracking power drops when the tracking voltage reduces. The algorithm in [80] detects the presence of the uniform insolation when the power reduction is larger than the critical value. It then considers the found local MPP as GP and set the OP at this local MPP. Since the three panels are under uniform insolation, the tracking powers reduce further when the OP is nearer to I_{sc} as discussed in [80]. The algorithm detected the presence of uniform insolation when the power reduction is larger than a critical value as proposed in [80]. It then considers the previous found local MPP as the GP and set the OP at this local MPP.

From the experimental data, the movement of OP in the first 3 samples for the last two stages is presented in Fig. 5.23 and Fig. 5.24 together with the changing characteristics curves. In Fig. 5.23, the blue lines represent the characteristic curves of uniform insolation condition while the red lines represent the characteristic curves of partially shaded condition 2. In Fig. 5.24, the green lines represent the characteristic curves of partially shaded condition 3.

Fig. 5.23 Illustration of the OP movement from uniform to partially condition 2

Fig. 5.24 Illustration of OP movement from partially shaded condition 2 to condition 3

In the 2nd stage of the experiment, the I - V curve changes shape as the environment changes from the uniform insolation to the partially shaded condition. Consequently, the OP shifts from 1 on the old I - V curve to 1' on the new I - V curve as illustrated in Fig.

5.23. The movement of OP results in a drop of the tracking power. This can be observed from Fig. 5.21 indicated by the dotted circle. This drop in tracking power activates the proposed algorithm to take three new samples. The information derived from the samples verifies the presence of partially shaded condition based on (3.42)-(3.43). Hence, the globally biased mode is set to explore the GP's region. This exploration results in the fluctuations of tracking voltage and current in Fig. 5.21. At the 9th sampling time, the system finds the GP's region and switches to local biased mode to track this GP. As shown in the P - V curve in Fig. 5.23, there is no other local MPP on the left of the nearest found local MPP. Thus, the algorithm in [80] keeps searching on the left until it reaches V_{min} as shown in Fig. 5.22. Then it searches on the right to find other local MPPs. Since the 2nd found local MPP is higher than the first, the algorithm continues searching on the right until it reaches V_{max} . The algorithm then considers the 2nd local MPP as the GP and set it to be the OP. This searching strategy is illustrated by the experimental results in Fig. 5.22. In the other two-peak P - V curve, the searching scenario is the same. Thus, this strategy would result in longer tracking time and larger power loss as compared to the proposed algorithm.

In the 3rd stage of the experiment, the partial shaded conditions changed again. This resulted in the presence of 3 local MPPs in the P - V curve. The OP shifts from 2 to 2' on the new I - V curve as shown in Fig. 5.24. Similar to the 2nd stage, DIRECT focuses on exploring new sampling interval until it finds the region of the GP at the 8th sampling cycle. Then it switches to the locally biased form to reach the GP as shown in Fig. 5.21. In this scenario, the algorithm in [80] has been favored since the 1st local MPP was also

the GP. When searching on the left, the algorithm found the 2nd local MPP that was smaller than the first. Thus, it reverses the searching direction and finds the 3rd local MPP. Since the 3rd local MPP was also smaller than the first, the algorithm stopped exploring and considered the 1st local MPP as GP. Tables 5.3 and 5.4 show the extracted results with different changing rates of environmental conditions.

Table 5.3 Tracking performance comparison at rate of change of 1.5s

Method	Average Tracking Efficiency	Tracking Efficiency and Speed		
		Uniform Inso.	Partially Shaded Cond. 2	Partially Shaded Cond. 3
DIRECT	95.1%	95.62% 8 cycles	94.96% 11 cycles	94.92% 10 cycles
Algorithm in [80]	88.9%	94.6 % 11 cycles	85.16 % 24 cycles	86.95% 22 cycles

Table 5.4 Tracking performance comparison at rate of change of 3s

Method	Average Tracking Efficiency	Tracking Efficiency		
		Uniform Inso.	Partially Shaded Cond. 2	Partially Shaded Cond. 3
DIRECT	97.55%	97.71%	97.48%	97.46%
Algorithm in [11]	94.44%	97.27%	92.56%	93.48%

In conclusion, the experiments show that both the algorithms can successfully track the GP. However, the proposed algorithm can track two times faster and its tracking efficiency is 10% higher than the existing algorithm during the rapidly changing environment. In slowly changing environmental conditions as shown in Table 5.4, the tracking efficiency of both the algorithms is more comparable, since both can track the global MPP.

(b) Experiments conducted with the real solar panels

To further evaluate the effectiveness of the proposed algorithm in an actual environment, some experiments have been conducted with the actual solar arrays as the power source. For these experiments, two branches of the solar arrays have been connected in parallel with each branch uses two 20W solar panels connected in series. To reduce the effect of shading, by-pass diodes are used across each panel and the blocking diodes have been installed in each branch. The experimental data have been collected continuously from 10am-4pm. Fig. 5.25 and Fig. 5.26 show the typical experimental results of DIRECT algorithm and the algorithm in [80] carried up on two different days.

Fig. 5.25 Test of DIRECT algorithm with actual solar panels

Fig. 5.26 Test of algorithm in [80] with actual solar panels

Fig. 5.27(a) and Fig. 5.28(a) show the details of experiments, corresponding to those circled by dotted lines in Fig. 5.25 and 5.26, respectively. They show the tracking ability of the DIRECT algorithm and the algorithm in [80] when partial shading happened. Fig. 5.27(b) and 5.28(b) show the corresponding $I-V$ curves of the two algorithms during the tracking time.

Fig. 5.27 Tracking characteristics of DIRECT
(a) Tracking power. (b) Corresponding I-V curve.

Fig. 5.28 Tracking characteristics of algorithm in [80]
(a) Tracking power. (b) Corresponding I-V curve.

From Fig. 5.27(b), it is observed that most of the sample points gather closely to the global MPP except a few points spreading through the $I-V$ curve. Thus, DIRECT has a

good tracking performance. On the other hand, the algorithm in [80] needs to scan almost 80% of the I - V curve to search for the global MPP as shown in Fig. 5.28(b). The density of the tracking points is distributed quite evenly in the I - V curve and slightly more at the global MPP. Thus, the algorithm in [80] needs to spend longer time to find the GP which results in lower tracking efficiency.

During the slowly reducing insolation level as indicated in Fig. 5.27(a), the proposed algorithm has followed the MPP by employing the fixed step size dP-P&O method that has been shown to perform well in slowly changing environmental conditions [20]. In the experiments shown in Fig. 5.28(a), the reducing insolation did not happen. However, the tracking performance of the algorithm in [80] is expected to be the same as the DIRECT algorithm since both uses the dP-P&O method to maintain the OP at the MPP.

5.5 Conclusion

This chapter discusses the design of an 80W prototype PV system that is used to evaluate the performance of the proposed algorithms. The design of sensor circuit and their interfacing circuit to the microcontroller have also been carefully considered to minimize noises and to increase the sensor accuracy. This is crucial as the sensor's accuracy strongly affects the tracking precision of the MPPT algorithms.

To evaluate the effectiveness of the proposed MPPT algorithms, their performances are compared with one of the latest algorithms. Different tests using SAS has been conducted under various atmospheric conditions. Besides, the field experiments with real solar

panels have also been conducted to justify the algorithms' performance in practice. The experimental results have proved that the proposed algorithms have a better steady-state performance and faster tracking speed, especially in the presence of the multiple maximum power points and rapid changing insolation.

Chapter 6

Conclusion and Recommendation

6.1 Conclusion

The design and performance evaluation of the novel maximum power point tracking algorithms for a PV power system have been presented in this thesis. A new photovoltaic maximum power point tracking algorithm optimized for rapidly changing temperature and irradiation conditions has been proposed. The new approach can effectively improve the tracking speed and accuracy simultaneously, which is the contradiction in conventional methods such as P&O or INC. The algorithm can also be implemented by using a low cost microcontroller.

When the PV panels operate on cloudy days or in an area surrounded with high buildings, there is a high possibility that they will be partially shaded. This would result in multi-peaks P - V characteristic curve. Very often, the global peak is hidden from the conventional MPPT algorithms. To overcome this limitation, we propose a novel global MPPT algorithm. The proposed approach is based on the DIRECT (DIviding RECTangles) algorithm that was developed in [82] for searching the global extreme of a Lipschitz function in an interval. In this thesis, it has been shown that the function describing the Power/Voltage relationship of PV cells is a Lipschitz function. To validate the performance of the proposed scheme, various simulation and experimental studies have been conducted.

For the simulation evaluation, we have developed a system-level simulation model of the PV system. All PV power system components, e.g., the environment, the PV arrays, the power processing system and the electrical load, have been modeled modularly to the required level of complexity. Thus, any simple model developed in the early stage can be easily substituted with a more accurate model in the later stage if required. The model is elaborated by Simulink that is a window-oriented dynamics modeling software package built on top of the MatLab numerical workspace. The model can be used to study the dynamic behavior of the PV system with different control algorithms or operating conditions. The on-going simulation results can be viewed via a virtual oscilloscope or exported to the MatLab workspace for subsequent off-line analysis. The model has also been developed such that the optimized designs obtained can be easily implemented in the real system design with minimum modifications.

For the experimental evaluation, a prototype of an 80W PV power system has been constructed. The experimental results have shown that the proposed approaches outperform the existing approaches in terms of tracking performance and robustness, especially in fast changing environmental conditions. Furthermore, the algorithm has been implemented using a low cost microcontroller.

6.2 Future recommendation

The parallel operation of photovoltaic power modules is one interesting subject for future work. The existing MPPT algorithms have not been tested when the modules are

connected in parallel. Further evaluations are important. The advantages of parallel operation can be summarized as:

- Increasing the flexibility in power capacity.
- Optimization of load sharing can increase the overall system efficiency since the efficiency of each module is related to the load condition.
- Reducing the power loss caused by the centralized PV-MPPT systems by separating a big PV array into several small groups.

The MPPT algorithm is only the first step to build the complete Energy Management System (EMS), i.e. the control systems that are designed to meet the requirements of various operational and environmental conditions. They play a central role in transferring to the load and/or to the grid, the electric power produced by the next generation high-efficiency PV cells. In order to meet the expectations related to the use of solar energy for producing electrical energy, such systems must ensure high efficiency, modularity and especially high reliability [65]. If not, it results in a loss of confidence in the PV systems and has a restraining effect on the spreading of such technology, particularly in the rural electrification applications. The design and production of a high efficiency, low failure rate and low cost “Photovoltaic power processing systems” (P3Ss) will be the main challenge in the future. More work should be focused on reducing the costs at the component and/or system level while increasing or maintaining the overall performance of the systems.

Author's Publication

- [1] Tat Luat Nguyen and Kay-Soon Low, "A Global Maximum Power Point Tracking Scheme Employing DIRECT Search Algorithm for Photovoltaic Systems", *IEEE Transactions on Industrial Electronics*, Accepted for special issue on PV system publication, 2009.

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Appendix A –Derivations of Mathematical Equations

A.1 Theoretical Maximum Power Point Derivation

The following described how the maximum power derived from the PV mathematical model. From (3.3), it can be verified that:

$$\frac{\partial i}{\partial v} = - \frac{Kn_p I_{rs} e^{K(v + I_{rs} \frac{n_s}{n_p} R_s)} + \frac{n_p}{n_s R_{SH}}}{1 + Kn_p I_{rs} \frac{n_s}{n_p} R_s e^{K(v + I_{rs} \frac{n_s}{n_p} R_s)} + \frac{R_s}{R_{SH}}} \quad (A.1)$$

$$\text{where } K = \frac{q}{kTAn_s m_s} \quad (A.2)$$

$$\text{At the MPP: } \left. \frac{\partial p}{\partial v} \right|_{MPP} = I_{MMP} + V_{MMP} \left. \frac{\partial i}{\partial v} \right|_{MMP} = 0 \quad (A.3)$$

$$\text{where } \left. \frac{\partial i}{\partial v} \right|_{MMP} = - \frac{Kn_p I_{rs} e^{K(V_{MMP} + I_{MMP} \frac{n_s}{n_p} R_s)} + \frac{n_p}{n_s R_{SH}}}{1 + Kn_p I_{rs} \frac{n_s}{n_p} R_s e^{K(V_{MMP} + I_{MMP} \frac{n_s}{n_p} R_s)} + \frac{R_s}{R_{SH}}} \quad (A.4)$$

Substituting (A.4) into (A.3) yields

$$\left. \frac{\partial p}{\partial v} \right|_{MPP} = I_{MPP} - V_{MMP} \frac{Kn_p I_{rs} e^{K(V_{MPP} + I_{MMP} \frac{n_s}{n_p} R_s)} + \frac{n_p}{n_s R_{SH}}}{1 + K \frac{n_s}{n_p} R_s n_p I_{rs} e^{K(V_{MPP} + I_{MMP} \frac{n_s}{n_p} R_s)} + \frac{R_s}{R_{SH}}} = 0 \quad (A.5)$$

From (A.5) and (3.3), we have

$$n_p I_{rs} e^{K(V_{MPP} + I_{MMP} \frac{n_s}{n_p} R_s)} = n_p \left(I_{ph} + I_{rs} \right) - I_{MPP} - \frac{V_{MPP} + I_{MMP} \frac{n_s}{n_p} R_s}{\frac{n_s}{n_p} R_{SH}} \quad (A.6)$$

Substituting (A.6) into (A.5) yields the following

$$\left. \frac{\partial p}{\partial v} \right|_{MPP} = I_{MPP} - V_{MPP} \frac{\left[K \left[n_p (I_{ph} + I_{rs}) - I_{MPP} - \frac{V_{MPP} + I_{MPP} \frac{n_S}{n_P} R_S}{\frac{n_S}{n_P} R_{SH}} \right] + \frac{n_p}{n_S R_{SH}} \right]}{1 + K \frac{n_S}{n_P} R_S \left[n_p (I_{ph} + I_{rs}) - I_{MPP} - \frac{V_{MPP} + I_{MPP} \frac{n_S}{n_P} R_S}{\frac{n_S}{n_P} R_{SH}} \right] + \frac{R_S}{R_{SH}}} = 0 \quad (A.7)$$

As the effect of R_{SH} is negligible, $R_{SH} \rightarrow \infty$, (A.7) becomes

$$I_{MPP} \left\{ 1 + K \frac{n_S}{n_P} R_S \left[n_p (I_{ph} + I_{rs}) - I_{MPP} \right] \right\} = V_{MPP} \left\{ K \left[n_p (I_{ph} + I_{rs}) - I_{MPP} \right] \right\} \quad (A.8)$$

Thus, (A.8) can be rewritten as

$$V_{MPP} = \frac{1 + K \frac{n_S}{n_P} R_S \left[n_p (I_{ph} + I_{rs}) - I_{MPP} \right]}{K \left[n_p (I_{ph} + I_{rs}) - I_{MPP} \right]} I_{MPP} \quad (A.9)$$

Adding $I_{MPP} \frac{n_S}{n_P} R_S$ to both sides of (A.9), we have

$$\begin{aligned} V_{MPP} + I_{MPP} \frac{n_S}{n_P} R_S &= \frac{1 + K \frac{n_S}{n_P} R_S \left[n_p (I_{ph} + I_{rs}) - I_{MPP} \right]}{K \left[n_p (I_{ph} + I_{rs}) - I_{MPP} \right]} I_{MPP} + I_{MPP} \frac{n_S}{n_P} R_S \\ &= \frac{1 + K \frac{n_S}{n_P} R_S \left[n_p (I_{ph} + I_{rs}) - I_{MPP} \right] + K \frac{n_S}{n_P} R_S \left[n_p (I_{ph} + I_{rs}) - I_{MPP} \right]}{K \left[n_p (I_{ph} + I_{rs}) - I_{MPP} \right]} I_{MPP} \end{aligned} \quad (A.10)$$

Further simplification of (A.10) yields

$$V_{MPP} + I_{MPP} \frac{n_S}{n_P} R_S = \frac{1 + 2K \frac{n_S}{n_P} R_S \left[n_P (I_{ph} + I_{rs}) - I_{MPP} \right]}{K \left[n_P (I_{ph} + I_{rs}) - I_{MPP} \right]} I_{MPP} \quad (A.11)$$

Substituting (A.11) into (A.6), we have

$$I_{MPP} = n_P I_{ph} - n_P I_{rs} \left[e^{\frac{1 + 2K \frac{n_S}{n_P} R_S \left[n_P I_{ph} + n_P I_{rs} - I_{MPP} \right]}{n_P I_{ph} + n_P I_{rs} - I_{MPP}} I_{MPP}} - 1 \right] \quad (A.12)$$

Substituting (A.12) into (A.9), we have the value of V_{MPP}

$$V_{MPP} = \left[\frac{1}{K(n_P I_{ph} + n_P I_{rs} - I_{MPP})} + \frac{n_S}{n_P} R_S \right] \times I_{MPP} \quad (A.13)$$

$$P_{MPP} = V_{MPP} I_{MPP} \quad (A.14)$$

Based on (A.12), (A.13) and (A.14), a sub-model in PV model could be developed to find the value of I_{MPP} , V_{MPP} , P_{MPP} according to the variance of environment.

A.2 D_{max} derivation for buck-boost topology

For the buck – boost topology, the relationship between $\tilde{R}_{pv}$ and R_{load} is [86]

$$D = \frac{\sqrt{\eta R_{load}}}{\sqrt{\tilde{R}_{pv}} + \sqrt{\eta R_{load}}} \quad (A.15)$$

Inverse both side of (A.15), we have

$$\frac{1}{D} = 1 + \frac{\sqrt{\tilde{R}_{pv}}}{\sqrt{\eta R_{load}}} \quad (\text{A.16})$$

In (A.16), $\tilde{R}_{pv}$ is the target equivalent load at PV array output that the dc-dc converter will transform R_{load} into by adjusting duty cycle D . Hence, $\tilde{R}_{pv}$ is constant. Assuming η is constant, D is maximum if R_{load} is maximum, i.e.

$$\frac{1}{D_{\max}} = 1 + \frac{\sqrt{\tilde{R}_{pv}}}{\sqrt{\eta R_{load\_max}}} \quad (\text{A.17})$$

Inversing both sides, (A.17) becomes

$$D_{\max} = \frac{\sqrt{\eta R_{load\_max}}}{\sqrt{\tilde{R}_{pv}} + \sqrt{\eta R_{load\_max}}} \quad (\text{A.18})$$

Similarly, D is minimum if R_{load} is minimum. Thus, $D_{\min}$ can be calculated as follows

$$D_{\min} = \frac{\sqrt{\eta R_{load\_min}}}{\sqrt{\tilde{R}_{pv}} + \sqrt{\eta R_{load\_min}}} \quad (\text{A.19})$$

A.3 Derivation of equation (3.32)

From (3.31), the number of iteration when the search is terminated can be calculated as

$$n = \frac{1}{\ln 3} \times \ln \left(\frac{D_{\max} - D_{\min}}{\Delta d_{cr}} \right) \quad (\text{A.20})$$

Let τ_s be the sampling time for the system. Since the algorithm takes two samples in each iteration, the tracking speed of the algorithm is

$$t_{abs} \cong 2n \times \tau_s \cong \frac{2}{\ln 3} \times \ln \left(\frac{D_{\max} - D_{\min}}{\Delta d_{cr}} \right) \times \tau_s \quad (\text{A.21})$$

Appendix B – Matlab Source Code for PV Model

B.1 PV cell source code

```
function Ia = arrayI(Va,Suns,TaC,Ns,Np)
% msx60.m model for the MSX-60 solar array
% current given voltage, illumination and temperature
% Ia,Va = array current,voltage

k = 1.38e-23; % Boltzman's const
q = 1.60e-19; % charge on an electron

% enter the following constants here, and the model will be
% calculated based on these. for 1000W/m^2
A = 1.2; % "diode quality" factor, =2 for crystalline, <2 for amorphous
Vg = 1.12; % band gap voltage, 1.12eV for xtal Si, ~1.75 for amorphous Si.

T1 = 273 + 25;
Voc_T1 = 21.06 /Ns; % open cct voltage per cell at temperature T1
Isc_T1 = 3.80; % short cct current per cell at temp T1
T2 = 273 + 75;
Voc_T2 = 17.05 /Ns; % open cct voltage per cell at temperature T2
Isc_T2 = 3.92; % short cct current per cell at temp T2
TaK = 273 + TaC; % array working temp
TrK = 273 + 25; % reference temp

% when Va = 0, light generated current Iph_T1 = array short cct current
% constant "a" can be determined from Isc vs T
Iph_T1 = Isc_T1 * Suns;
a = (Isc_T2 - Isc_T1)/Isc_T1 * 1/(T2 - T1);
Iph = Iph_T1 * (1 + a*(TaK - T1));
Vt_T1 = k * T1 / q; % = A * kT/q
Ir_T1 = Isc_T1 / (exp(Voc_T1/(A*Vt_T1))-1);
Ir_T2 = Isc_T2 / (exp(Voc_T2/(A*Vt_T1))-1);
b = Vg * q/(A*k);
Ir = Ir_T1 * (TaK/T1).^(3/A) .* exp(-b.*(1./TaK - 1/T1));
X2v = Ir_T1/(A*Vt_T1) * exp(Voc_T1/(A*Vt_T1));
dVdI_Voc = - 1.15/Ns / 2; % dV/dI at Voc per cell --
% from manufacturers graph
Rs = - dVdI_Voc - 1/X2v; % series resistance per cell
% Ia = 0:0.01:Iph;
Vt_Ta = A * 1.38e-23 * TaK / 1.60e-19; % = A * kT/q
% Ial = Iph - Ir.*( exp((Vc+Ia.*Rs)./Vt_Ta) -1);
% solve for Ia: f(Ia) = Iph - Ia - Ir.*( exp((Vc+Ia.*Rs)./Vt_Ta) -1) = 0;
% Newton's method: Ia2 = Ial - f(Ial)/f'(Ial)
Vc = Va/Ns;
Ia = zeros(size(Vc));
Iav = Ia;
for j=1:5;
Ia = Ia - ...
(Iph - Ia - Ir.*( exp((Vc+Ia.*Rs)./Vt_Ta) -1))...
./ (-1 - (Ir.*( exp((Vc+Ia.*Rs)./Vt_Ta) -1)).*Rs./Vt_Ta);
Iav = [Iav;Ia]; % to observe convergence for debugging.
end
Ia = Np*Ia;
```

B.2 PV cell source code for s_function

```

function [sys,x0,str,ts] = arrayI_sf(t,x,u,flag)
%S-function file, protocol in which Simulink access information from MATLAB
%t - the time variable
%x - the column-vector of state variables
%u - the column-vector of input variables,value will come from other
%Simulink blocks
%flag - indicator of which group of information and/or calculations is being
%requested by Simulink.

switch abs(flag)
case 0
    % initialize
    % Setup of input/output vector sizes and other setup modes
    % Specification/calculation of initial conditions for the state
    % variables.

    str=[]
    ts = [0 0] ; % specify sampling time, time offsets

    s = simsizes ;

        s.NumContStates = 0 ;
        s.NumDiscStates = 0 ;
        s.NumOutputs = 1 ;
        s.NumInputs = 5 ;
        s.DirFeedthrough = 1 ;
        s.NumSampleTimes = 1 ;

    sys = simsizes(s) ; % sys = [ 2 0 2 1 0(default) 0 1]

    x0 = [] ; % column vector of initial conditions

case 1 % derivatives
    % Calculations involving input vectors
    % Calculation of the derivatives
    sys=[];

case 3 % output calculation
    % Evaluating output variables as a function of the elements
    % of the state vector,
    % for some case, also the elements of the input vector

    Va = u(1) ;
    Suns = u(2);
    TaC = u(3);
    Ns = u(4);
    Np = u(5);

    %sys = x; % a column vector of the output variables
    sys = arrayI( Va,Suns,TaC,Ns, Np);

case {2 4 9} % 2:discrete
    % 4:calcTimeHit
    % 9:termination
    sys=[];

otherwise

    error(['unhandled flag =',num2str(flag)]) ;

end

```

B.3 Flow chart of the function that extracts temperature condition

Fig. B.3 Flow chart of the function that extracts temperature condition

As shown in Fig. B.3, the function first reads the control flag and other parameters to update the state of the simulink environment and the characteristics of the “temperature file”, i.e. how the temperature data are stored and their sampling time. Then depending on the current run time of the simulation, the raw data or the interpolation data will be outputted to the Simulink.

Appendix C - Buck-boost Converter Design

C.1 Selection of inductor

For a buck-boost converter as shown in Fig. 5.2, the value of the inductor can be calculated as

$$L = \frac{V_o + V_D}{I_o r f} (1 - D)^2 10^6 \mu H \quad (C.1)$$

Where r is the desired ripple of inductor current I_L , f is switching frequency (Hz), V_o is the output voltage (V), V_D is the forward voltage of diode.

Rearrange (C.1), the ripple r can be derived as

$$r = \frac{V_o + V_D}{I_o L f} (1 - D)^2 10^6 \quad (C.2)$$

As $V_D \ll V_o$, (C.2) can be approximated as

$$r \approx \frac{V_o}{I_o} \frac{(1 - D)^2}{L f} 10^6 = R_{load} \frac{(1 - D)^2}{L f} 10^6 \quad (C.3)$$

Thus, the maximum ripple of I_L can be calculated as

$$r_{max} = R_{load\_max} \frac{(1 - D_{min})^2}{L f} 10^6 \quad (C.4)$$

From (C.4), the minimum value of inductor so that r_{max} is less than 30% can be calculated as

$$L_{min} = R_{load\_max} \frac{(1 - D_{min})^2}{r_{max} f} 10^6 \quad (C.5)$$

Substitute values from Table 5.2 into (C.5), we have

$$L_{\min} = 20\Omega \frac{(1-0.336)^2}{0.3 \times 20 \times 10^3} 10^6 = 1.47mH \quad (C.6)$$

The RMS inductor current is

$$I_{L\_RMS} = \frac{I_o}{1-D} \sqrt{1 + \frac{r^2}{12}} \quad (C.7)$$

Assume an ideal converter, we have

$$\frac{I_{in}}{I_o} = \frac{I_{pv}}{I_o} = \frac{D}{1-D} \quad (C.8)$$

Substituting (C.8) into (C.7) yields

$$I_{L\_RMS} = \frac{1}{D} I_{pv} \sqrt{1 + \frac{r^2}{12}} \quad (C.9)$$

From (C.9), I_{L_RMS} is mathematically maximum at $D_{\min}$ and I_{sc_max} since $I_{pv\_max} = I_{sc\_max}$. If D is at $D_{\min}$, I_{pv} would fall in voltage source region of the I - V curve and this results in a significant drop of the tracking current. To let I_{pv} be closer to I_{sc_max} as compared to using $D_{\min}$, D_{avg} is used in calculating $I_{L\_RMS\_max}$. From (C.9), $I_{L\_RMS\_max}$ can be estimated as

$$I_{L\_RMS\_max} = \frac{1}{D_{avg}} I_{sc\_max} \sqrt{1 + \frac{r_{\max}^2}{12}} \quad (C.10)$$

Substituting values from Table 5.2 into (C.10) gives

$$I_{L\_RMS\_max} = \frac{1}{0.55} 4A \sqrt{1 + \frac{0.3^2}{12}} = 7.32A \quad (C.11)$$

The waveform of the inductor current is shown in Fig. C.1

Fig. C.1 Waveform of inductor current

The peak current through the inductor can be calculated according to the duty cycle and the output current as follows

$$I_{L\_peak} = \frac{I_o}{1-D} \left[1 + \frac{r}{2} \right] \quad (C.12)$$

In PV applications, the maximum peak current through inductor can be estimated by substituting (C.8) into (C.12)

$$I_{L\_peak} = \frac{1}{D} I_{pv} \left[1 + \frac{r}{2} \right] = \frac{1}{D_{avg}} I_{sc\_max} \left[1 + \frac{r}{2} \right] \quad (C.13)$$

Substituting values into (C.13) gives

$$I_{L\_peak\_max} = \frac{1}{0.55} 4A \left[1 + \frac{0.3}{2} \right] \approx 8.51A \quad (C.14)$$

In summary, (C.6), (C.11) and (C.14) provide the minimum requirements for the inductor selection. Other consideration is the power loss of inductor which is a function of equivalent series resistance (ESR) of the inductor. The ESR varies inversely with the wire gauge. Another major power loss is due to the ripples of the current and voltage. This causes a ripple off the MPP depending on the inductor value and the switching frequency. For a constant switching frequency, the ripple reduces as the inductance increases. The

drawback is the size and cost of the bigger inductor. Therefore, there is a trade off among low internal resistance, ripple, size and cost when selecting an appropriate inductor.

C.2 Selection of output capacitor

In our application, the minimum output voltage is much larger than 10V and the maximum output voltage is about 30V when PV arrays operate in extreme conditions. Thus ΔV_{out} is maximum at about 3V when choosing the output ripple voltage to be smaller than 30%. The output capacitor has to be selected mainly on its ESR value, and the capacitance must be able to deliver the load current when the switch is on. The ESR is the main parameter in determining the output voltage ripple. In the initial stage, when the free wheeling diode becomes forward biased only the output capacitor ESR determines the load impedance and that in turn affects the ripple voltage. Thus, the required ESR for an output ripple voltage of 3V is calculated as

$$ESR = \frac{\Delta V_{out}}{I_{L\_peak}} = \frac{3V}{8A} \approx 0.375\Omega \quad (C.15)$$

The minimum capacitor for the desired output ripple voltage at load current I_{out} can be calculated as

$$C_{out\_min} = \frac{I_{out}D}{f\Delta V_{out}} \quad (C.16)$$

Substituting (C.8) into (C.16) and consider the input current to the converter to be the PV array's current, we have

$$C_{out\_min} = (1 - D_{avg}) I_{sc\_max} \frac{1}{f\Delta V_{out}} \quad (C.17)$$

Substituting values in (C.17) gives

$$C_{out\_min} = (1 - 0.55) 4A \frac{1}{20 \times 10^3 \times 3V} \approx 30 \mu F \quad (C.18)$$

In practice, the output filter capacitor should be chosen as about 10-20 times the calculated C_{out_min} to encounter non ideal factor in the circuit and ideal assumptions when deriving the estimation.

C.3 Selection of diodes

The diode attributes to the highest power loss. The power loss is mainly due to the forward voltage drop. The Schottky diode has the lowest turn-on voltage (0.2 – 0.9V) as compared to other silicon diodes (0.7 – 2.5 V). There is a trade-off between the recovery speed, the breakdown voltage and the forward voltage drop. In this case, a lower forward voltage drop is preferred than a fast recovery speed. Thus, the Schottky diode is used in the design. In the buck-boost topology, the diode is in series with the inductor when it is conducted. Thus the diode current rating has been selected based on the inductor's ratings. The model MBR20100CTKPbF schottky diode has been used in our prototype design.

C.4 Selection of switching device

The bipolar transistor requires a high base current to turn on, a relatively slow turn-off characteristics (known as current tail), and is liable for thermal runaway due to a negative temperature co-efficient. On the other hand, the MOSFET is a voltage-controlled device and has a positive temperature coefficient preventing the thermal runaway. MOSFET also

has low on-state losses since the on-state-resistance has no theoretical limit and also useful in dealing with limited free wheeling currents since it has a body-drain diode. The IGBT has the output switching and conduction characteristics of a bipolar transistor but is voltage-controlled like a MOSFET. In general, this means it has the advantages of high-current handling capability of a bipolar with the ease of control of a MOSFET. In our design, the IGBT IRG4BC30WPbF has been used.

Appendix D Snubber Circuit Design

D.1 Snubber design

D.1.1 The polarized dissipative current snubbers

Fig. D.1 shows the implementation of the polarized current snubber network in a buck-boost converter.

Fig. D.1 The implementation of current snubber network in buck-boost converter

To prevent a direct switching current flowing through the snubber resistor, a diode is added in series with the resistor in the polarized current snubber network. Then only the energy stored in snubber inductor during switching is dissipated in the resistance. Without the snubber, the output diode is driven off suddenly by the switch, which results in a high reverse current as shown in Fig. D.2. This current adds to the switching current and results a high spike as seen in Fig. D.3.

Fig. D.2 Diode current and its zoom when driving off by the switch

At the switch turns on, the snubber inductor L_{snub} in series with the switch presents the switch with an inductive load so that it reduces the rising rate of the switch's current. The switching current will increase the L_{snub} voltage by an amount

$$\Delta V_{SW} = L_{snub} \frac{dI_{SW}}{dt} \quad (D.1)$$

Later when the switch turns off, the discharge of the energy stored in L_{snub} will add ΔV_{SW} into the switching voltage V_{SW} . ΔV_{SW} is chosen as 100V that is about 1.5 times of the V_{SW} peak value without adding the snubber. Based on the switching current's rising time t_{ri} and the peak switching current, the value of L_{snub} can be estimated as

$$L_{snub} = \Delta V_{SW} \frac{t_{ri}}{I_{SW\_peak}} \quad (D.2)$$

To obtain the initial estimated value of L_{snub} , the rising time (Δt) and the switching current's peak (ΔI_{SW}) as shown in Fig. 5.6 have been used. Replacing $\Delta t = 47.33$ ns, $\Delta I_{SW} = 26.56$ A and $\Delta V_{SW} = 100$ V into (D.2), we have $L_{snub} = 0.14 \mu H$.

Fig. D.3 Switching current and its zoom when the switch turns on

To significantly reduce the switching current's peak without largely reducing the switching time, the choice of L_{snub} should be reasonably larger than $0.14\mu\text{H}$. The $10\mu\text{H}$ value has been chosen for the compromised between the practical value and the I_{sw_peak} reduction. The current snubber on the switch also controls the decreasing rate of the diode's current. By reducing di/dt , it reduces the peak reverse current and the power dissipation in the diode.

The snubber diode in series with the resistance ensures that the current only flows through the resistor when it is needed to dissipate the energy stored in the inductor. The amount of power dissipated by the resistor is equal to $\frac{1}{2} LI^2f$ where I is the inductor current's peak. It includes the diode reverse recovery current as well as the switching current. The value of the resistance tends to be small for a good damping. A 20Ω has been chosen to give a 500ns reset time constant which is reasonable for a 20 kHz

switching frequency. Fig. D.4 shows the circuit behavior after adding the current snubber network.

Fig. D.4 Waveform after adding current snubber

As shown by the red rectangle area in Fig. D.4, the current snubber has significantly reduced the 30A peak of the output diode reversed current (also the peak of the switching current) to about 5A. However, when the switch turns off, the discharge of the energy stored in the snubber inductor has contributed to a higher spike in the switching voltage V_{SW} (about 100V in addition). Adding a resistor-capacitor-diode (RCD) voltage snubber across the switching can reduce this spike's amplitude.

(b) The RCD voltage snubbers

The RCD snubber is used to control the voltage's rising rate on the drain or on the collector of a switching transistor. The snubber increases the switch reliability by

reducing the switch's peak power dissipation. Fig. D.5 shows the implementation of the RCD snubber in a buck-boost converter.

The snubber is only active during the switching transition. When the switch turns off, the current from the inductor is diverted through the snubber diode to the snubber capacitor. This current charges the capacitor to the rail voltage until the main diode turns on to carry the inductor current. When the switch turns on the snubber capacitor discharges through the resistor and the switch. The switch's power dissipation during turning off is transferred into the snubber. Besides, the rising rate of the voltage is also reduced.

Fig. D.5 The implementation of voltage snubber network in buck-boost converter

Based on the rise time Δt of the I_{SW_peak} and the peak voltage ΔV_{SW} that the snubber capacitor C_{RCD} will charge to, the C_{RCD} value can be calculated as

$$C_{RCD} = I_{SW} \frac{\Delta t}{\Delta V_{SW}} \quad (D.3)$$

From Fig. D.6, $\Delta t = 114$ ns, $\Delta V_{SW} = 200$ V, and $I_{SW\_peak} = 20$ A. Substitute these values into (D.3) yields $C_{RCD} = 11.5$ nF. To significantly reduce the switching voltage's peak, the value of C_{RCD} must be much larger than 11.5 nF. In our case, the value of $C_{RCD} = 0.22$ μ F

has been chosen for the compromise between the available practical value and the V_{sw_peak} reduction.

Fig. D.6 Voltage across switch waveform

On each cycle, the capacitor must be fully discharged to control the rising rate of the switching voltage. Thus the RC time constant must be short comparing to the switching frequency. The resistor is then chosen to have a time constant that is much smaller than the switching period. A 75Ω has been chosen to give a $16\mu s$ reset time constant which is reasonable for a 20 kHz switching frequency. Fig. D.7 shows the behavior of the circuit after adding the voltage snubber network. As compared to Fig. D.1, the snubbers have significantly reduced the spikes' amplitude presented in the switch current and the switch voltage.

Fig. D.7 Currents and voltage waveform after adding voltage snubber