Photovoltaic Power Smoothing Prediction Algorithm

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Power output from PV arrays is vulnerable to shadows caused by trees and buildings, but most commonly clouds. It is for this reason that an algorithm with the ability to predict power drops caused by such shadows has been explored and produced. Through a literature review, this paper is aimed at providing insight into existing technology in the field of prediction and detection of shadows, such as optical methods of prediction in clouds. A photovoltaic power smoothing prediction algorithm that is targeted to improve existing methods is described through this paper. In this project, results of the prediction algorithm, which subsystems include; obtaining data from a solar panel, shadow detection, battery storage are presented, and future recommendations are explored. The final product of this fourth-year project was a developed power smoothing prediction algorithm that was based on short term and minor long term predictions of changing photovoltaic power, giving the ability to supply controlled power to a load under all weather conditions. The algorithm presented 76.77% detection accuracy and reduction in duration of fluctuations of more than 66.8%.

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1. Introduction

Renewable energy is a rapidly advancing industry of power generation, with officials in Canberra announcing with that it will be 100 percent powered by renewable energy by 2020. Solar energy is predicted to be 76 per cent that number. For this reason, there is a lot of focus on solar power and a number of methods being suggested to implement this type of energy. Supplying solar power isn’t as simple as the sun shining down on a PV Array (solar panel), and their outputs produce fluctuations due to shadows. This paper focused on the problem of fluctuations in PV power output caused by shadows and produced a power smoothing algorithm to supply constant power to a load. PV arrays are vulnerable to three main type of shadows, caused by trees, buildings and, most commonly, clouds. Fluctuations in both weather conditions and irradiance have a significant effect on photovoltaic (PV) power outputs in terms of stability and system operation. To reduce PV power fluctuations, numerous scholars mainly focus their study on photovoltaic grid inverters to achieve smooth grid power [1].

It has been identified that “large size generation systems such as a hydroelectric power generator and a diesel generator need time to prepare for the steady running. It is therefore necessary to be able to predict output change.”[2]. A prediction algorithm to stabilise the power delivered to a load will be explored by both reviewing the current technology and approaches in ‘Photovoltaic Power Smoothing’ as well as practically analysing a developed photovoltaic power smoothing controller in order to meet this project’s aim.

Battery Energy Storage Systems (BESS) are the current and most common form of smoothing generated power fluctuations. Through numerous algorithms, BESS can provide energy management that delivers higher power quality in renewable energy systems.

Figure 1 depicts a recoded power output of a 5W solar panel. Solar Data 02 May 2017, was recorded using a PV array on top of the School of Engineering & Information Technology building at UNSW Canberra on a relatively cloudy day. In this position, the solar panel had complete exposure to the sun throughout the day with no variable or fixed shadows. This can be seen through the multiple fluctuations of power throughout the eleven hour period. A prediction algorithm will predict incoming cloud cover, as well as record previous fixed and variable data to inform the battery system to store extra power as a means of providing constant power through its output. This short-term prediction will remove the uncertainty in short term PV power output and will, in turn, reduce the necessity of battery systems and their involvement in solar power smoothing systems.

1. A Project Aim

The aim of this project was to design and construct a power smoothing control algorithm to supply a load with controlled power through short-term (from one to up to five minutes) predictions as well as minor long-term predictions of changing photovoltaic power. This involved analysing multiple prediction and detection methods and analysing the effectiveness of the prediction algorithm in modern solar power solutions. The prediction algorithm was designed to work under all weather conditions for local battery systems within household solar power systems.

1. B Project Approach

The project was broken into three phases in order to achieve the desired aims and provide aRepeatable structured method for further testing if required:

1. Research and Data collection: Phase one focused on conducting a literature review and initial data acquisition. This provided awareness of current solar power smoothing methods and techniques and gave an overall image on how the solar power is delivered to the Australian power grid. The initial data acquisition provided analysis on the weather patterns in Canberra as well as recorded data for fixed and variable shadows.

2. Analysis: Analysis continually occurred throughout the project once data was recorded. The data provided key information to record any fixed or variable shadows that were present in the testing region.

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as well as the typical power distribution of a PV array throughout the hours of day. This also provided expected output requirements for the system.

3. Design and Development Test and Evaluation of a developed algorithm: The design of the developed algorithm consisted of both hardware and software components. Continual testing and evaluation of the integration of these components was conducted to ensure a viable result was produced.

The success in development of a power smoothing solution that focused on prediction was attributed to the chosen method, in which the project was broken down into. The management fundamentals of engineering were adhered to throughout the project to provide viable concluding results. A detailed explanation of the prediction algorithm is discussed within section 3.A.

2. Literature Review

2.A Power Smoothing with Battery Energy Storage Systems

Battery energy storage systems have recently become popular due to their affordability and their ability to provide off grid and on grid households smooth power form PV arrays. The general operation of a BESS is that it stores excess power throughout the day, which can then be utilised during solar outage periods. This is essential as a BESS can be used to reduce photovoltaic power fluctuations caused by light intensity and temperature [1]. A BESS firstly needs to determine the power and capacity required within its local system. Using this, the battery control systems are able to meet the maximum effective power fluctuation limit through charges and discharges. There are no fixed methods of operating a battery energy storage system, however the most common is one which enforces limits on the range of state of charge (SOC) within which the battery is allowed to operate [3]. Energy storage consists of many types of batteries however, the one chosen in most instances, and thus simulated in this project is the lithium ion battery due to their storage capacities and charge and discharge rates of 0.5 C.

2.B Shadow Detection and Identification

A key part of maximising PV production is the good diagnosis and monitoring of the respective PV systems. A common method in shadow detection and analyses of faults on a PV system in real time is based on DC power measurements [1]. The method of using DC power measurements instead of climate sensors and/or meteorological data bases reduces costs in cloud detection and provides a localised data for the PV array. There are three states at which a solar panel will reduce its power output due to shadows which are categorised as a function of their behavior of the DC power output. There are three types of shadowing, which consist of;

1) Fixed shadows caused by dust, leaves and bird feathers/droppings;
2) Temporary shadows caused by trees, antenna or electric poles; and
3) Discontinuous shadows caused by clouds or embedded obstacles (these are hard to predict) [4].

From this, a shadow detection procedure using current and voltage analysis to derive a power measurement is investigated. This can be seen in Figure 2.

Through using a data logger that consists of voltage and current sensors, data can be collected and utilised to diagnose the source of shadows in real time. This can be achieved through a developed algorithm which firstly initialised variables such as timings of each shadow type and then determines the shadow type by the duration of DC output [4]. The authors of the above algorithm have defined a shadow to be registered when there is a 10% drop in power output within a predefined range of sample. A ‘Fixed’ shadow occurs when there is a shadow detected for more than 60 minutes, a ‘Temporary’ shadow is classed as being between 10 and 60 minutes, while an 'Intermittent' shadow are present for less than 10 minutes. After configuring a similar algorithm, it was found that the values for fixed temporary and intermittent clouds depends on the testing environment and differ for the localised location of any given solar panel. It is for this reason that a variant algorithm was pursued and
characterised to correctly define the respective variables. Initial testing found that some clouds were present for longer periods of time due to an entirely cloudy day for example. Due to this being a foreseeable problem for the algorithm, other avenues of detecting cloud cover were explored.

2.C Cloud Detection
Clouds are a major influence in the solar energy domain as they both reflect incoming solar radiation but also keep outgoing radiation from leaving the atmosphere, affecting both temperature and irradiance. For this reason, solar prediction algorithms must be developed to ensure that power from solar panels is smooth and constant. Due to the locality scope of this project, a cloud detection method that consists of ground based camera was implemented in conjunction with digital signal processing to determine the location of clouds in the respective region. However, a ‘cloud’ must be clearly defined when conducting such tests.

2.D Cloud Classification (Definitions)
There are multiple papers that discuss cloud classification, however the principle in which they classify a cloud remains constant. A paper written by Hashimoto and Nagakura, states there are a number of methods to classify a cloud [2]. These consist of; brightness, falling generation of output, cloud contour and by intensity. All methods have merit in detecting and classifying clouds.

i. Brightness:
This approach uses a live image of the sky and checks each pixel along the radial line from the sun. Using a calculated gray level, a pixel is compared to the previous pixel detected, if it is brighter than the previous pixel then the process resets by making that pixel the comparison pixel.

ii. Falling Generation of Output:
This technique uses a percentage range of the output power to determine and then classify what type of cloud is present. This technique relies heavily on the characterisation of the solar panel and comparison to image taken at the same time. It was found this method had an 85% accuracy.

iii. By Cloud Contour:
Classifying a cloud by contours uses the ‘Hough transformation’ which extracts straight lines and circles based on the cloud contours. From this technique two cloud types can be determined, Stratus clouds and Convection clouds. This method shows good technique however the size of the radius thresholds are required to be characterised independently.

iv. By intensity of cloud:
This technique adds another parameter to the previous technique which uses three-dimensional imaging to determine a vertical radius to classify two more types of clouds. If the radius is small it is recognised as a cumulonimbus cloud and if large an assembled cloud [5].

Due to the restrictions in time and resources of this project, neither of the above methods appeared viable and hence, the method of examining the colour intensity of an image taken from the sky was explored.

v. Red-to-Blue Ratio (RBR)
The Red-to-Blue Ratio technique was first established by the Scripps Institution of Oceanography and uses RBR values to determine cloud coverage. If the value of the ratio is ‘one’, than a cloud present in the image, if it is “very less” than one then it is a cloudless blue sky [6]. This approach in determining a ‘cloud’ also has issues, with misclassification of thick or very transparent clouds and areas close to the sun. To combat this a ‘Clear Sky Library’ (CSL) can be created from multiple images taken on a clear day and provides a reference RBR for each pixel and time. This can then be used to classify the intensity of R and B pixels. Equation (1) shows the RBR formula, with R being the intensity of the red pixel and B the intensity of the blue pixel. It should be noted that the NRBR is classified the same as RBR in terms of the values to determine cloud coverage. However, taking a ratio of the intensity means that the absolute intensity is lost which would be necessary in future predictions of power generation.

\[
RBR = \frac{(R-B)}{(R+B)} \quad (1)
\]

vi. Hue- Saturation-Intensity (HSI)
The HSI method consists of converting an image to hue, saturation and intensity which allows each pixel in an image to be broken down into a three-dimensional array with each number representing the hue, saturation and intensity value respectively ([Hue, Saturation, Intensity]). This allows more information to exist for each pixel. The hue of an image varies from 0 to 1, the corresponding colors vary from red through yellow, green, cyan, blue, magenta, and back to red. Saturation also varies from 0 to 1.0, the corresponding colors (hues) vary from unsaturated to fully saturated or other known as no white components. The intensity value, or brightness, varies from 0 to 1. Starting at 0 and as the corresponding colors become increasingly brighter coming closer to 1 [7].
With the three-dimensional array, the colour of cloud can be characterised and used as information for the prediction algorithm.

2.E Cloud Detection and Prediction (Via Optics)
There are generally two approaches in cloud detection, one being by optics and the other being by satellite images. Both techniques are appropriate in the prediction of cloud coverage with satellite being able to provide long term predictions however, due to the project’s locality scope the optics approach was pursued. This approach provides a localised solution to identifying clouds, and exhibits good results in predicting cloud coverage using cameras. As explored above, a method in determining cloud cover from cameras is the RBR approach. A HSI approach can then utilise a CSL in order to characterise clouds and their respective intensities.

Observing the sky via optics for solar power generation is a relatively new practice where typically, a fish-eyed lens is used to capture a 180° view of the sky. Fulcrum 3D, an Australian company has adopted this initial approach of cloud detection in order to provide solar power short term prediction for 10 to 20 minutes [8]. Their algorithm in both prediction and tracking of clouds is not shared to the public, however from their initial results the lessons learnt from operating the system were discussed. It was found that a prediction of cloud coverage of 2 to 5 minutes was more practical. It was also discussed that high resolution cameras were required in order to provide accurate detection of clouds. It was suggested that a filter was necessary to assist in removing glare from the image caused by the sun, which was being incorrectly registered as clouds. In terms of results, a similar company, Sun Edison, produced a system called the ‘Cloud Predictive Technology’ which has reduced their battery storage by more than 20%; however its accuracy of cloud detection was not mentioned [9].

As stated previously, cloud coverage prediction using ground based cameras to reduce fluctuations in solar power generation is a relatively new technique of providing control to PV output with accuracy. Due to this, many companies and researchers are currently in the prototyping or marketing stage of their prediction techniques. There have been no prediction algorithms provided to the public at this point in time. For this reason, the system designed for this paper considers the feasibility of a solar power smoothing algorithm to provide household solar systems one to five minutes of cloud coverage prediction. The prediction algorithm designed will be discussed further in this report.


3.A Methodology
Figure 3 shows a flowchart that describes the technique that was implemented to provide controlled short term confidence from a PV array.

![Solar Panel](Figure 3: Solar Smoothing Prediction Algorithm)
The designed solar smoothing prediction algorithm is broken into five subsystems; the Solar Panel, Obtain Data, Shadow Detection Algorithm, Prediction Algorithm and the BESS.

**Solar Panel:** A 5W solar panel is used to obtain the power generated throughout the day.

**Data Logger:** The data logger is connected to the solar panel and records the incoming data. This consisted of a MAX417 voltage/current sensor to read the output current of the solar panel over a load of 100Ω. This current is then multiplied by the input voltage to determine the power from the PV array. This utilised an Arduino UNO to communicate with MATLAB and SIMULINK software.

**Shadow Detection Algorithm:** Analysed the data from the data logger and then compared the current power output (at t) to the previous output (at t-1) to determine if a shadow is present through a characterised 10% drop at the output occurs. This percentage changed with regard to location and local surroundings and hence, it should be noted that this percentage applies for the School of Engineering & Information Technology building at UNSW Canberra. This algorithm also has the ability to record the timing of fixed and variable shadows that repeat daily and communicate this information to the prediction algorithm.

**Prediction Algorithm:** The prediction algorithm operated in two ways concurrently. The first method received data from the ‘Shadow Detection Algorithm’ and predicted reoccurring fixed and variable shadows. The second method was utilised to capture images of the sun and its immediate surroundings. This method utilised a developed solar tracker designed off the ‘Arduino Solar Tracker’ created by Bruce Helsen; however, in this project, a camera and supporting infrastructure were added to capture images [10]. The solar tracker comprised of; four Light Dependent Resistors (LDRs) with two cards split between them, two servo motors, a 720p webcam and an Arduino UNO which controlled the servos to face the webcam towards the sun based on the four LDRs receiving the same voltage (only occurs when they are facing the sun). This formed the basis of the prediction algorithm as the webcam is responsible for taking a photo every ten seconds to determine whether a cloud is present using the process below.

To determine whether a cloud is present, the following algorithm was used to perform digital signal processing through the following steps:

1. Remove the sun from the image by changing the colour of all white pixels above a given `threshold (this will change with each camera and must therefore be characterised).
2. Perform a Hue, Saturation and Intensity filter on the image
3. Perform prediction algorithm (mentioned below)

![Original Image From Solar Tracker Webcam](image1)

![Process used to identify and change the colour of the sun](image2)

![HSI Image](image3)
In the beginning stages of analysing and characterising the HSI images, two key errors were identified. This firstly, being that the photos of the sun caused the entire image to be white due to the sensitivity of the webcam utilised. This was rectified by adding a polarised lens on the webcam, which then resulted in a correct depiction of the sky as seen in Figure 4. The second issue was identified once the first was rectified, which saw the HSI images depicting the sun as a similar colour to the clouds in the image (purple). This causing an issue as the prediction algorithm relies on purely clouds to be identified. Thus, further characterisation and processing was required to the prediction algorithm images. A white intensity threshold of 253.9 W/m² was defined, this identified all pixels that had an intensity greater than 253.9 W/m² as the colour of the sun had an intensity of 254 W/m². With modification to the algorithm, the colour of the sun was changed to a fluorescent green, a contrast colour to the cloud colour of purple, this can be seen in Figure 6.

Using the HSI images from the polarised webcam, the clouds were characterised to be within a range of [0.17 0 0.41] and [0.48 0.07 0.99]. The final step of the algorithm was to separate the HSI images into three sections (Area 1, Area 2 and Area 3) as seen in Figure 7. The areas are broken down in such a way that Area 2 boarders begin at 1/6 the length and width of the original image and Area 3 boarders 1/3 the length and width of the original image, this accounting for the uncertainty in tracking the sun across the sky. This formed the basis of the of the prediction algorithm. The percentage of cloud cover is then taken in each area and this is then communicated to the battery system using an algorithm to determine if there is an incoming cloud that will cause a power drop to smoothen delivered power to a load to a programable minimum output depending on the battery’s state of charge.

**BESS:** The BESS forms the concluding stages of the power smoothing prediction algorithm and consisted of a simulated 12V lithium ion Smart Battery from and a control algorithm [11]. Its core function was to supply smooth power through autonomously deciding whether more power may need to be stored in the battery to combat a predicted drop. The BESS considers the: state of charge (SOC) of the recharging battery, the percentage of cloud cover in area one, area two and area three, the power input, whether a variable shadow has occurred previously and whether an intermittent shadow is occurring to act as a back-up control method incase the suns glare causes a cloud to be misinterpreted as the sun. The BESS had a programmable minimum output power of 4W and thus, used any excess power from the solar panel to charge if required and discharge when the power output is lower than 4W to maintain a smooth power output as long as the SOC was greater than 40%. In order to simulate the charge and discharge rates of a lithium ion battery it was assumed that battery discharges at a linear rate. A typical lithium ion battery charge/discharge rate is 0.5 C meaning it discharges a full battery in two hours. This meant the battery had a charge/discharge rate of 10.6W/minute.

As a contingency, if the battery SOC dropped below 40% the programmable minimum output power is dropped by 5% each iteration until there is a positive power flow to charge the battery. Once a positive flow is present and the cloud cover would allow a continual growth in power the programable minimum would raise by 5% until 4W is obtained.
4. Results and Discussion

The photovoltaic power smoothing algorithm was tested over five days on the roof of the School of Engineering & Information Technology building at UNSW Canberra. This allowed enough time to test the robustness of the algorithm in different weather conditions such as completely sunny days, partly cloudy and complete cloud cover at times. To assure testing was accurate of the use of the cloud detection technique, the battery system was only activated when the prediction algorithm allowed through the HSI percentage thresholds.

The results in this section do appear to have power fluctuations in the output of the algorithm, however, it should be noted that a controlled output was delivered to a simulated load indicating success of the photovoltaic power smoothing prediction algorithm. Through characterising the system, it was found that the prototype developed was capable of making short term prediction from 15 secs to 2 minutes as well as the minor long-term predictions though identifying variable shadows that occur daily. This timeframe does not adhere to the aim of this project however, a short term prediction of incoming cloud cover was achieved. With an upgrade in equipment the prediction timeframe can be extended to potentially up to 20-minute prediction of incoming cloud cover. During characterisation it was also found that a variable shadow from the building is detected at approximately 4:00pm and 6:00pm every day, this was accounted for in the following tests.

Figure 8 depicts the results that were recorded and a partially cloudy day with the density of cloud cover being large at the beginning of testing, 10:00 am and 10:45 am as well as the concluding stages of testing, 12:40pm and 01:15pm. This test provided a range of weather conditions that tested both the battery system and the prediction algorithm’s HSI technique for cloud detection. The battery started with an initial charge of 78% and increased its charge to 100% until the cloud cover was detected. This caused a drop in the state of charge as the battery began to discharge to the load to maintain the minimum power output of 4W, this phenomenon continued to occur throughout the day. This suggested success of the algorithm with the duration of fluctuation being reduced from 66.8%. Figure 9 depicts a zoomed in view of the initial cloud cover. It should be noted that the simulated battery system does not contain an internal capacitance and thus that has the ability to discharge at a higher rate than the battery and hence the batter could not discharge immediately to combat the instant drops. Another observation was the immediate drops throughout the day that caused a power output of 0W. This can be attributed to an error in the MAX417 chip used as part of the data logging subsystem as these drops only occurred at one sample at a time or for approximately 0.33 seconds.

In order to test the prediction algorithm’s input to the BESS, challenging weather conditions were investigated. This would test the system in its autonomous decision making to reduce the minimum power output once the battery’s SOC dropped below a certain threshold (SOC < 40%) to maintain a constant output. This was tested on an overcast day with testing halted due to rainfall. Figure 10 shows the battery had an initial state of 78% and is accompanied with the power output prior to the ‘Photovoltaic Power Smoothing Prediction Algorithm’ and the power post the algorithm. The plot shows initial success in maintain a 4W power output with drops in the power outputed from the BESS being reduced in both magnitude and duration. At approximately 11:30am the algorithm realised that it did not have enough charge to maintain a 4W output with either incoming cloud cover or already present cloud cover so it gradually reduced its programmable minimum power output by 5% per iteration to be able to store charge to maintain a constant output. As shown, at 11:40 am the new programmable minimum output was set at approximately 0.9W.
At this point, the prediction algorithm detected more cloud cover throughout the day and hence did not allow the power to rise again until the cloud cover was removed in the aim to maintain a constant output. It can be seen however, that even though the prediction algorithm detected cloud cover, the power from the PV array grew to more than 4W on six separate occasions post the new programable minimum output was updated. This indicated that the prediction algorithm was not working 100% as expected and an investigation into the cause of this was undertaken.

Figure 10: Power Information – Overcast/Rainy Day

It was observed that on average, the power smoothing algorithm experienced a reduction in PV output power 76.77% of the time there was a cloud detected. This meant that clouds were being detected that were not actually causing drops, such as the glare from the sun on the camera lens as well as clouds being detected in high percentages in area one and two but not in area three. This resulted in the power smoothing algorithm to maintain a smaller minimum power output that what would be necessary as seen above. The plot below depicts how this accuracy was calculated. Each time a power drop occurred that was greater than a 10% it was recorded and then compared to whether a cloud above the characterised threshold was detected. Cloud detection by the HSI method combined with the prediction algorithm (area breakdown) has previously been untested and thus a baseline for success in accuracy is not available. However, when compared to other techniques such as the RBR techniques which papers have described an accuracy of 88.53%, and up to 96.3% of accuracy in detecting cloud by contours, the developed power smoothing algorithm in this report underperforms existing short-term prediction methods [12][13]. This indicating that the developed power smoothing prediction algorithm has the capability of making short term predictions however will need to be further developed past its current prototype stage to increase its accuracy.

Figure 11: Cloud Detection and Power Drop Detection
5. Conclusions

The aim of this fourth-year project was to design and construct a power smoothing control algorithm that was capable of making short-term predictions as well as minor long-term predictions of fluctuations within a PV array’s output and deliver controlled power to a load. This was completed through use of system engineering principles which ensured correct testing and development principles were applied. In order to understand the fundamentals and issues that are present in today’s solar power generation and use, a literature review was conducted. This consisted of presenting solar smoothing techniques such as BESS, as well as shadow detections and cloud detection practices currently used. It was this research that lead to a project that involved investigating and implementing a solution in reducing the fluctuations in short term power output of a PV array.

A combination of hardware and software subsystems were used to develop the ‘Photovoltaic Power Smoothing Prediction Algorithm’. These consisted of; a Solar Panel, Data Logger, Shadow Detection, Prediction Algorithm (cloud detection) and a BESS which utilised a simulated 12V lithium ion battery. Once integrated, the algorithm was further characterised to determine the programable inputs required such as HSI range for clouds, the percentage of cloud threshold and the desired programable minimum power output from the BESS when running the algorithm.

The algorithm was tested over five days to demonstrate its robustness over a variety of weather conditions. Its initial results which were recorded on a partly cloudy mostly sunny day, indicated success in achieving a smooth constant output that met the programable minimum of 4W with reduction of more than 66.8% in duration of fluctuations present. To further test the robustness of the algorithm it was tested on a challenging weather day which was very overcast with rain occurring at the concluding stages of the test causing a halt of the testing. The results demonstrated two key findings. One, that the algorithm was capable of autonomously deciding a new programable output but more importantly that the prediction algorithm used caused the programable output not to rise when it was necessary to due to clouds being detected that were not interfering with the PV array. Although a constant power was achieved it was not optimised and thus, further testing was conducted to determine that the prediction algorithm had an accuracy of 76.77%, under that of previously published solutions to cloud detection in solar power predictions. Although the solution presented during this project was outperformed by those found in the literature review, the role of the research into a new cloud detection (HSI percentages) method and prediction algorithm as power smoothing technique provides a small but worthwhile contribution to the rapidly advancing area of power generation.

6. Recommendations

A considerable amount of time spent on this project was dedicated to the design on the prediction algorithm and its processes as the basis for ongoing PV power smoothing research using the HSI method and developed prediction method. While the results found in this report indicated that the accuracy of the method used to detect clouds was 76.77% accurate, the HSI method and prediction algorithm can still be perused in short term power prediction to potentially surpass other algorithms and methods in accuracy.

This can be achieved by further developing the system past its current prototype stage. The use of a higher resolution camera such a 1080p webcam with a polarised fisheye lens would increase the quality of images to provide more accurate information from the prediction algorithm as well as provide an entire sky image increasing the prediction timeframe of the algorithm. It should be noted that, the upgrade in camera and lens would require further configuration of the components of the algorithm. In addition to the hardware upgrade, the supporting infrastructure could also be designed in such a way that the hardware devices could remain in all weather conditions such as rain and fog. This furthering the capability of the algorithm in its aim to remove the uncertainty of short term PV power output.

If a fisheye lens upgrade is pursued, the need for a solar tracker can be removed and replaced with a software solution, cloud motion estimation. In general, this technique uses two methods to estimate the motion of clouds to provide more accurate sky prediction [14]. This in combination with the HSI method has the potential to increase the accuracy of the power smoothing algorithm developed during this project.

Finally, the computational power of this algorithm consisted of a PC and this is recommended to be maintained. This allowed MATLAB software to process all images for the prediction algorithm and produced data to the BESS in real time to provide live results which could be viewed and stored with ease.
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References


