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Multi-parametric Optimization of Multi-functional Battery Energy Storage Operation

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DISSERTATION

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Dedication

To my LORD, Jesus Christ, for His wonderful love and marvellous guidance in the process.

May be able to comprehend with all the saints what is the width and length and depth and height, to know the love of Christ which passes knowledge; that you may be filled with all the fullness of God. (Ephesians 3:18-19)

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To my parents, who gave me support over the years, their encouragement is greatly appreciated.

Finally to my husband, his love is the greatest gift of all.

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Abstract

Smart grid is no longer a novel idea discussed only in research articles, but rather it has spawned a great amount of practical investments and applications in commercial and industrial area. One of these is a Smart Grid demonstration project implemented within Public Service Company of New Mexico (PNM) distribution network. This project combines both residential and commercial loads on a dedicated feeder, with high PV penetration ratio, equipped with a substation-sited photovoltaic (PV) system and utility-scale Battery Energy Storage System (BESS). Often renewable energy such as PV has multiple benefits, but raise reliability concerns due to their inherent intermittency. This project shows BESS could play a vital role in assisting high penetration PV connections to the power grid. Its overall goal of this project includes peak-load reduction and PV output smoothing at a specific feeder through BESS.

Based on observation of the smoothing battery operation, we conducted a thorough analysis of smoothing algorithm and determined some key findings, including calculation of the power used for maintaining State of Charge (SoC), optimal size of smoothing BESS, and finally we design a new algorithm with high energy efficiency. This work addresses the primary problems for smoothing from planning to BESS operation. The results will be of value in practical implementations.

This work also covers shifting algorithm in detail. The shifting optimization is constructed with three main functions: peak shaving, firming and arbitrage. It is the first time for a utility scale project that all of these three shifting functions are implemented into one platform. Islanding refers to the condition in which a location can operate autonomously with Distributed Energy Resources (DER) when power from the electric utility is absent. Both islanding mode and Grid-tied mode are discussed. The extensive field experiences and results from site operations are also demonstrated. Besides these three main functions, we also introduce several other principal shifting functions which are involved in the ongoing storage system demonstration. The control strategy and current results of modelling for this Smart Grid project are given.

Contents

List of Figures

List of Tables

Glossary

BESS	Battery Energy Storage System
ESS	Energy Storage System
DER	Distributed Energy Resource
DEG	Distributed Energy generator
MG	Microgrid
SoC	State of Charge
DG	distributed generator
PV	Photovaltic
MPC	Model Predictive Control
SVM	Support Vector Machine
MA	moving average
VRLA	valve-regulated lead-acid battery
CAISO	California Independent System Operator
RMSE	root-mean-square error

Glossary

ROI	Return On Investment
PID	proportional-integral-derivative

Chapter 1

Introduction

1.1 Overview

The electricity grid has already served human society for more than 100 years. From the invention of DC generator to today's far more complex network, reliability is viewed as the first priority of this industry.

However, the exiting aged power grids are reaching its power delivery limits. Much of the grid is outdated and overloaded. It is becoming increasingly difficult to place more new conventional overhead transmission lines, especially for urban area. According to [2], "the supreme engineering achievement of the 20th century," is ageing, inefficient, and congested, and incapable of meeting the future energy needs of the Information Economy without operational changes and substantial capital investment over the next several decades. A pressure is placed on this very old industry to initiate revolutionary changes.

At the same time, fossil fuel consumption leads to global warming and climate change. According to statistic, the majority of greenhouse gases come from burning fossil fuels to produce energy [3]. Between 1990 and 2012, the increase in CO_2 emissions corresponded with an overall growth in emissions from electricity generation. The traditional electricity generation becomes a huge concern for environment along with more and more serious global warming and other environmental issues. The need for electricity generation to be clean and safe has never been more evident.

Due to all of these reasons, a great challenge exists for the power industry to provide electricity continually, while also increasing energy efficiency in a variety of ways and using more environmentally friendly energy resources.

The U.S. Department of Energy set a national vision for electricity's second 100 years, which is called "GRID 2030" [2]. Modernizing America's electric system becomes a significant task.

1.2 Smart grid

The concept of smart grid has developed quickly owing to this trend. The term "smart grid" has been used since 2005, which means a new era of power system. The "smart grid" is a developing network of new technologies, equipment, and controls working together to respond quickly to the demand for electricity [4]. Smart grid also means the deployment and integration of new high technologies such as communications, control and information technology into current power grids infrastructure. In smart grid the load and supply is dynamically balanced. Demand response and customer participation will change the profile of power consumption [5].

Table 1.1 shows brief comparison between the smart gird and existing grid. In this table the existing grid differs with smart grid in 9 aspects. In smart grid, two-way digital communication device is designed to replace the traditional electromechanical meter. Customer is empowered to interact with the energy system to adjust their

Table 1.1: A brief comparison between the smart grid and the existing grid [1].

Existing grid	Smart grid
Electromechanical	Digital
One-way communication	Two-way communication
Centralized generation	Distributed generation
Few sensors	Sensors throughout
Manual monitoring	Self-monitoring
Manual restoration	Self-healing
Failures and blackouts	Adaptive and islanding
Limited control	Pervasive control
Few customer choices	Many customer choices

energy use and reduce their energy costs. The two-way communication also helps utility to optimize the investment of generators, and takes corrective action to avoid or mitigate system problems by predicting possible failure [1]. Since nearly 90% of power outages and disturbances are rooted in the distribution network, smart grid starts to change from distribution system.

In smart grid, different systems will be able to exchange information and have interaction. Therefore, the smart grid will be a system of interoperable systems. In order to achieve interoperability of smart grid devices and systems, National Institute of Standards and Technology (NIST) is responsible to coordinate development of a framework that includes protocols and model standards for information management [6]. These standard will help the transformation to smart grid infrastructure.

From the end of 2004, worldwide renewable energy capacity grew at rates of 10 $\sim$ 60% annually for many technologies [7]. A large amount of renewable energy will be installed in more and more households as well as at centralized locations (PV and wind farms). In past several decades, electricity only flows in one direction , which is from power plant to customer. Increasingly, power start to flow in two directions due to development of DERs. The power flowing bidirectionally in smart grid, means that power customers (nodes) could also be the power providers when the energy from installed PV or wind turbine exceeds their needs, and the excess energy can be sold back to power grid. If the regulatory structure allows, they also could use power which is generated by their neighbourhood. All nodes could interact in parallel in real time [8]. Thus, the nodes in the network are able to exchange energy with each other based on the real-time needs just like the internet exchange data through network nodes on the web. As a consequence of the smart grid, power will flow more efficiently in the power grid more than ever.

In contrast to other energy sources which are concentrated, renewable energy resources exist over wide geographical areas. The growth of the renewable energy resources capacity makes the power grids change greatly not only in the perspective of expanding geographically, but especially in the perspective of the interaction of network nodes.

In this process, additional new concepts such as Distributed energy resource, Microgrids, smart meters, smart houses, and demand response are put forward and are gradually accepted by customers. All of these concepts assume that every node (customer) plays an active role in the whole system instead of traditional power plant domination in the past. In the following section, DER and Microgrid are introduced separately.

1.3 DER

Distributed Energy Resources(DER) is generated or stored by a variety of small, grid-connected devices [9]. DER comprise several technologies, such as diesel engines, micro turbines, fuel cells, photovoltaic, small wind turbines and etc. DER include, but are not limited to renewable energy resources.

Conventional power generation is centralized like coal-fired power plant or large scale PV plant, but DER is decentralized, and usually located near customers. Energy production of DER could be from any sources, for instance, it could be from traditional generators or renewable energy sources. The quantity of DER would be larger than the quantity of large centralized power plant since capacity of DER is usually smaller. It is possible that a small power networks consist of thousands of small DER. In addition, DER units have different owners, and decisions should be taken locally. Hence it's very impractical to have centralized control over large quantity of DERs [10]. In smart grid, the trend of energy generation is to change from large centralized facilities into distributed energy generation. Therefore power system control will gradually change from centralized control into distributed control.

1.4 MG

Microgrid(MG) is an electrical system that includes localized multiple loads and distributed energy resources that can be operated in parallel with the broader utility grid or as an electrical island [4]. Department of Energy (DOE) gives a similar definition: a group of interconnected loads and distributed energy resources (DER) with clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid (and can) connect and disconnect from the grid to enable it to operate in both grid-connected or islanding mode.

Microgrids are an important component of smart grid. They can increase grid resilience and can operate autonomously to keep one electrical system from the disturbance of power grid.

Microgrids have many merits, including reducing transmission power loss due to the short distance between load and power supply; relieving the investment of transmission and distribution system; reducing the transmission constrains, and improving energy efficiency and power quality [11].

Research on the topic of Microgrids is focused on two broad areas: planning and design; operational optimization. The first defines the Microgrids internal service, the interface, and modelling and design the Microgrid integration. After a Microgrid is built, the next part focuses on control optimization, which would consider three different time frames: day-ahead to hour-ahead optimization, steady state control optimization, and transient state control optimization [12]. All of these topics are applied to two cases: single MicroGrid (MG) and multiple MicroGrids.

MG typically is composed of three important parts: micro sources, inverter controller and ESS (Energy Storage System) [10]. These resources are put near the load. Micro Sources include the small scale DERs, including micro turbines, PV arrays, fuel cells, gas engine. Part of the energy generated by DERs is not capable to connect with power grid or load directly. That is why we need inverter controller to regulate voltage, and convert DC to AC, or AC to DC. This interface is a very important in MG due to different type of micro sources.

ESS(Energy Storage System) is found to be a central element for MG since it could provide power when MG goes into islanding mode or the system load has sudden significant changes [13]. When demand varies greatly, the power devices should respond to the fluctuations immediately in order to maintain load balance. The response time of common micro sources is $10 \sim 200$ seconds. ESS has a short response time to help keep load balance.

Renewable energy resources like PV or wind are weather-based. ESS can shift energy from one time period to another. For instance, ESS can shift energy from the time when generation exceeds demand to a time when demand is high. Usually power plants supply should be equal to power consumption in the time dimension continually. ESS works like a bridge, and it could move energy from one period to another period to mitigate the difference between supply and consumption. ESS have the potential to revolutionize the way in which electrical power grids are designed and operated [14].

Currently there are many types of ESS running in the power grid, such as flywheels, batteries, compressed air energy storage, thermal storage and so on. Among all of these ESS, Lead-acid battery is considered a suitable and competitive energy storage system for MG since it can provide relatively large power for a short interval of time, and have comparative low cost.

1.5 BESS

BESS has two main functions: smoothing and shifting. Smoothing is to smooth out the PV fluctuation by using BESS. Shifting is to shift energy from one period to another.

1.5.1 Smoothing

PV production can be split into a relatively smooth signal, and a high-frequency intermittent component, due to variable cloud cover, that has characteristic times on the order of seconds. PV production fluctuation can bring serious reliability issue since it may lead to frequency fluctuations. BESS have the potential to fill an important role coupled with the implementation of renewable energy systems by smoothing out the fluctuation.

1.5.2 Shifting

Electricity demand can be divided into base load, intermediate load, and peak load. Base load is large and constant. Base load plants are used to produce electricity for base load. This type of plants are often nuclear or coal-fired plants, and generally

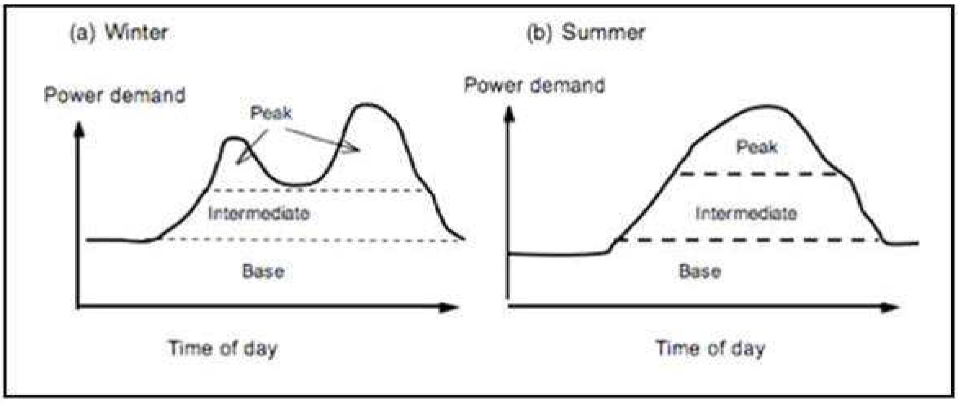

Figure 1.1: Daily base load power variations by season;From Understanding Base Load Power, October 2008, New York Affordable Reliable Electricity Alliance

are run at full output. Base load plants have high capital costs, but low variable costs. Base load plants continuously operate to meet the minimum load. This type of plants can't have rapid changes in output, so they can't follow load changes. Peaking load plants are used to meet peak load. Peaking load plants such as diesel generators and natural gas plants have high variable cost. Generally they only run several hundred hours a year. The intermediate load plants are used to provide the rest of load demand. Intermediate load plants operate less frequently than base load plants [15].

Peak-to-average electricity demand ratio is used to measure the ratio of the peak load to the time-averaged load level. It is a serious issue that the peak-to-average electricity demand ratio rising in many U.S. regions. The data published in EIA(U.S. Energy Information Adiministration: http://www.eia.gov), show that in 2012 peak-to-average electricity demand ratio is rising to 1.78 in New England area [16]. High ratio indicates decreasing average utilization levels for generators. A large amount of peaking plants are invested, but only run less than 20% of time. The cost of whole power system increases due to large assets investment.

Table 1.2: Comparison among traditional power plants and renewable energy power plants

Power plants type	Examples	Purpose	Controllability
Base load plant	Nuclear plants; Coal-fired plants;	Meet daily minimum level of demand.	Cannot be started and stopped quickly. Output is constant most of time;
Intermediate load plants	Combined cycle natural gas plants;	Meet most of the day-to-day variable demand;	Output can be changed within hours.
Peaking plants	Diesel generators ; Simple cycle natural gas plants;	Meet daily peak load;	Output can be changed within a few minutes.
Renewable energy power plants	PV; Wind turbine;		Output is dependent on weather.

At the same time, the rapid development of renewable energy technologies lead to continued increase of renewable energy penetration to power grids. However, the weather-dependent renewable energy generation won't follow power consumption in the time dimension like the traditional power plant generations are controlled to do. Lack of concurrence of energy generation and energy consumption could be a substantial difficulty to overcome for power grids. Renewable energy doesn't seem like traditional power generation which is controllable in time and in the amount of power to be delivered. Since the power of most of renewable energy are weather dependent, it can't operate on schedule strictly. Table 1.2 shows the comparison among traditional power plants and renewable energy power plants.

BESS appears to be a suitable approach for these two problems since it could be an alternative to peaking plants to save assets investment, and shift renewable energy to the time of peak load. BESS could shift the energy from one time period into another, and charge or discharge power as system demands. It could effectively absorb the excess energy or supply energy as needed.

Variability and unpredictability of renewable resources could be mitigated by BESS. It is an essential element in smart grid to help keep load balance for the feeder with high renewable energy penetration and shave the peak load. The study in [17] shows that reliability is increased after BESS is introduced to power system.

Hence key benefits from storage systems are the ability to smooth out the PV output spikes, and perform peak load shaving by charging from grid or renewable energy. Price arbitrage and energy firming are two other benefits, which will be introduced in Chapter 4 in detail.

1.6 MPC

MPC (Model Predictive Control) is a good technique to apply process control in smart grid situation. The industrial application of MPC occurred earlier than the method's reliability was proven and developed. Prior to 1980, chemical plants and oil refineries begin to use MPC for process control. Soon it becomes the most popular advanced control method in industry.

There are a large amount of renewable energy resources in smart grid, and the renewable power generation has uncertainty. MPC involves the prediction of state, and it is well-suited for a system with many uncertainties. Future control inputs and future plant responses are predicted using a system model and optimized at regular intervals. It seeks an optimized solution for next short period to reach the optimization for a long term finally. But it never actually operates optimally over any period of time [18].

MPC is composed of three components: prediction, optimization and receding horizon implements. In the prediction, a variety of methods could be incorporated in a predictive control strategy, such as deterministic, stochastic, or fuzzy. The great merit of MPC is to linearise the plant in a small interval when the plant might not be linear function at all for a long time. Based on linearisation at each specified operating point, linear optimization method could be used for the interval.

Uncertainties existing in the renewable energy output is a big issue for the maintain of power balance. Hence, the forecast becomes a very important means to help maintain the system in a reliable state. MPC is a suitable optimization method for renewable energy management in two ways: MPC involves the predictions, and output will be adjusted based on the ongoing states constantly.

In this project MPC is operated in a Microgrid which includes a PV plant, battery energy storage system, and a gas engine. The prediction consists of load, solar power, and electricity price.

1.7 Dissertation Contributions

The main contributions of this dissertation can be summarized as follows:

- Machine learning is introduced into load prediction.
- Exploiting the available primary parameters of smoothing algorithm including the required battery charge and discharge rate, window size of moving average(MA) algorithm, power reference input for MA, required battery capacity and so on. The main work includes 1) proposing a way to calculate the restoring power to help maintain State of Charge (SoC) in a certain range; 2) proposing a self-adjusted smoothing algorithm; 3) proposing a rule-based smoothing algorithm with low-complexity resulting in better control over ramping rate of smoothed signal; It is showed that our proposed smoothing algorithm outperforms the existing moving average algorithm; 4)A method is proposed to

estimate the optimal battery size for a given area according to historic weather data. The estimation method is to extract the frequency characteristic of historic PV ramping rate, and then to find optimal battery size. That will avoid unnecessary investment due to improper battery size.

- The proposed shifting algorithm includes three main functions in one platform. Based on observation of a long term site operation, several other functions are designed to involve in shifting. The main work includes: 1) recognizing three main shifting goals from all major concerns; 2) first put three main shifting functions in one platform in utility scale; 3)proposing a way to unify various benefits, and it could be compared and find the overall best operation plan from the three functions. 4) develop day-ahead schedule and hour-ahead optimization. These two schedules are combined together to dismiss the deviation of day-ahead schedule when running in real time.

1.8 Structure of the Dissertation

The remainder of this dissertation is organized as follows: Chapter 2 gives a short introduction about two smart grid projects. Chapter 3 introduces several methods in load prediction. PV prediction is presented also. In Chapter 4, we propose the shifting algorithm, which include making day-ahead schedule for grid-tied mode, and implementing MPC for islanding mode. In Chapter 5, the proposed smoothing algorithm is presented. Several important aspects for smoothing algorithm are analysed, especially the optimal battery size calculation method is put forward. Finally, we conclude the dissertation in Chapter 6.

Chapter 2

Project introduction

2.1 PNM/DOE Solar and Battery Storage project

In order to explore how to use the storage system to benefit PV and Microgrid, PNM, in collaboration with other partners (Department of Energy (DOE), EPRI, and University of New Mexico (UNM), East Penn Manufacturing Inc. (EPM), Sandia National Laboratories, and Northern New Mexico College (NNMC)) has Launched a Smart Grid Demonstration project that couples an advanced lead acid battery with the output of a 500kW PV installation [19] [20]. The project was commissioned in September, 2011. The goal of this project was to demonstrate how a utility-scale (1 MWhr) storage system application would help provide a stable PV output from an adjacent PV array.

An aerial view of BESS is shown in figure 2.1. The schematic representation is shown in figure 2.3, which displays a power system one-line diagram of the BESS combination with the 500kW Solar PV power plant. Two feeder configurations, beginning and end of feeder are connected to the PV and BESS by reconfiguring switches: at the end of the Sewer Plant 14 feeder and at the beginning of the Studio

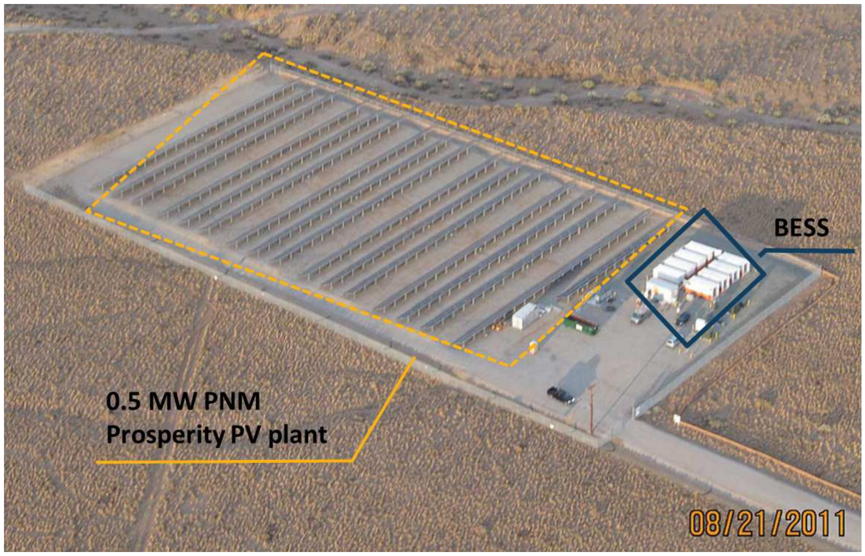

Figure 2.1: Aerial view of the 0.5 MW PNM Prosperity PV plant with battery storage

14 feeder.

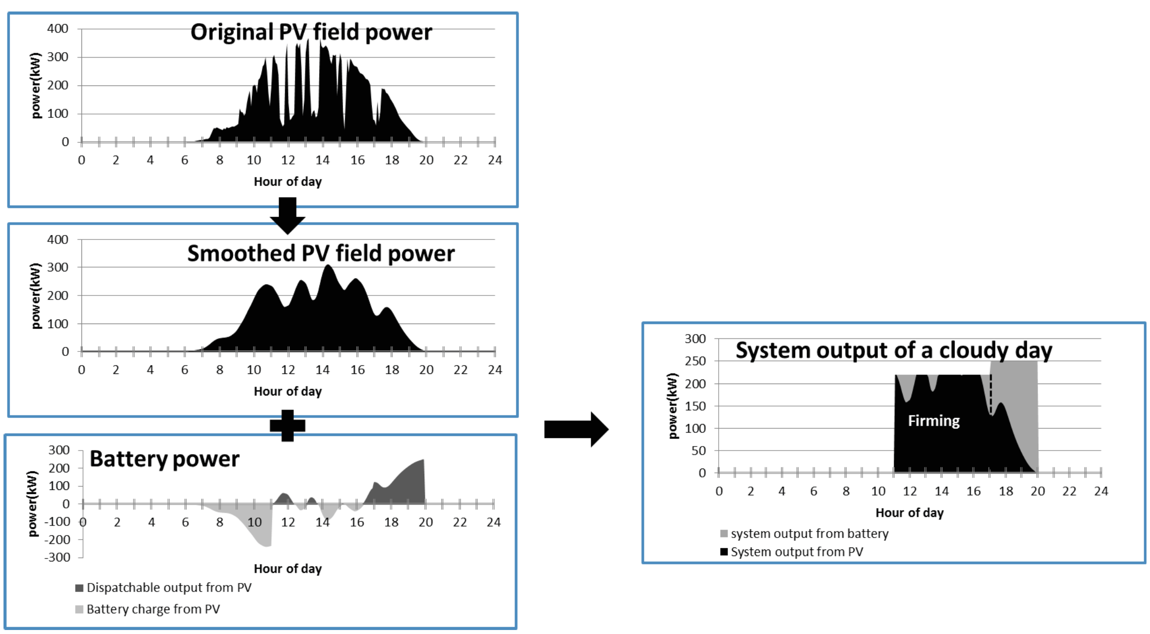

Figure 2.2: The two main applications of BESS

The two main applications of BESS are smoothing and shifting. In figure 2.2, smoothed PV production doesn't have spikes like original PV power. When shifting battery outputs power based on PV output, the sum of PV and shifting battery power is rectangle in shape which is showed in the right side of figure 2.2. This example shows that smoothing and shifting help PV to become into a controllable and reliable energy resource.

Smoothing is power based and relates to removing the short time PV output intermittency. Shifting is energy based and relates to energy shift. It functions in three ways: firming, price arbitrage and peak shaving. Firming is to make PV output into a firm value for a certain hours with the aid of shifting battery. Arbitrage means to buy electricity when price is low, and sell it when price is high. Peak shaving means to shave the load during peak load time through a day.

Based on the needs from smoothing and shifting, BESS system combines two technologies: UltraBattery and Advanced Carbon Synergy Battery. Both of technologies are invented by Australias Commonwealth Scientific and Industrial Research Organisation (CSIRO). The UltraBattery which provides 0.5MW smoothing capacity. This technology enables long-life VRLA batteries (valve-regulated lead-acid battery) to be deployed with Solar PV power plants to smooth highly variable fluctuation of PV power generation. This storage technology can respond fast enough to compensate the rapid changes. The rating of smoothing battery is 0.5MW, which is same as the rating of PV plant. Hence the smoothing battery can smooth out any amount of variations generated from PV.

Advanced Carbon Energy Battery with 1MWh storage capacity is dedicated to shifting energy comprises the other technology of enabling large energy capacity.

The unique aspect of this demonstration project is that the Battery Energy Storage System (BESS) is composed of these two types of advanced lead acid battery:

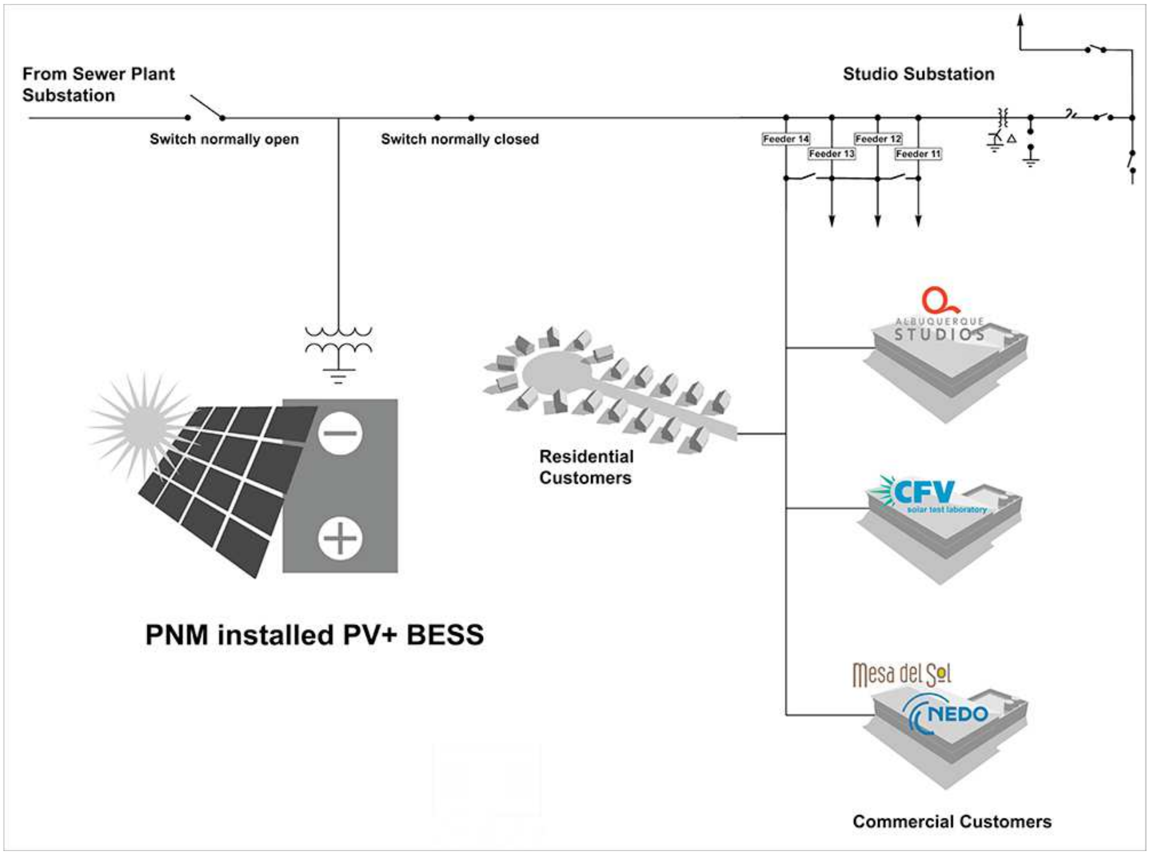

Figure 2.3: Schematic layouts of Mesa del Sol area, PV and BESS system and serving feeder

one is dedicated to shifting the energy; the other is dedicated to smoothing the power. The inclusive goal is to provide a firm, dispatchable, distributed renewable generation that simultaneously smooth intermittent PV output. The combination of these two technologies enables long-life VRLA batteries to be deployed with PV power plants to both smooth power generation, and shift power delivery to times of high power demand [4].

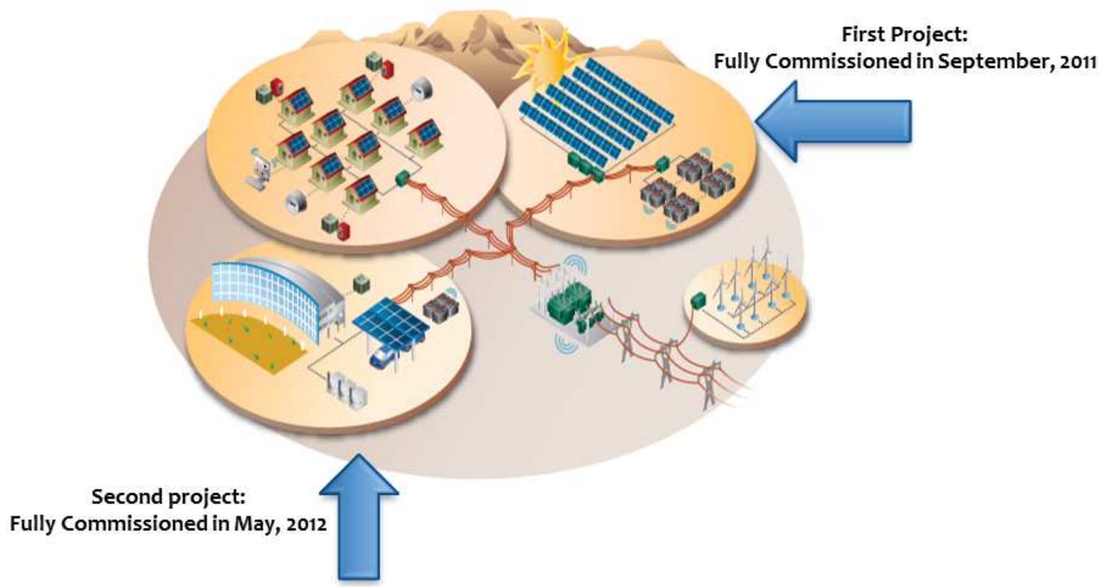

Figure 2.4: System layout of Smart grid demonstration project and Micro-grid demonstration project

2.2 Mesa del Sol Micro-Grid Demonstration

"Mesa del Sol Micro-Grid Demonstration" project, is a collaboration between New energy and Industrial Technology Development Organization (NEDO) and UNM. The Aperture Center in Mesa del Sol, Albuquerque, New Mexico is the test site for the microgrid. This Microgrid is a small-scale version of the larger electrical grid, and is installed at the aperture center at Mesa del Sol where UNM, PNM, Mesa del Sol and Sandia National Labs are involved in a collaboration aimed at making renewable energy a workable reality that can be incorporated into the nation's electrical grid.The left corner in figure 2.4 shows this project.

This Microgrid comprises a 50 kW solar PV system, a 80 kW fuel cell, a 240 kW natural gas-powered generator, a lead-acid storage battery power system, and hot and cold thermal storage. All of these generating resources together supply as much as 50% of the aperture centre's required energy. These resources are interconnected through a control room and building management system in the Aperture Center. The project is commissioned since spring of 2012 [21].

The goal of the project is to research how to integrate large amounts of intermittent renewable energy to the existing electrical power grid. The project enables the Aperture Center to respond to demand/supply signals from the power grid, and also can operate independently.

This Micro-Grid Demonstration project examines behaviour of individual components (such as individual houses, EVs, appliances, storage (fuel cell or other type)) in detail, both spatially and temporally. The Microgrid can be connected to the smart grid demonstration project, but can also operate independently as a stand-alone system.

Chapter 3

Prediction

3.1 PV prediction

This section is accomplished by Wesley Greenwood. An important aspect of forecasting solar irradiance, is to explore the applicability of using percent cloud cover predictions, which are typically used to determine visibility for aviation, for irradiance prediction. Using known equations which define solar trigonometry and position, a theoretical clear-day irradiance profile was calculated specifically for the array orientation at Mesa del Sol in Albuquerque, New Mexico. From this, percent cloud cover predictions posted by the National Oceanic and Atmospheric Administration (NOAA) were applied to the theoretical clear-day data such that:

$$I_{predicted} = I_{theoretical}(1 - k * \%C) \tag{3.1}$$

Where, $I_{theoretical}$ means the theoretical clear-day irradiance for PV array located at Mesa del Sol in Albuquerque. k is a constant which is chosen to best correlate to historical data. The constant was initially given a value to weight the percent cloud cover's effect. $\%C$ means percent cloud cover [22].

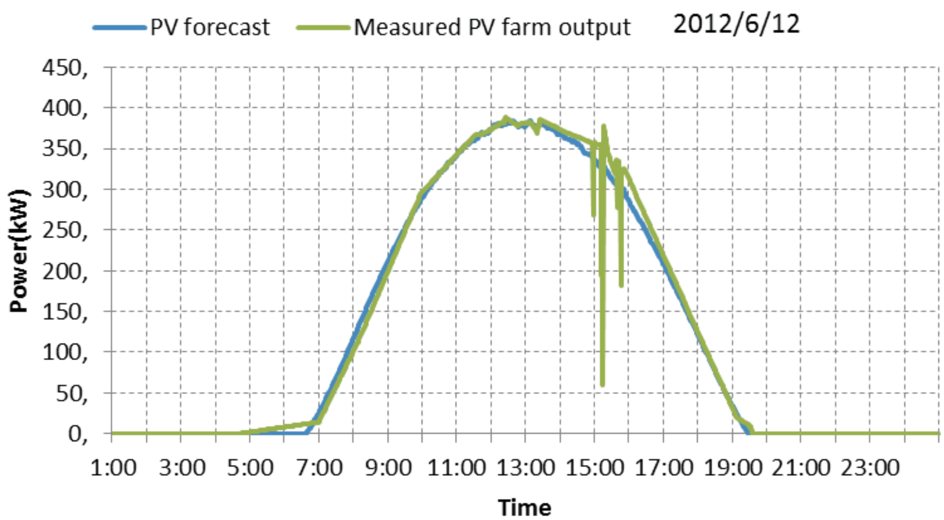

Figure 3.1: Comparison between the PV output forecast and measured PV output on June 12nd, 2012

Figure 3.1 shows an example of PV prediction on a sunny day. Even the percent cloud cover can't not be predicted in very short period, PV production prediction still follow main trend.

After developing this prediction method, it became apparent that there is room for improvement over using percent cloud cover predictions, but, depending on need, the method could be used to estimate energy. It becomes a very important input for optimization theory.

The prediction discussed above is based on site-specific ground data. Since the ground data is not available anywhere, satellite derived weather inputs start to be used to predict PV output. According to [23], PV performance models run with site-specific ground data provide the most accurate energy prediction. However, the satellite derived weather inputs with same model can bring very good estimates for longer time periods of energy.

More PV performance models are introduced in [24]. In order to test the ability of various PV performance models for different system designs and technologies in varied climates, [25] provide a common approach for a standard model validation procedure.

3.2 Load prediction

3.2.1 Short Term Load Prediction

Autoregressive model

Linear regression is based on a time series analysis. An autoregressive model is a common type of linear regression. Consider a series $y_1, y_2, \cdots, y_n,$; an autoregressive model of order p (denoted $AR(p)$) states that y_i is the linear function of the previous p values of the series plus error term.

$$y_i = \phi_0 + \phi_1 * y_{i-1} + \phi_2 * y_{i-2} + \cdots + \phi_p * y_{i-p}; \tag{3.2}$$

The order p of linear regression could be decided by using the partial autocorrelation function (PACF). PACF can find out the correlation of data with a certain lag by removing all of the low order of autocorrelation. After finding out the order of autoregressive model, the Levinson-Durbin algorithm can be used to calculate the AR coefficients $\phi_1, \phi_2, \cdots, \phi_p$ [26]. Then y_i could be obtained by equation 3.2.

Slope-Predictor Functions

$$y_i = y_{i-1} + \left(\frac{f_{i-1} - f_{i-h}}{h} \right) \tag{3.3}$$

The slope prediction is to use the average slope of h previous values as the predicted slope used for next value. The slope will be calculated for every new point.

Here, the mean squared error (MSE) is used to evaluate the prediction methods. It is the average of the squares of difference between the estimator and what is estimated. In figure 3.2,the MSE of the two predictors are 347 and 135. The slope-predictor function has less MSE than quadratic regression.

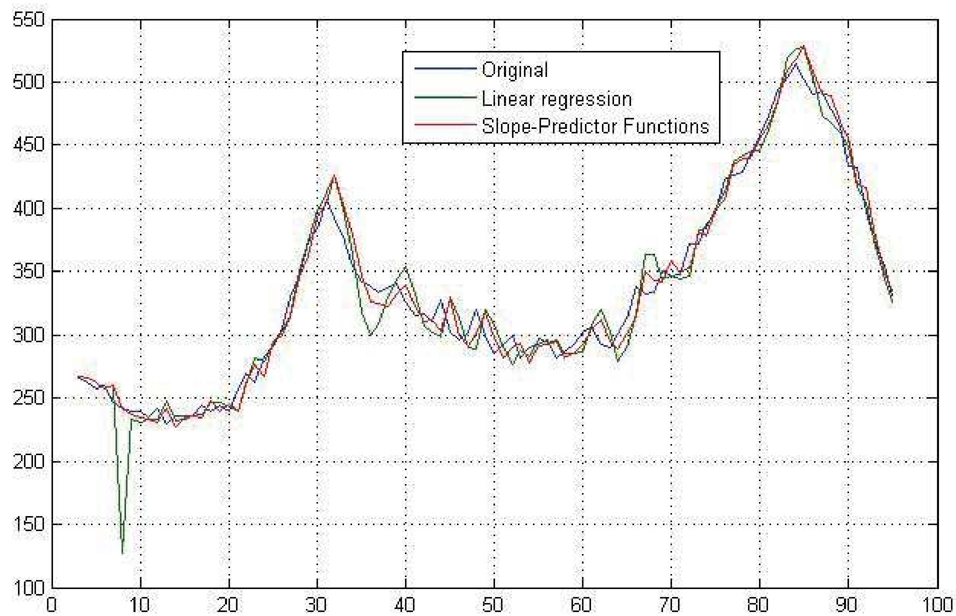

Figure 3.2: Comparisons of prediction results with two methods

Support vector machine (SVM)

SVM is a broadly used tool for classification and prediction. As for prediction, the empirical data is used to train a model, and further the model is used for prediction. SVM are also called maximum margin classifiers, because it minimizes the empirical classification error and maximize the geometric margin [27].

Comparing with other machine learning methods, SVM converges quickly, isn't liable to get trapped in a local minimum and is able to reach the global optimization.

The input data are mapped into a high dimensional space. Though the data are non-linearly mapped, SVM attempts to find the linear relationship between the mapped data and labels [28]. The optimization problem is given as follows:

$$\text{Min: } \frac{1}{2} * \|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^{\star}) \tag{3.4}$$

Subject to:

$$\begin{cases} y_i - w * \phi(x_i) - b \leq \epsilon + \xi_i \\ w * \phi(x_i) + b - y_i \leq \epsilon + \xi_i^{*} \end{cases} \tag{3.5}$$

The first term in the optimization problem represents regularization of control system. The second term means error. The $\epsilon -$ insensitive loss function is used to control the loss. The RBF(Radial Basis Function) kernel is used in this work since a linear model is a special case of RBF, and a sigmoid kernel behaves like RBF for certain parameters [29]. The RBF kernel is as follows:

$$K(x_i, x_j) = exp(-\gamma\|x_i - x_j\|^2), \gamma > 0 \tag{3.6}$$

For RBF kernel, the penalty parameter C and kernel parameter γ together need to be chosen.

LIBSVM is an integrated software for support vector classification, regression and distribution estimation. In this project, we use LIBSVM as a tool to run SVM [30].

Usage interface svmtrain

$model = svmtrain(trainlable, traindata, parameter)$

This interface is from LIBSVM. It is used to train SVM regression model. The input arguments are the available data measured in the past:

- l[n-N], Measured load.

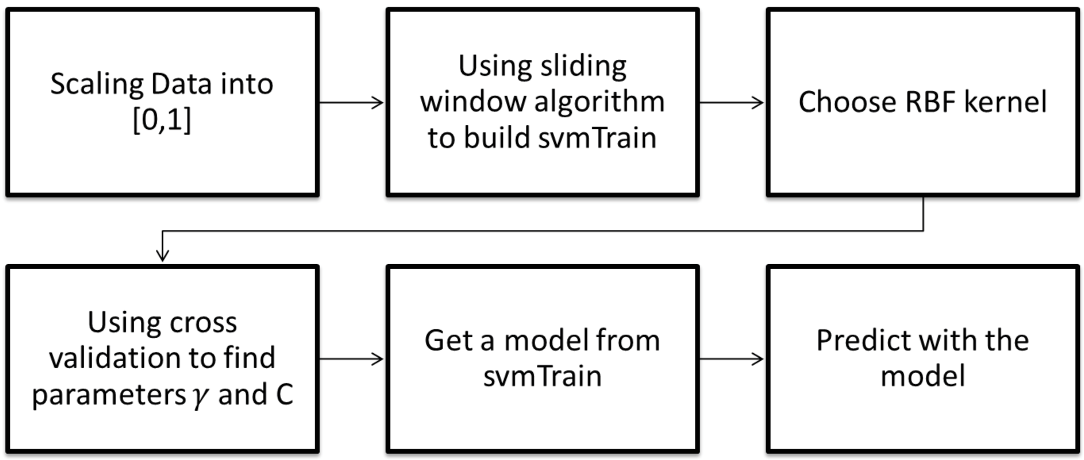

Figure 3.3: The load prediction process by using LIBSVM

- t[n-N], Temperature
- c[n-N], Cloud coverage.
- wd[n-N], Day of the week

l[n-N] means the measured load, which is N time steps before present time. The load shape for the consecutive days usually share very similar pattern. The previous days' load shape will be a good reference for the next day's load shape. t[n-N] means measured temperature. Temperature is found to have strong correlation with every day's load. In some papers, temperature is the only parameter which is used for load prediction. c[n-N] means the historical cloud cover. wd[n-N] means what day the day is since the load on weekday is different with load on weekend. Even for weekday, everyday load will have a slight change.

The load consumption largely depends on if the day to be predicted is a working day, a weekend or a holiday. The historical measured load data together with weather are the input data for load prediction. Each column of trainData includes the four types of data as follows:

$$trainData = [l[n], t[n], c[n], wd[n]]$$

As [29] suggests, the data would be first scaled into same range in order that the value with large magnitude will not dominate in the calculation. Since SVM would put data in a predefined format, the train date should follow the format, and put the data into a matrix named trainData. The column of trainData means different features of input data. The row means the data collected at different time.

Each column holds the content of all sliding windows at instants Nl, Nl+1 etc., assuming that all windows of data have the same length:N_l. This matrix has then 4*N_l rows which means that we have a total of 4 training vectors, and the number of each vector is N_l. In this case, we use 4 different data concatenated, and a window of 75 time instants, and then the matrix has 4*75=300 rows. For each instance, the previous measured 75 data are used to predict the load for next instance.

A certain days' data is used, n=7*96 in the test; 7 means the window size is 7 days; 96 means 96 samples per day, and one sample is obtained every 15 minutes. The size of trainData is 4*(7*96). This method works appropriately. The last 96 samples are utilized to predict the value for next 15 minutes.

Cross-validation and grid-search together are run to find the best parameter C and γ. By using the best parameters, the model is obtained using training data and svmtrain interface, and later the model is utilized to predict with a test data sample.

User interface svmpredict [31]

$$[Prediction, Accuracy, Probability] = svmpredict(testLabel, testData, model)$$

This interface is used to predict with the model calculated from svmtrain.

testLabel is a n $\times$ 1 vector. It is true value of prediction data. n is the total number of samples, and also means the number of predicted data. testData is supposed to be a n $\times$ 1 test data input matrix, where n also is the number of features. For this project, d is equal to 4 since we have 4 types of information related to load. Since we use sliding window algorithm, testData will adopt the same format as trainData. The format is as follows:

$$\mathbf{trainData} = \begin{bmatrix} l[1] & l[2] & \cdots & l[N-N_l] \\ l[2] & l[3] & \cdots & l[N-N_l+1] \\ \vdots & \vdots & \vdots & \vdots \\ l[N_l] & l[N_l+1] & \ldots & l[N] \\ t[1] & t[2] & \cdots & t[N-N_l] \\ t[2] & t[3] & \cdots & t[N-N_l+1] \\ \vdots & \vdots & \vdots & \vdots \\ t[N_l] & t[N_l+1] & \ldots & t[N] \\ \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

The measured data up to the current moment are used for 15 minutes-ahead prediction. The result is shown in figure 3.4.

Figure 3.4 shows load prediction is very close to actual load. In this figure, the 96 load value are predicted. For every point, the measured data up to the moment is used. That means the prediction at any instant uses the actual load data as inputs.

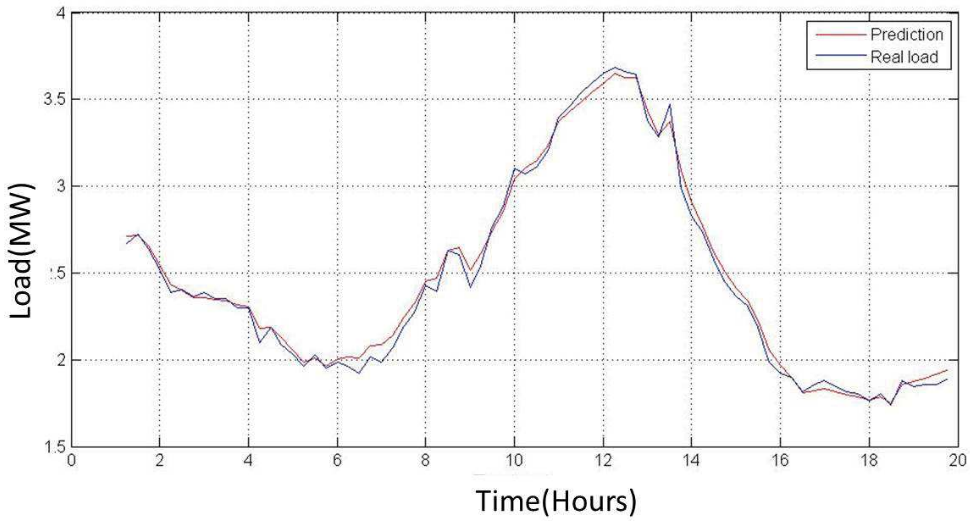

Figure 3.4: 15 minutes-ahead load prediction with SVM

Hence there is no accumulated errors. The prediction result in the earlier time won't influence the following prediction.

How many measured points should involve in the prediction will decide how well the prediction can track the load variation. PACF is a good tool to find out the lag. Within the certain lag, the correlation of data by removing all of the low order of autocorrelation is the maximum value comparing with other lags. That means the data within the certain lag is the best date entry used for prediction.

3.2.2 Day-ahead prediction

Short term load forecasting handles the prediction of the system load over an interval ranging from an hour to one week [32]. Day-ahead load forecasting still belongs to short term load forecasting. Monthly or yearly load demand is easier to be modelled since variations are smoothed out in long term. In fact short term load vary greatly with the temperature, holiday, humidity, human behaviour and so on. Usually the prediction made in the city level or large substation is better than the prediction in the distribution feeder level since loads change more greatly in the feeder level. For this project, the prediction is made for a 4 megawatt distribution feeder. Many factors can lead it to have large variations due to small number of residents. We choose SVM to do day-ahead load prediction. 15 minutes-ahead prediction is more accurate comparing with day-ahead prediction.

Data analysis and approach

The data used for day-ahead load prediction is the stored data from previous days and forecast temperature and cloud coverage for the day to be predicted.

The data used for the day-ahead prediction are same with the data for 15-minutes ahead prediction.

- l[n-N], Measured power load.
- t[n-N], Temperature
- c[n-N], Cloud coverage.
- wd[n-N], day of the week

The past measured data together with forecasted weather data construct the input data for load prediction.

$$
\begin{aligned}
t[n] &= \{t[n-N], \cdots, t[n+N_f]\}^T, \text{ Temperature} \\
c[n] &= \{c[n-N], \cdots, c[n+N_f]\}^T, \text{ Cloud coverage} \\
wd[n] &= \{wd[n-N], \cdots, wd[n+N_f]\}^T, \text{ Day of the week}
\end{aligned}
$$

Prediction models

$$
\textbf{testData} = \begin{bmatrix}
l[1-1d] & l[2-1d] & \cdots & l[N-N_l] \\
l[2-1d] & l[2-1d] & \cdots & l[N-N_l+1] \\
\vdots & \vdots & \vdots & \vdots \\
l[N_l-1d] & l[N_l+1-1d] & \dots & l[N] \\
t[1-1d] & t[2-1d] & \cdots & t[N-N_l] \\
t[2-1d] & t[2-1d] & \cdots & t[N-N_l+1] \\
\vdots & \vdots & \vdots & \vdots \\
t[N_l-1d] & t[N_l+1-1d] & \dots & t[N] \\
\vdots & \vdots & \vdots & \vdots
\end{bmatrix}
$$

Here load and weather data up to the current moment is used to predict load. Every column is composed of previous load and weather. In the first column of testData, we can see the load data, which is from same time on yesterday. The following vector t is the temperature forecast. We assume the next day's load will largely follow the load pattern from yesterday, but will have corresponding change according to weather. For instance, the higher temperature will increase the load.

Figure 3.5 is an example of prediction result. SVM using sliding window algorithm is compared with SVM without using sliding window algorithm. The result of SVM with sliding window is more close to actual load.

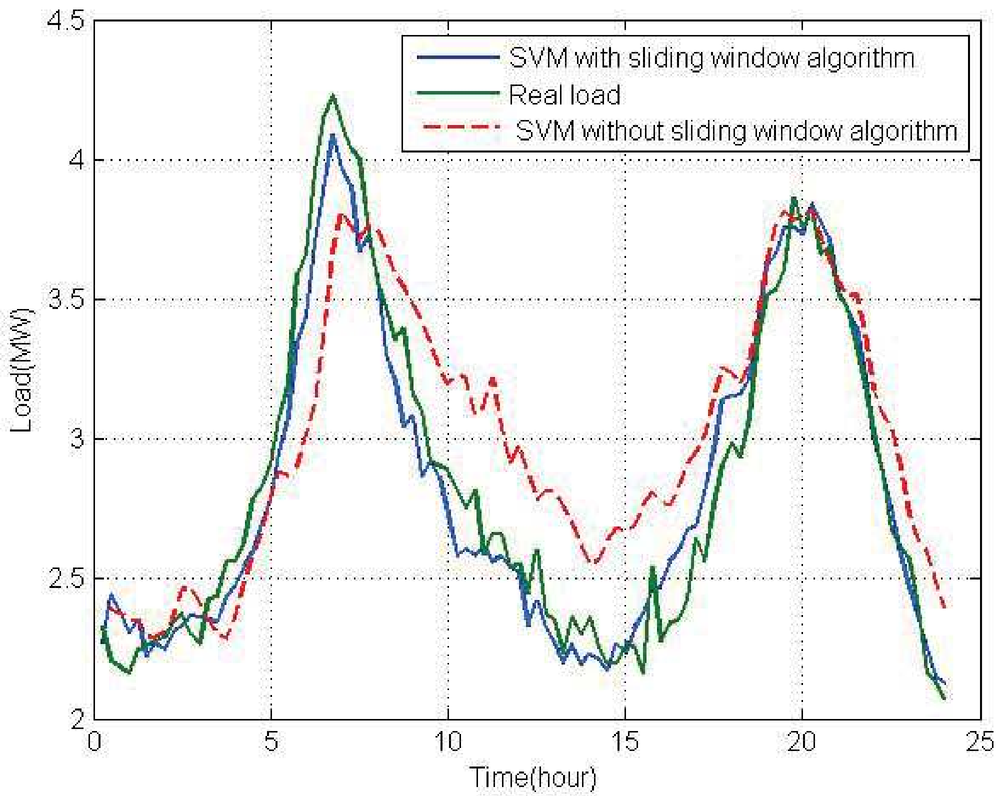

Figure 3.5: Day-ahead prediction result with SVM

Chapter 4

The Shifting Algorithm

4.1 Introduction

Along with the rapid development of the renewable energy technologies, the energy storage system is a key component to enable the intermittent and weather-based renewable energy to be a reliable energy resource [33]. BESS can not only provide power to simultaneously smooth the renewable generation variation, but also provide large energy by storing renewable energy and delivering it to the period of highly needed. Commonly there are three typical shifting functions: peak shaving, firming and arbitrage. In this work, it is the first time for a utility scale system that all three shifting functions are incorporated into a single platform. The optimization formulas are constructed for these three functions with the data of predications, such as PV prediction, load prediction and price forecast. Both islanding mode and grid-tied mode are discussed.

In islanding mode, the day-ahead schedule and hour-ahead schedule are combined together. Comparing with hour-ahead schedule, the day-ahead schedule could better dispatch energy based on day-ahead load and weather prediction. Hour-ahead schedule could help to correct the day-ahead schedule with actual data and short-term prediction.

The extensive field experience and result from filed site are also shown. Besides the three main functions, seven important shifting functions are introduced, which are involved in an ongoing storage system demonstration property.

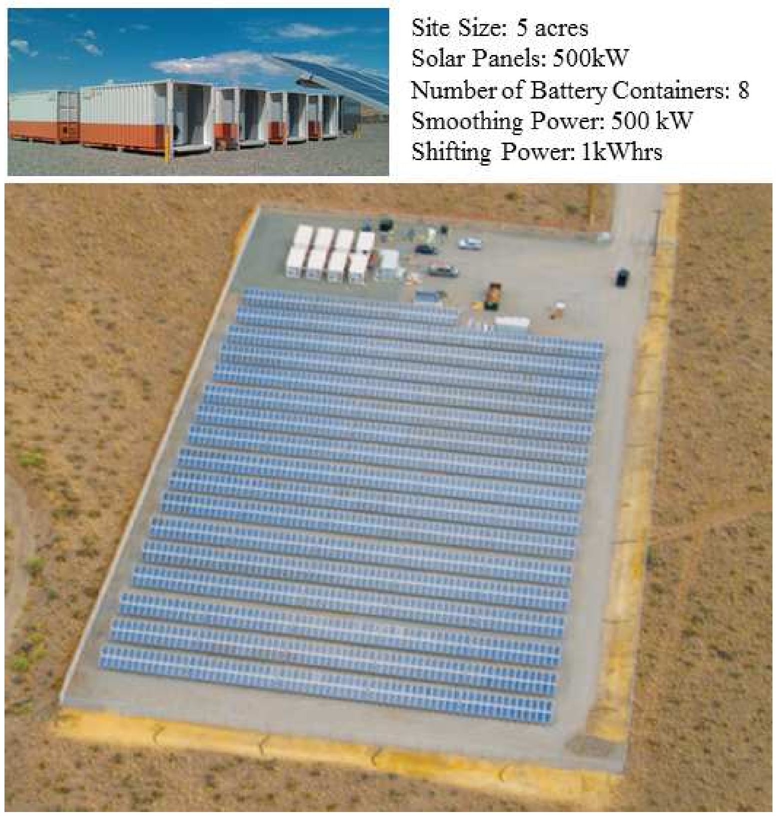

Figure 4.1: 0.5 MW PNM Prosperity PV plant with BESS

When BESS cooperates with PV to dispatch power, multiple issues need to be considered carefully, including the setting of objectives, objective priorities, and the control strategy. How to maximize the benefit of energy storage system is a problem to consider since BESS could do a multiple of jobs. This work needs to cooperate with the utility to get inputs from field sites. During three-year DOE demonstration project ongoing in New Mexico, University of New Mexico (UNM) partnered with PNM and other institutions to set the shifting goals based on the real needs from the utility, and also basing the solution on the advanced optimization theory. Normally shifting is conducted in three aspects: peak shaving, firming, and arbitrage. These three aspects are described separately in what follows.

Peak shaving means to shave the peak load to a point that fewer or no peaking generators will be needed. Usually utility maintains relatively expensive peaking generators to provide power for on-peak load, which are only used during on-peak load time. Such an investment increases the electricity cost since a peaking generator is only used for several hundred hours a year. Peak shaving could be realized by using storage system or other DERs to provide energy during peak load time to avoid investment in peaking generators.

Firming means BESS produces power to make the output of PV and BESS to become a desired shape and last for a certain time. WSM (Whole Sale Market) is the utility unit which is responsible for trading electricity in the market, and generate energy supply plan for the following hours or next day. If a fixed value of power could be provided for four consecutive hours, then it is considered as a firmed power resource, and could participate in the energy supply plan. Under a perfect sunny day, the power profile of PV is close to a sine wave form. With the additional energy from BESS, the final output which includes PV generation and battery output could be firmed into a square wave.

Arbitrage means BESS could exploit the price difference to make profit. BESS cost needs to be considered into arbitrage calculation.

Normally single purpose operation optimization is discussed and reached by most of papers [34] [35] [36] [37]. In the real world, all of the conditions comprising weather, price and load are changing. For a day with great price variation, arbitrage might be a good way to have BESS to operate. However, if price variation is too small, BESS might stay idle until the price margin gets large enough. To guarantee a certain profit, BESS can't be used everyday. Same thing applies to other two functions. If peak load is not high enough, BESS is not necessary to function considering high operation expenses of BESS. Hence any single purpose function can't bring maximum benefit to power system. Every day's BESS schedule should be based on the weather, electricity price and load of the specific day. For example, during summer season, peak load is very high comparing with other seasons. Most of time, peak shaving is the one to bring most benefit to system.

In this project, these three functions are combined together into one platform. Weather, electricity price and other key factors collectively determine the function to be operated for a particular day. Benefit is maximized for utility by considering more than one single function.

By performing these functions in the BESS, the operation results are accumulated, and help us to design a practical and comprehensive algorithm. Several other functions which are involved in BESS operation are introduced.

The major contributions of this work related to shifting include:

- Differentiate three main shifting goals from all major concerns. Further the calculation method is described in detail. These three main shifting goals are peak shaving, arbitrage and firming.

- Develop a way to transfer the benefits from different units, for example, energy and power into same unit: monetary value. Therefore the various benefits could be compared, and the overall best operation plan is found out from the three functions.

- Develop the optimization method to calculate the maximum benefit from those three . Day-ahead schedule and hour-ahead optimization is combined together to correct the deviation of day-ahead schedule when running in real time.

This chapter is organized as follows: in section 2, the demonstration system will be presented. In section 3, additional seven shifting functions are proposed from various perspectives. These functions are introduced including its importance and how they will operate together. The logic flow chart is presented to show the relationship of these functions. In section 4, a detailed description on optimization is presented. The key aspects related with MPC are discussed. The simulation result and the real data from filed site are both given. Future work is discussed. All of these control strategies assume the availability of PV output prediction, price forecast and load prediction, introduced and partly described in chapter 2.

4.2 System setup description

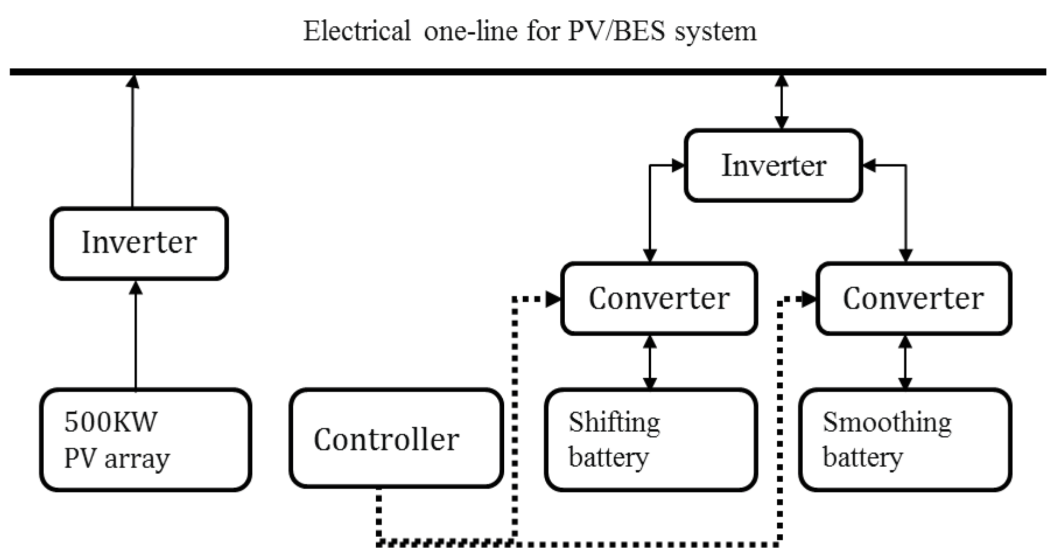

Figure 4.2: Schematic representation of integrated BESS and PV system

The schematic representation of the battery storage system under analysis is shown in figure 2.3. BESS combines two technologies. One is the UltraBattery which provides 0.5MW smoothing capacity. The UltraBattery technology enables long-life VRLA batteries to be deployed with Solar PV power plant to smooth variable power generation caused by clouds disruption. Advanced lead acid batteries dedicated to shifting energy are the advanced Carbon Synergy Battery. It provides 1MWh storage capacity. The combination of these two battery technologies enables long-life VRLA batteries to be deployed with PV power plants to both smooth power generation that is disrupted by clouds, and shift power to satisfy operational objectives. The requirement for the shifting battery is to have enough capacity to store energy for a specified duration of time. The BESS used in the present project has the capability to do just that.

Two controllers are implemented in the BESS. One is the application controller which is dedicated to derive the active and reactive power references for BESS. The other is the BESS Master Controller, which is used to collect battery system information, and sends the control signal to the PCS (power Conditioning System). The PCS will be responsible for converting DC power into the AC power as Master controller commands.

4.3 Prediction

The predictions are necessary for conducting a successful control of renewable energy. Three predictions are involved including electricity price prediction, load prediction and PV generation prediction.

Load shape prediction

Since the optimization is made for the next whole day, day-ahead prediction is very important. The more accurate the prediction is, the more optimal the solution would be. SVM (support vector machine) is used for load shape prediction by learning the load shape from the past. SVM learns the correlation among the load shape, temperature, and cloud coverage. A model found based on the historical data is used for next day's load prediction.

Price prediction

Some electric utility operators publish price forecasts online. CAISO is one of them. CAISO publishes the day-ahead electricity price forecast online. In this project, the day ahead price forecast is extracted directly from this website.

PV forecast

According to the cloud coverage published by NOAA, PV production is predicted for the next day. The prediction in sunny day is more accurate since the change of local cloud cover is less. The prediction is used to help making BESS operation schedule, and the degree of accuracy can basically satisfy the needs.

Among of these three predictions, accurate load prediction is the most difficult one to get since it is influenced by many factors like weather, human behaviours, season and etc. Comparatively, other two predictions are simpler.

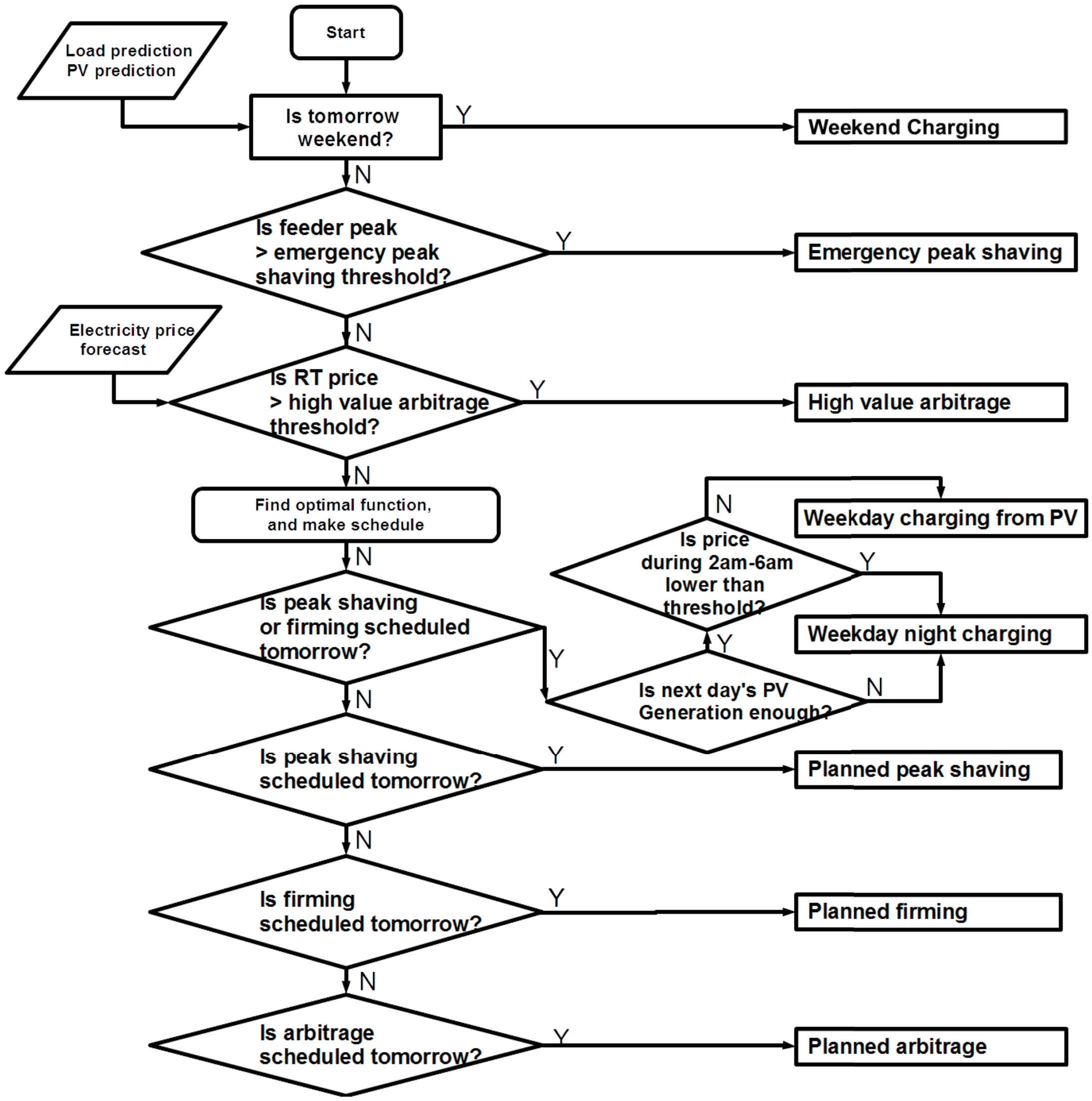

Figure 4.3: Complete flow chart of shifting algorithm

4.4 Control strategy

4.4.1 Flow chart

Figure 4.3 is the flow chart for the shifting algorithm. It shows the functions operation sequence. First, if it's weekend, weekend mode will be selected. In this mode, BESS will only keep SoC within rated range. During weekday, the emergency peak shaving and high value arbitrage are used to provide immediate power supply to shave the load, or sell electricity at high price by monitoring the real time load or price.

By comparing the benefits of shifting functions, the optimal main function is chosen among peak shaving, arbitrage and firming. After that, if peak shaving or firming is chosen, the system is going to decide the charging mode based on PV generation and price prediction. BESS prioritizes charging from PV since it's co-located, and saving distribution power loss. If next day's predicted PV generation is not enough to fully charge BESS, system will charge from the power grid during the early morning. This case rarely happens since cloud cover need to exceed 50% for such case. In Albuquerque, such weather is rare. Most of time, BESS is charged from PV to avoid transmission and distribution loss. It is reported that transmission and distribution losses amount to about 7 percent of whole electricity generation in US. As a consequence, in this project corrected electricity cost generated from PV is actual cost multiplied with 0.93. However, if electricity price in the early morning during 1am to 6am is lower than corrected electricity cost from PV, BESS would charge from power grid. This is how BESS choose the charging power when the function to run is peak shaving or firming.

When arbitrage is chosen, when to charge and discharge BESS becomes an important aspect. The charging time will not be limited to one period. Usually BESS will switch among charging and discharging according to electricity price variation. It just seems like stock trading in the market. Charging seems like to buy electricity from market, and discharging seems like to sell it back to grid. Shifting algorithm will automatically calculate when to charge, and the charging amount for any function.

According to load prediction and shifting algorithm flow chart, the system will make day-ahead schedule, which includes when to start discharging, when to start charging, the charging and discharging rate setting, and when to stop.

The prioritization of the following three main functions by default are: peak shaving, arbitrage and firming. There are seven other specific functions which are derived from these three functions and serve different purposes. Ranked by priority, these ten functions are:

- Emergency peak shaving

  Peak load on the feeder is greater than a certain threshold, the battery will stop any other ongoing functions, and provide full power to system in order to reduce the exceptional high peak.

- High value arbitrage

  When the real time electricity price is greater than a certain value, the battery will stop any other ongoing functions, and sell all of the energy back to system in order to have benefit from arbitrage.

- Peak shaving

  The peak load of next day will be predicted one day ahead based on the weather prediction. The start and stop time of peak shaving is calculated also based on the weather prediction.

- Arbitrage

  According to the PV production prediction and price forecast, the battery will schedule when to store power, and will provide power when the price per unit falls into the scheduled range.

- Firming

  Providing a firm resource has a lot of value for the utility operations responsible for determining generation resource allocation. Based on the need for a defined magnitude and duration, a rectangle was defined for that dispatch. In this function, the smoothing battery should also compensate for fluctuation of the PV production to improve the firmed PV dispatch during firming periods.

- Weekday daytime charging(Charge due to SoC)

  Once the SoC (state of charge) falls below a defined value, the function of weekday daytime charging will override other functions and start to keep battery charge within its defined limits.

- Weekday night charging due to weather

  This function attempts to predict PV production. If PV is not likely to be able to produce enough power the next day to charge the battery fully due to projected cloud cover, the battery will be charged during the night from grid electricity.

- Weekday night charging due to price

  This function monitors the electricity prices. If the price is lower than a given value, the battery will begin charging immediately instead of charging from PV.

- Weekday charging from PV

  This function monitors the PV generation, and then charge battery in the morning with PV generation.

- Weekend mode

  During the weekend, the battery will only maintain SoC in the safe range, and will not perform other functions except during emergency condition.

Besides three main functions (peak shaving, arbitrage and firming), the other six functions could be classified into two groups: exception case and charging case. The first two functions (emergency peak shaving and high value arbitrage) are in the first group. They operate when peak load or electricity price are exceptional high. These two functions could override any other ongoing functions once the condition is satisfied. In the second group, there are five types of charging functions. Weekday daytime charging is used to charge battery to maintain SoC above the low threshold during weekday. The three functions(weekday night charging due to weather; weekday night charging due to price; weekday charging from PV) are responsible to fully charge battery before any one of three main functions starts to operate. Basically battery could be charged from two power sources: PV or power grid. We prefers to charge BESS from PV. However, if PV output couldn't fully charge battery, battery will charge during night. This is called weekday night charging due to weather. If the electricity price during night is very low, BESS will charge during night instead of charging from PV. This function is called weekday night charging due to price. The charging method is selected each day by running pre-calculation. Only one method will be selected among the three methods. Day-ahead schedule will include choosing the right charging function. The last function is weekend mode. This mode is used for weekend.

4.4.2 Unify units

The unit of each function is different, for instance, the unit of peak shaving is MW; the unit of arbitrage is dollar value; the unit of firming is kWh. It is fundamental to transfer entire units into uniform unit in order to compare one benefit with another. In same unit, finally the optimal solution from those three functions can be chosen. For the simplicity of calculation, monetary value(for example, dollar) is chosen as the final unit for all of the functions. All non-dollar units will be converted into dollar value. Our method is to first convert unit of peak shaving from MW into MWh, which means to consider how much energy the peaking generator provide instead of how much MW of load is shaved during time of peak load. Then the energy is converted into dollars by using gas price. For the function of firming, the unit is kWh. We also convert the energy into dollar value according to gas price.

The general idea is to calculate how much energy is provided for each function, and convert the energy into dollar value. Finally the dollar value is easy to be compared.

This method is very easy to implement. The drawback is that the benefit of peak shaving and firming is not completely considered. For peak shaving, same amount of the shaved energy doesn't mean to have same effect to power system. When shaved energy is same, shaving more peak load will be better since it mitigates the needs for peaking generator. How to better convert peak shaving and firming into same unit will become our future work.

Transfer the unit of peak shaving into dollar

During peak load period, peaking generators are used to support the rapid increase of power consumption. The peaking generator cost of providing same output as BESS, will be accounted as the benefit of peak shaving. The cost of electricity generated from such generators includes two parts: the investment of peaking generators and operation cost. The investment is split into the cost for every day. The operation cost usually indicates gas cost of running generators. The overall gas consumption is integrated based on the day-ahead BESS output schedule. The seasonal average gas price is used to calculate operation cost.

Transfer the unit of firming into dollars value

Unlike peak shaving, firming is not related to peaking generators or gas price, but related to whole sale market electricity price. First, the integration of energy during firming is calculated. Secondly, the average whole sale market electricity price is used to calculate energy monetary value.

4.5 Optimization for Grid-tied mode

After transferring all of units into dollar, the three functions are as represented as F_1; F_2; F_3; $F_1 = Peakshaving; F_2 = Arbitrage; F_3 = Firming$; Our goal is to calculate which function has highest value on a specific day.

By setting the value of α_i, operators can manually make one function to have higher priority than others. How to set the value of α_i is a topic worthy of careful consideration. Currently α_1 is assumed to be higher than others, and other α_i is equal since peak shaving is the main goal of BESS. The optimization function is as follows:

$$F_i = \alpha_i c_i f_i(x) \tag{4.1}$$

$$\alpha_1 = 1.2; \alpha_2 = 1; \alpha_3 = 1;$$

where, α_i is the weight factor which determines which of the function has high priority. α_i is the weight factor for each function. c_i is the coefficient which is used to transfer the unit of each function into dollar value. This optimization is to be performed daily or even hourly and it could be used as battery output reference value by the utility.

Once the F_1, F_2, F_3 are calculated, only the function with highest benefit value will be chosen to perform on that day. Other two main functions won't perform for any time of that day. For instance, if peak shaving is chosen, firming and arbitrage won't be performed. The reason is that any one of those three functions can consume the whole capacity of BESS.

4.5.1 Peak shaving

According to day-ahead load prediction, peak load is found for the next day. The peak shaving threshold would be tentatively set as predicted peak load minus 250kW since BESS can supply 250kW at most. By integrating energy above the threshold from the day-ahead load prediction, the energy needed during peak load time is calculated. BESS has 1 MWh as its rated energy limit. If the energy required is beyond this value, the threshold needs to have corresponding adjustment. The optimization function is as follows.

$$F_1 = \alpha_1 c_1 f_1(x) = \alpha_1 c_1 A_1 X$$

$$-1000 \leq A_1 X \leq 1000 \tag{4.2}$$

$$-250 \leq X \leq 250 \tag{4.3}$$

A_1=

$$\begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ 1 & 1 & 0 & \cdots & 0 \\ 1 & 1 & 1 & \ddots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ 1 & 1 & 1 & \cdots & 1 \end{bmatrix} \tag{4.4}$$

A_1 is a vector in R^{1440}. 1440 means there are 1440 minutes on each day. c_1A_1X represents integration of monetary value of peak shaving for every minute. In order to get the accurate result, the resolution of optimization solution is one minute.

The optimization is constrained by the two conditions: the power boundary and the capacity boundary. The two constrained conditions are represented as equation 4.2 and equation 4.3. A_1X stands for the accumulated energy consumption. In equation 4.3, the maximum discharge rate and charge rate of battery are +/-250kW. Because this optimization is used for day ahead planning, the ramping rate of each resource is not taken into account. The ramping rate will be considered in hour-ahead MPC. The benefit of peak shaving will be monetized into dollar value as described in previous subsection .

4.5.2 Firming

Usually BESS is used as a separate storage device to provide power during peak load by using a load forecast and price forecast [38] [39] [40]. However, firming focuses on how to dispatch PV power combined with the BESS. This implies that the sum of power provided by BESS and PV output will be optimized. Firming is the ability to guarantee constant power output to the electricity market during a certain period of time [19]. In the summer, the peak load time is from 2pm to 6pm. PV also produces a large amount of power during this time. By using the PV and BESS together, multiple benefits can be quantified for the feeder and substation transformer during the peak load times. In the winter, peak load time is from 5pm to 9pm. BESS will store energy before 5pm, and deliver power from 5pm to 9pm.

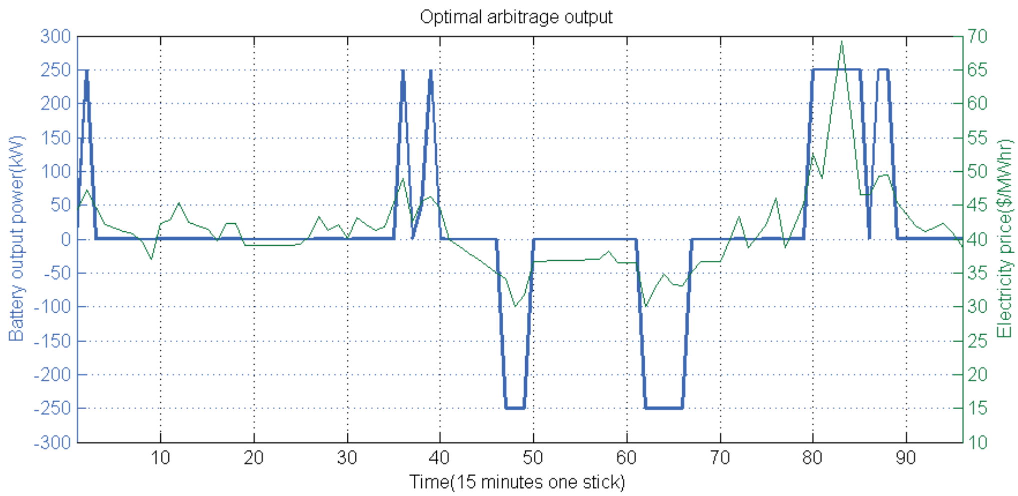

Figure 4.4: Arbitrage output

4.5.3 Arbitrage

Arbitrage is to take advantage of price difference to make profit. Electricity price will vary every day when flexible pricing policy takes effect. Flexible pricing allows electricity customers to choose to pay different rates for electricity during different times of the day. Most of the time price variation coincides with the load changes. For arbitrage the most important thing is to find the highest and lowest price for the day, then according to the difference to decide whether or not the arbitrage will be beneficial for the day.

Arbitrage is to use the energy storage to move the energy from low-price periods to high-price period in order to gain the margin. The price differential between on-peak and off-peak operation is the factor on which the battery controller plans charging or discharging. Besides earning the price difference, using the battery has the following additional benefits:

- Defer the investment of utility;

If the maximum load rarely appears for some distribution load, or the peak load only stay for a short time of a whole day, the installation of battery would defer the transmission and distribution upgrade cost. The benefits range from 15,000$ $\sim$ 1,000,000$/MW. Benefits from deferral of system upgrades may be important in the decision to deploy energy storage system [41].

- Charging is also useful for the system;

  When electricity price is very low, it could mean that a large amount of wind power is coming into the system. This usually happens around midnight till early morning. Charging battery during this period is more valuable than getting lower-priced energy, which also helps to regulate the system, and to absorb the excess renewable energy. When the sun rises, the power supplied by PV increases till solar noon. During this period, the price could be low if abundant PV power flows into the power grid, the battery could regulate the extra power from PV by charging during the morning.

Estimate of BESS cost

Currently the investment of BESS is still very expensive. For this project the cost of each MWh provided by BESS (the whole BESS cost is divided by the energy that BESS could provide in its lifetime.)is above 100$. Since most of time the price difference is in the range of under 100$ through a day. That means BESS couldn't make any profit. However, if considering the other benefits of arbitrage, the cost could be lower than 100$. For the purpose of the experiment in this work, the cost of each MWh is marked down to 10$. It's a rough approximation for future BESS cost. Determining an accurate cost based on the additional benefits from BESS should be a topic worthy to discover.

Arbitrage strategy

Thus, this section focuses on the cost effectiveness of using energy storage as an arbitrage instrument to mitigate congestion-induced high electricity prices and/or to reduce potential low load conditions in cases where there is insufficient load (commonly at night) coincident with large electricity production attributable to growing RE generation capacity.

A common way to find the price difference is to acquire the time when highest price and lowest price happens. Then the time span near these two prices will be considered as the time span for charging and discharging if the price difference is big enough to make profit. The battery could sustain 4 hours charge. The time when the highest price happens will be center of these four hours time span for discharging. The same thing goes for the time span for charging.

This method is simple, but not reliable. Firstly, the time span where the lowest price falls is not necessary the right charging span. The price may be high in the time span except the lowest price. Secondly, the predicted price doesn't align with the real time price. The scheduled charging span maybe is totally off the true charging time span.

Due to these two reasons, a method is proposed to do arbitrage. First, according to linear programming, the possible charging span and discharging span is calculated. The time span isn't four hours since the price changes more often than hourly. The minimum charging or discharging time is 15 minutes instead of hours which guarantees the price trend could be caught. After the optimal charging and discharging schedule is determined, another problem would arise. In reality, the real price could deviate from the day ahead predicted price greatly. In order to solve this problem, the relation between price and optimal battery behaviour is obtained to make a schedule based on price instead of on time. Hence the scheduled battery behaviour will rely on the price threshold, not a time schedule.

By setting the optimization function and constraints properly, the two price boundaries are determined. The lower price boundary is for charging the battery. The higher price boundary is for discharging battery. The gaps of these two boundaries are the battery cost. In this paper, $10 is used as the battery cost for the energy of per MWh. The following diagram shows the day-ahead charging and discharging schedule. In real time, the two price boundaries will be used to determine when to charge or discharge, which are $35 and $45 for this case.

In order to catch the descendent trend of the price, the discharging rate will decrease along with decline of price. To keep battery from tracking small ripples, the battery will only respond to the price drops greater than $5. Similar to the charging process, the battery will respond to any price increase greater than $5.

4.5.4 Day ahead planning

Day-ahead planning is a multi-objective optimization problem. By means of all of predictions, the day-ahead planning tries to find the optimal solution for power dispatch of BESS and other distributed energy generators for the next day.

The shifting battery of BESS normally operates at a SoC less than 100% of charge, and is operated within upper and lower limits set by the BESS Controller. The difference between these two SoC limits is the "Useable Energy". Only the useable energy can be used for shifting applications.

The goal of day-ahead planning is to identify the thresholds for main functions (peak shaving, firming, arbitrage), then BESS will have a combination of start/stop times for both charging and discharging of the shifting battery, along with the optimal charge/discharge rates for a given feeder configuration.

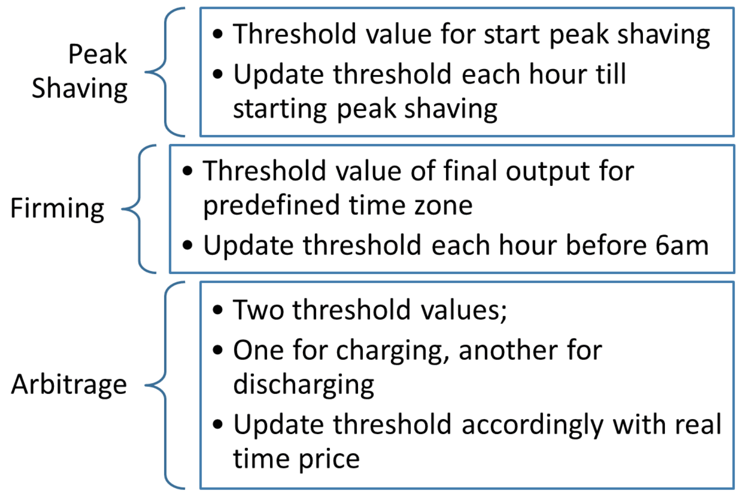

Figure 4.5: Shifting configuration for day-ahead planning

Generally the threshold needs to be calculated for each main function. In some papers the day ahead schedule is created for each timeslot of next whole day according to prediction. However, the prediction can't be prefect as the real data. The error will substantially influence the calculated optimal output especially when the prediction deviates from actual data by a high percentage. The effectiveness of optimal result could be weakened for the case. In order to reduce the dependence on weather or load predictions, a new method is proposed. Instead of making a schedule minute by minute, the threshold will be calculated to open or stop a function. For example, for arbitrage, when price rises to the discharging threshold, BESS will start to discharge. On the contrary, when price decreases below the discharge threshold, the function will stop discharging.

For each main function, the threshold to be calculated is different. For the function of peak shaving, the threshold is a load value. When the load is beyond this threshold, BESS will start to discharge to shave the peak load. The charging value is equal to the difference between real time load and load threshold. On the contrary, when load is below the threshold, BESS will stop charging to power grids. The load

% CC	% Correction factor
0-20	90
20-40	85
40-60	75
60-80	75
80-100	80

Table 4.1: Correction factor for days experiencing stated percent of cloud cover

may cross the threshold several times a day. BESS will switch between charging and discharging back and forth. The purpose is to shave all of load above the threshold.

If firming is chosen, the threshold for the final output is calculated. This output is the sum of PV generation and BESS output. During the time of firming, BESS will output with PV to make total output equal to the threshold. When to charge or discharge, and charging or discharging rate are decided by the threshold and real time PV generation. WSM would be informed of the threshold every morning before 6am. Hence the firmed power could be made into energy dispatch schedule.

PV generation forecast is used for threshold computation. The prediction couldn't exactly follow actual value. According to Greenwood's work [22], RMSE (root-mean-square error) will increase along with the increase of cloudy cover. For example, the monthly RMSE for 80-100% of clear day insolation is 0.6449 kWh/mm, which is around 8.6% of daily PV production. the monthly RMSE for 0-20% of clear day insolation is 1.3224 kWh/mm, which is around 16.5% of daily PV production. Due to RMSE, predicted PV generation may be lower than the actual generation. The firming threshold is calculated based on the predicted PV generation, not actual one. Therefore, in order to guarantee there is enough power to provide during firming, 90% of calculated firming threshold will be used as the final threshold for the 80-100% clear sunny day. If it is cloudy day, the prediction error is comparatively larger. 75%-85% of calculated threshold will be used. The correction factor is based on percentage of cloud cover. In table 4.1, the correct factor is given for days experiencing stated percent of cloud cover.

As for the function of arbitrage, there are two price thresholds to control BESS charge or discharge. One is higher, and another is lower. The higher threshold controls when BESS sells energy to grid. The lower one determines when BESS starts to buy energy from grid. Both of charging rate and discharging rate are 250kW, which is the rating of shifting battery.

There are two factors which influence how BESS responds to real time price change. The first factor is the limit of ramping rate. Theoretically BESS can increase to 250kW from 0kW, or decrease to 0kW from 250kW in one second. However, fast charging or discharging will shorten battery's lifetime. 15kW/minute is set as the limit for ramping rate. It protects battery charging or discharging rate from severe changes. For every minute, the rate can only increase 15kW, or decrease 15kW. On the one hand, this method protects battery from potential damage; on the other hand, it may cause shifting battery to miss the moment when price goes very high.

4.5.5 A special day-ahead planning for firming

In the previous section, the firming time is four hours long, and the output is constant for the whole period. In this case, it is assumed that the firmed output could be constant for each hour. Hence the output value can be different for each hour. Then it becomes a multi-objective optimization problem. Reliability, economics and environment are taken into consideration. Specifically, the objectives include peak load reduction, avoided generation, arbitrage and CO_2 emission.

The peak load reduction is the most important factor. PV power production displacing peaking plant operation can have a very short attractive ROI (Return On Investment). The second factor, avoided generation, is all of the energy displaced by PV (not only during the peak load periods). Production of CO_2 also need to be minimized. The resulting avoidance of production of CO_2 is related to avoided power generation. The third factor, arbitrage means to use the battery and distributed energy generators in an economic way. Considering the high cost of the battery storage system and distributed energy generators, these resources are tend to provide power at the time when there is profit. The last factor is production of CO_2. As for firming, the system output needs to be constant within the hour. The constant value is convenient and necessary for operation personnel to dispatch electricity. However PV output in sunny day is close to a sine wave, and can't be constant during an hour. The battery will firm the PV output to make it a square shape for each hour.

These merit functions are referred as f_1, f_2, f_3 and f_4 correspondingly. f_1= feeder peak reduction; f_2=avoided generation; f_3=arbitrage; f_4=production of CO_2; X is the only variable, and it represents the power output including the battery system and other distributed energy generators, where $X \in R^{240}$. Our goal is to optimize the overall merit function:

$$F(x) = \sum_{i=1}^{4} \alpha_i c_i f_i(x) \tag{4.5}$$

where, α_i is the weight factor which determines which of the merit functions among f_1, f_2, f_3, f_4 has high priority. This optimization is to be performed daily, and could be used by the utility. Among of these four functions, the peak shaving has high priority. From 2pm to 6 pm is the time when peak load happens for summer. Usually the system output would provide most power for these 4 hours. By adjusting the value of α_i, operators can make the final output to reduce more peak load on a specific hour, or provide more energy during whole four hours.

A_1X stands for the feeder peak shaving. A_2X stands for the avoided generation. $A_3X * price$ is the monetary value of the energy from battery based on the electricity price. $A_2X * 1.341$ indicates the pounds of CO_2 which are prevented from emitting to environment due to renewable resources. A_1, A_2, A_3 are vectors in R^{240}. 240 means 240 minutes since firming time is 4 hours long. This optimization problem is constrained by two conditions: power capacity and energy capacity.

$$F(x) = \int_{t_1}^{t_2} \sum_{i=1}^{4} c_i x_i dt \tag{4.6}$$

c_i means the cost for each resource. x_i is the scheduled output for each resource. Equation 4.6 represents the function to be optimized. X is the optimal solution which makes F(x) to have maximum value. X would satisfy two constraints. One is capacity constraint, another one is power constraint. The power constraint is based on the characteristic of each resource.

$$\begin{aligned} -1000 \leq AX &\leq 1000 \\ -250 \leq X &\leq 250 \\ A_{eq}X &= B_{eq} \end{aligned} \tag{4.7}$$

Vector AX represents the accumulated battery energy consumption. The energy capacity of battery system is 1000 kWh. The higher boundary for battery energy is 1000 kWh, and the lower boundary is -1000 kWh. The number is from battery's own capacity rating. The maximum discharge or charge rate of battery are +/-250 kW. Because this optimization is used for day ahead planning, the ramping rate of each resource isn't taken into account. The energy capacity is 1 kWh, thus the battery system can output 250 kW for four hours if the battery is fully charged. In order to have a constant output value within each hour, the system power reference is the sum of minimum PV output in that hour and BESS output.

This optimization problem is the constrained linear programming problem. There is one linear inequality constraint, one lower bound and one upper bound, and one linear equality constraints for X. The interior point method is used to solve this problem. In order to get the accurate result, the optimization precision is one minute.

The three inputs are the PV generation prediction, electricity price and load prediction. The PV generation is decided by the weather conditions, accounting for cloud cover, irradiance, temperature, and wind. The four weight factors will affect the optimization result greatly. The factors will alter according to the different situations. Figure 4.6 is the firming result. It shows two firmed PV outputs when BESS gets fully charged and not get fully charged before 2pm.

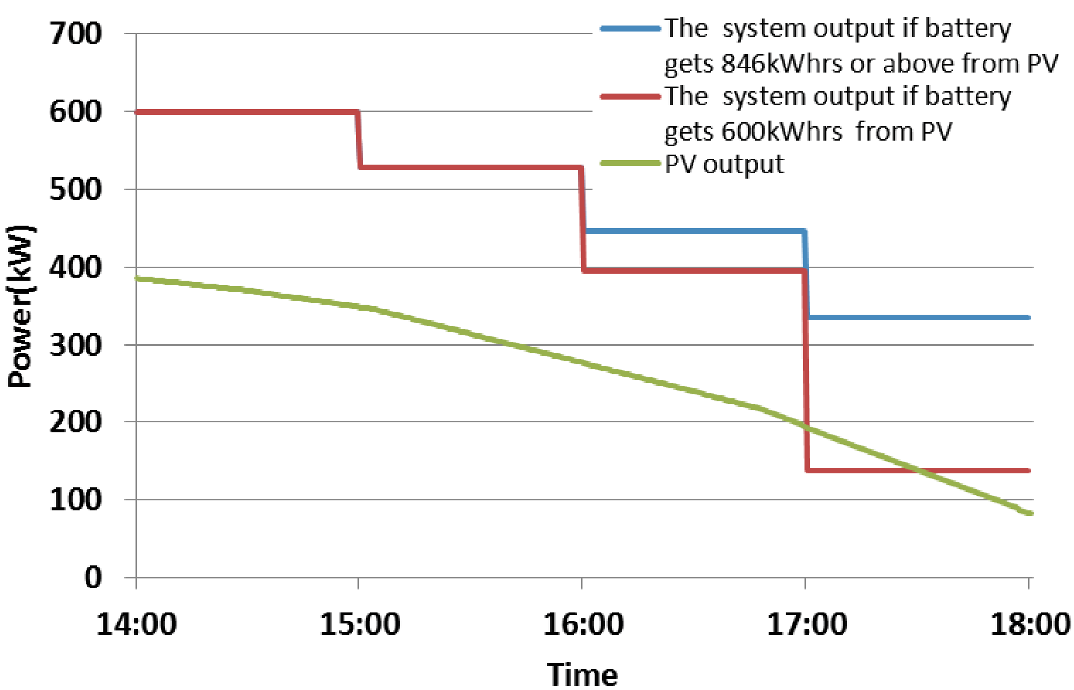

Figure 4.6: Firming result

Name	Capacity(kW)	Power Output(kW)	Maximum Ramp Rate(kW/sec)
Gas Engine	N/A	180+(-60∼60)	0.45
Fuel Cell	N/A	60+(-30∼20)	0.064
Battery	1000	-500∼500	500
PV	N/A	0∼250	$\leq$ 250

Table 4.2: Characteristics of distributed resources in Microgrid project

4.6 Optimization for islanding mode

Mesa del Sol Microgrid demonstration consists of an array of generating resources including PV, a fuel cell, and a natural gas engine. It cooperates with BESS to test the islanding mode of this Microgrid. Each distributed energy resource in Microgrid demonstration has its own characteristic. The table 4.2 lists such constraints.

In islanding mode, there is no need to consider arbitrage, peak shaving or firming since all of energy resources need to meet the demand. The goal is not to shave the peak or firm the PV. Since there is no electricity trading between the power grid and energy resources, arbitrage is not applicable. The object function will become minimizing the energy cost while maintaining power balance. For a Microgrid, various resources cooperate together. The different operation characteristic of each resource is fully considered in optimization.

Since it's important to know when to store energy in BESS in order to provide power later during peak load time, day-ahead schedule is needed.

The function to calculate the day-ahead schedule is:

$$F(x) = \int_{t_1}^{t_2} \sum_{i=1}^{3} c_i x_i dt \tag{4.8}$$

c_i means the cost for each resource. x_i is the scheduled output for each resource. The function is the whole energy cost of Microgrid. X would satisfy two constraints.

One is capacity constraint, another one is power constraint. The day ahead schedule designates power contribution from each resource to make the whole day's output optimal.

In islanding mode, one difference from grid-tied mode is no need of considering electricity price information. All of resources need to track the day ahead schedule, and minimize the energy cost of the deviation at the same time.

Model Predictive Control(MPC) The information from prediction can be used for optimization. MPC makes calculated decision every small step based on prediction. For this optimization problem, load prediction and PV generation prediction are required.

Renewable energy is used broadly currently. A major concern coming along with it is the integration of the renewable energy into power grid. A lot of research has been done is about how to integrate a single type of renewable energy into power grid. However co-optimization of different types of renewable energy to work effectively and reliably is also very important. It is highly possible that several different renewable resources exist in a same area with different operation characteristic. Even for the same type of renewable resources, the different capacity size, the output power and other parameters could be a problem to be addressed. At the same time optimization usually run under a lot of uncertainties. Under these requirements, model predictive controller (MPC) is chosen to optimize the dispatch of the renewable energy resources.

MPC is a very good optimization method for the renewable energy management in two ways: MPC involves the predictions, and adjusts the output based on the ongoing states. In this project MPC run in a Microgrid which includes a PV plant, battery energy storage system, and a gas engine. The prediction consists of load, and PV generation.

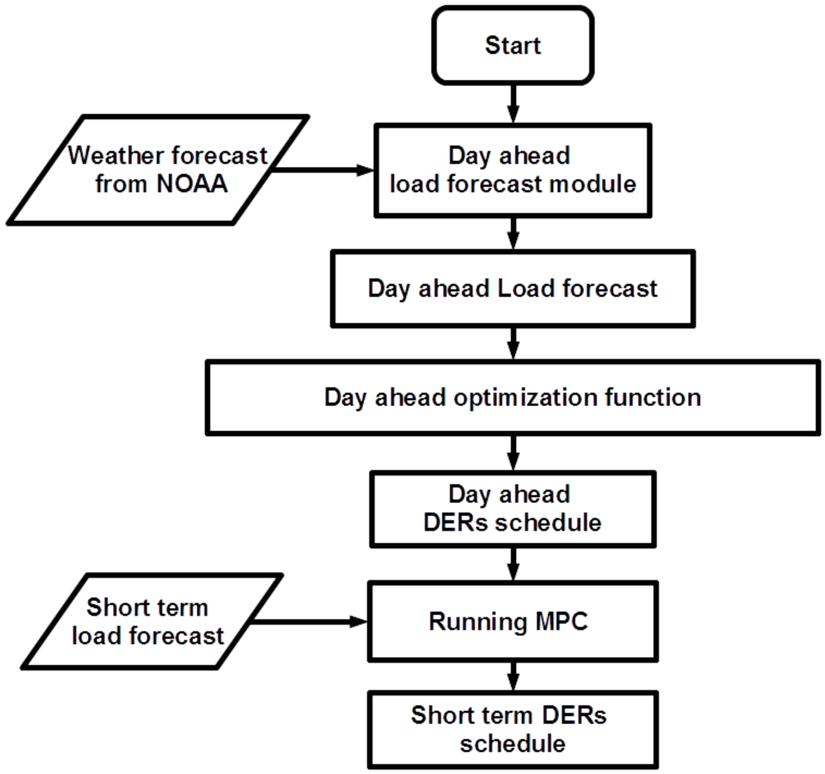

Figure 4.7: Flow chart for hourly ahead MPC

The following cost function to be minimized is proposed for this MPC optimization problem [42]:

Renewable energy have high penetration ratio in Microgrid. Hence Microgrid has ability to sustain while the accidents happen and the power is not available from the grid. The energy storage system is an essential component for Microgrid. It can be used to remove the time gap between the load and power supply. Also it can be used for emergency power usage.

Figure 4.8 shows the system diagram. The MPC first obtains the data of PV production and load forecast, and then calculates the optimal output of battery storage system, fuel engine and gas generator. Meanwhile, the state of charge (SoC) of BESS would be kept in a safe range. In this section, how to optimize different energy resources such as gas generator and fuel cell with BESS is studied.

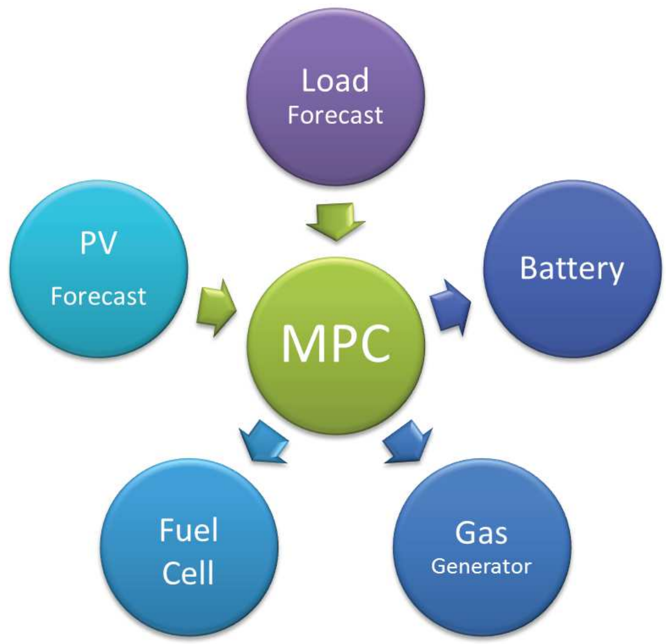

Figure 4.8: MPC system structure diagram

The characteristic of BESS is high power rating, short response time, and relatively low energy rating. The gas generator and fuel cell have the almost opposite characteristic with battery. It can provide energy continually as long as the fuel is enough, but has comparative low power rating and the longer response time. These are two typical energy resources considering the differences. The goal is to make use of advantages of these resources and make them work together efficiently. Using less energy from BESS will be an important standard to determine the efficiency of control algorithm. In this project one of the main power supplies comes from PV. The PV production varies along with the weather. PV generation forecast is covered in chapter 2.

$$J(t_k) = \int_{t_k}^{t_k+N} \sum_{i=1}^{N_{DER}} c_i(P_i)\sqrt{(P_i(t_k|t) - P_{DA})^2}dt \tag{4.9}$$

where N_{DER} is the number of controllable DERs (e.g. fuel cell, battery). N is the prediction horizon of MPC, P_{DA} is the calculated output from day-ahead optimization. $P_i(t = t_k)(i = 1; 2; 3)$ is power output of battery, gas generator and fuel cell which are variables of this optimization problem.

The objective of this control system is to make the total amount of these three variables always near the day ahead schedule while minimizing the whole cost of three resources. c_i is the energy cost for each type of resource. The term which multiplied with c_i is the square root of the squared power deviation from its day-ahead optimized value. c_i multiplying with it means the monetary value of energy deviation from the day-ahead schedule. Note that the value of each c_i is not necessarily a constant, as it may vary based on power level.

The purpose is to minimize the energy cost of deviation, and keep the energy output always track the day-ahead schedule. In Grid-tied module, the battery system tries to gain highest monetary value by doing peak shaving, firming and arbitrage. But in islanding module, since there is no connection with the grid, the battery system tries to keep the cost lowest and at same time provide enough power for the residential area.

The MPC problem at time t_k can be formulated as $minJ(t_k)$.

$$\begin{aligned} P^m_{BESS}in \leq P_{BESS}(t \mid t_k) \leq P^{max}_{BESS}; \\ P^{min}_{GE} \leq P_{GE}(t \mid t_k) \leq P^{max}_{GE}; \\ P^{min}_{FC} \leq P_{FC}(t \mid t_k) \leq P^{max}_{FC}; \end{aligned} \tag{4.10}$$

$$SoC_{BESS}^{min} \leq SoC_{BESS}(t \mid t_k) \leq SoC_{BESS}^{max}; \tag{4.11}$$

$$\begin{aligned} R_{BESS}^{min} &\leq R_{BESS}(t \mid t_k) \leq R_{BESS}^{max}; \\ R_{GE}^{min} &\leq R_{GE}(t \mid t_k) \leq R_{GE}^{max}; \\ R_{FC}^{min} &\leq R_{FC}(t \mid t_k) \leq R_{FC}^{max}; \end{aligned} \tag{4.12}$$

$$x(k+1 \mid k) = A * x(k) + B * u(k \mid k), \tag{4.13}$$

where $A = I$,

$$B = \begin{bmatrix} \frac{1}{1000*60} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix},$$

$$u = (P_{BESS}, P_{GE}, P_{FC}),$$

$$x(k+1 \mid k) = \begin{bmatrix} SoC_{BESS}(k+1 \mid k) & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

In the above optimization problem, equation 4.10-4.13 impose constraints on the trajectories of the variables.

Equation (4.10) shows the power range in which power could be provided by three energy resources separately. Equation (4.11) is about the State of Charge (SoC) of battery which should be regulated into a certain range in order to maintain a long lifetime of battery. Equation (4.12) is used to make the ramp rate of each energy resource less than the specified value. Equation (4.13) define how SoC changes with the battery output. x means SoC, and u means BESS output.

The following procedure shows how to convert a constrained MPC controller to a constrained LQR problem that provides performance equivalent to a MPC controller. The predicted state trajectory could be expressed as follows:

$$x(k+1 \mid k) = A * x(k) + B * u(k \mid k)$$

Here C is the (convolution) matrix with rows C_i defined by

$$C = \begin{bmatrix} B & 0 & \cdots & 0 \\ AB & B & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ A^{N-1}B & A^{B-2} & \cdots & B \end{bmatrix}$$

C_i=ith block row of C

With the trajectory of x prediction, the cost function evolves into the following form.

$$\begin{aligned} &\sum_{i=0}^{N-1}[x^T(k+i \mid k)Qx(k+i \mid k)] + [-I - I] * x(k+i \mid k) \\ &= u^T(k)Hu(k) + 2x^T(k)F^T u(k) + x^T(k)Gx(k) + [-I - I] * [Cu(k)+ \\ &\qquad (1 + \cdots + A^{N-1})x(k)] \end{aligned}$$

where

$$H = C^T\tilde{Q}C + \tilde{R}; F = C^T\tilde{Q}M; G = M^T\tilde{Q}M + Q;$$

with :

$$\tilde{Q} = \begin{bmatrix} Q & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & 0 & Q & 0 \\ 0 & \cdots & 0 & Q \end{bmatrix}$$

$$\tilde{R} = \begin{bmatrix} R & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & 0 & R & 0 \\ 0 & \cdots & 0 & R \end{bmatrix}$$

The matrices H, Q and R can be computed offline. Secondly, the constraints are converted. Equations (4.10) can be converted into the following.

$$\begin{bmatrix} I \\ -I \end{bmatrix} u(k) = \begin{bmatrix} P_b^{max} \\ P_g^{max} \\ -p_b^{min} \\ -P_b^{min} \end{bmatrix} \tag{4.14}$$

Equations 4.11 can be converted into the following format

$$\begin{bmatrix} C_i \\ -C_i \end{bmatrix} u(k) \leq \begin{bmatrix} SoC_b^{max} \\ SoC_g^{max} \\ -SoC_b^{min} \\ -SoC_b^{min} \end{bmatrix} \tag{4.15}$$

Equations (4.12) can be expressed as follows.

$$\begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 \end{bmatrix} u(k) \leq \begin{bmatrix} P_s^{for} - P_d^{for} \\ P_s^{for} - P_d^{for} \\ P_d^{for} - P_s^{for} \\ P_d^{for} - P_s^{for} \end{bmatrix} \tag{4.16}$$

The combination of (4.10), (4.11),and (4.12) can be expressed as constraints on $u(k)$ of the form

$$A_c u(k) \leq b_0 + B_x x(k) \tag{4.17}$$

So far, the problem is converted into quadratic programming, which is a special type of mathematical optimization problem. It optimizes a quadratic function of several variables which are subject to linear constraints [43].

`Quadprog` is a Matlab function used to solve quadratic programming. `Quadprog` function is operated to calculate the optimal power output for next hour from the current time. Since the electricity price will change along the time, the whole day schedule is updated regularly. `Quadprog` will use most updated price information and updated whole day output schedule as inputs in order to get the output for the current time.

4.7 Simulation and result

Figure 4.9 shows that PV plant and BESS work together to provide peaking energy for the feeder. The peak load is reduced evidently. Peak shaving is successfully implemented.

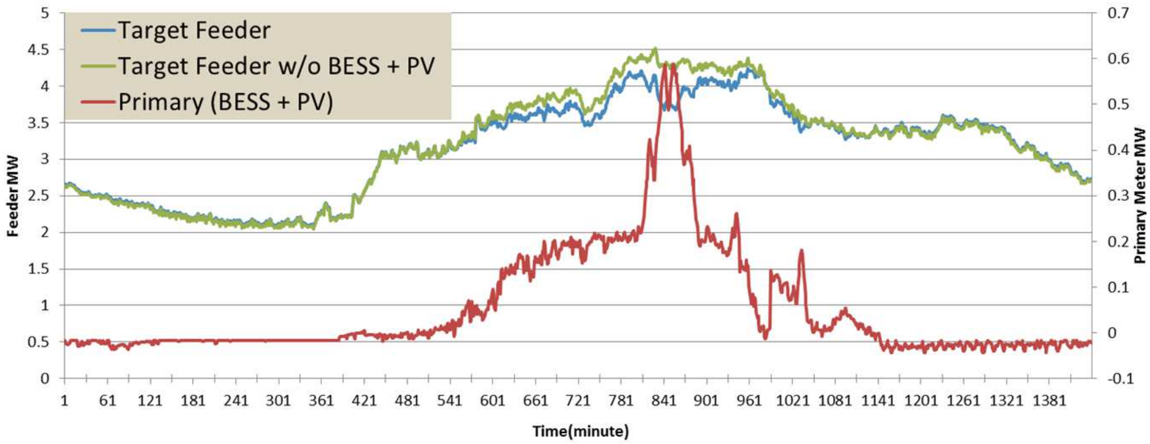

Figure 4.9: Peak shaving result at PNM prosperity

Figure 4.10 shows an example of firming. The firming starts from 2pm. The combination of PV production and BESS is square shaped. The power output value is 150kW. Before firming, BESS also performs charging due to price, emergency peak

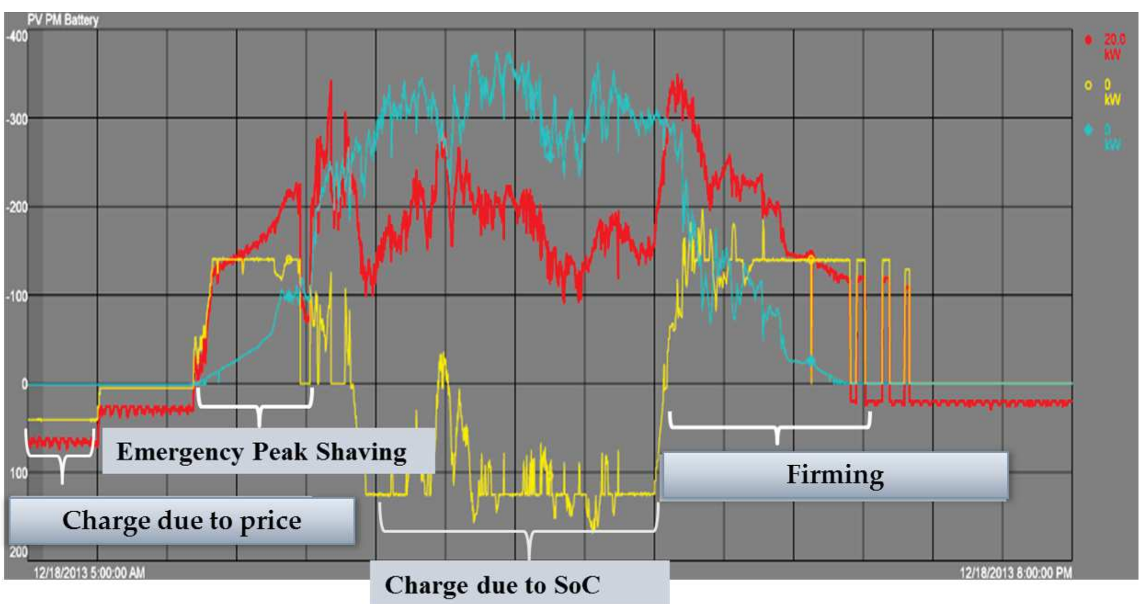

Figure 4.10: Shifting algorithm result composing multiple functions

shaving, and charging due to SoC. Multiple functions are implemented on one day according to the specific situation of that day. The maximum benefits are obtained by performing the combination of multiple functions comparing with single function.

4.8 Discussion

Utility sized BESS will play an important role for power system with high renewable energy penetration in supporting energy during peak load time, firming the PV output and doing arbitrage. The following conclusions are learned from experiments.

- The threshold for each function is calculated day ahead, and the future predictions are considered in the calculation. The prediction needed includes: electricity price, average gas price, and load forecast. Besides these predictions, the PV cost is evaluated also. The accuracy of prediction determines the quality of control strategy in a high degree.
- The function threshold should be calculated regularly to compensate changes in circumstances.
- Battery use one cycle each day in order to maintain the lifetime of battery.

4.9 Future work

Support Vector Machine (SVM) aided MPC

MPC could be affected by time-horizon and timeslot. The first term means the period over which optimization is made. MPC calculates the optimal result for a finite time-horizon, but the system is only implementing the current timeslot. Timeslot is the second term which matters for MPC.

PV generation is an important input for MPC, but it is variable. PV generation doesn't change too often for a sunny day. The ramp rate per minute could be less than 1% of the PV generation rating. However, as clouds pass by PV plant, a 2 kW system can exhibit 50% drop in just 3 seconds. 1.6 MW system still fluctuates rapidly with an observed worse case drop out of 50% in 9 seconds. During cloudy day, PV generation as one input of MPC varies greatly. Since the rapid changes can't be fully considered in MPC, the optimal result might not be optimal for a long timeslot. It would be good to implement MPC result only for a short timeslot.

Since the load and PV prediction are implemented into MPC, the accuracy level determines whether MPC result is optimal in reality.

The time-horizon should be adjusted based on the accuracy of both predictions. Usually the prediction result would be more accurate for a relatively short time horizon. For instance, the prediction accuracy of next fifteen minutes would be more accurate than the prediction accuracy of next 5 hours.

Since long time-horizon will bring more optimal result, longer time-horizon is better. Because prediction will become inaccurate along with time, shorter time-horizon is preferred. There is a trade off between accuracy and optimal result when choosing length of time-horizon. Hence, longest time horizon which satisfies a certain accuracy rate would be searched. Based on learning the pattern of the weather and load trend, the longest time-horizon which assures a certain accuracy could be recognized.

In future, SVM could be used to help MPC to find the best time-horizon and timeslots of MPC based on load and PV prediction.

Chapter 5

Smoothing algorithm

Shifting is connected to the energy efficiency, while smoothing is a reliability issue. This chapter will discuss the simultaneous smoothing by fast-response counter-action from the battery.

Due to PV output variability, it is desirable to select a smoothing algorithm that would filter out the high frequency transitions, but would still be fast enough to avoid significant lag with respect to current power production. One of the algorithms that can be used for this application is a moving average algorithm, which is commonly used with time series data to smooth out short-term fluctuations and reflect longer-term trends.

The smoothing algorithm implementation of the utility-scale smoothing battery are described including the charge and discharge rate needed to perform the smoothing, the input of the smoothing algorithm, restoration of the battery SoC, and the choice of the right window size used for the smoothing algorithm. An method is proposed to calculate the window size of smoothing algorithm according to the requirement of smoothness. SoC must be kept in a certain range for the purpose of a normal lifetime. A key issue is to provide power to smooth PV generation and at the same time leave the SoC in a desirable range. Usually the power which is used to restore the SoC will produce spikes in the smoothing output. A new method is proposed to resolve this issue. The smoothing output won't be influenced with this method.

A new smoothing algorithm has put forward as a comparison to moving average algorithm. It's called rule-based smoothing algorithm. This method greatly reduces the BESS energy usage without compromising the smoothing effect. These two algorithms are introduced in detail in the following sections.

Along with the simulation results, the real data from the installed battery energy storage system and PV system is showed. The output shows the smoothing algorithm successfully improves the smoothness of PV output. The intermittency of PV output is essentially removed, making the PV power more desirable for loading into power grids.

5.1 PV Variability

The total PV production can be split into a relatively smooth signal, which changes on the time scales of minutes to hours, and a high-frequency intermittent component, due to variable cloud cover, that has characteristic times on the order of seconds. Such high frequency changes may be difficult (or impossible) to compensate for by using current utility control devices, such as Load Tap Changers (LTCs), moreover it is beneficial to absorb such high frequency as close to the source as possible.

The power change event is called a ramp event. The rate of a ramp event is the ramp rate, which indicates the power difference of one time interval [44]. It equals to time derivative of PV generation. According to the observation of a 0.5 MegaWatt PV plant, the ramp rate per second is less than 1kW on a typical sunny day for the

500kW plant considered above, corresponding to 0.2% of PV plant rating. However for a severe cloudy day the ramp rate could be 20 % of the PV plant rating.

When ramp rate is high, BESS needs to provide large power to compensate the great changes in PV generation. On the contrary, BESS only provides less power when ramp rate is low. It is natural that BESS will supply more energy for an area with continued high ramp rate comparing with an area with low ramp rate. Therefore, the ramp rate is a very important factor to determine the parameters of smoothing algorithm and smoothing cost. Figure 5.1 shows the maximum ramp rate of PV output on each day in March 2012.

The solar variability is related to cloud type. Cloud categories can be used directly to model the expected statistical variability of ground irradiance. The results in [45] are presented that ramp rates can be grouped according to the cloud category. Since cloud classification is correlated with solar variability, it could be used to model the solar variability for a given location and time [45]. Studies show the effects of solar variability must consider the effects of aggregation over the geographical area, otherwise the result will tend to overestimate the variability [46]. Site diversity may reduce the solar variability, but may not reduce it sufficiently. According to [47], site diversity over a 280 km range does not dampen PV intermittency sufficiently to eliminate the need for smoothing. However, the costs of mitigating PV variability are dramatically reduced by geographic diversity [48].

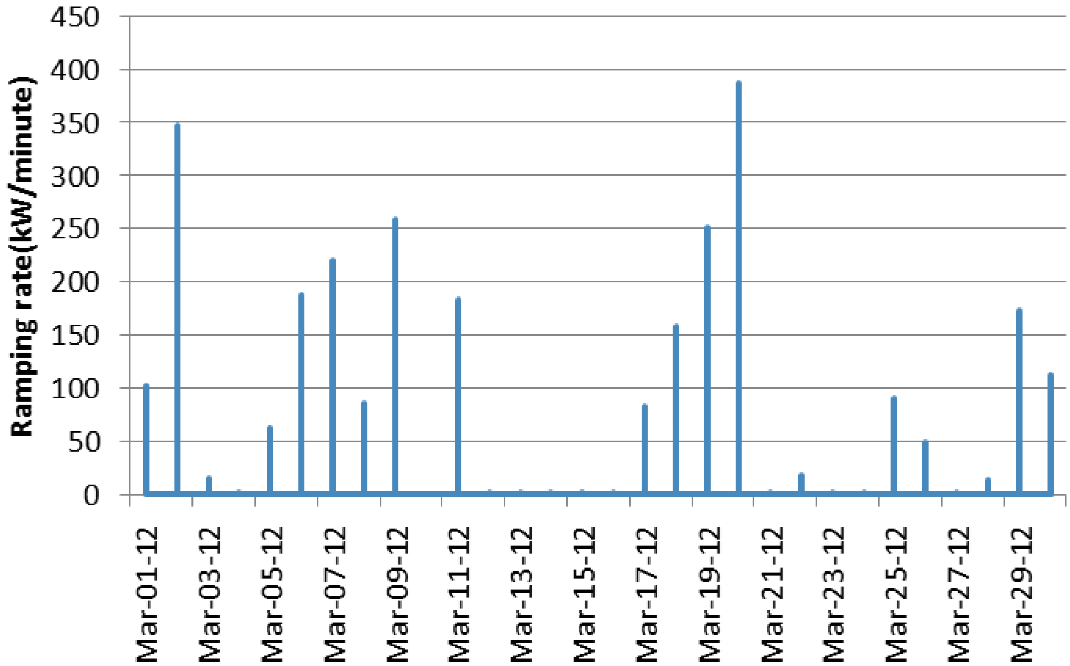

Figure 5.1: Maximum ramp rate on each day for a 0.5M PV plant in Albuquerque, in March 2012

5.2 Moving average algorithm

5.2.1 Control strategy of the smoothing battery system

Due to PV output variability, it is desirable to select a smoothing algorithm that would filter out the high frequency transitions, but would still be fast enough to avoid significant lag with respect to current power production. One of the algorithms that can be used for this application is moving average algorithm, which is commonly used with time series data to smooth out short-term fluctuations and reflect longer-term trends [26]. A new method is proposed as a comparison to moving average. It's rule-based smoothing algorithm. This method increases the smoothing efficiency greatly by reducing the BESS energy usage. These two algorithms considered here will be described in detail in the following.

The most important and also the only parameter for the moving average algorithm is the time interval over which the average is calculated, i.e. the window size. Independently of the weather pattern, a larger window size leads to a smoother battery output because more averaging data points involved will result in smoother output. A larger window size can ensure a smoother output, but produces a larger lag in the output. Therefore the window size shouldn't be too large, and it would be chosen based on the requirement of the smoothness. When moving average algorithm is used, the following aspects need to be addressed: the needed battery charge and discharge rate, the reference SoC domain, and the restoring power to maintain the SoC .

Maximum battery charge and discharge rate

The PV output ramp rate depends greatly on cloud type. For a significantly cloudy day, the PV system output could fluctuate significantly and rapidly. An important concern with the control of the BESS is the charge/discharge power, which need to be kept to meet the need of smoothing out the ramp of PV output. Applying the moving average algorithm, charge or discharge rates required from the battery are smaller than the maximum PV output. 500kW is the power rating of the smoothing battery. It is just the right size for smoothing out PV production variation from the co-located 500kW PV array.

State of charge (SoC)

SoC is another important parameter which needs to be controlled precisely within the battery manufacturers recommended settings.

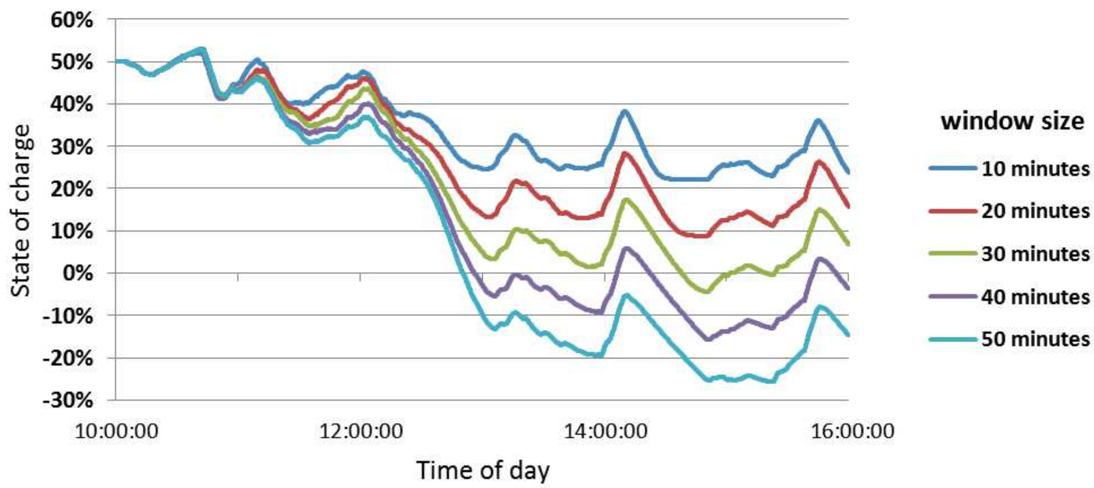

Figure 5.2: Comparison of SoC for 5 different moving average window sizes

In this project, the battery performance is based upon maintaining SoC within a range while maintaining an average SoC over an hour equal to 50%. According to this constraint, SoC needs to be maintained between established lower and upper limits of the rating 250 kWh. Figure 5.2 shows that SoC varies with the window size proportionally without setting the limit to the SoC. The SoC is even lower than 0% in the figure. To keep SoC from exceeding the limit, a restoring power is needed for smoothing algorithm.

Restoring power

Restoring power is the additional power which is used to restore SoC to the nominal SoC. In the beginning, it is chosen to be proportional to the difference between SoC at the moment and 50 % (the nominal SoC) [49]. Since the battery switches between charge state and discharge state very fast in order to smooth the spikes, SoC also changes accordingly. The required restoring power changes dynamically along with the change of SoC. Consequentially there are a lot of smaller spikes within restoring power. The value of smoothing power and the value of restoring power are added together directly as an command value of the battery output. The smoothing power will smooth the PV, but the spikes of restoring power will reduce the smoothness of output which of course is undesirable. In this work, a method is developed to resolve this issue. Through this method, the restoring power won't affect the smoothness of final output. The detail is as follows.

First, the desired restoring power is calculated based on the SoC difference. For instance, if the current SoC is 40% and the reference SoC is 50 %, the SoC difference is calculated as $40\% - 50\% = -10\%$. After calculating the SoC difference, next step is to set restoring power based on the difference.

$$Power_{restoring} = a * 250 * \Delta SoC; \tag{5.1}$$

In equation (5.1), 250 represent 250kWh, which is the capacity of the smoothing battery. ΔSoC is the SoC difference. $250 * \Delta SoC$ is the required energy which can restore SoC to 50%. The restoring power would be a certain multiple of the required energy. The bigger the factor is, the faster the SoC goes back to the nominal value. Here, this factor is denoted as a. It represents the ratio of the restoring power to required energy. When a is set to 1, it means the restoring power can restore SoC in one hour if the battery won't have any other charge or discharge activities. However the SoC of battery changes dynamically since the battery performs its smoothing function at the same time. In order to make the average of SoC close to 50% in one hour, a number larger than 1 needs to be chosen. Different values of a are tried , and $a = 5$ is best for this case. If a is too high, it may lead to oscillation of the SoC. If a is too low, it may not offset the difference in a timely fashion. How this factor is set for different weather conditions is an important topic.

Secondly, the moving average algorithm is used to smooth the spikes of restoring power. Adding smoothed restoring power to the calculated smoothing power won't

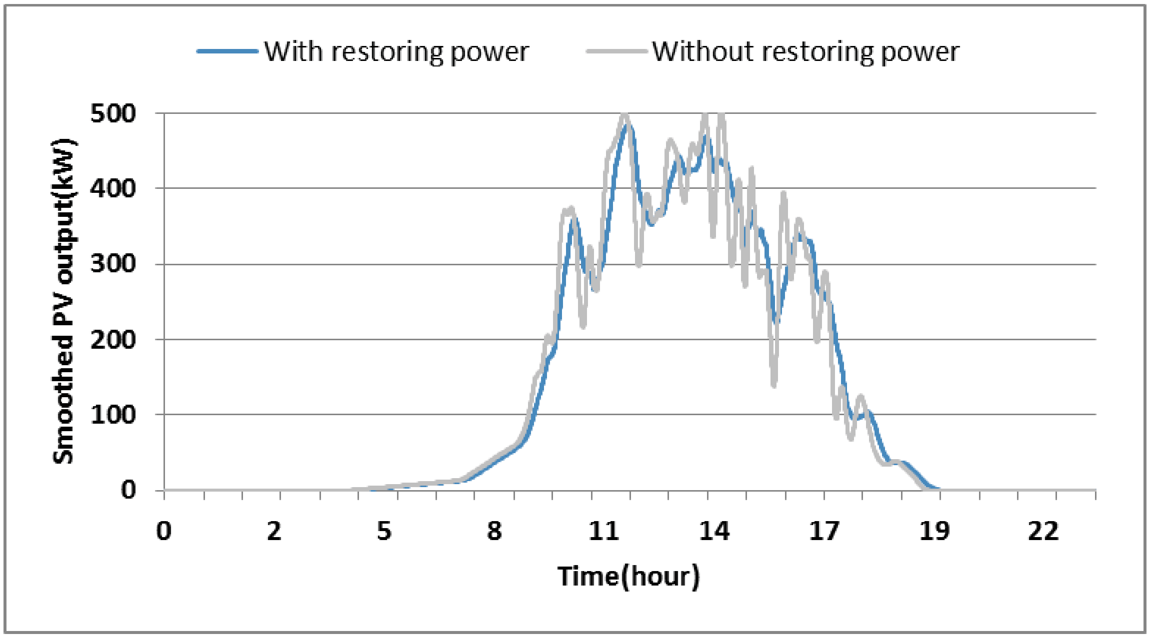

Figure 5.3: Output comparison of the smoothed PV outputs with restoring power and without restoring power

affect the smoothness of the output. The results are even smoother than without restoring power, and the SoC of battery using restoring power is much closer to the nominal value. In figure 5.3 and figure 5.4, SoC change around the nominal value and the PV output has fewer fluctuations. In summary, the restoring power can help restore SoC of battery, and increase the smoothness of PV output at the same time. Figure 5.4 also shows the decreased variation range of SoC of the smoothed PV output.

Power reference input for the smoothing algorithm

There are 5 irradiance sensors located at the four corners and one center of the PV array. The variability of irradiance observed by a point generally does not directly correspond to the variability of PV output, since the irradiance measured with sensors

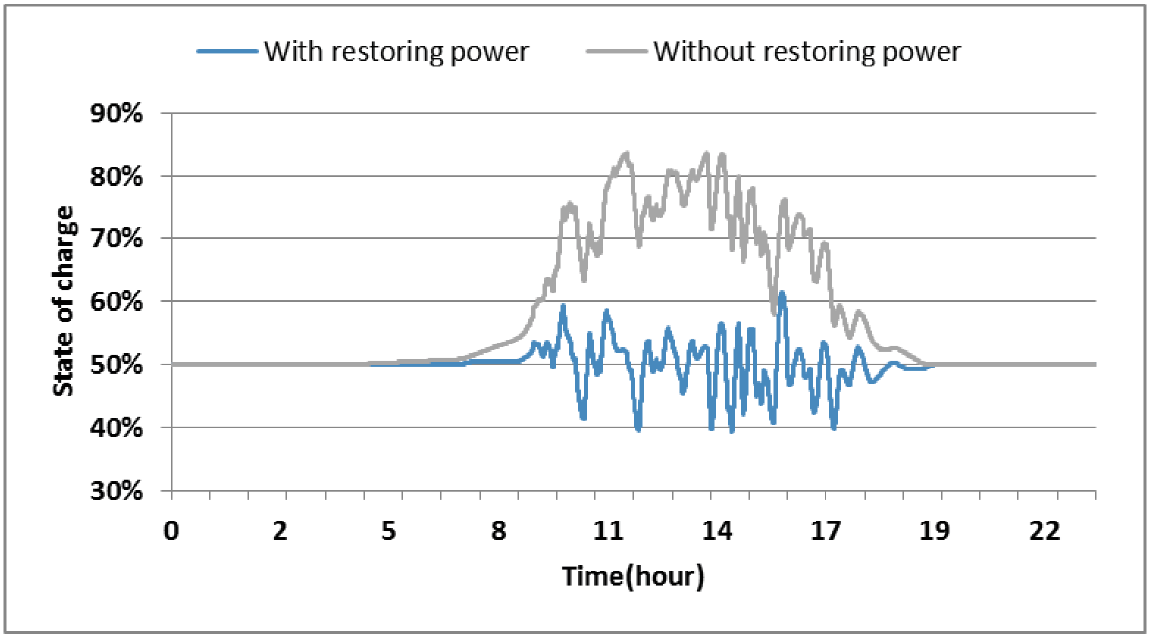

Figure 5.4: SoC comparison of the smoothed PV outputs with restoring power and without restoring power

fluctuates much more than that of the entire PV array. Figure 5.5 compares the measured PV output with the calculated PV output based on the irradiance from one sensor. Here, it is assumed there is a linear relationship between irradiance and PV output.

In [50], the author finds that large 1-s, 10-s, and 1-min ramps in the multi-megawatt PV plant are approximately 60%, 40%, and $\geq$ 10% less severe, respectively, than those observed at a point. Hence PV plant output is smoother than the irradiance in every single point for a cloudy day.

In addition, PV output is influenced by the temperature, wind, inverter rating, maximum power point tracking and other factors. It's not a linear relationship between PV output and irradiance. It's difficult to get the accurate PV output from the irradiance. The PV plant output will be the optimal input for the smoothing

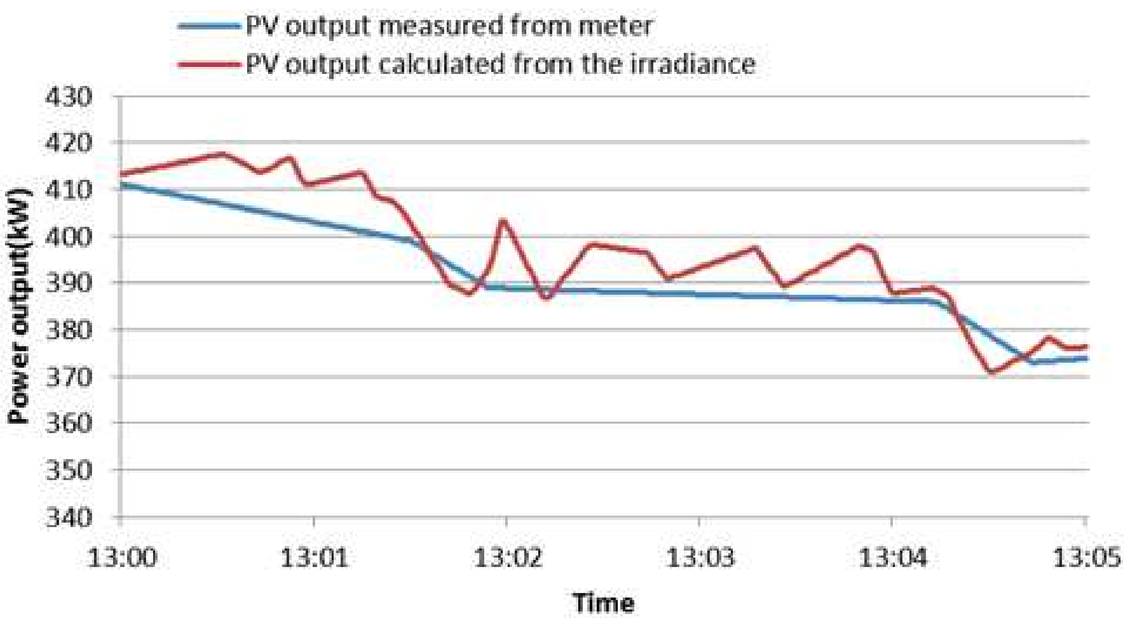

Figure 5.5: Comparison of measured PV output and calculated PV output based on irradiance at one point

algorithm.

Choosing the window size

There is a trade off between the smoothness of smoothed PV output and battery lifetime. From the simulation, the lag between the original PV and smoothed PV is close to half of the window size. A larger window size leads to smoother result, but also means a larger lag. A larger lag indicates battery should provide more energy to mitigate the gap between the original PV and smoothing goal. Hence, a large lag will cause greater change of SoC. Consequently, it causes larger battery energy consumption. The battery lifetime is determined by the cumulative energy used. As a consequence, a larger window leads to the shorter lifetime. Therefore, choosing an appropriate window size is critical for implementing a successful smoothing algorithm.

In order to get the minimal lag, window size needs to be selected depending on weather conditions. If a day is sunny, without any cloud cover, it may not be necessary to use the battery smoothing system at all. However, for a cloudy day, the window size would be chosen based on the requirements of smoothness and the severity of the cloud cover, which can be represented by the amount of ramp rate. Ramp rate is the difference between two consecutive values for a certain sampling rate. According to the definition of moving average, the following equations can be derived:

$$\begin{aligned} O_t &= \tfrac{P_{t-1}+P_{t-2}+\cdots+P_{t-N}}{N} \\ O_{t-1} &= \tfrac{P_{t-2}+P_{t-2}+\cdots+Pt-N-1}{N} \end{aligned} \tag{5.2}$$

Here O_t is current power reference output. It is equal to the mean of N previous data. N is the window size, also represents the seconds over which the PV data point is summed. Here, the sampling rate is assumed to be one sample obtained in one second. As the time moves forward, a new value comes into the sum and an old value drops out. The following formula is used to calculate the ramp rate.

$$\begin{aligned} O_t - O_{t-1} &= \tfrac{P_{t-1}}{N} - \tfrac{P_{t-N}}{N} \\ R = O_t - O_{t-1} &= \tfrac{P_{t-1}-P_{t-N}}{N} \\ \text{since } P_{t-1} - P_{t-N} &< P_R, \\ R &< \tfrac{P_R}{N} kW \end{aligned} \tag{5.3}$$

where, P_R means PV power rating; R means ramp rate of smoothed PV. For this project, 500kW is the PV plant rating. So under any weather conditions, the ramp rate is smaller than 1kW/sec when N is above 500. According to 1kW/sec, the ramp rate per minute will be less than 60kW/min. For any weather condition, if the ramp rate of PV output is already lower than the required value, the moving average algorithm needn't to be applied since it will cause the unnecessary lag. A dead band could be set before implementing the algorithm, and the algorithm would turn on or off dynamically according to the PV output.

Battery capacity needed

Figure 5.6: System transfer function

This section shows that how SoC variation range is derived from PV output. Later the SoC variation range is used to estimate optimal battery capacity. Due to implementation of the restoring power, the SoC range of the battery can be controlled. Hence the smoothing battery capacity needed can be relatively small.

Using moving average, smoothing power are calculated based on PV output. By comparing current SoC and SoC reference, restoring power is calculated. Smoothing power and restoring power are added together as battery output, which affects SoC variation. This whole process can be viewed as a system function. PV output is the input for the system function, and SoC is output. According to PV output and system function, daily SoC variation could be calculated. The maximum variation could be chosen as the battery capacity. The calculation of capacity is carried out in frequency domain. The PV output spectrum for a given area is used.

SoC variation comes from cloud cover variation in a certain degree. Restoring power is related to SoC variation. Hence, the restoring reflects the cloud variation in a certain degree. In order to best compensate the SoC change due to cloud cover variation, a PID controller is designed here to calculate the proper value of the restoring power.

According to the criteria of ISTES (Integral of Squared Time Multiplied by Squared Error), the parameters are presented in [51]:

$$G_{PID} = K_p(1 + \frac{1}{T_i s} + T_d s) \tag{5.4}$$

The optimal parameters of PID controller are set as: k_p=1.34/KL; T_i=1.83L; T_d=0.49L [51]. The SoC could be viewed as an integrator of battery output P_{batt}.

$$SoC = \frac{1}{250 * 3600} \int_0^T P_{batt} dt + 50\% \tag{5.5}$$

In the equation above, P_{Batt} is the battery power output value. When it is divided by 3600, the result should represent the change of SoC every second. The energy rating of the battery is 250 kWh, so the integration of battery output divided by 250 reflects the SoC changes in the format of percent. 50% represents the initial value of SoC.

The SoC mathematical description after Laplace transform is:

$$\begin{aligned} &G_{SoC}(s) = \tfrac{Ke^{-Ls}}{s}; \\ &K = \tfrac{1}{3600*1000}; \end{aligned} \tag{5.6}$$

Equation (5.6) refers to a integrator plus dead time model.

The whole PID control diagram is showed in figure 5.7. $G_{PI}$is Laplace transform of PI controller. G_{SoC} is integrator which is used to calculate the battery SoC. H

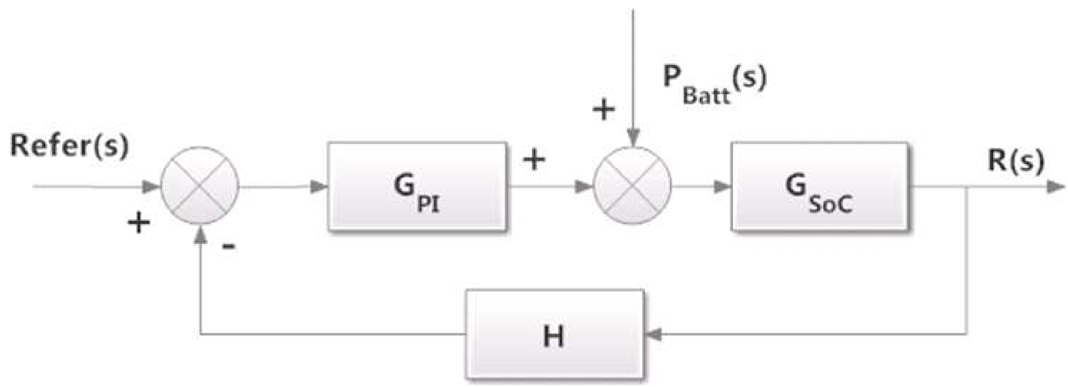

Figure 5.7: PID controller diagram

is the feedback control, and it is 1 in this project. Refer(s) is the reference value of SoC, and the value is 0.5. R(s) is final SoC. The difference between SoC and its reference value (R(s) and Refer(s)) is PI controller input. The output of G_{PI} is restoring power. It's added together with P_{Batt} (smoothing power) to influence the final battery SoC.

As mentioned before, the moving average is chosen to filter the PV output. Based on the raw data of PV production, the moving average will calculate a smoothed baseline which is close to the PV production, but without high frequency spikes. The battery will provide the difference between these two values.

$$P_{Batt} = Power_{refer} - PV = MA(PV) - PV \tag{5.7}$$

The whole PID system response relationship is as follows:

$$\begin{aligned}\frac{R(s)}{Refer(s)} &= \frac{G_{PID}G_{SoC}}{1+G_{PID}G_{SoC}};\\ \frac{R(s)}{P_{Batt}s} &= \frac{G_{SoC}}{1+G_{PID}G_{SoC}};\\ \text{So } R(s) &= \frac{G_{PID}G_{SoC}}{1+G_{PID}G_{SoC}}Refer(s) + \frac{G_{SoC}}{1+G_{PID}G_{SoC}}P_{Batt}(s)\end{aligned} \tag{5.8}$$

where, Refer(s) can be represented with a step function with the output of 50 %.

$$\begin{aligned}Refer(s) &= 0.5\\ P_{Batt}(s) &= (MA-1)*PV = G_MA*PV;\\ R(s) &= \frac{G_{PID}G_{SoC}}{1+G_{PID}G_{SoC}}Refer(s) + G_SG_{MA}P_{Batt}(s);\\ \text{where, } G_S &= \frac{G_{SoC}}{1+G_{PID}G_{SoC}}; G_{MA} = MA-1;\end{aligned} \tag{5.9}$$

Figure5.8-figure5.10 show the Fourier transform of three transfer functions: G_{MA}, G_{PID}, and $G_{MA}G_{PID}$.

Figure 5.11 shows the spectrum of PV output for February. The data precision is 1Hz. The highest frequency in this plot is 1Hz. It's easily observed that the energy of PV is mainly concentrated in the frequency of range from 10^{-3} to 10^{-5}. For this frequency range, the energy is relatively constant, and the energy variation range is less than the variation range for the frequency higher than 10^{-3}. This means the energy variation usually happens in the frequency range of seconds to around 20 minutes.

Figure 5.12 is the spectrum of PV output for a whole month. Similar to the previous plot, the spectrum reflects fluctuations for the high frequency part. For the low frequency part, the spectrum of this range for 28 days is very close to each other. The black line in the plot is the PV spectrum boundary. The spectrum of PV output should be bounded in a certain area considering the limited PV output capacity and limited solar irradiance. The boundary may vary along the different months, but it

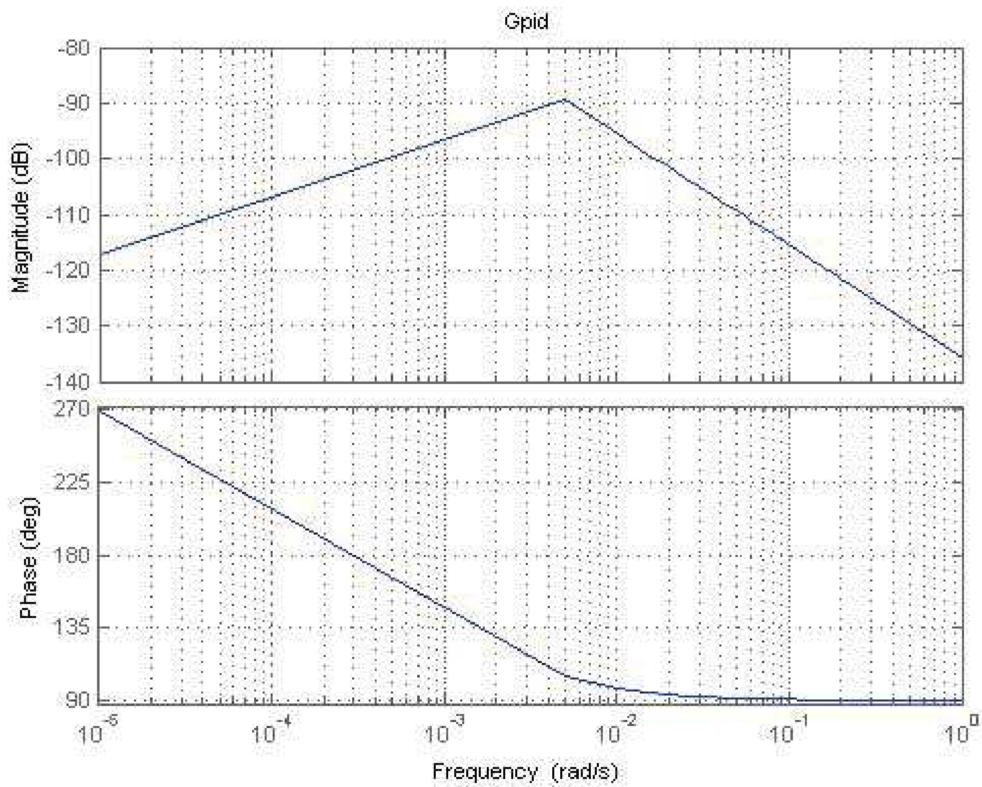

Figure 5.8: Fourier transform of G_{PID}

is a limited value. These boundaries could represent PV output characteristic of a given area. The long term statistic data will be more representative.

Once SoC variation is calculated using monthly PV spectrum and system transfer function , the variation range could be viewed as the minimal capacity value for the given area. The yearlong PV output spectrums will be used in future to estimate SoC variation.

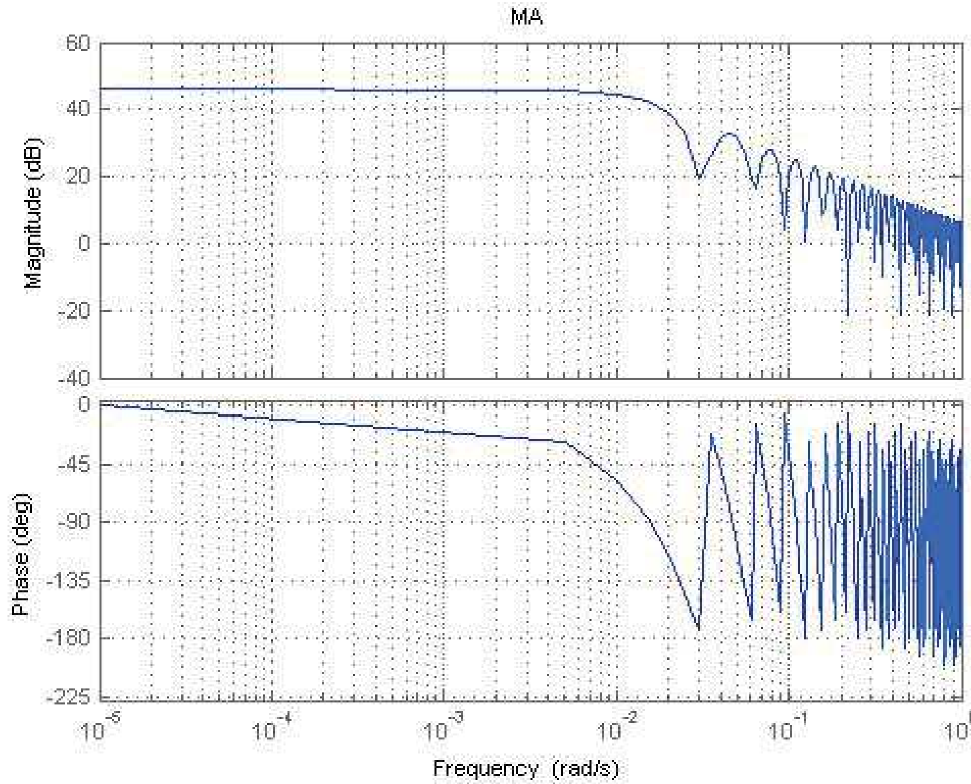

Figure 5.9: Fourier transform of G_{MA}

5.2.2 Self-adjusted smoothing algorithm

Based on existing weather conditions, the smoothing algorithm may turn on and off, and the window size can be adjusted. For stable PV output (sunny day, no severe cloud intermittency), if the ramp rate of the PV system is already lower that required safe value, smoothing is not needed, and could be turned off. On the other hand, for cloudy weather, the smoothing window needs to be selected depending on the requirements for smoothness and PV output ramp rates. Equation (5.11) is used to calculate the minimum window size when PV rating and real time ramp rate are known. It is developed according to equation (5.3). In the equation (5.11), N is the

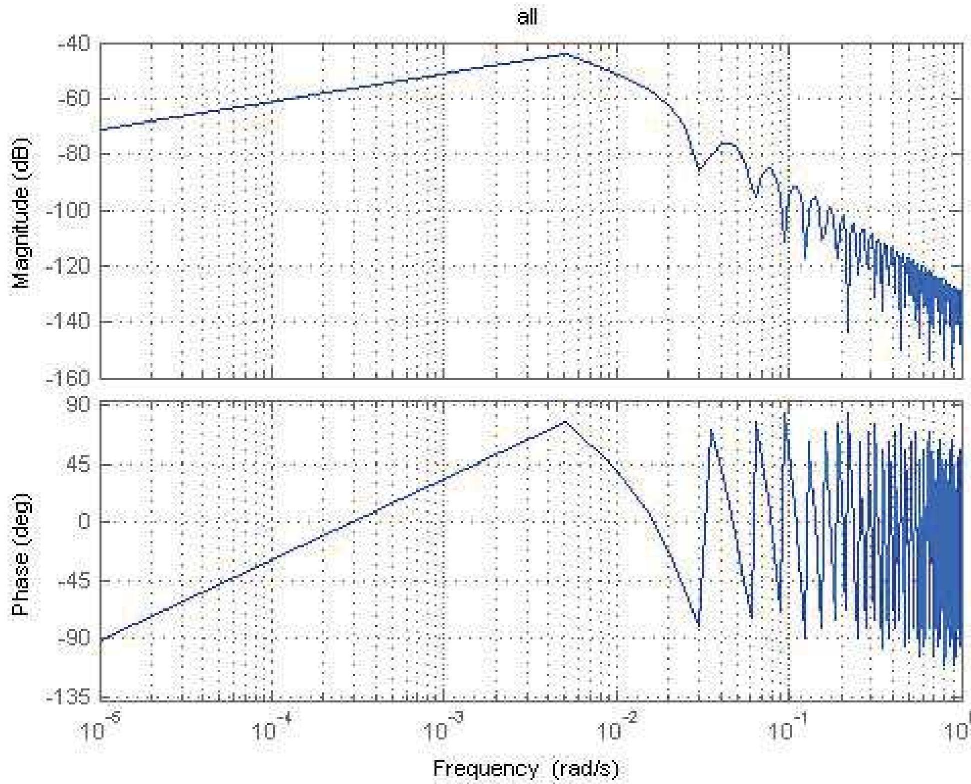

Figure 5.10: Fourier transform of $G_{PID}G_{MA}$

minimal window size. The window size could be continuously adjusted according to the minimal window size.

$$N < \frac{P_R}{R} \tag{5.10}$$

The smoothing system will be used less in the area with most of sunny day. According to the statistic data of PV output in a given area, the approximate smoothing cost for a PV farm can be calculated for each year.

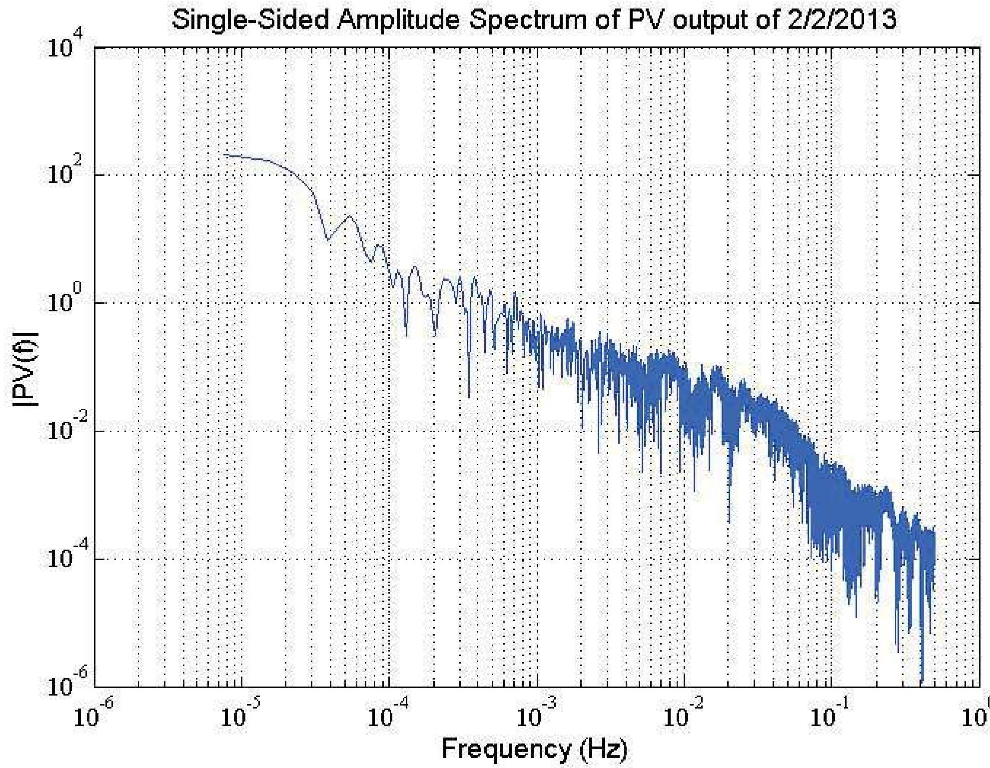

Figure 5.11: Amplitude spectrum of PV output for February 2nd, 2013

5.2.3 Result

The goal of the smoothing experiment presented here is to counteract the power intermittency from PV by controlled discharging and charging of the energy from the fast Utrabattery. Figure (5.13) illustrates actual field demonstration data of fast charging and discharging of the Ultrabattery. The data shows smoothing battery is sufficient to meet the smoothing control strategy for the given feeder load. This data set verifies that both the smoothing battery and the smoothing algorithm utilized are adequate for counteracting PV intermittency.

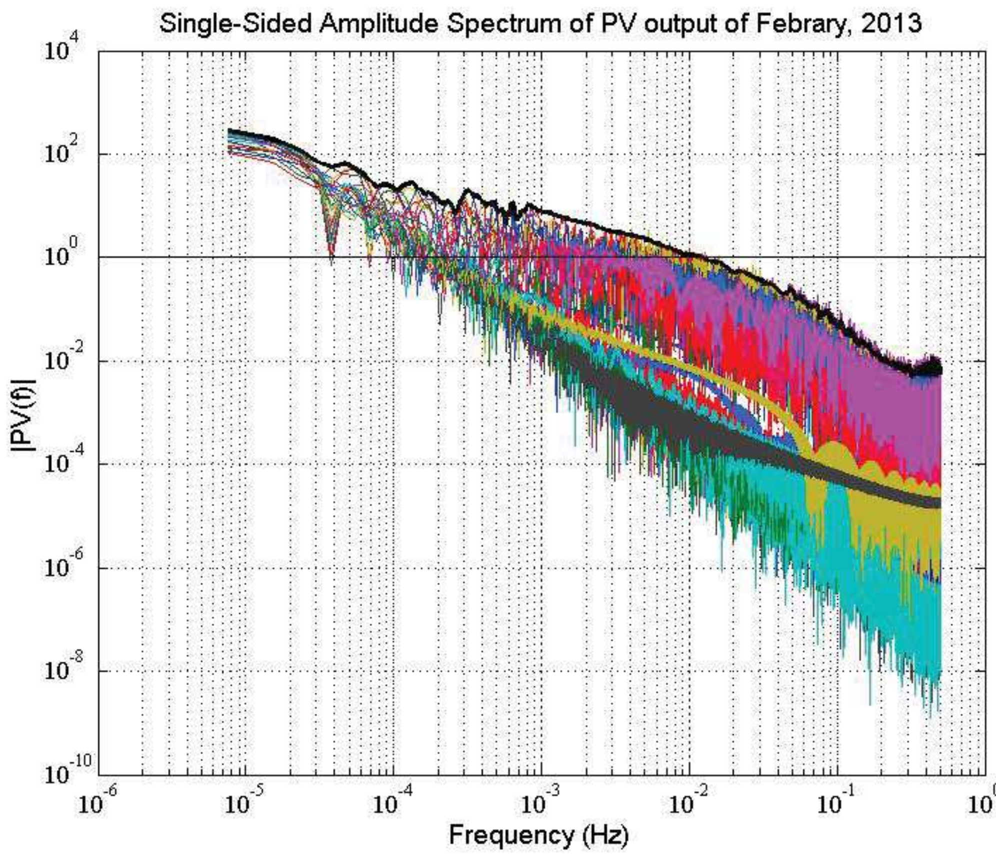

Figure 5.12: Amplitude spectrum of PV output for February, 2013

5.2.4 Summary

A description of moving average smoothing algorithm is presented, along with the detailed analysis in several aspects. Modelling results and real field results are presented showing successful smoothing with the PV power output. The calculation method of restoring power solves the first important problem usually faced when the smoothing storage system is deployed.

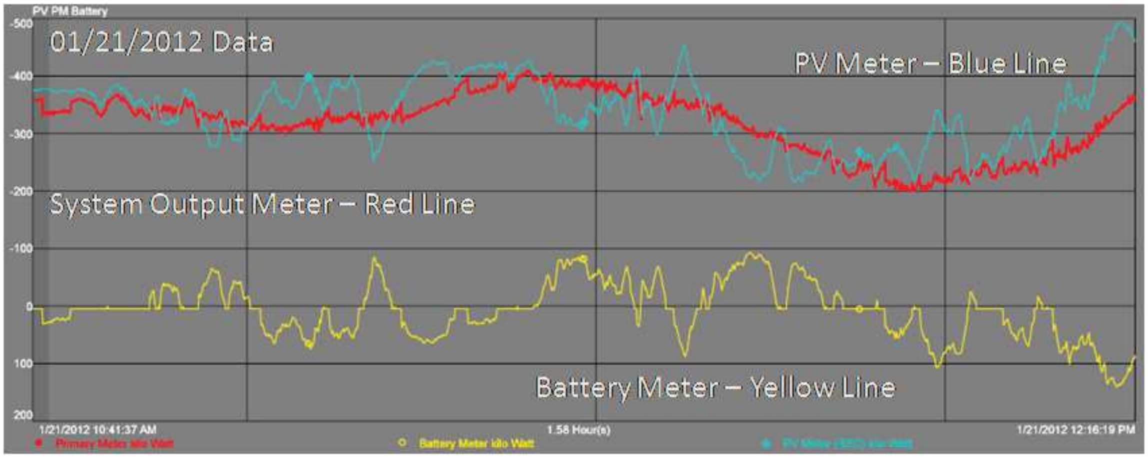

Figure 5.13: Smoothing for a sample reference power level for a vastly varying PV output day

5.3 Rule-based smoothing algorithm

The defect of moving average smoothing algorithm is the lag. The lag is a built-in characteristic of the moving average algorithm. A PV forecast could help to reduce or remove the lag. Here, a new smoothing algorithm is proposed, which can remove the lag. This algorithm is rule-based smoothing algorithm, which is easy to implement.

The rule-based smoothing algorithm tries to get the underline baseline by limiting the ramp rate in every second. The ramp rate can set equal to or smaller than the ramp rate boundary. There are no other parameters needed in this algorithm. In every second, the algorithm checks the real time ramp rate. If it's above 5kW/second, or below than -5kW/second, the battery will provide power to make sure the power increase or decrease is less than 5. The battery will only provide power when the ramp rate is higher than the requirement. It's very energy efficient. In the table 5.1 the energy usage of rule-based smoothing is compared with MA. In each row, the two algorithms could have the ramp rate of the smoothed PV within same range, but the energy usage of rule-based algorithm would be greatly smaller than MA algorithm.

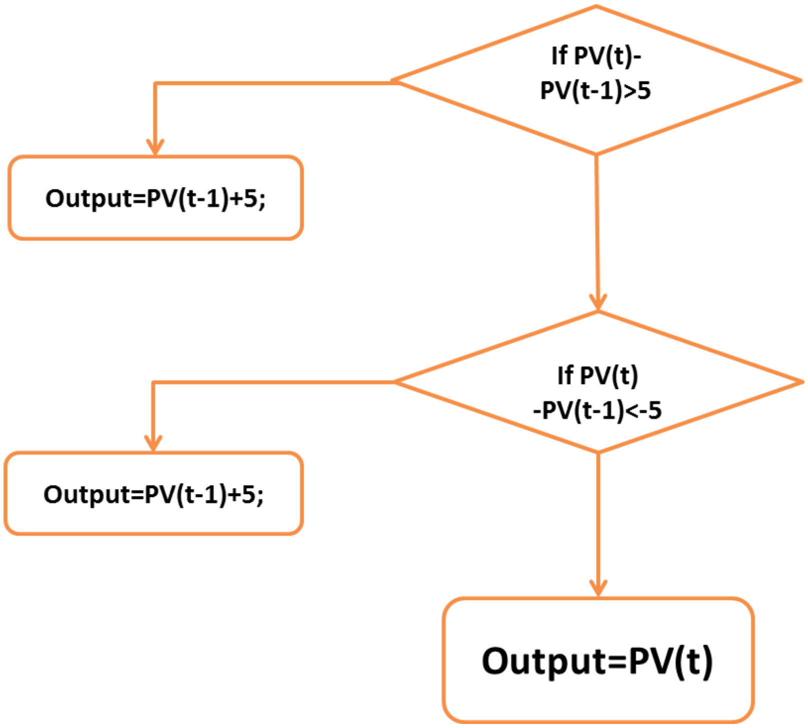

Figure 5.14: Rule-based smoothing algorithm flow chart

Figure 5.15 shows both algorithms reduce the ramp rate below 5kW/sec. The original ramp rate is also showed in the diagram. The original ramp rate is high as 150kW/sec. Figure 5.16 shows the smoothed PV is very close to the original PV. It can track the PV without time latency.

Table 5.1: Energy usage comparison of rule-based moving algorithm and MA

Ramping rate of rule-based algorithm	Window size of moving average algorithm	Energy usage ratio of rule-based algorithm to moving average
3.2	300	0.5309
4	240	0.5008
4.5	200	0.4618
5	180	0.4529
8	120	0.4277

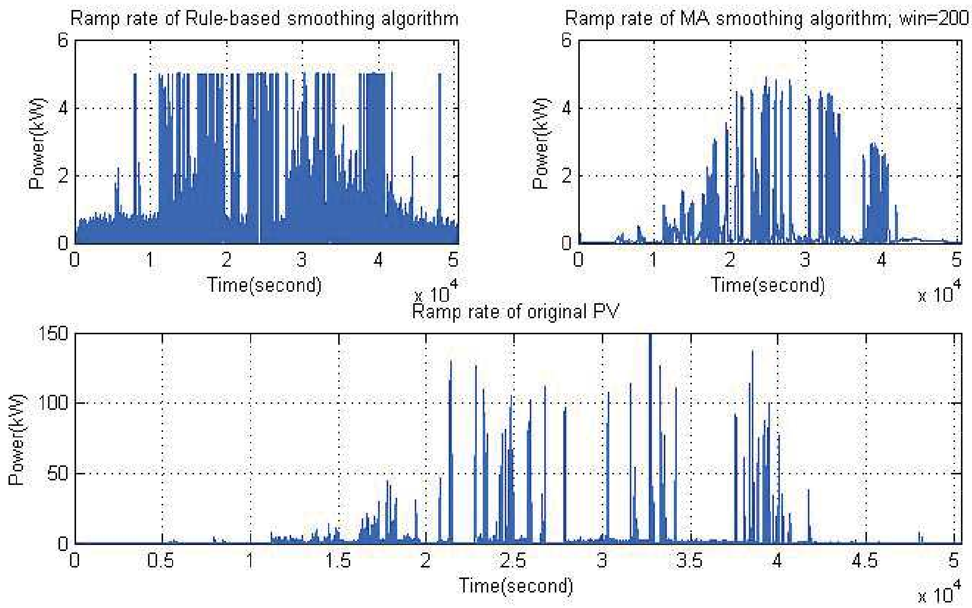

Figure 5.15: Ramp rate of the smoothed PV by rule-based smoothing algorithm and MA smoothing algorithm

5.3.1 Optimal battery size

$$Capacity = \int_0^T (R - R_{ref})dt \tag{5.11}$$

where, R means real time ramp rate. R_{ref} is ramp rate reference.

Smoothing battery will absorb all of the ramp rate which is above ramp rate reference. By integrating the difference between ramp rate and ramp rate reference over a day, the minimum capacity for that day could be estimated. Figure 5.17 shows the minimum battery size for everyday in February, 2013. In this figure, the minimum battery size is around 10kWh, which is very small comparing with existing smoothing battery size. It turns out that rule-based algorithm could reduce the needed battery size greatly.

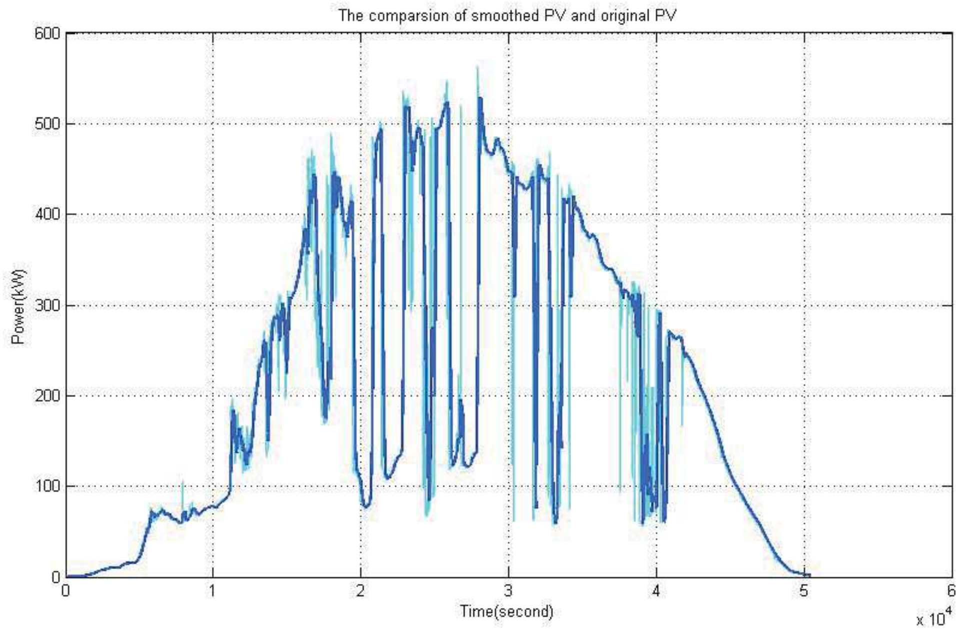

Figure 5.16: Comparison of the smoothed PV by rule-based smoothing algorithm with original PV

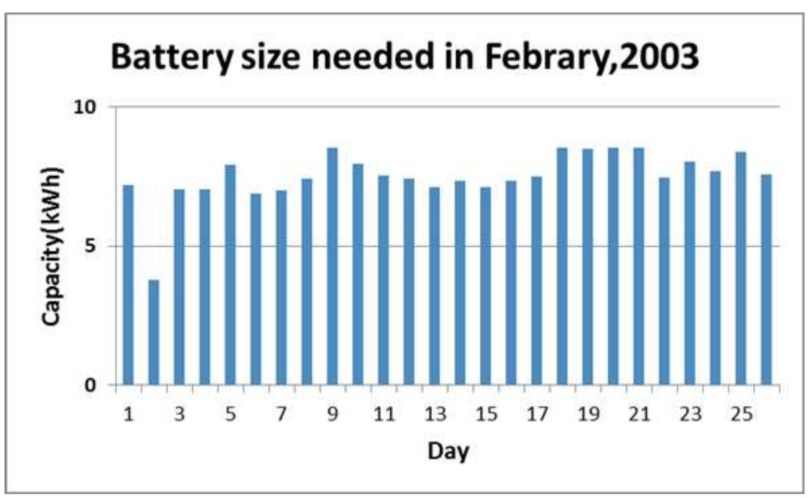

Figure 5.17: Minimum battery size in Febrary,2013 Unit(kWh)

Chapter 6

Summary of the Dissertation and Research Directions

In this dissertation, smoothing algorithm and shifting algorithm have been developed for the operation of BESS. The target is to to create a firm, dispatchable, distributed renewable generation resource with the aid of BESS. Although load prediction is not a major research topic in this dissertation, machine learning technique is introduced. In the followings, the main aspects and contributions of this dissertation are summarized. The possible research directions are proposed that can be addressed in the near future.

6.1 Summary of the Dissertation

In Chapter 2, PNM/DOE Solar and Battery Storage project and Mesa del Sol Micro-Grid Demonstration are introduced including the project goal, system set up and system parameters. These two projects are the platform used to test battery energy storage operation algorithm.

In Chapter 3, PV prediction and load prediction are introduced, which are used together as the BESS optimization function inputs. Machine learning technique helps day-ahead load prediction to achieve high level of quality in prediction.

In Chapter 4, shifting algorithm is developed when BESS works with variable renewable energy. It is multi-parametric optimization problem. Multi-functional battery energy storage operation is designed to optimize the comprehensive control strategy. Both grid-tied mode and islanding mode are taken into consideration. For grid-tied mode, the shifting algorithm is able to choose the best function among peak shaving, arbitrage and firming according to specific weather and load situation.

In Chapter 5, smoothing algorithm is introduced. A series of analysis around algorithm is given. How to set window size for MA is presented. Rule-based algorithm is proposed. It consumes less energy comparing with MA.

6.2 Future Research Directions

What is next needed to consider is how to extend the smoothing and shifting results presented above to a large area. For example, multiple BESS, PV plant in a same area. How they cooperate with each other is a problem worthy of discovering.

- how to negotiate objectives for different BESS will be explored. Then a optimization function will be developed among multiple BESS [12].
- SVM will be explored more in order to increase the current accuracy of prediction.
- To complete the shifting algorithm in three time-scales for islanding mode: day-ahead optimization, hourly MPC, near real time optimization.
- To calculate the real time control by using non-linear power flow theory.

- To find optimal shifting battery size for a given area by considering benefit of three main functions.

Appendix A

Day-ahead load prediction results

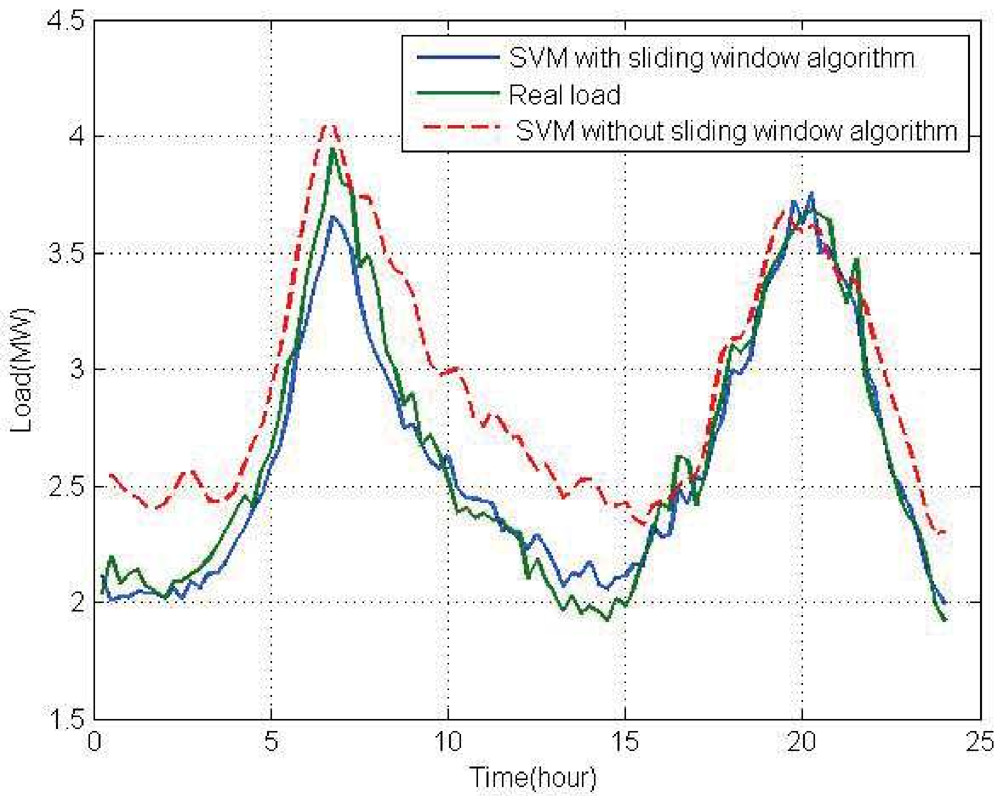

Figure A.1: Day-ahead load prediction result: example 1

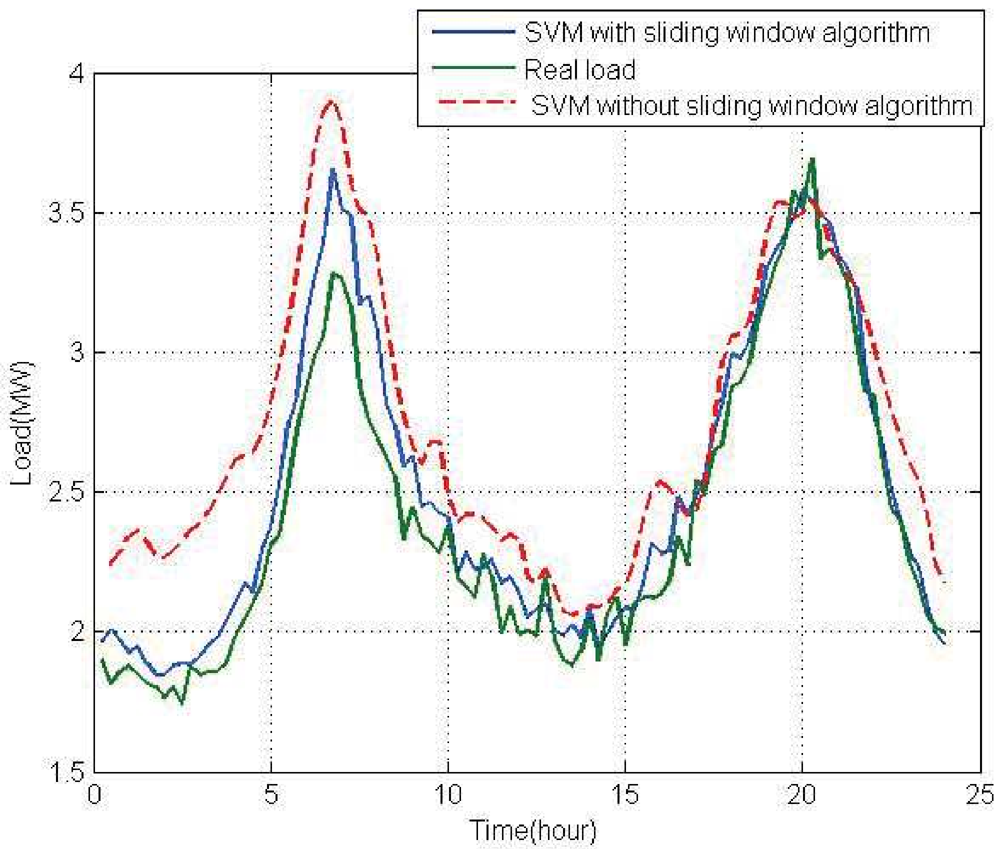

Figure A.2: Day-ahead load prediction result: example 2

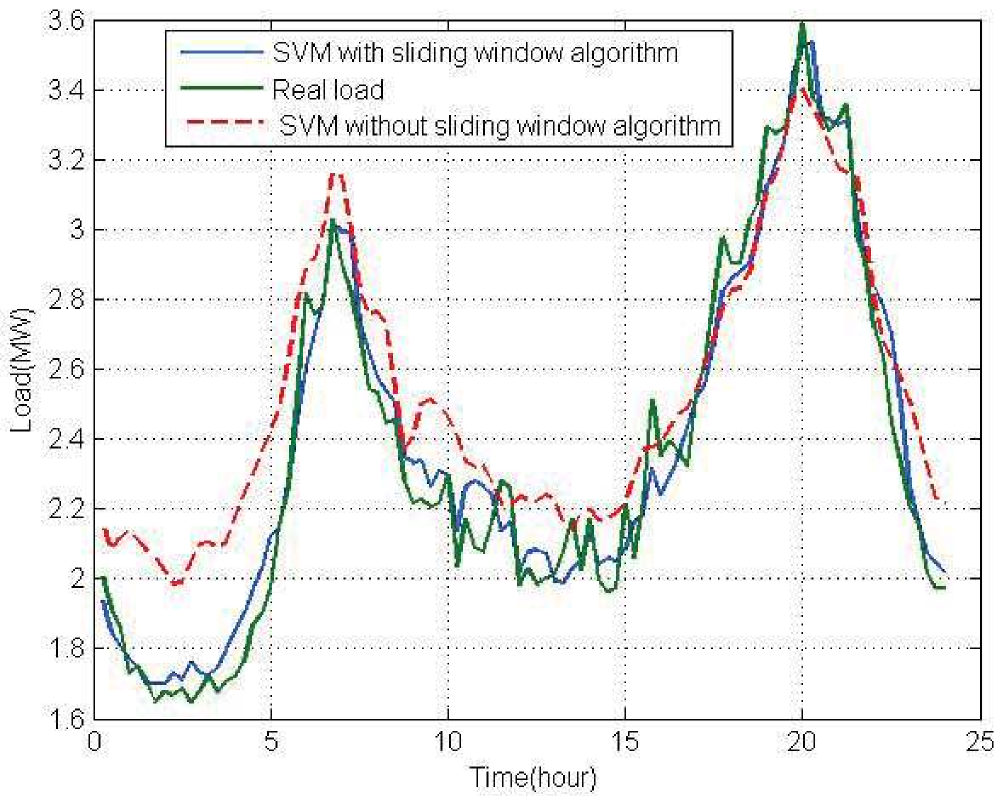

Figure A.3: Day-ahead load prediction result: example 3

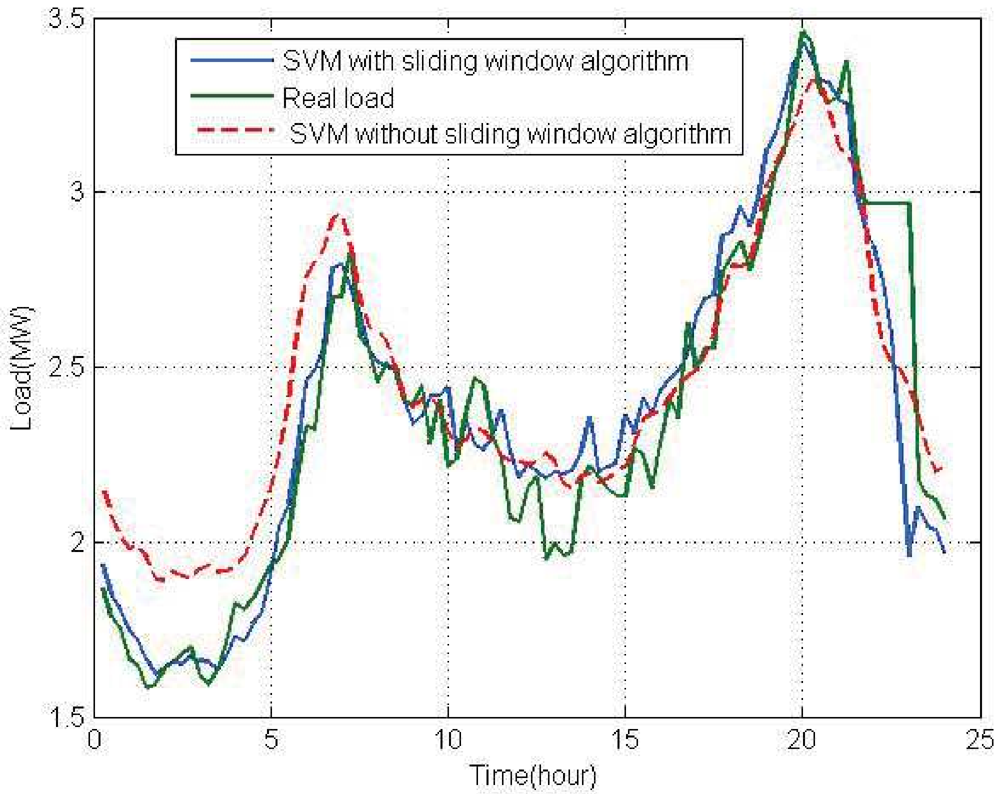

Figure A.4: Day-ahead load prediction result: example 4

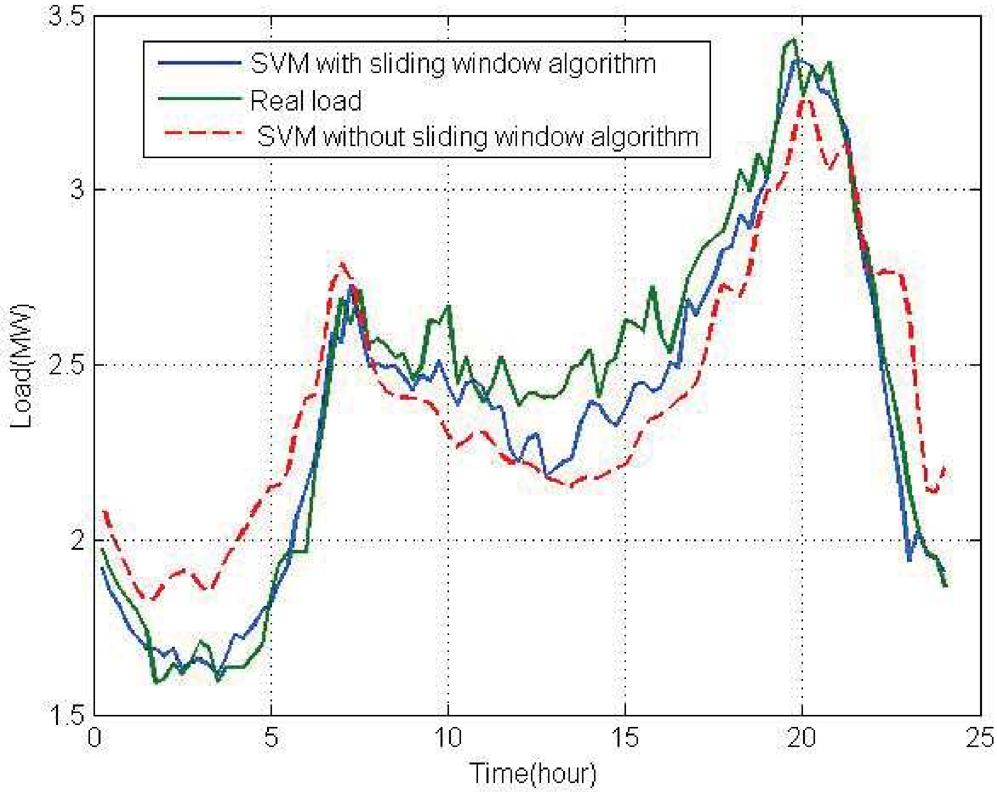

Figure A.5: Day-ahead load prediction result: example 5

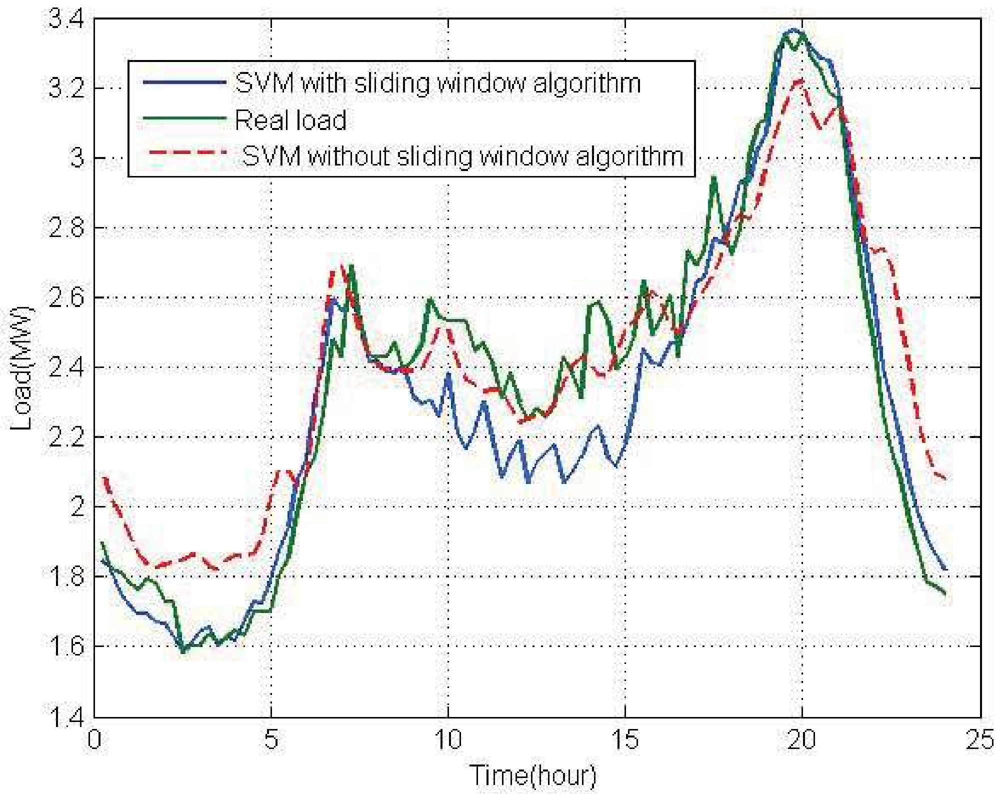

Figure A.6: Day-ahead load prediction result: example 6

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