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OPTIMAL CONTROL, INVESTMENT AND UTILIZATION SCHEMES FOR ENERGY STORAGE UNDER UNCERTAINTY

By

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ABSTRACT OF THE DISSERTATION

Optimal Control, Investment and Utilization Schemes for Energy Storage under Uncertainty

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Energy storage has the potential to offer new means for added flexibility on the electricity systems. This flexibility can be used in a number of ways, including adding value towards asset management, power quality and reliability, integration of renewable resources and energy bill savings for the end users. However, uncertainty about system states and volatility in system dynamics can complicate the question of when to invest in energy storage and how best to manage and utilize it.

This work proposes models to address different problems associated with energy storage within a microgrid, including optimal control, investment, and utilization. Electric load, renewable resources output, storage technology cost and electricity day-ahead and spot prices are the factors that bring uncertainty to the problem. A number of analytical methodologies have been adopted to develop the aforementioned models. Model Predictive Control and discretized dynamic programming, along with a new decomposition algorithm are used to develop optimal control schemes for energy storage for two different levels of renewable penetration. Real option theory and Monte Carlo simulation, coupled with an optimal control approach, are used to obtain optimal incremental investment decisions, considering multiple sources of uncertainty. Two stage

stochastic programming is used to develop a novel and holistic methodology, including utilization of energy storage within a microgrid, in order to optimally interact with energy market. Energy storage can contribute in terms of value generation and risk reduction for the microgrid.

The integration of the models developed here are the basis for a framework which extends from long term investments in storage capacity to short term operational control (charge/discharge) of storage within a microgrid. In particular, the following practical goals are achieved: (i) optimal investment on storage capacity over time to maximize savings during normal and emergency operations; (ii) optimal market strategy of buy and sell over 24-hour periods; (iii) optimal storage charge and discharge in much shorter time intervals.

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In the Name of God

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DEDICATION

To my beloved family,

for their endless love and support

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1 INTRODUCTION

1.1 Objective

The proposed work intends to address and tackle the following problems:

- Optimal control of energy storage for a privately-owned microgrid with low penetration of renewables, taking into account uncertainties from electric load and renewable resources, to minimize microgrid electric bill, including energy costs and demand charges paid to the utility.
- Optimal control of energy storage in a utility-owned microgrid with high penetration of renewables, to minimize the damage to distribution grid when renewable output exceeds electric load, and to optimally use renewable output taking into account the electricity price.
- Optimal incremental investment decisions (initial and expansions) in energy storage, using Monte Carlo simulation for compound options, considering stochasticity in storage technology cost. Microgrid savings from energy storage are estimated based on optimal control of storage with stochastic electric load and renewable output during normal operation and storage impact on power reliability during grid outages.
- Optimal market strategy in terms of microgrid interactions with the power grid, including sales and purchase commitments, price bidding, and sales and purchases in the real-time market under uncertainties due to electric load, day-ahead and spot electricity prices, and renewable generation.

- Optimal utilization of microgrid storage capacity and valuating storage in terms of revenue generation and risk reduction.
- Characterization of microgrid interactions with the power grid according to a set of internal and environmental parameters.

1.2 Brief Overview of Thesis Accomplishments

Chapter 2 proposes two control strategy models for two different use cases of energy storage. The first model is an optimal control strategy for a privately-owned microgrid with low penetration of renewables, taking into account uncertainties from electric load and renewable resources. The objective is to minimize microgrid electric bill, including energy costs and demand charges paid to the utility.

The second model is a novel decomposition algorithm for sub-optimal control of energy storage in a utility-owned microgrid with high penetration on renewables, where the objective is to minimize the damage to power infrastructure when renewable output exceeds electric load, and to optimally use renewable output taking into account the electricity price.

Chapter 3 extends the current state of art in compound real option approach to incremental investment in energy storage with two sources of random variations. In this model, it is assumed that microgrid is either operating in normal condition or in an islanding mode during grid outages. Savings from energy storage in normal condition are calculated using the first model proposed in Chapter 2, which takes into account the impact of stochastic parameter forecasts on energy storage benefit.

Chapter 4 strategizes microgrid interaction with the market taking into account different sources of uncertainty, i.e. day-ahead and spot electricity prices, renewable excessive capacity and electric load. A two-stage stochastic programming approach is used in this chapter.

1.3 Synopsis of Contributions

1.3.1 Chapter 2: Exact and Approximate Control Schemes for Energy Storage Systems

In this chapter, we introduce two methodologies for control of energy storage, under different configurations of electricity load and renewable resources. The first model, deals with a microgrid with low renewable generation capacity, where the renewable output is used to supply electric load. The objective is to minimize microgrid electric bill paid for the remaining electric load, which includes energy costs and demand charges, through optimal charge and discharge of storage unit. In this model, we take into account the impact of stochastic parameters forecast errors, i.e. electric load and renewable output, on the effectiveness of control scheme. For this purpose, we use Model Predictive Control to dynamically update control decisions based on new observations on stochastic parameters. The amount of peak shaving with three methods, i.e. dynamic controls with MPC, static controls on forecasted values, and static controls on real values, are compared and levels of error or over-estimation of each model are assessed. The results from dynamic controls with MPC are then used as realistic estimate of storage benefit for the microgrid in an optimal investment approach proposed in Chapter 3. The existing models which use MPC for storage control are either focused on other applications or types of storage, or do not include a proper objective function composed of all

corresponding costs. Another contribution of this section is coupling the MPC model results with the investment model in Chapter 3.

The second model introduced in Chapter 2 includes a new decomposition algorithm for a specific use case of energy storage, including high penetration of renewables. To the best of our knowledge, this is the first time that such a decomposition algorithm based on relative values of renewable generation and electricity load has been proposed. In this model, we adopt concepts from traditional inventory control problems, divide the solution space into distinct zones, and develop sub-optimal aggregate charge and discharge control commands.

1.3.2 Chapter 3: A Simulation-Based Real Option Model for Microgrid Investment in Energy Storage under Uncertainty

In this chapter we propose a methodology for optimal and incremental investment of microgrid in energy storage. Energy storage is assumed to be used to enhance renewable benefit for the microgrid through optimal charge and discharge scheme from Model I in Chapter 2. This work extends the current state of investment modeling in energy storage by considering: (i) multiple sources of uncertainties, (ii) using compound options theory to deal with incremental decisions, (iii) using more realistic saving functions for energy storage, and (iv) calculating storage benefit in two normal and islanding modes of microgrid.

1.3.3 Chapter 4: Energy Storage and Microgrid Market Strategy in an Uncertain and Distributed Energy Market

In this chapter we propose a novel and holistic approach to strategize market interactions of a microgrid for day-ahead decisions, with the objective to maximize microgrid annual profit through optimal commitments in day-ahead market and optimal daily operation of generation resources and energy storage. The main contributions of this model are (i) taking into account different important aspects of market strategy, i.e. sales and purchase commitments and bidding prices, (ii) considering different sources of uncertainty in day-ahead electricity price, renewable generation and electricity load and using two-stage stochastic programming to deal with stochasticity in parameters, and (iii) defining decision maker's risk attributed by using Conditional Value at Risk.

1.4 Motivation

The deregulation of energy environment has paved the way for a transition from centralized power systems to distributed systems. Microgrid is a concept characterized by low voltage distribution network, micro generators, loads and storage devices with locally coordinated functions [1]. A typical microgrid portfolio consists of renewable resources, fuel cells, co-generation units, natural gas turbines, and storage devices.

The coordinated operation and control of generation sources together with storage devices and electricity load is central to the concept of microgrids. In a macro point of view, a microgrid can be regarded as a controlled entity within the power network that can be operated as a single aggregated load and, given attractive remuneration, as a generation node or provider of ancillary services. Also, being able to operate in isolation,

microgrids can play an important role in load alleviation and risk reduction in the power market.

Energy storage has the potential to offer new means for added flexibility on the electricity distribution systems. This flexibility can be used in a number of ways, including adding value towards asset management, power quality and reliability, and energy bill savings for the end users. With the use of energy storage on distribution systems for multiple applications, however, comes the challenge of determining how best to control storage units. To maximize the value of a storage investment, the decisions on when to charge and discharge must account for the opportunity cost of using storage towards one application versus another. Furthermore, uncertainty about system states and volatility in system dynamics can complicate the question of how best to manage storage.

With increasing penetration of renewable resources, energy storage is becoming more popular, as they are used to mitigate different reliability and power quality-related issues caused by intermittency of renewable resources. Energy storage can also be beneficial for its capabilities which do not exist in renewable resources, such as controllable charge and discharging. However, since the cost of technology for energy storage drops with technology innovations and market penetration, investment timing and sizing is still an issue for microgrid owners. Price of electricity is another source of uncertainty which should be considered.

With this background in mind, we are motivated to build necessary tools to optimally control energy storage within microgrids, make investment decisions, and strategize microgrids interactions with the power grid, considering various sources of uncertainty

rising from the forecast of renewable energy resources, electricity demand and day-ahead and spot prices.

1.5 Brief Introduction on Microgrids

A microgrid is a localized grouping of electricity generation, energy storage, and loads that normally operate connected to a centralized grid.

Generation and loads in a microgrid are usually connected at low to medium voltage. Microgrid generation resources include wind turbines, solar panels, fuel cells, natural gas turbines, or other generation resources. On a macro level, microgrid works as single point node in the network, which is capable of running on its own resources if necessary.

With the introduction of microgrids, the dynamics of the electricity market is expected to change in the future. Microgrids act as dual purpose nodes in power systems. As a generatos, a microgrid can sell power in the wholesale electricity market. While as a customer, it can buy electricity from the power grid when its internal demand exceeds its supply capacity. While distributed generation in the power system can reduce volatility to high peak demands, microgrids add their own risks to the market as well. For this reason, new modeling tools are needed to capture the behaviors of microgrids with respect to the power grid, including dynamically changing economics, finance, and regulatory requirements.

1.6 Brief introduction to electricity Storage

Electricity Storage sets the path between electricity generation and delivery industry, and includes any non-immediate use of generated power. Storage has the capability to help manage the electricity generation and delivery, especially with the integration of

renewable generation, the addition of smart grid technologies, and greater interest in demand response and higher electric system efficiencies. Energy storage technologies include electro-chemical, electro-mechanical and electro-thermal. Benefits expected from electricity storage applications include but are not limited to: improved asset utilization and efficiency, increased penetration of renewable generation, enhanced reliability, availability and power quality, peak load management, flexibility in meeting customer demand.

2 EXACT AND APPROXIMATE CONTROL SCHEMES FOR ENERGY STORAGE SYSTEMS

In this chapter, we tackle the problem of optimal control of energy storage in microgrids. Our purpose is to maximize energy storage benefits for the utility (when microgrid is owned by the utility) and end-users. Two models are presented - In the first model, we assume a residential microgrid, with low renewable penetration, and examine the impact of electric load and renewable output forecast errors on energy storage benefit and cost effectiveness. In the second model, we assume a system with high renewable penetration, where reverse flow of power is an issue when renewable output is high compared to electric load. In such a system, energy storage can be used to absorb the reverse power and use it during peak hours. For the first model, a mixed integer linear programming with Model Predictive Control (MPC) is used. Although similar approaches to this model already exist in the literature, the main contribution of our work here is to include exogenous sources of uncertainty, e.g. renewable output and electricity load, use a cost function composed of both energy cost and monthly demand charges, and combine the MPC results with an optimal investment model (proposed in Chapter 3) to make more reliable investment decisions. For the second model, we propose a heuristic approximation, based on a new decomposition algorithm, where the (time-power) space is divided into zones depending on the comparative levels of electricity load and renewable power output. Discrete dynamic programming is then used to find the aggregate charge or discharge levels of storage during each zone. This approach decreases the solution space intensively, hence can be applied to larger problems, with larger energy and power ratings for the energy storage unit, and for longer periods. The

results are examined against exact solutions of a mixed integer linear programming model with the same objective function and constraints, solved using GAMS.

2.1 Introduction

Energy storage has the potential to offer new means for added flexibility on the electricity distribution systems. This flexibility can be used in a number of ways, including adding value towards asset management, power quality and reliability, and energy bill savings for the end users. With the use of energy storage on distribution systems for multiple applications, however, comes the challenge of determining how best to control storage units. To maximize the value of a storage investment, the decisions on when to charge and discharge must account for the opportunity cost of using storage towards one application versus another. Furthermore, uncertainty about system states and volatility in system dynamics can complicate the question of how best to manage storage. We intend to present solutions for different configurations of renewable penetration and energy storage that are simple to implement and account for system characteristics and system state. Furthermore, we intend to explicitly assess how well such methodology approximates the optimal usage of storage.

Storage systems can be used in various applications in electricity distribution systems. These applications include but are not limited to: renewable value enhancement, shift in time of use, and peak shaving. Systems with renewable generation can enhance their benefit using energy storage, especially when peak demand and renewable peak do not coincide. In such conditions, adding more renewable capacity cannot do much in terms of savings for the system. However, when coupled with energy storage, renewable generation value can be increased. *Shift in time of use* involves purchasing and storing

inexpensive electricity when electricity load and cost are low; and then using the stored energy to supply electricity load when the load and price are high. Utility customers can shave their peak consumption and avoid peak penalties or reduce demand charges by using their energy storage state of charge in peak periods. This is one of the main applications of distribution energy storage systems.

In this chapter, we propose two optimization models which tackle two different use cases of energy storage, each including multiple applications. The first model is a Model Predictive Control (MPC) which finds the optimal charge and discharge of energy storage for the next time step, e.g., next hour, taking into account the forecast errors of electricity load and renewable output within the next 24-hour period. The basic idea of MPC is to form a model that is able to represent the future dynamics of the system and to provide optimal control actions for a specific time horizon [2]. A mixed integer optimization program is used at each time step to find the future charge and discharge control commands for the 24-hour period ahead such that microgrid energy bill, composed of energy cost and demand charge paid to the utility and/or retailers, is minimized. From the 24 charge and discharge commands, only the ones corresponding to the next immediately hour are executed. As more information is obtained from stochastic variable realizations, forecast values for the next (new) 24-hour period are updated and the optimization is repeated. The results of this model are compared to the same model solved using a static approach, which finds optimal control commands of energy storage once every 24 hours, assuming no forecast errors. By comparing microgrid savings using these two approaches, we show the impact of MPC on energy storage benefit. This model is used to estimate microgrid's savings in the investment model introduced in Chapter 3, where it

will be shown that realistic estimations are crucial for efficient investment decisions, and that investment decisions made on the basis of artificially inflated saving values (obtained from static models) can be misleading. In this Chapter, we also examine the inflated estimations of saving values if no random errors are assumed. MPC-based models for control problems and different storage applications have been traditionally used in the literature. However, as stated before, the main contribution of our work here is to include exogenous sources of uncertainty, e.g. renewable output and electricity load, use a cost function composed of both energy cost and monthly demand charges, and combine the MPC results with an optimal investment model (proposed in Chapter 3) to make more reliable investment decisions.

In the second model, we introduce a new approximation algorithm for control of storage, which decomposes the optimization period according to loads and renewable forecast curves. By aggregating solutions over each zone, we reduce the feasible region of the problem significantly. The intention is to decrease the solution space and increase the computational efficiency of the methodology, especially when used in online optimal control of storage. Discretized dynamic programming is applied on the basis of these zones rather than hourly time steps; it yields the aggregate amounts of charge or discharge (in kWh) within each zone. For validation, results from this approximation model are compared to the results of an exact model solved by mixed integer linear programming. The level of error due to aggregation is assessed. It is observed that the model performance is higher for smaller storage units, where storage is primarily used for mitigating the reverse power flow from renewable resource, as well as arbitrage between different zones, and not within each zone.

2.2 Background and Literature Review

2.2.1 Borrowing Ideas from Classical Inventory Control

Inventory systems have been part of traditional supply chain systems for many years, with enormous volume of supporting research and practice. In supply chain applications, inventory system is part of the network backbone to deliver the velocity and reliability that is required by these systems. Furthermore, inventory systems are considered as hedging mechanism against random variations in lead time, demand and production. Work In Process (WIP) is also used for regulation between two consecutive processes which may run at different random speeds. Rarely, inventory system in traditional sense have been used for arbitrage.

Traditional inventory control models fall into two main categories; single period models with immediate replenishment and gradual sales or discharge and mutli-period models. Single period models are used for one time ordering decision, so that the orders can be sold during a specific period. The objective of this model is to balance the impact of running out of stock with the impact of being left with stock that does not sell. The most famous model in this category is the newsvendor problem.

A multi period inventory model can have two variations. Fixed order quantity systems are where orders are placed for a fixed amount each time they are placed. The placement of an order is done when an event occurs, such as reaching a minimum stock level. The second variation is fixed time period models where orders are placed at specific times, e.g. when there is a monthly review of stock levels. The amount of the order will depend on the amount of inventory that is needed. The objective in these two models is to minimize

total cost including cost of placing an order (setup cost), holding or storage cost, cost of units purchased, and in some cases, shortage cost.

The problem of storage control in power systems falls into the category of multi-period inventory systems. Conceptually speaking, the formulation of cost functions and optimization schemes are quite similar, but some of the individual cost terms are fundamentally different. For instance, holding costs term does not make much sense in power systems, whereas in traditional inventory systems, it is a balancing factor between costs and benefits. Table 0.1 in Appendix I shows some of the parallels between the two systems. Without dwelling too long on this topic, it suffices to say that our knowledge of inventory systems has been a major driver behind our formulations here. In particular, we emphasize the decomposition approach, which takes advantage of multi-period inventory systems and breaks down the storage control problem into smaller problem domains of charge and/or discharge characterized by intersection points between supply and demand (closely connected to period inventory control, except that periodicity is random).

2.2.2 Optimal Control of Energy Storage

Optimal control of energy storage units has been an interesting topic for utilities and other storage owner and operators for the last few years. In [3] the optimal energy storage control problem is addressed from the utility point of view. The model is focused on arbitrage application of energy storage, and the authors show that it can be extended to account for a renewable source that feeds the storage device. The same problem is considered in [4], where the problem of minimizing the cost of energy storage purchase, subject to both user demands and prices, is formulated as a Markov Decision Process. Renewable resource integration is an important application of energy storage, and charge-

discharge control policy of energy storage to serve this application is presented in [5]. Renewable energy sources are considered in [6] too, where an open-loop optimal control scheme is considered to incorporate the operating constraints of the battery energy storage systems. The goal of the control in [6] is to have the battery energy storage system to provide as much smoothing as possible, so that the wind farm can be dispatched on an hourly basis based on the forecasted wind conditions. The same problem is considered in [7], where sizing and control methodologies for a battery-based energy storage system are presented for wind farm applications. Authors in [8] consider a smart grid including renewable generation units and formulate a single-objective optimization problem whose objective function is power loss minimization while satisfying constraints on active and reactive power at the interconnection bus. This work is one of the rare works which combines internal and external applications of energy storage units to some extent. The application of renewable generation integration is also considered in [9], [10] and [11]. In [12], authors present a battery control policy, which minimizes the total discounted costs, taking into account arbitrage application of energy storage. In [13], energy storage power reliability application is considered, and the concept of using the central energy storage system is presented as the main source in micro-grid island mode.

2.2.3 Model Predictive Control for Energy Storage

Concept of Model Predictive Control has been used for control of energy storage within power systems. Khalid and Savkin [14] design a controller based on model predictive control (MPC), to smooth the wind power output, which is generated from a wind farm, and subject to a variety of constraints on the system. Their proposed controller is capable

of smoothing wind power by utilizing inputs from a prediction system, which is capable of predicting the wind power several steps ahead, and optimizes the maximum ramp rate requirement and also the state of the charge of the battery under system constraints.

Xie et al. [15] address potential benefits of applying MPC to solving the energy dispatch problem in electric energy systems with many intermittent renewable resources. Based on predicting the output from the intermittent resources, they propose a look-ahead optimal control algorithm for dispatching the available generation with the objective of minimizing the total production cost. Nottrott et al. [16] implement a linear programming routine to optimize the energy storage dispatch schedule for demand charge management in a grid-connected and combined photovoltaic-battery storage system. Their model is supposed to leverage PV power output and load forecasts to minimize peak loads subject to elementary dynamical and electrical constraints of the system. Although the problem statement in their work is similar to one of the problems we tackle in this chapter, the solution approaches are different. They take into account demand charge and other system costs in their example to quantify the advantage of their model. However, these costs are not considered in their linear programming, which does not guarantee the answers to yield to minimum peak demand. This drawback is addressed in the way we set up the mixed integer linear programming in this chapter, which considers real demand charge and energy cost. van Staden et al. [17] define and simulate a closed-loop optimal control strategy for load shifting and demand charge management in a water pumping scheme. They use a model predictive control approach to implement the closed-loop optimal control model, and the optimization problem is solved with integer programming.

They do not consider any exogenous stochastic factor like renewables or electricity demand.

2.2.4 Rule-based and Aggregated Energy Storage Control

Teleke et al. [6] develop a control strategy for optimal use of the energy storage for making intermittent renewable energy sources more dispatchable. They consider a rule-based control scheme, which is the solution of the optimal control problem defined to have the energy storage provide as much smoothing as possible so that the renewable resource can be dispatched on an hourly basis based on the forecasted solar/wind conditions. Armas et al. [18] introduce a heuristic technique for scheduling a residential Distributed Energy Resource (DER) installation containing photovoltaic arrays and local energy storage, which is also interfaced to the grid through a single phase voltage source inverter. The technique is based on the DER installation's ability to sell specified amounts of real and reactive power to the utility grid. The technique is implemented in an algorithm that determines the operating points for the inverter for the next 24 hours of operation based on forecasts of the residential demand, solar irradiance, and the price of real and reactive power. They divide. Operational rules are defined depending on levels of PV generation and storage state of charge, as well as the corresponding zone.

The idea of dividing each day (24-hour period) into zones and finding aggregate control commands is common between the second model proposed in this chapter and the algorithm presented by Armas et al. [18]. However, the two works are dissimilar in a number of ways: in their work, the maximum number of zones in each day is fixed, while in our model, the number of zones depends on the relative amount of renewable output and electricity load. Also, in their model, control commands are pure rule-based controls,

while we propose a dynamic programming approach that guarantees higher levels of accuracy and computational efficiency. As stated by the authors, their model only covers specific load and PV profiles and cannot be applied to general cases, which is a major drawback addressed by the algorithm introduced in this chapter.

2.3 Problem statement and Preliminaries

Nomenclature

t	Time index
i	Zone index
K	Maximum daily power demand
$p_t^{ch,g}$	Charge from grid (kW)
$p_t^{ch,r}$	Charge from renewable (kW)
p_t^d	Power discharge (kW)
c_t	Binary variable: $\begin{cases} 1 & if\ battery\ is\ charging \\ 0 & otherwise \end{cases}$
d_t	Binary variable: $\begin{cases} 1 & if\ battery\ is\ discharging \\ 0 & otherwise \end{cases}$
st_t	Storage energy level at the end of time step t (kWh)
Pr_t^u	Utility price of electricity ($/kWh)
Pr_t^w	Wholesale price of electricity ($/kWh)
dc	Demand charge ($/kW)
$\hat{L}_t$	Forecast of electricity demand
$\hat{R}_t$	Forecast of renewable output power
L_i	Total electricity load during zone i

R_i	Total renewable generation during zone i
$e_i^{ch,g}$	Total energy charged from grid during zone i (kWh)
$e_i^{ch,r}$	Total energy charged from renewable during zone i (kWh)
e_i^{d}	Total energy discharged during zone i (kWh)
St_{max}	Storage energy capacity (kWh)
D_{max}	Energy storage power rating (kW)
St_{dur}	Energy storage charge/discharge duration at power rating (hour)
St_{eff}	Energy storage one-way efficiency
St_{res}	Percent of energy reserved in storage
St_{init}	Initial level of storage
St_{step}	Discretization interval
Pn_{sub}	Penalty for damage to substation due to reverse flow of power
dr_i	Duration of zone i

2.3.1 Model I – Model Predictive Control for storage dispatch under demand and renewable output uncertainty

The system we consider in this section is a microgrid consisting of stochastic energy demand, conventional generation units and renewable generation units with intermittent output. It is assumed that demand constantly exceeds conventional and renewable generation capacity of the microgrid. Hence, microgrid has to supply its remaining power from an electric utility. Microgrid bill includes energy cost, which is paid based on hourly energy consumption and hourly electricity prices, and demand charge, which is the cost paid for microgrid monthly peak demand.

2.3.1.1 Model Predictive Control

The proposed approach is a control scheme, which uses MPC to update optimal solutions for charge and discharge commands for the next 24 hours, as soon as it receives a new actual data. Different modeling approaches can be used for implementing an MPC strategy. A common approach is to use a data-driven MPC by fitting a meta-model to the historical data. In this work, we assume that at each time step, *t*, times series forecasts of renewable output and electricity load are available for the next 24 hours, which provide both forecast mean and standard deviation. It is also assumed that forecast standard deviation increase as we move farther from t. Using MPC-based optimization models for reducing electric bills has already been studied, however, including exogenous stochastic parameter errors and coupling such a model with the investment model introduced in Chapter 3 are the main contributions of the work presented in this section.

An MPC based optimal control of storage is applied as follows: At each time step *t*, the optimal control values for times $t+1, t+2, \dots, t+24$ are found using optimization model. We formulate a multi-objective dynamic programing to search for optimal charge and discharge controls for the next 24 hours based on the available forecasts. The objective function includes total energy cost and demand charge on microgrid utility bill. When time $t+1$ is reached, control commands for that time step are executed. Then optimal solutions for $t+2, t+3, \dots, t+25$ are updated, when new information on the system and storage state of charge are received. A schematic view of the process is shown in Figure 2.1.

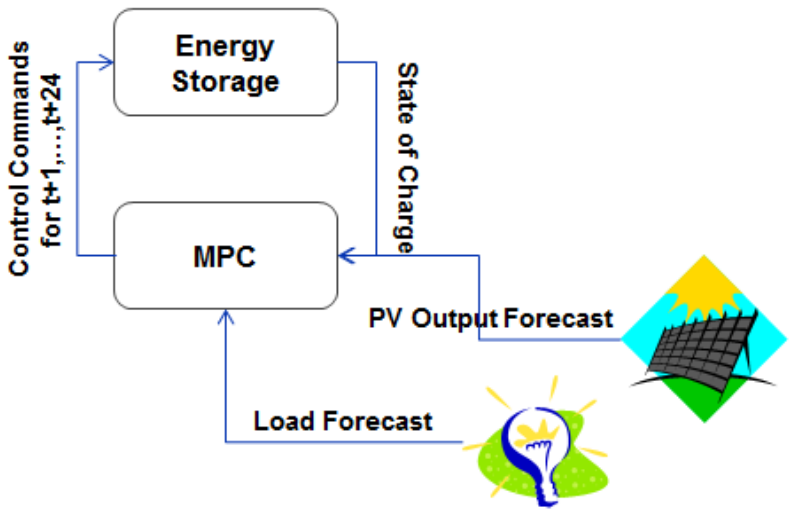

Figure 2.1 A schematic presentation of proposed control strategy

2.3.1.2 Optimization Model

<u>Objective Function</u>

The objective function is the total monthly bill for microgrid, including energy costs and demand charges. The optimization runs for 24 hours at a time, but since in reality, demand charge is determined based on monthly peak demand, we assume the peak demand during each 24-hour period is a representative of monthly peak demand. This assumption is valid, because minimizing demand peak for each 24-hour period, eventually results in minimizing monthly demand peak. Since demand charges are defined based on monthly charges, the 24-hour period energy costs are extrapolated to a monthly value by multiplying by a factor of 30. The objective function, Equation (2.1), is then a representative of microgrid monthly costs:

$$K \times dc + 30 \times \sum_{t=1}^{24} Pr_t^u \times \left[\left(\hat{L}_t - \hat{R}_t\right) + p_t^{ch,g} - p_t^d\right] \tag{2.1}$$

Constraints

The constraint presented in Equation (2.2), sets K as the maximum power consumption of microgrid during a 24-hour period. As mentioned before, K estimates monthly peak load.

$$K \geq \left(\hat{L}_t - \hat{R}_t\right) + p_t^{ch,g} - p_t^d \qquad \forall t \tag{2.2}$$

Energy storage level in each hour is updated based on Equation (2.3), which takes into account storage level at the end of previous hour, as well as power charged and discharged, and one-way efficiency of the battery.

$$st_t = st_{t-1} + p_t^{ch,g} \times St_{eff} - (\frac{p_t^d}{St_{eff}}) \tag{2.3}$$

Equation (2.4) guarantees that battery is either charging or discharging in each time period.

$$d_t + c_t \leq 1 \tag{2.4}$$

Equations (2.5) and (2.6) define the maximum allowable discharge and charge based on battery power rating and corresponding discharge and charge binary variables, respectively.

$$p_t^d / St_{eff} \leq d_t \times D_{max} \tag{2.5}$$

$$p_t^{ch,g} \times St_{eff} \leq c_t \times D_{max} \tag{2.6}$$

Equations (2.5) and (2.6), respectively, define the maximum allowable discharge and charge based on storage level in the battery:

$$p_t^d / St_{eff} \leq st_{t-1} \tag{2.7}$$

$$p_t^{ch,g} \times St_{eff} \leq St_{max} - st_{t-1} \tag{2.8}$$

And Equation (2.9) defines the boundaries for storage level based on reserve requirement and maximum energy capacity of the battery.

$$St_{max} \times St_{res} \leq st_t \leq St_{max} \tag{2.9}$$

2.3.1.3 Electricity Load and Renewable Output Forecast

There are numerous times series models already existing in the literature. In this work, we assume that required forecast models are readily available, and that the variations in each of load and renewable outputs can be explained by a seasonal Autoregressive Moving Average (ARMA) model. Using ARMA models for forecasting electricity load and renewable output has been proposed by Huang et al. [19] and Subbaya et al. [20]. An ARMA model can be written as a Moving Average (MA) model with infinite terms, called the MA representation of the ARMA model [21]. As a general discussion, suppose X_t is a variable with an infinite MA representation

$$X_t = \varepsilon_t + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + \cdots \tag{2.10}$$

Then the forecast error for the h-step-ahead forecast of X has the following distribution [21]:

$$\hat{x}_h - X_h = -(\varepsilon_t + \varphi_1 \varepsilon_{t-1} + \cdots + \varphi_{h-1} \varepsilon_{t-h-1}) \sim N(0, (1 + \sum_{j=1}^{h-1} \varphi_j^2)\sigma^2) \tag{2.11}$$

where σ^2 is the variance of model residuals. It can be clearly observed that forecast error of prediction increases as forecast term increases. We use the same concept in our model, assuming model coefficients, i.e. φ_j's to be available. We consider two separate forecast

models for electricity load and renewable output, assuming that predictions are made at hour 24 of each day for the next 24 hours.

2.3.1.4 Algorithm

Below, is a summary of the algorithm we use for storage control using MPC:

Step 1: *Set current time to* t

Step 2: *Using forecast models for renewable generation and electricity load at time* t, *forecast these two variables for* $t+1, t+2, \ldots, t+24$.

Step 3: *Using the optimization model, find optimal charge and discharge commands for* $t+1, t+2, \ldots, t+24$.

Step 4: *Execute the control commands for* $t+1$, *and update state of charge.*

Step 5: *Get realized values of renewable generation and electricity load for* $t+1$

Step 6: *Set the current time to* $t+1$ *and go to Step 2.*

2.3.1.5 Model Validation

Our objective is to show that MPC based hourly control of storage yields solution strategies that are more cost effective and lead to higher savings when compared to the static model based on forecasted values which is solved once every 24 hours. Results of this model are validated by comparing them to optimal control solutions of the same problem solved based on perfect information. Results are presented for different power ratings for the energy storage.

2.3.1.6 Numerical Experiments

Table 2.1 shows the input data used to validate MPC results against static models solved on realized values and 24-hour forecasted values.

Table 2.1 Input data for MPC-based model

Parameter	Unit	Level
Storage power rating	kW	100, 150, 200, 250
Storage duration	Hour	2
Storage minimum reserve	% of energy capacity	20
Storage one-way efficiency	%	94
PV maximum output	kW	100

Figure 2.2 and Figure 2.3 below illustrate the real and forecasted values of electricity load and renewable generation, for five consecutive weekdays in winter. Forecasts are made every 24 hours and at the beginning, i.e. hour 1, of each day. It can also be observed in the following two figures how forecast errors increase by moving farther from hour 1 of each day. Data for electricity load and PV output profiles are based on real data from an office building, and solar panels in California. The values are scaled to fit the specific use cases for each model.

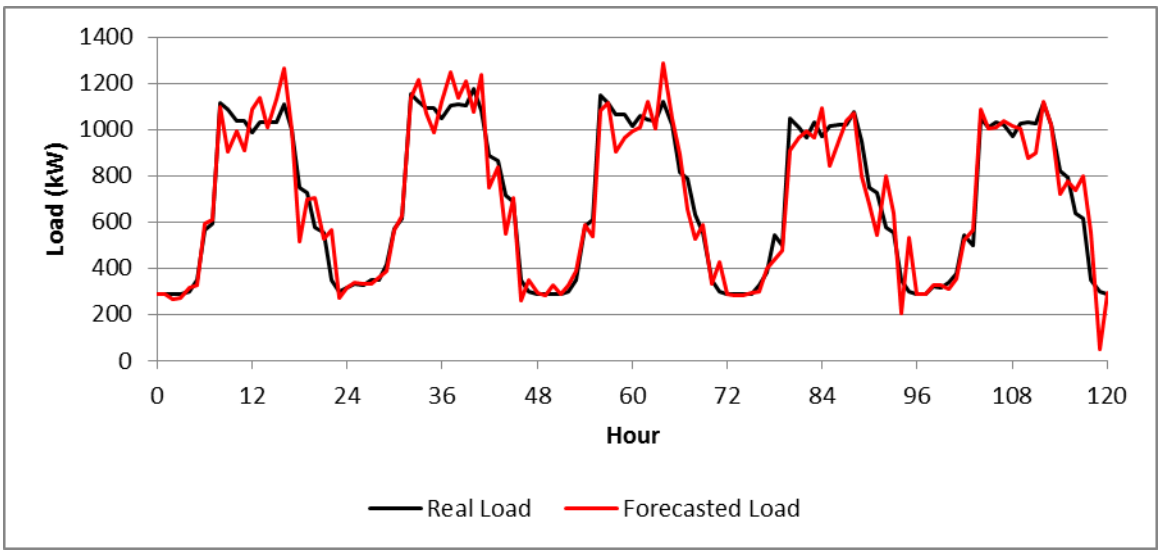

Figure 2.2 Real vs. forecasted electricity load for a winter week

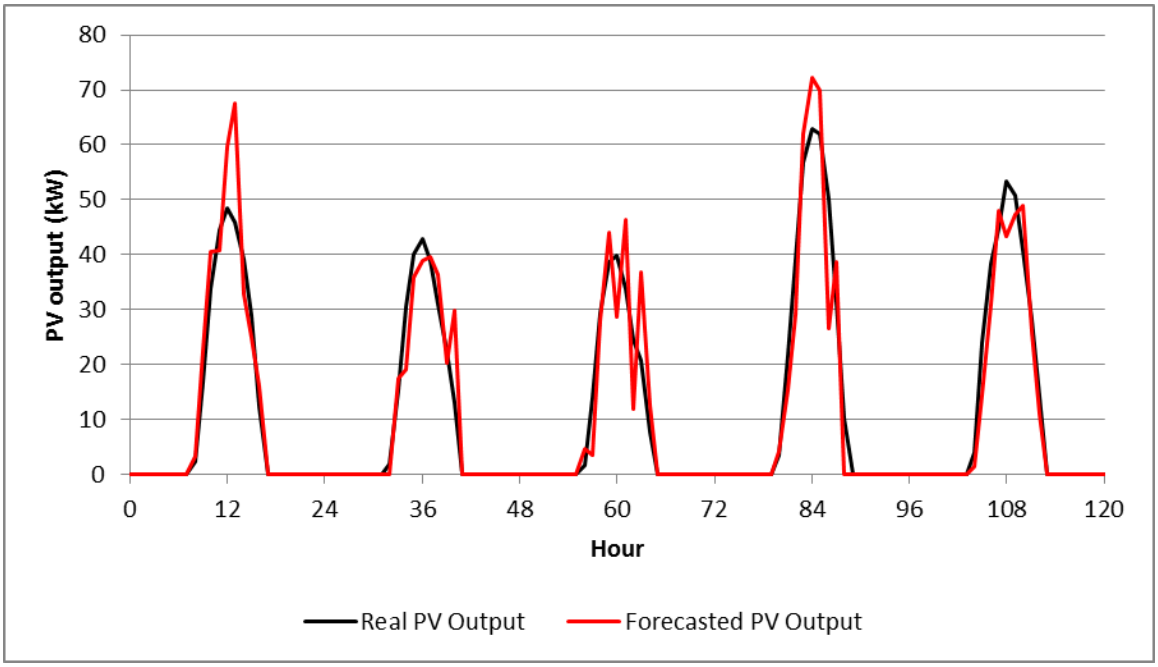

Figure 2.3 Real vs. forecasted PV output for a winter week

Next, we examine the performance of (i) static model, which is solved once every 24 hours based on forecasted values and (ii) MPC model, the inputs and solutions of which are updated based on the proposed algorithm, by comparing the two models with results of an optimization model assuming no stochasticity in input data (solved based on real data). Results of this comparison are presented in Table 2.2 below.

Table 2.2 Comparing MPC vs. Static Model and Perfect Information

Storage Capacity (kWh)	PV Capacity (kW)	Original Peak (kW)	Peak Perfect Info (kW)	Peak MPC (kW)	Peak Static (kW)
100	100	1176.58	1082.59	1114.38	1176.58
150	100	1176.58	1063.21	1114.38	1195.57
200	100	1176.58	1055.42	1102.29	1221.78
250	100	1176.58	1047.68	1075.35	1208.56

As it can be observed in Table 2.2, the peak is lowest when assuming perfect information. However, as there are sources on uncertainty in the system, relying on the peak value

assuming deterministic perfect information, results in over-estimation of value of storage. This over-estimation of value is not desirable for investment purposes nor is it desirable for storage valuation. On the other hand, applying controls statically with forecasted values of stochastic variable makes the peak even higher than its original value (where there is no energy storage applied). This is because storage charge may take place at the real peak period, which leads to a load that is higher than its initial amount.

Table 2.3 presents the annual savings in demand charge paid to the electric utility by considering uncertainty from stochastic parameters and applying MPC model. It also shows how applying static controls based on perfect information can over-estimate storage value, and also the negative impact of applying static model based on forecasted values.

Table 2.3 Annual Saving with different models – Winter Week

Storage Capacity (kWh)	PV Capacity (kW)	Annual Saving with Perfect Info ($)	Annual Saving with MPC Model ($)	Annual Saving with Static Model ($)
100	100	28,197	18,661	0
150	100	34,011	18,661	-5,697
200	100	36,348	22,288	-13,560
250	100	38,670	30,370	-9,594

Figure 2.4 and Figure 2.5 below illustrate the forecast errors for 1-hour up to 24-hour-ahead predictions for five consecutive summer weekdays, for electricity and renewable output, respectively.

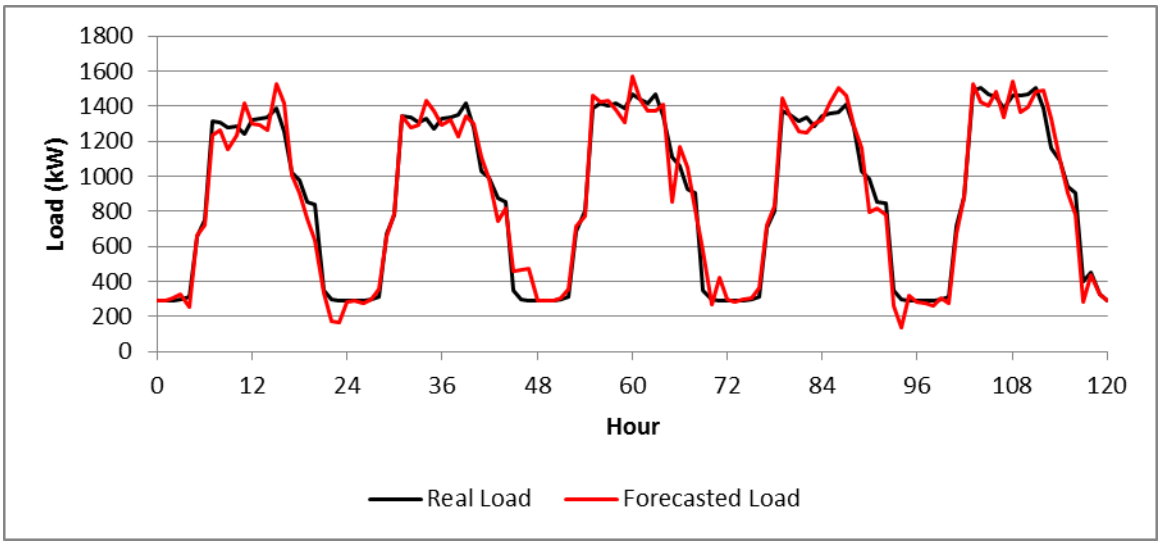

Figure 2.4 Real vs. forecasted electricity demand for a summer week

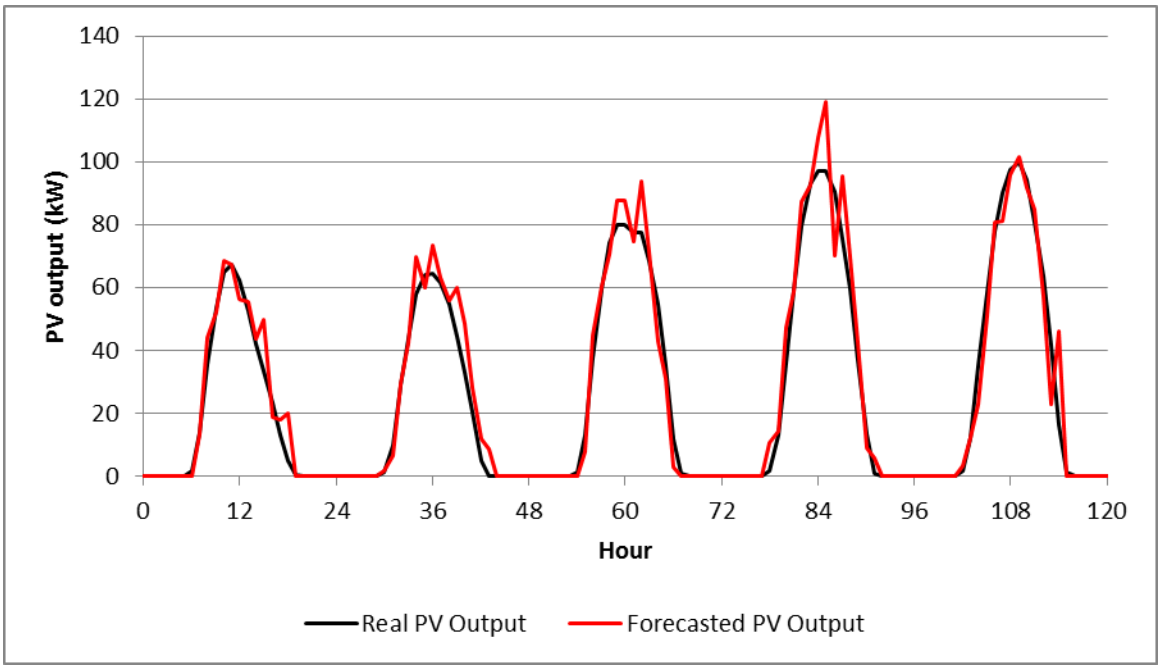

Figure 2.5 Real vs. forecasted PV output for a summer week

Results for this case are presented in Table 2.4 below.

Table 2.4 Comparing MPC vs. Static Model and Perfect Information

Storage Capacity (kWh)	PV Capacity (kW)	Original Peak (kW)	Peak Perfect Info (kW)	Peak MPC (kW)	Peak Static (kW)
100	100	1506.28	1449.94	1481.00	1490.92
150	100	1506.28	1441.48	1472.91	1527.55
200	100	1506.28	1433.01	1465.50	1585.20
250	100	1506.28	1424.55	1465.50	1571.25

Table 2.5 presents the annual savings in demand charge paid to the electric utility by considering uncertainty from stochastic parameters and applying MPC model.

Table 2.5 Annual Saving with Different Models – Summer Week

Storage Capacity (kWh)	PV Capacity (kW)	Annual Saving with Perfect Info ($)	Annual Saving with MPC Model ($)	Annual Saving with Static Model ($)
100	100	16,902	7,584	4,608
150	100	19,441	10,011	-6,379
200	100	21,981	12,233	-23,674
250	100	24,520	12,233	-19,489

2.3.2 Model II – Heuristic optimization technique for storage control with high penetration of renewables

In this section, we consider a utility-owned distribution system or microgrid with high penetration of renewable resources, such that renewable output may exceed system load from time to time. The reverse flow of power, resulting from high level of renewable output and load inability to absorb the excessive power, could cause damage to distribution system infrastructure. Energy storage can be deployed in such systems to absorb the excessive power from renewables and mitigate the damages. The energy

charged from excessive renewable output can be used to reduce energy purchase from the grid during peak hours, given that renewable peak and price peak do not coincide.

Here we develop an approximate optimal control model that decomposes the optimization problem into local zones defined by the relative levels of renewable generation and electricity load. An optimization model is applied with total operation cost as objective function, and aggregate charge and discharge within each zone (in kWh) as decision variables. Below is the description of the algorithm and optimization model being used, as well as illustrative examples to examine the effectiveness of the approach by comparing the results with optimal results of the same model which is solved on an hourly basis (which is supposedly closer to actual optimal solution).

The model can be seen as a multi-period inventory control problem, each zone representing a single period. The remaining inventory (energy in storage) at the end of each period defines the state of storage at the beginning of the next period. Similar to newsvendor model [22], overage cost can be defined as the damage to infrastructure due to reverse power flow from renewable generation. This happens if battery is over-charged in the previous or within the same period, which leads to insufficient charge capacity to absorb the excessive power from renewables. On the other hand, underage cost is the lost demand penalty when storage is not charged enough to supply the remaining load when load exceeds renewable output.

The advantage of the aggregate model over mixed integer linear programming is that in the aggregate model, the time period is decomposed into several zones, and the only variable which is moved from one zone to the next is the state of charge at the end of the zone. By using this decomposition algorithm, solving the problem for longer periods,

means repeating the same problem over many times. While in the mixed integer programming, solving for longer periods, leads to higher dimensions of the problem with many variables, including integer variables.

2.3.2.1 Algorithm

<u>Step 1:</u> Set t as current time.

<u>Step 2:</u> Based on the following criteria, divide the current day (time between t and $t + 24$) into distinct zones, and assign a mode to each zone:

Zone Z_i is in mode 1, if $R_t > L_t$ for every hour within zone Z_i, and

Zone Z_i is in mode 2, if $R_t > L_t$ for every hour within zone Z_i

Figure 2.6 illustrates the zones and modes assigned to each zone for a sample day.

<u>Step 2:</u> Calculate total electricity load and total renewable output within each zone.

<u>Step 3:</u> Using the optimization model presented in sections 0 and 2.3.2.3, find aggregate charge and discharge controls within each zone.

<u>Step 4:</u> Go to the next day and start from Step 1.

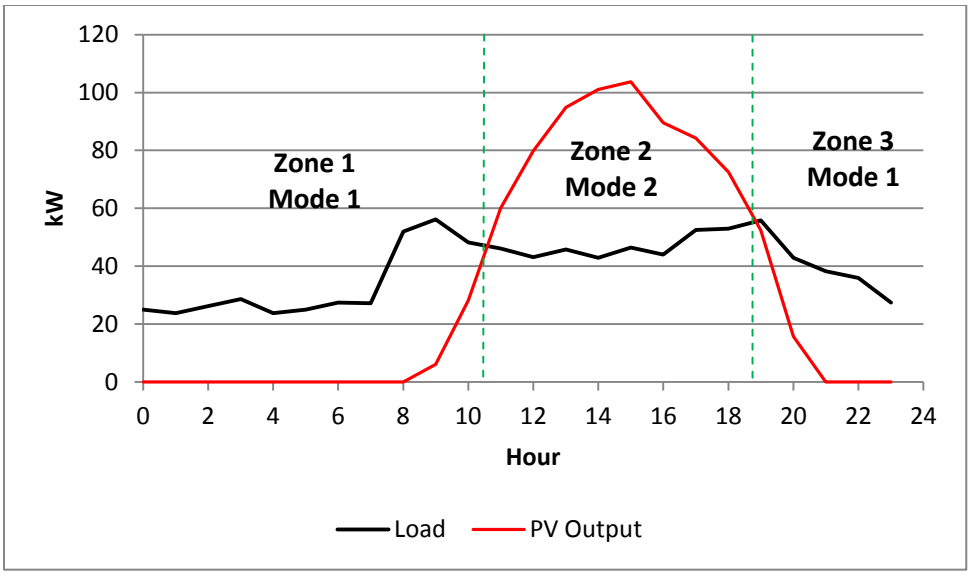

Figure 2.6 Dividing one sample day in zones

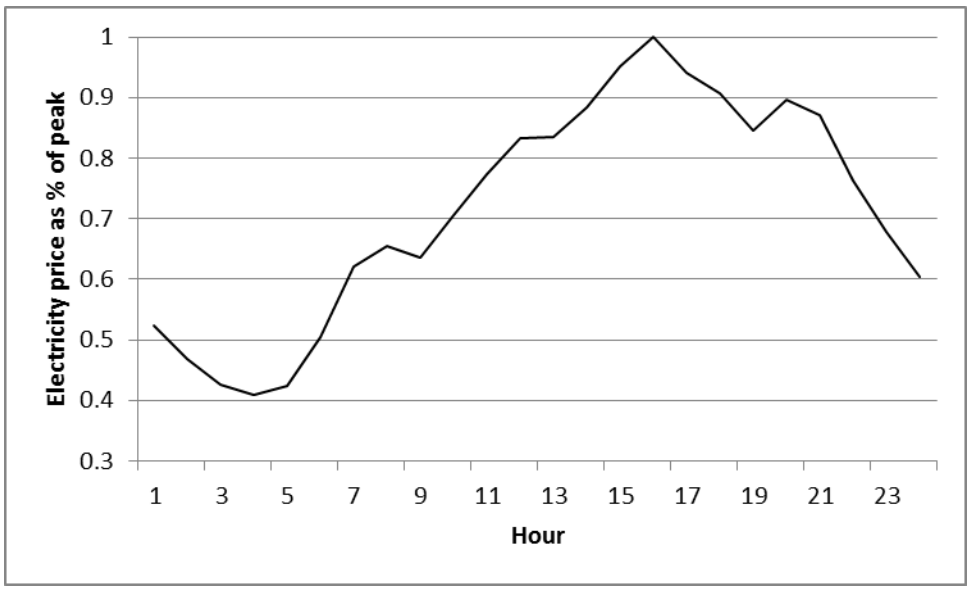

Figure 2.7 Electricity price curve as % of peak price

2.3.2.2 Objective function

Cost for each mode is calculated separately, based on the objective functions presented below.

Mode 1:

In this mode, demand exceeds renewable output. Hence, renewable output is used to supply a portion of electricity demand. The rest of the demand plus any amount to be stored in storage will be supplied by the purchase from grid, less the energy discharged from storage.

$$(L_i - R_i - e_i^d + e_i^{ch,g}) \times Pr_i^w \tag{2.12}$$

Mode 2:

In this mode, all demand is satisfied using renewable output. It is assumed that the remaining power from renewable creates a reverse flow of power at the substation if it is not absorbed by storage. Cost of damage to substation due to the reverse power is estimated by multiplying the remaining renewable output by a penalty factor. If the storage is charged from grid in this mode, cost of energy is added to the objective function.

$$(R_i - L_i - e_i^{ch,r}) \times Pn_{sub} + e_i^{ch,g} \times Pr_i^w \tag{2.13}$$

2.3.2.3 Constraints

Equations (2.14) through (2.16) define the upper bound for energy discharged from storage at zone i based on amount of energy available in storage at the end of zone $i-1$, remaining demand, and storage power rating.

$$e_i^d \leq St_{eff} \times st_{i-1} \tag{2.14}$$

$$e_i^d \leq L_i - R_i \tag{2.15}$$

$$e_i^d \leq D_{max} \times dr_i \tag{2.16}$$

Equations (2.17) and (2.18) define the limit for energy obtained from grid based on empty storage capacity less the energy charged from renewable resources and storage battery rating.

$$e_i^{ch,g} \leq (St_{max} - st_{i-1})/St_{eff} - e_i^{ch,r} \tag{2.17}$$

$$e_i^{ch,g} \leq D_{max} \times dr_i \tag{2.18}$$

Equations (2.19) through (2.21) define the limits for energy charged from renewable resources based on available empty capacity in storage, power rating and available renewable energy in period t.

$$e_i^{ch,r} \leq (St_{max} - st_{i-1})/St_{eff} \tag{2.19}$$

$$e_i^{ch,r} \leq D_{max} \times dr_i \tag{2.20}$$

$$e_i^{ch,r} \leq R_i - L_i \tag{2.21}$$

Storage level is updated based on Equation (2.22).

$$st_i = st_{i-1} + (e_i^{ch,g} + e_i^{ch,r}) \times St_{eff} - (\frac{e_i^d}{St_{eff}}) \tag{2.22}$$

2.3.2.4 Model Validation and Illustrative Examples

Table 2.6 presents the input assumptions for zonal control case studies.

Table 2.6 Input assumptions for zonal control of storage

Parameter	Unit	Level
Storage power rating	kW	100, 150, 200
Storage duration	Hour	2
Storage minimum reserve	% of energy capacity	20
Storage one-way efficiency	%	94
PV maximum output	kW	157

Data for electricity load and PV output profiles are based on real data from an office building and solar panels in California; however the values are scaled to fit the specific use cases for each model. In Figure 2.8, we show energy demand and PV output for a sample week. In this example, all days are divided into three periods, but with different durations.

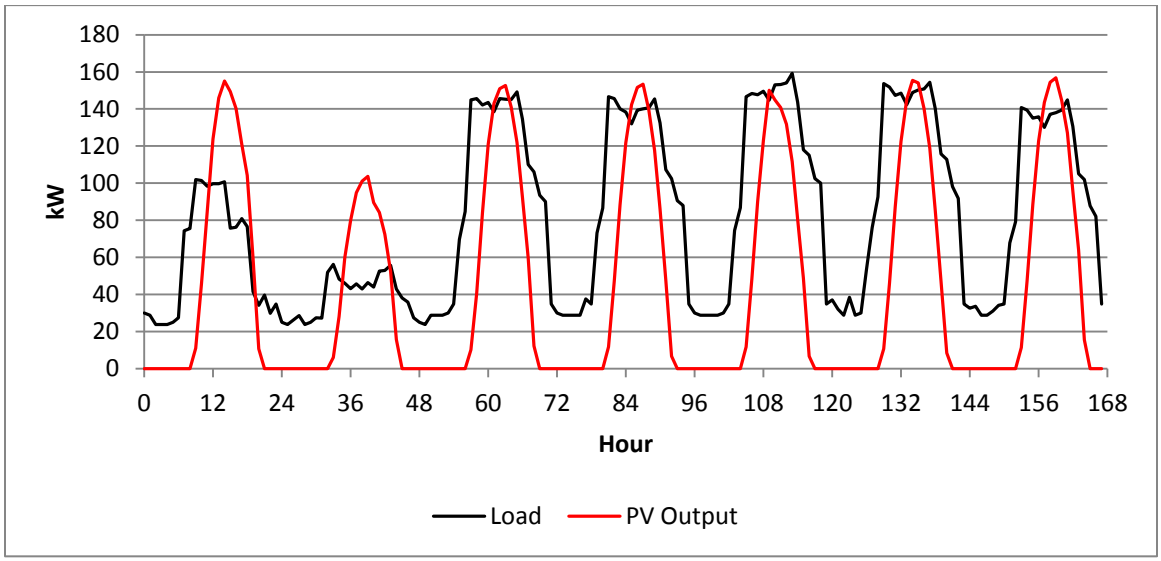

Figure 2.8 Energy demand and PV output for a sample week

We solved the optimization problem introduced in this section using the decomposition model introduced in this section, by applying discretized dynamic programming where

discrete levels of storage, charge and discharge values are used as candidates for optimal solution.

We validate the results of the aggregate model by comparing them to results of an exact model with the same objective function and constraints which us solved using mixed integer linear programming in GAMS. Results from the two models for a 100 kW storage unit, and errors of the aggregate model are presented in Table 2.7 and Table 2.8, respectively.

Table 2.7 Aggregate Models Results Compared to Exact Model Results – 100 kW

Day	Zone	Discharge Agg.	Charge Grid Agg.	Charge Ren. Agg.	Discharge Exact	Charge Grid Exact	Charge Ren Exact
1	1	160	0	0	317	157	0
	2	0	0	160	0	0	160
	3	120	0	0	128	0	0
2	1	40	0	0	192	160	0
	2	0	0	160	0	0	160
	3	130	0	0	132	0	0
3	1	0	120	0	115	230	0
	2	0	0	10	0	0	17
	3	160	0	0	175	15	0
4	1	0	130	0	109	233	0
	2	0	0	30	0	0	36
	3	160	0	0	184	24	0
5	1	0	160	0	80	234	0
	2	0	0	0	0	0	5
	3	160	0	0	250	90	0
6	1	0	150	0	89	236	0
	2	0	0	10	0	0	13
	3	160	0	0	206	46	0
7	1	0	110	0	123	228	0
	2	0	0	50	0	0	55
	3	160	0	0	160	0	0

Table 2.8 Aggregate model errors – 100kW

Days	Zone	|Discharge –Charge Grid| Agg. Error	Charge Ren. Agg. Error
1	1	0%	-
	2	-	0%
	3	6%	-
2	1	25%	-
	2	-	0%
	3	1%	-
3	1	4%	-
	2	-	41%
	3	0%	-
4	1	5%	-
	2	-	17%
	3	0%	-
5	1	3%	-
	2	-	100%
	3	0%	-
6	1	2%	-
	2	-	23%
	3	0%	-
7	1	5%	-
	2	-	9%
	3	0%	-

Results from the two models for a 150 kW storage unit, and errors of the aggregate model are presented in Table 2.9 and Table 2.10, respectively.

Table 2.9 Aggregate Models Results Compared to Exact Model Results – 150 kW

Days	Zone	Discharge Agg.	Charge Grid Agg.	Charge Ren. Agg.	Discharge Exact	Charge Grid Exact	Charge Ren Exact
1	1	240	0	0	323	83	0
	2	0	0	240	0	0	240
	3	120	0	0	128	0	0
2	1	120	0	0	277	165	0
	2	0	0	240	0	0	240
	3	130	0	0	132	0	0
3	1	0	120	0	187	280	0
	2	0	0	10	0	0	17
	3	240	0	0	218	0	0
4	1	0	210	0	118	313	0
	2	0	0	30	0	0	36
	3	240	0	0	230	0	0
5	1	0	240	0	80	315	0
	2	0	0	0	0	0	5
	3	240	0	0	268	28	0
6	1	0	230	0	89	316	0
	2	0	0	10	0	0	13
	3	240	0	0	240	0	0
7	1	0	190	0	183	308	0
	2	0	0	50	0	0	55
	3	240	0	0	180	0	0

Table 2.10 Aggregate model errors – 150kW

Days	Zone	|Discharge – Charge Grid| Agg. Error	Charge Ren. Agg. Error
1	1	0%	-
	2	-	0%
	3	6%	-
2	1	7%	-
	2	-	0%
	3	1%	-
3	1	29%	-
	2	-	41%
	3	10%	-
4	1	8%	-
	2	-	16%
	3	4%	-
5	1	2%	-
	2	-	100%
	3	0%	-
6	1	1%	-
	2	-	23%
	3	17%	-
7	1	52%	-
	2	-	9%
	3	33%	-

Results for another case study with a storage unit with higher power rating (200 kW) are presented in Table 2.11 and Table 2.12.

Table 2.11 Aggregate Models Results Compared to Exact Model Results – 200 kW

Days	Zone	Discharge Agg.	Charge Grid Agg.	Charge Ren. Agg.	Discharge Exact	Charge Grid Exact	Charge Ren Exact
1	1	320	0	0	403	83	0
	2	0	0	320	0	0	320
	3	120	0	0	128	0	0
2	1	200	0	0	301	117	0
	2	0	0	310	0	0	312
	3	130	0	0	132	0	0
3	1	0	130	0	267	280	0
	2	0	0	10	0	0	17
	3	320	0	0	218	0	0
4	1	0	290	0	198	394	0
	2	0	0	30	0	0	36
	3	320	0	0	230	0	0
5	1	0	320	0	80	395	0
	2	0	0	0	0	0	5
	3	320	0	0	320	0	0
6	1	0	310	0	136	396	0
	2	0	0	10	0	0	13
	3	320	0	0	274	0	0
7	1	0	270	0	220	387	0
	2	0	0	50	0	0	55
	3	320	0	0	220	0	0

Table 2.12 Aggregate model errors – 200kW

Days	Zone	|Discharge – Charge Grid| Agg. Error	Charge Ren. Agg. Error
1	1	0%	-
	2	-	0%
	3	6%	-
2	1	9%	-
	2	-	0.6%
	3	1%	-
3	1	900%	-
	2	-	41%
	3	47%	-
4	1	48%	-
	2	-	16%
	3	39%	-
5	1	2%	-
	2	-	100%
	3	0%	-
6	1	19%	-
	2	-	23%
	3	17%	-
7	1	62%	-
	2	-	9%
	3	46%	-

As it is seen in **Error! Reference source not found.** through Table 2.12, aggregate model errors increase with the size of energy storage. The reason is that in the exact model, real electricity price values are observed, hence, as size of storage increase, it is more likely to be used for arbitrage within each zone. However, since average price in each zone is used for optimization in the aggregate model, storage is never used for

arbitrage within one zone. In other words, the approximation model performance is higher for smaller storage sizes, when storage is primarily used for mitigating reverse power from excessive renewable output, and arbitrage between zones. Also, when storage size is relatively large comparing to load and renewable output, storage is not totally utilized to mitigate reverse power damages, which leads to increase in approximation algorithm errors. In Chapter 5 we propose possible extension paths to overcome the drawbacks of this model for large storage units.

2.4 Conclusion

In this chapter, we proposed two energy storage control schemes, for two different use cases, in a microgrid. The first part is an MPC-based optimization model which minimizes microgrid electric bill, composed of energy and maximum demand charges. Uncertainties from renewable resources and electric load are taken into account. Based on a data-driven MPC approach, storage operations are optimized at every hour for the next 24 hours. As new observations are made on the stochastic variables, the corresponding forecasted values, and optimal solutions are updated. Proposed methodology results are assessed against two other solution approaches for the same model; static approach with forecasted values, and static approach with perfect information. It is shown that using static approach with forecasted values may result in increase in peak, due to wrong charge and discharge schedules due to large forecast errors. On the other hand, static approach with perfect information can wrongly over-estimate minimum peak using energy storage.

The second part is a decomposition approach for cases with high penetration of renewable, where renewable output results in high reverse power from its source to the

substation, and can harm the system. To increase the efficiency of the model, solution region is decomposed into distinct zones based on the relative values of renewable output and electric load. Optimal solution includes aggregate charge and discharge within each zone. Comparing the results with a model with exact optimal solutions show that while storage is small enough to serve primarily for renewable output mitigation, approximation model errors are acceptable. However, when storage is used for arbitrage within each zone, approximation errors are higher.

3 A REAL OPTION MODEL FOR MICROGRID INVESTMENT IN ENERGY STORAGE UNDER UNCERTAINTY

In this section, we present a real option model for optimal investment in energy storage within a microgrid under technology cost and electricity price uncertainty. It is assumed that the microgrid owner is given the option of delaying investment decisions depending on price of electricity and cost of technology. Microgrid configuration includes distributed generation assets, such as solar PVs and energy storage. The objective is to find the optimal timing of initial investment in energy storage, as well as the expansion of existing energy storage capacity within a microgrid, such that total savings are maximized. Energy storage has two value streams for the microgrid, depending on the type of operation, e.g. normal or emergency. Under normal conditions, the model assumes optimal operation of energy storage under uncertainty adopted from Chapter 2 of this thesis. The value stream during normal operation includes demand charge and energy cost reduction. The microgrid has also the capability of islanding during grid outages, and energy storage is able to mitigate microgrid load loss fully or partially during these outages, and increase its reliability. It is assumed that the capacity configurations of initial investment and expansion of energy storage are parametrically fixed. This work extends the current state of investment modeling within the context of energy storage for microgrid by considering: (i) Modular or incremental investment, i.e. both initial investment and expansion of existing energy storage capacity; (ii) Multiple sources of uncertainties along with more realistic probability distributions, (iii) interdependencies

between savings from initial capacity and expanded capacity of storage are considered, (iv) Optimal operation of storage is considered, which results in more realistic saving estimations.

3.1 Introduction

Investment in a microgrid is subject to exogenous and endogenous sources of uncertainty, resulting in high risk exposures for both private and public investors, unless the uncertainties are taken into account for decision making. With increasing penetration of renewable resources, energy storage is becoming more popular, as they are used to mitigate different reliability and power quality-related issues caused by intermittency of renewable resources. Energy storage can also be beneficial for its capabilities which do not exist in renewable resources, such as controllable charge and discharging. However, since the cost of technology for energy storage drops with technology innovations and market penetration, investment timing and sizing is still an issue for microgrid owners. Price of electricity is another source of uncertainty which should be considered.

The traditional Net Present Value (NPV) approach for investment does not consider different sources of uncertainty in fuel or electricity prices or cost of technology explicitly. The option to postpone the investment gives the decision maker the opportunity to wait for more information about the uncertain future, which is also ignored in NPV [23] and can adversely impact the investment decision. Using real options approach makes it possible to examine if there is positive value in postponing the investment to obtain more information about uncertain future. In that case the investor has the option to invest only if the stochastic parameters move in a favorable direction. In

this chapter, we use real option theory to derive optimal investment strategies in energy storage, taking into account a number of uncertainty sources.

As stated in [24], the valuation and optimal exercise of American options is one of the most challenging problems especially when there is more than one source of uncertainty. This is primarily because finite difference and binomial techniques become impractical in situations where there are multiple factors. By its nature, simulation is a promising alternative to traditional finite difference and binomial techniques and has many advantages as a framework for valuing, risk managing, and optimally exercising American options. Unlike other methodologies, simulation is readily applied when the value of the option depends on multiple factors. Simulation can also be used to value derivatives with both path-dependent and American-exercise features. It allows state variables to follow general stochastic processes. Finally, simulation techniques are simple, transparent and flexible.

To take into account realistic saving functions and other complexities in the proposed investment problem, Least Squares Monte Carlo simulation method (LSM) for compound options (proposed by Longstaff and Schwartz [25]) is used in this chapter to find optimal investment decisions. To demonstrate the impact of uncertainty in the form of opportunity cost, we compare the simulation results to the results from an NPV model. We also examine the impact of different model parameters on optimal investment thresholds and investment decisions.

3.2 Literature Review

3.2.1 Real Options

Monte Carlo simulation is a powerful and flexible tool for capital budgeting. It makes it possible to include a wide range of value drivers, it is flexible enough to cope with many realistic assumptions and it does not suffer the curse of dimensionality which affects other numerical methods.

Mason and Merton [26] first described a capital budgeting problem as a collection of real options. The value of a portfolio of interacting options is not necessarily additive over its individual options, hence, the problem of decomposing a complex investment decisions into a set of individual options does not ususally have a straightforward solution. This observation prevents the use of valuation techniques that are normally developed for individual option analysis. Kulatilaka and Trigeorgis [27] proposed a valuation approach based on the idea of switching among different operating modes. In their work, decisions to be made are modeled as options to switch from the current mode to a different one. According to their approach, a flexible capital budgeting problem can be seen as a complex compound switch option among several modes. However, the main drawback of their work is its computational efficiency. Gamba and Trigeorgis [28] propose an approach to map a real options problem into a set of simple options, taking into account the hierarchical structure of the options. This approach always provides well defined problems with a finite solution, given that each individual option has a finite solution.

Based on [25], real options embedded in a capital budgeting problem are usually American type claims, meaning that closed-form solutions are rarely available for them,

and hence some numerical methodologies should be used. Many methods have been proposed for real option pricing. These methods can be divided into three main categories; finite difference methods which directly deal with PDE's (e.g. [29]), Monte Carlo simulation-based methods (e.g. [30]) and lattice methods (e.g. [31]). Below is a brief description for each category.

Finite difference is a quite hard method to implement if the problem consists of multiple interacting options. On the other hand, although being very flexible for multiple options, lattice methods suffer the curse of dimensionality. For the above mentioned reasons, simulation seems to be the most suited numerical technique for valuing real options. A promising approach to apply Monte Carlo Simulation for real options valuation has been proposed by Longstaff and Schwartz [24]. This method, called Least Squares Monte Carlo (LSM) approach, uses least squares linear regression to determine the optimal exercise time of the option. Gamba [25] provide an extension of LSM algorithm to evaluate complex investment projects with many interacting options, called compound options, and also many state variables. This approach covers three types of multi-option problems, i.e. independent options, mutually exclusive options, and compound options. In our work, we adopted the methodology proposed for compound options in Gamba [25], and used it in our energy storage investment problem.

3.2.2 Investment in Energy Storage

Muche [32] provide a real option based simulation model to evaluate investments in pump storage plants. Two methods are applied for performing the investment appraisal. The first method is based on the classic investment appraisal, which takes expected cash flows from an investment as a basis for the valuation of it, and the second method

simulates different price paths for the future, and makes investment decisions based on the optimal unit commitment for that simulated price path for more realistic evaluation.

Xiu and Li [33] investigate energy storage investment decisions based on real option, and use binary tree option pricing model for their analysis. Reuter et al. [34] formulate the investment problem in wind power and pumped storage using a real option model. The resulting problem is a stochastic optimal control problem in discrete time with all the underlying variables being discrete in each time step. This is solved by recursive dynamic programming. Farzan [35] used real option theory to find optimal investment strategies for microgrid assets, with parametrically fixed capacities. The model utilizes both finite difference and LSM, and considers uncertainty in electricity price and PV technology cost.

3.3 Problem Statement and Preliminaries

We consider investment in energy storage within a microgrid that has electricity load which is partially supplied by distribution generation assets, including PV renewable generation, and is also connected to the grid to supply its remaining load.

Nomenclature

C_{st}	Investment cost of storage ($/kW)
α_{st}	Annual percentage growth rate of storage cost
σ_{st}	Annual percentage volatility of storage cost
r	Risk-free rate of return
μ	Risk-adjusted rate of return
$C_{e,t}$	Electricity price ($/kWh)

C_{dc}	Demand charge ($/kW)
$C_{e,p}$	Electricity price at peak ($/kWh)
$\alpha_{e,p}$	Annual percentage growth rate of electricity price at peak
$\sigma_{e,p}$	Annual percentage volatility of electricity price at peak
Z	Standard Geometric Brownian Motion
ρ_i	Percentage of the year microgrid operates in mode i
p_{ll}	Penalty of lost load during outages ($/kW)
Cap_{init}	Capacity of initial investment
Cap_{exp}	Capacity of expansion investment
NPV	Net Present Value
$C^*_{st,i}$	Storage technology price threshold for initial investment
$C^*_{st,e}$	Storage technology price threshold for expanded investment
$S^{total}_{lifetime}$	Microgrid savings during energy storage lifetime
S^{total}	Microgrid total annual savings
S^{normal}	Microgrid annual savings in normal mode
$S^{islanding}$	Microgrid annual saving in islanding mode
C^{ns}	Microgrid annual energy and demand charges with no storage capacity
C^{ws}	Microgrid annual energy and demand charges with storage capacity
K^{ns}_m	Microgrid peak demand with no storage capacity
K^{ws}_m	Microgrid peak demand with storage capacity
L^{ns}_t	Microgrid hourly load with no storage capacity
L^{ws}_t	Microgrid hourly load with storage capacity
n^{out}	Annual rate of grid outages

t^{out} Average restoration time for grid outages

d_{st} Storage duration

3.4 Dynamics of Uncertainty

There is no stochastic process identified for storage investment cost, however, it is believed that storage technology price drops in the next few years will slow down, as storage technologies become more mature [36]. Following [23], uncertainty on the value of a new technology can be modeled as a Geometric Brownian Motion (GMB). By definition, a Brownian Motion is a Markov process, which implies that only current information is useful in forecasting the future path of the process. We assume a decreasing trend according to a Geometric Brownian Motion for energy storage technology cost.

$$dC_{st} = \alpha_{st} C_{st} dt + \sigma_{st} C_{st} dZ_{st} \tag{3.1}$$

where C_{st} is energy storage investment cost (\$/kW), α_{st} is the investment cost annual percentage growth rate and σ_{st} is the investment cost annual percentage volatility. Z_{st} is standard Brownian Motion.

Although using a Geometric Brownian Motion to model price dynamics ignores short term mean reversion, a storage unit must be regarded as a long term investment where the short term mean reversion barely influences values and investment decisions. Motivated by this, we assume the long term electricity prices also follow a Geometric Brownian Motion, as proposed in [37], where the change in price over a small time interval is written as

$$dC_{e,p} = \alpha_{e,p} C_{e,p} dt + \sigma_{e,p} C_{e,p} dZ_{e,p} \tag{3.2}$$

where $C_{e,p}$ is electricity price at peak (\$/kWh), $\alpha_{e,p}$ is the electricity price annual percentage growth rate and $\sigma_{e,p}$ is the electricity price annual percentage volatility. $Z_{e,p}$ is standard Brownian Motion.

The hourly profile for electricity price, $C_{e,t}$ based on price at peak is shown in Figure 3.1.

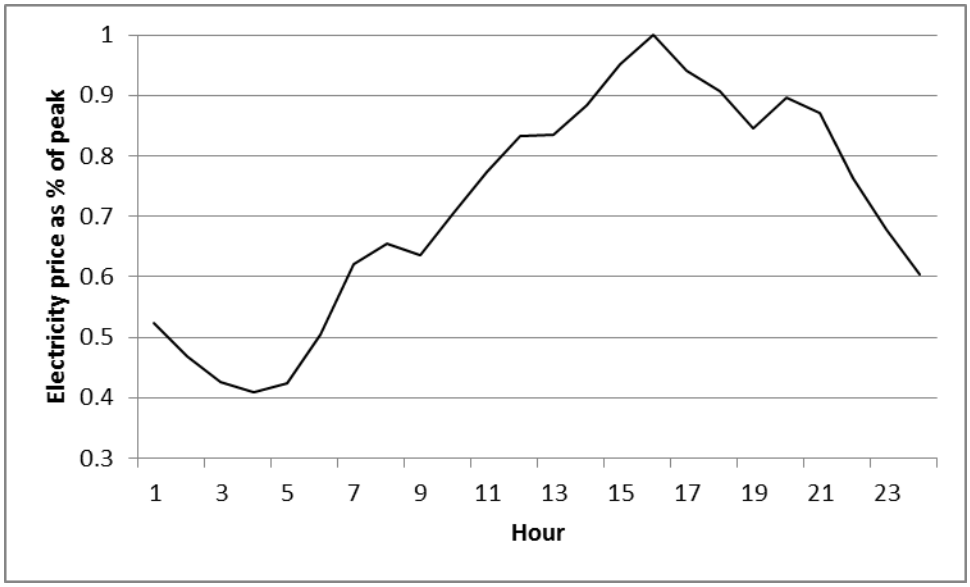

Figure 3.1 Electricity price as % of peak price

3.4.1 Calculation of Savings

Savings from energy storage are estimated based on two operational modes; normal mode and islanding mode. During normal mode, energy storage is assumed to contribute to microgrid bill savings in two ways, namely, peak shaving which results in demand charge reduction and change in time of use which results in energy cost reduction. During islanding mode, i.e. when there is a grid outage, storage benefit is estimated by monetized value of load loss reduction, using a penalty cost.

Calculation of Savings during Normal Mode

One of the primary benefits of energy storage is microgrid electric utility bill reduction through removal or reduction of demand charges and shifting PV output to reduce energy related bill charges. In this chapter, we utilize the Model Predictive Control-based model presented in Chapter 2 of this thesis to estimate savings in microgrid bill by operating storage optimally, taking into account electricity load and renewable generation uncertainties for more realistic saving values.

Annual savings from energy storage during normal operation is defined by Equation (3.3).

$$S^{normal} = C^{ns} - C^{ws} \tag{3.3}$$

where C^{ns} is total demand charge and energy cost of microgrid with no storage capacity, and C^{ws} is total demand charge and energy cost of microgrid with storage capacity. By definition, demand charge is a monthly payment to the utility for monthly peak load. Hence, C^{ns} is calculated based on Equation (3.4).

$$C^{ns} = \sum_{m=1}^{12} (dc \times K_m^{ns}) + \sum_{t=1}^{24\times365} (pr_t \times L_t^{ns}) \tag{3.4}$$

where dc is demand charge, K_m^{ns} is monthly peak load with no energy storage (Equation (3.5)), pr_t is electricity price at time t, and L_t^{ns} is microgrid load at time t without energy storage. The first summation in Equation (3.4) sums the demand charges over the course of a year, and the second summation, calculates annual energy cost of microgrid.

$$K_m^{ns} = \max_{t \in T_m} L_t^{ns} \tag{3.5}$$

Total demand charge and energy cost of microgrid with storage capacity is calculated in a similar way.

$$C^{ws} = \sum_{m=1}^{12} (dc \times K_m^{ws}) + \sum_{t=1}^{24\times365} (pr_t \times L_t^{ws}) \tag{3.6}$$

where K_m^{ws} is monthly peak load (Equation (3.7)), and L_t^{ws} is microgrid load at time t with energy storage.

$$K_m^{ws} = \max_{t\in T_m} L_t^{ws} \tag{3.7}$$

Hourly load can be controlled by storage charge and discharge, as shown in Equation (3.8). Optimal values of ch_t and d_t, charge and discharge at time t, are obtained from MPC- base optimization model proposed in Chapter 2.

$$L_t^{ws} = L_t^{ns} + ch_t - d_t \tag{3.8}$$

Calculation of Savings during Islanding Mode

We assume that grid outages occur according to a random process with an annual rate of n^{out} and each time an outage occurs, restoration takes an average of t^{out} hours. Hence, during the course of a year, on the average, a total of $n^{out} \times t^{out}$ hours are spent in islanding mode. For simplicity, we also assume that battery is fully charged at the time of an outage. Then, annual savings of microgrid from energy storage during islanding mode can be calculated as:

$$S^{islanding} = \begin{cases} n^{out} \times t^{out} \times D_{max} \times p_{ll} & if\ t^{out} < d_{st} \\ n^{out} \times d_{st} \times D_{max} \times p_{ll} & if\ t^{out} > d_{st} \end{cases} \tag{3.9}$$

Total Annual Saving

Total annual saving is a weighted sum of savings in normal and islanding modes, calculated based on Equation (3.10).

$$S^{total} = \frac{8760 - n^{out} \times t^{out}}{8760} \times S^{normal} + S^{islanding} \tag{3.10}$$

Savings over Energy Storage Lifetime

Energy storage lifetime is estimated to be 15 years, starting from the time of investment, and during each year, microgrid saves S^{total} by owning and operating energy storage. Hence, present value of total savings from energy storage during its lifetime (at the time of investment) is calculated by discounting the savings cash flow with a discount rate of *r*, as shown in Equation (3.11).

$$S_{lifetime}^{total} = \sum_{i=1}^{15} \frac{S^{total}}{(1+r)^{i-1}} \tag{3.11}$$

3.4.2 Monte Carlo Simulation of Real Option

In this section, we use Monte Carlo simulation to solve real option investment in energy storage for consecutive and dependent options, i.e., option on an initial investment in energy storage and option on further expansions of the storage capacity. This section includes a short description of the methodology, followed by mathematical representation of the algorithm.

The idea of using Monte Carlo simulation for real option problems is adopted from [24]. They provide a valuation algorithm based on simulation that implements backward dynamic programming. The algorithm provides a way to determine the optimal stopping time of an American-like option and to find the estimate of the option value. The problem of optimal timing in investment with option to postpone the investment is similar to financial American style option. At each exercise date, the option holder decides whether to immediately exercise the option or to keep the option alive until some later time. Therefore, the optimal exercise strategy is determined by comparing the immediate payoff obtained from investment in a storage unit and the conditional expectation of

payoffs from keeping the option alive. The conditional expectation is estimated from cross-sectional information in the simulation paths using least squares regression. The future realized payoffs from continuation are regressed on the values of state variables, i.e. electricity price and storage investment cost. This function is then used to calculate the conditional expectation of option continuation at each exercise date. The problem is solved as a backward dynamic programming, starting from the last time period in the investment horizon. The calculation procedure is applied over all generated simulation paths and conditional distributions of investment thresholds for storage investment cost are obtained. Gamba [25] further extended the idea of individual option to compound options. The idea underlying their approach is that a capital budgeting problem can be decomposed into a hierarchical set of simple options. In this chapter, we consider a real option (for initial investment), which when exercised, can offer more opportunities (for expansion).

3.4.2.1 Methodology

Assume that there are two state variables defined by $C = (C_{st}, C_{e,p})$. Also, suppose that the decision maker has the option to invest in storage within the microgrid, with maturity date of T and payoff $\Pi(T, C_T)$. Let $F(t, C_t)$ be the value of the option at $t \leq T$, with $F(T, C_T) = \Pi(T, C_T)$. For American option we have:

$$F(t, C_t) = \max_{\tau \in \Gamma(t,T)} \left\{ e^{-r(\tau - t)} \mathbb{E}_t^*[\Pi(\tau, C_\tau)] \right\} \tag{3.12}$$

where $\Gamma(\mathrm{t}, \mathrm{T})$ is the set of stopping times and $\mathbb{E}_{\mathrm{t}}^*[.]$ is the expectation, conditional on the information available at t. Given the valuation problem for an American option on C, an approximation of the option value is obtained by dividing the time span $[0, \mathrm{T}]$ into N

intervals, with the length of each interval to be $\Delta t = T/N$. Then, K simulated paths of the stochastic process $\{C_t\}$ are generated. We denote by $C_t(\omega)$ the value of the process at time t along the ω-th simulation path and $\tau(\omega)$ the path-wise stopping time with respect to the information generated by $\{C\}$.

Our goal is to find the optimal exercise time restricted to the set of dates

$$\{t_0 = 0, t_1 = \Delta t, \dots, t_N = N\Delta t\}.$$

The optimal policy is obtained by backward dynamic programming: if at time t_n and along the path ω, the option is still alive, the optimal decision is made by comparing the payoff of immediate investment, $\Pi(t_n, C_t(\omega))$ with option value, $F(t, C_t(\omega))$. In our model, payoff $\Pi(t_n, C_t(\omega))$ is defined as the discounted savings of energy storage for microgrid over its lifetime period of 15 years, from which capital cost of investment is subtracted (Equation (3.13)).

$$\Pi\big(t_n, C_t(\omega)\big) = S_{lifetime}^{total} - C_t(\omega) \tag{3.13}$$

A detailed explanation of savings calculations is presented in section 0. If $F\big(t, C_t(\omega)\big) = \Pi(t_n, C_t(\omega))$ then $\tau(\omega) = t_n$, and the optimal stopping time along the ω-th path is updated. In other words, the stopping time satisfies the following condition:

$$\tau = inf\{t | F(t, C_t) = \Pi(t, C_t)\} \tag{3.14}$$

A way to estimate $F(t, C_t)$, is offered by the Bellman equation of the optimal stopping problem in discrete time:

$$F(t, C_t) = max\big\{\Pi(t_n, C_{t_n}), e^{-r(t_{n+1}-t_n)}\mathbb{E}_{t_n}^{*}\big[F\big(t_{n+1}, C_{t_{n+1}}\big)\big]\big)\big\} \tag{3.15}$$

Using this equation, the path-wise optimal policy, restricted to the given dates, can be determined by comparing the continuation value,

$$\Phi\left(t_n, C_{t_n}\right) = e^{-r(t_{n+1}-t_n)} E_{t_n}^{*}\left[F\left(t_{n+1}, C_{t_{n+1}}\right) | \mathcal{F}_{t_n}\right] \tag{3.16}$$

with the payoff, $\Pi(t_n, C_{t_n})$. In our context, $\Phi\left(t_n, C_{t_n}\right)$, the expected continuation value of the investment option, is the benefit less the cost of investment in energy storage in future years along the planning horizon, expected over all generated paths.

In other words, $\Phi\left(t_n, C_{t_n}\right)$ is the expected value of savings less investment cost, if the decision maker decides to invest in one of the remaining years following t_n along the time horizon.

The decision rule at time step t_n along the ω-th path is then defined as:

$$\Phi\left(t_n, C_{t_n}(\omega)\right) \leq \Pi(t_n, C_{t_n}(\omega)) \quad \text{then} \quad \tau(\omega) = t_n \tag{3.17}$$

At $t_n = T$, since the option is expiring, $\Phi\left(t_n, C_{t_n}\right) = 0$, and the rule is to exercise the option if the payoff is positive. At any t_n, the optimal stopping time is found by recursively applying the decision rule in (3.17), from $t_n = T$ back to t_n. If at some previous step of this procedure, $\tau(\omega) > t_n$, and condition (3.17) holds at the current step, then the stopping time along path ω is updated: $\tau(\omega) = t_n$. At $t_n = 0$, when the optimal stopping times along all paths are determined, the value of the option is estimated by averaging the path-wise values:

$$F(0, C) = \frac{1}{K} \sum_{\omega=1}^{K} e^{-r\tau(\omega)} \Pi(\tau(\omega), C_{\tau(\omega)}(\omega)) \tag{3.18}$$

In this work, we use Least Squares Monte Carlo (LSM) method to find the continuation value at (t, C_t), in order to apply the decision rule in (3.17). The intuition behind LSM is the following: if at t the option is still available, the continuation value is the expectation, conditional on the information available at that date, of future optimal payoffs from the contingent claim. Let $\Pi(t, s, \tau, \omega)$ be the cash flow from the option optimally exercised at time s (with respect to the stopping time $\tau(\omega)$, conditional on not being exercised at $t < s$, along the ω-th path. Hence,

$$\Pi(t, s, \tau, \omega) = \begin{cases} \Pi(s, X_s(\omega)) & if\ s = \tau(\omega) \\ 0 & if\ s \neq \tau(\omega) \end{cases} \tag{3.19}$$

The continuation value at t_n is the present value of all future expected cash flows from the contingent claim

$$\Phi\left(t_n, C_{t_n}\right) = \mathbb{E}^*_{t_n}\left[\sum_{i=n+1}^{N} e^{-r(t_i - t_n)} \Pi(t_n, t_i, \tau, .)\right] \tag{3.20}$$

Longstaff and Shwartz [24] suggest the following methodology to estimate continuation value over all paths. To determine the expected conditional continuation values, future realized payoffs from continuation are regressed on state variable(s), e.g. storage investment cost. Hence, we can calculate the continuation value at time t_n as

$$\Phi\left(t_n, C_{t_n}\right) = \beta_0 + \beta_1 C_{st}(t_n) + \beta_2 C_{st}^2(t_n) \tag{3.21}$$

$\Phi\left(t_n, C_{t_n}\right)$ is then used to apply recursively the decision rule in (3.17).

For the case with 2 interdependent options, i.e. initial investment and expansion, the algorithm is the following. We assume that the path-wise stopping time for the 2nd option (expansion) has been already determined using the method described above for a single

option. We then compute the path-wise stopping time for the 1st option (initial investment). The Bellman equation for this option is presented in Equation (3.22).

$$F_1(t_n, C_{t_n}) = \max\{\Pi_1(t_n, C_{t_n}) + F_2(t_n, C_{t_n}), e^{-r(t_{n+1}-t_n)}\mathbb{E}^*_{t_n}[F_1(t_{n+1}, C_{t_{n+1}})]\} \quad (3.22)$$

where F_1 is the value of initial investment option, Π_1 is the payoff of initial investment option, and F_2 is the value of the expansion option. Hence, to compute the stopping time $\tau_1(\omega)$ for initial investment option at t_n and on the ω-th path, decision rule is:

$$\text{If} \quad \Phi_1(t_n, X_{t_n}(\omega)) \leq \Pi_1\left(t_n, X_{t_n}(\omega)\right) + F_2\left(t_n, X_{t_n}(\omega)\right) \quad \text{then} \quad \tau_1(\omega) = t_n \quad (3.23)$$

where Φ_1 is the continuation value from the Bellman equation, and τ_1 is the stopping time for the initial investment option.

3.5 Illustrative Example I

In this section, we present results for an example case and examine the impact of different model parameters on investor decision strategies for both initial investment and expansion options.

3.5.1 Input Assumptions

Table 3.1 Input Assumptions for Real Option Simulation Model - Example I

Parameter	Unit	Value
Storage technology	-	Lithium-Ion High Energy Battery
Storage rated power for initial investment	kW	50
Storage rated power for expansion	kW	50
Discharge duration at rated power	Hrs	2
One-way storage efficiency	-	0.94
Installed cost of storage	$/kW	From a GBM process
Engineering life of storage	yrs	15
Demand charge	$/kW	45

It is assumed that GBM governs both electricity price and PV investment cost. The parameters of the two processes are listed in Table 3.2.

Table 3.2 Stochastic parameters of GMB

	α	σ
Electricity price	0.01	0.075
Storage cost	-0.06	0.06

3.5.2 Results from Sample Simulation Paths

Table 3.3 illustrates the results for 10 sample paths. Realized electricity peak prices and storage investment costs are obtained by Monte Carlo simulation. Based on these realized values and optimal operation of storage, annual and lifetime savings for the microgrid are calculated.

We will take one path in the simulation and explain the solution. In path one, storage investment costs are shown as they realize over 4 years. In years 1 and 2, microgrid savings from storage are 6.02×10^4 and 6.86×10^4 dollars respectively. Immediate investment on those years would lead to values of 0 and 1.37×10^5 dollars, respectively. However the conditional expectation of continuation (i.e., wait instead of immediate investment) is higher than its corresponding value for year 1 (1.29×10^4 vs. 0) and lower for year 1 (1.36×10^5 vs 1.37×10^5). Therefore, the investor continues to wait and does not undertake the investment in year 1, and invests in year 2. Once the initial investment decision is made in year 2, the investor now has the option to either expand storage capacity in one of the years 3 or 4, or not to do any further investments. Value of expansion in year 3 is 7.29×10^4 in year 1, while the continuation value is 7.22×10^4. Hence, the investor decides to expand the storage capacity in year 3.

Table 3.3 Real option simulation results for 10 sample paths – Example I

Investment Cost (C_{st})					Saving - Initial (Π_1)				
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	1.60E+03	1.41E+03	1.35E+03	1.32E+03	**1**	6.02E+04	6.86E+04	7.29E+04	7.42E+04
2	1.60E+03	1.54E+03	1.53E+03	1.54E+03	**2**	6.02E+04	6.31E+04	6.36E+04	6.32E+04
3	1.60E+03	1.44E+03	1.32E+03	1.29E+03	**3**	6.02E+04	6.81E+04	7.42E+04	7.54E+04
4	1.60E+03	1.49E+03	1.43E+03	1.30E+03	**4**	6.02E+04	6.55E+04	6.84E+04	7.51E+04
5	1.60E+03	1.42E+03	1.37E+03	1.45E+03	**5**	6.02E+04	6.91E+04	7.17E+04	6.77E+04
6	1.60E+03	1.52E+03	1.50E+03	1.40E+03	**6**	6.02E+04	6.43E+04	6.49E+04	7.00E+04
7	1.60E+03	1.41E+03	1.20E+03	9.86E+02	**7**	6.02E+04	6.95E+04	7.99E+04	9.22E+04
8	1.60E+03	1.46E+03	1.39E+03	1.36E+03	**8**	6.02E+04	6.73E+04	7.08E+04	7.22E+04
9	1.60E+03	1.41E+03	1.26E+03	1.11E+03	**9**	6.02E+04	7.00E+04	7.27E+04	8.48E+04
10	1.60E+03	1.58E+03	1.63E+03	1.45E+03	**10**	6.02E+04	6.13E+04	5.86E+04	6.74E+04
Value - Initial (F_1)					**Expected Continuation – Initial (Φ_1)**				
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	0	1.37E+05	1.43E+05	7.42E+04	**1**	1.29E+05	1.36E+05	7.22E+04	0
2	0	0	1.23E+05	6.32E+04	**2**	0	1.29E+05	6.48E+04	0
3	0	1.38E+05	1.45E+05	7.54E+04	**3**	1.29E+05	1.36E+05	7.34E+05	0
4	0	1.32E+05	1.39E+05	7.51E+04	**4**	1.29E+05	1.32E+05	6.85E+05	0
5	0	0	1.36E+05	6.77E+04	**5**	0	1.37E+05	7.12E+04	0
6	0	0	1.31E+05	6.99E+04	**6**	0	1.30E+05	6.58E+04	0
7	0	1.45E+05	1.70E+05	9.22E+04	**7**	1.29E+05	1.37E+05	7.87E+05	0
8	0	0	1.39E+05	7.22E+04	**8**	0	1.35E+05	7.04E+04	0
9	0	1.43E+05	1.57E+05	8.48E+04	**9**	1.29E+05	1.38E+05	7.62E+05	0
10	0	0	1.22E+05	6.74E+04	**10**	0	1.26E+05	6.14E+04	0
Saving – Expansion (Π_2)					**Value - Expansion (F_2)**				
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	6.02E+04	6.86E+04	7.29E+04	7.42E+04	**1**	0	6.86E+04	7.29E+04	7.42E+04
2	6.02E+04	6.31E+04	6.36E+04	6.32E+04	**2**	0	6.31E+04	6.36E+04	6.32E+04
3	6.02E+04	6.81E+04	7.42E+04	7.54E+04	**3**	0	6.81E+04	7.42E+04	7.54E+04
4	6.02E+04	6.55E+04	6.84E+04	7.51E+04	**4**	0	6.55E+04	6.84E+04	7.51E+04
5	6.02E+04	6.91E+04	7.17E+04	6.77E+04	**5**	0	6.91E+04	7.17E+04	6.77E+04
6	6.02E+04	6.43E+04	6.49E+04	7.00E+04	**6**	0	6.43E+04	6.49E+04	7.00E+04
7	6.02E+04	6.95E+04	7.99E+04	9.22E+04	**7**	0	6.95E+04	7.99E+04	9.22E+04
8	6.02E+04	6.73E+04	7.08E+04	7.22E+04	**8**	0	6.73E+04	7.08E+04	7.22E+04
9	6.02E+04	7.00E+04	7.27E+04	8.48E+04	**9**	0	7.00E+04	7.27E+04	8.48E+04

10	6.02E+04	6.13E+04	5.86E+04	6.74E+04	**10**	0	6.13E+04	5.86E+04	6.74E+04

		Expected Continuation – Expansion|Initial @ 1 (Φ_2)					**Expected Continuation – Expansion|Initial @ 2 (Φ_2)**		
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	0	6.83E+04	0	0	**1**	0	0	7.22E+04	0
2	0	6.46E+04	0	0	**2**	0	0	6.48E+04	0
3	0	6.80E+04	0	0	**3**	0	0	7.34E+04	0
4	0	6.63E+04	0	0	**4**	0	0	6.85E+04	0
5	0	6.87E+04	0	0	**5**	0	0	7.12E+04	0
6	0	6.55E+04	0	0	**6**	0	0	6.58E+04	0
7	0	6.89E+04	0	0	**7**	0	0	7.87E+04	0
8	0	6.75E+04	0	0	**8**	0	0	7.04E+04	0
9	0	6.91E+04	0	0	**9**	0	0	7.62E+04	0
10	0	6.33E+04	0	0	**10**	0	0	6.14E+04	0

		Initial Decision					**Expansion Decision - year 2**		
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	0	1	0	0	**1**	0	1	0	0
2	0	0	1	0	**2**	0	0	0	1
3	0	1	0	0	**3**	0	1	0	0
4	0	1	0	0	**4**	0	0	0	1
5	0	0	1	0	**5**	0	1	0	0
6	0	0	1	0	**6**	0	0	0	1
7	0	1	0	0	**7**	0	1	0	0
8	0	0	1	0	**8**	0	0	1	0
9	0	1	0	0	**9**	0	1	0	0
10	0	0	1	0	**10**	0	0	0	1

		Expansion Decision - year 3					**Expansion Decision - year 4**		
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	0	0	1	0	**1**	0	0	0	1
2	0	0	0	1	**2**	0	0	0	1
3	0	0	1	0	**3**	0	0	0	1
4	0	0	0	1	**4**	0	0	0	1
5	0	0	1	0	**5**	0	0	0	1
6	0	0	0	1	**6**	0	0	0	1
7	0	0	1	0	**7**	0	0	0	1
8	0	0	1	0	**8**	0	0	0	1

9	0	1	1	0	**9**	0	0	0	1
10	0	0	0	1	**10**	0	0	0	1

3.5.3 Storage cost thresholds for initial investment and capacity expansion

The expectation of optimal thresholds can be calculated from the conditional distribution function presented in Equation (3.24).

$$E(C_{st}^{*}) = \sum_{i=1}^{4} E(C_{st}^{*}|\tau = i)P(\tau = i) \tag{3.24}$$

Using Equation (3.24), optimal thresholds for initial investment and expansion of existing capacity (for the example shown in Table 3.3) are presented below. Results in Table 3.4 can be a guide for the investor to make decisions to invest (either for initial investment or expansion) once the technology cost of storage reaches the thresholds shown in the table.

Table 3.4 Storage cost thresholds for initial investment and expansion

	Expected Value	Standard Deviation
Initial	1489.4	146.1
Expansion|initial @ 1	1393.3	144.80
Expansion|initial @ 2	1369.0	144.87
Expansion|initial @ 3	1318.7	145.64

The probability of investment in each of the four years of planning, as well as probability distribution of expansion given initial investment takes place in either of the last three years, are presented in Table 3.5.

Table 3.5 Probability distribution of decisions for initial investment and expansion

	$\mathbf{Pr}(\boldsymbol{\tau} = \mathbf{1})$	$\mathbf{Pr}(\boldsymbol{\tau} = \mathbf{2})$	$\mathbf{Pr}(\boldsymbol{\tau} = \mathbf{3})$	$\mathbf{Pr}(\boldsymbol{\tau} = \mathbf{4})$
Initial	0.080	0.440	0.480	0
Expansion|initial @ 1	0	0.340	0.295	0.365
Expansion|initial @ 2	0	0	0.625	0.275
Expansion|initial @ 3	0	0	0	1.000

Results in Table 3.5 provide an overall investment perspective during the planning horizon. For example, from this table, the investor knows that with a probability of 92% $(1 - 0.08)$, it is not cost effective to invest before year 2, hence, he/she should deal with different risks and costs of the microgrid assuming no energy storage for the system.

3.5.4 Impact of storage price decline rate

Figure 3.2 presents triggering thresholds for initial investment and expansion for different levels of annual growth rate of storage cost, α. As α increases in absolute value, investment thresholds decrease, meaning that decision maker should wait for lower costs to invest. The results imply that with higher decline rates, the investor should wait for lower storage costs to take an investment decision, both for initial investment and expansion.

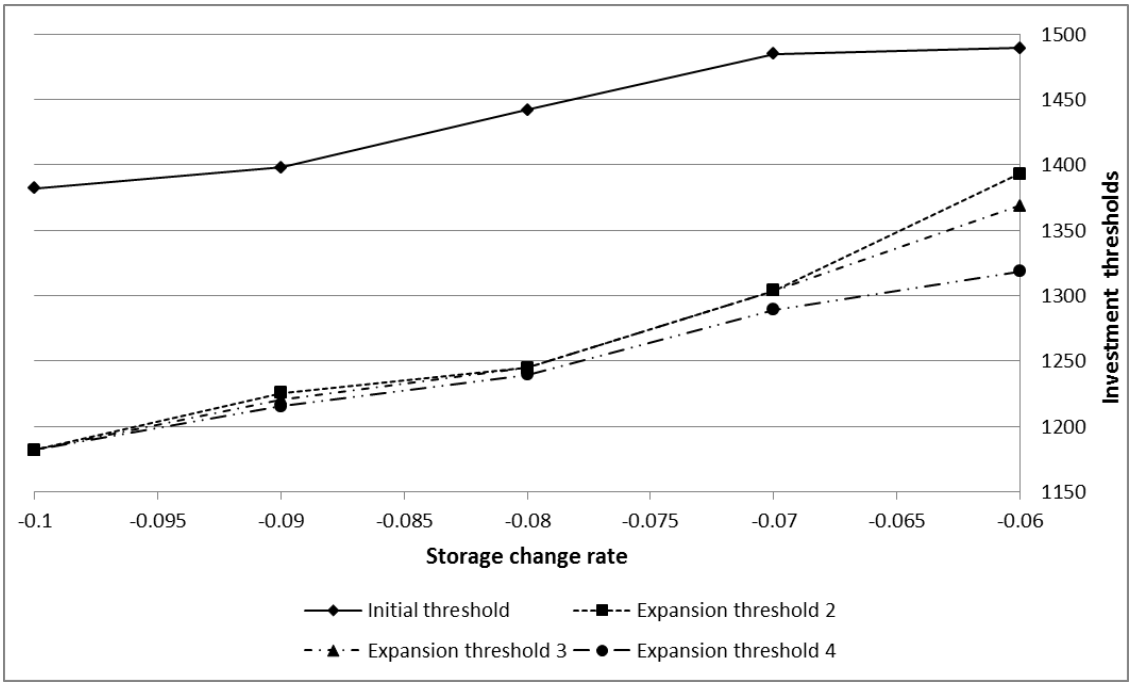

Figure 3.2 Impact of storage cost decline rate on investment decisions

3.5.5 Sensitivity Analysis on Grid Outage Parameters

In this section, we investigate the impact of grid outage frequency and duration, and penalty for lost demand on investment decisions and storage cost threshold for investment. Setting of parameters defining grid outage events are presented in Table 3.6. Figure 3.3 shows how the storage cost threshold for initial investment change with different grid outage parameters. This investment threshold can be an indication of storage value for the microgrid. The overall conclusion of this section is that storage value increases with higher outage frequencies and higher lost demand penalties.

Table 3.6 Grid outage parameters settings

Parameter	L1	L2	L3	L4	L5
Outage frequency (#/year)	0	50	100	150	200
Lost demand penalty ($/kW)	100	250	500	750	1000

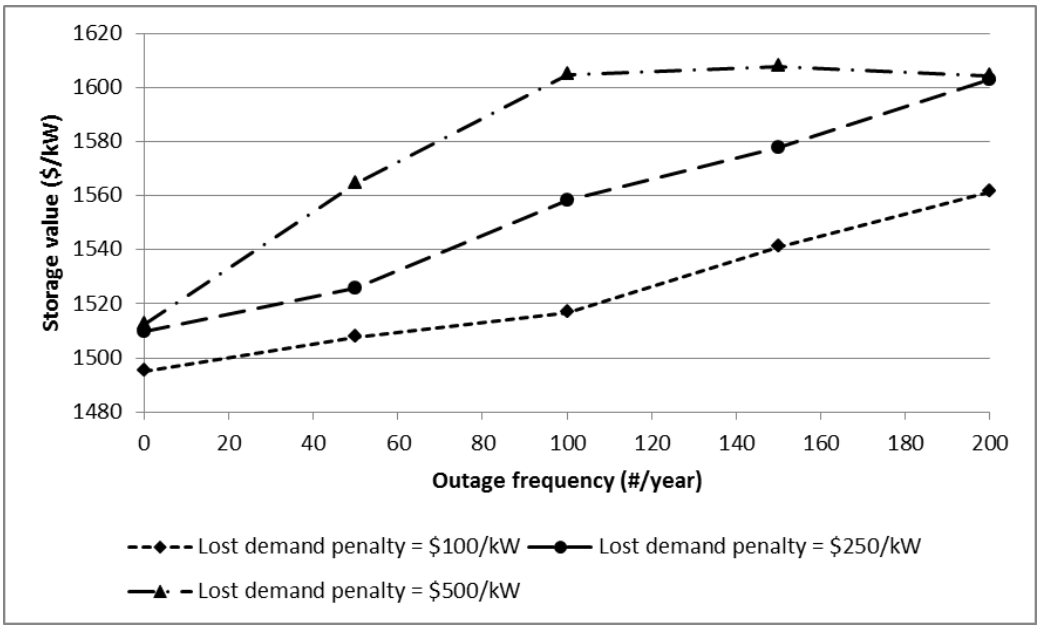

Figure 3.3 Impact of grid outage parameters of storage value

3.6 Illustrative Example II

Below, we show the results for an additional example with the input parameters shown in Table 3.7. Initial and expansion capacities are doubled in this example.

Table 3.7 Input Assumptions for Real Option Simulation Model - Example II

Parameter	Unit	Value
Storage technology	-	Lithium-Ion High Energy Battery
Storage rated power for initial investment	kW	100
Storage rated power for expansion	kW	100
Discharge duration at rated power	Hrs	2
One-way storage efficiency	-	0.94
Installed cost of storage	$/kW	From a GBM process
Engineering life of storage	yrs	15
Demand charge	$/kW	45

In this example, initial and expansion capacities are assumed to be 100 kW each. Results for this example are shown in Table 3.8. From MPC model in Chapter 2, it can be seen

that investment in expanded capacity has only a small contribution in microgrid savings. Comparing that with capital cost of expansion, shows that it is not cost effective for the investor to take any expansion investment decisions. For this reason, investor will wait until the last two years of the planning horizon, for the lower costs of storage, to undertake initial investment decisions.

Table 3.8 Real option simulation results for 10 sample paths – Example II

Investment Cost (C_{st})					Saving - Initial (Π_1)				
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	1.60E+03	1.60E+03	1.43E+03	1.35E+03	**1**	9.50E+04	9.46E+04	1.12E+05	1.20E+05
2	1.60E+03	1.44E+03	1.42E+03	1.37E+03	**2**	9.50E+04	1.11E+05	1.13E+05	1.17E+05
3	1.60E+03	1.39E+03	1.29E+03	1.33E+03	**3**	9.50E+04	1.16E+05	1.26E+05	1.22E+05
4	1.60E+03	1.44E+03	1.33E+03	1.19E+03	**4**	9.50E+04	1.11E+05	1.22E+05	1.36E+05
5	1.60E+03	1.41E+03	1.53E+03	1.50E+03	**5**	9.50E+04	1.14E+05	1.02E+05	1.05E+05
6	1.60E+03	1.38E+03	1.31E+03	1.15E+03	**6**	9.50E+04	1.17E+05	1.24E+05	1.40E+05
7	1.60E+03	1.59E+03	1.50E+03	1.37E+03	**7**	9.50E+04	9.55E+04	1.05E+05	1.18E+05
8	1.60E+03	1.48E+03	1.40E+03	1.43E+03	**8**	9.50E+04	1.07E+05	1.15E+05	1.12E+05
9	1.60E+03	1.50E+03	1.47E+03	1.48E+03	**9**	9.50E+04	1.05E+05	1.08E+05	1.07E+05
10	1.60E+03	1.47E+03	1.29E+03	1.27E+03	**10**	9.50E+04	1.08E+05	1.26E+05	1.28E+05
Value - Initial (F_1)					**Expected Continuation – Initial (Φ_1)**				
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	0	0	1.13E+05	1.20E+05	**1**	0	0	1.15E+05	0
2	0	0	1.11E+05	1.17E+05	**2**	0	0	1.16E+05	0
3	0	0	1.26E+05	1.22E+05	**3**	0	0	1.25E+05	0
4	0	0	1.29E+05	1.36E+05	**4**	0	0	1.22E+05	0
5	0	0	9.92E+04	1.05E+05	**5**	0	0	1.06E+05	0
6	0	0	1.24E+05	1.40E+05	**6**	0	0	1.23E+05	0
7	0	0	1.11E+05	1.18E+05	**7**	0	0	1.09E+05	0
8	0	0	1.06E+05	1.12E+05	**8**	0	0	1.17E+05	0
9	0	0	1.00E+05	1.07E+05	**9**	0	0	1.12E+05	0
10	0	0	1.26E+05	1.28E+05	**10**	0	0	1.25E+05	0
Saving – Expansion (Π_2)					**Value - Expansion (F_2)**				
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	6.02E+04	6.86E+04	7.29E+04	7.42E+04	**1**	0	0	0	0

2	6.02E+04	6.31E+04	6.36E+04	6.32E+04	**2**	0	0	0	0
3	6.02E+04	6.81E+04	7.42E+04	7.54E+04	**3**	0	0	0	0
4	6.02E+04	6.55E+04	6.84E+04	7.51E+04	**4**	0	0	0	0
5	6.02E+04	6.91E+04	7.17E+04	6.77E+04	**5**	0	0	0	0
6	6.02E+04	6.43E+04	6.49E+04	7.00E+04	**6**	0	0	0	0
7	6.02E+04	6.95E+04	7.99E+04	9.22E+04	**7**	0	0	0	0
8	6.02E+04	6.73E+04	7.08E+04	7.22E+04	**8**	0	0	0	0
9	6.02E+04	7.00E+04	7.27E+04	8.48E+04	**9**	0	0	0	0
10	6.02E+04	6.13E+04	5.86E+04	6.74E+04	**10**	0	0	0	0

	Expected Continuation – Expansion|Initial @ 1 (Φ_2)					**Expected Continuation – Expansion|Initial @ 2 (Φ_2)**			
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	0	0	0	0	**1**	0	0	0	0
2	0	0	0	0	**2**	0	0	0	0
3	0	0	0	0	**3**	0	0	0	0
4	0	0	0	0	**4**	0	0	0	0
5	0	0	0	0	**5**	0	0	0	0
6	0	0	0	0	**6**	0	0	0	0
7	0	0	0	0	**7**	0	0	0	0
8	0	0	0	0	**8**	0	0	0	0
9	0	0	0	0	**9**	0	0	0	0
10	0	0	0	0	**10**	0	0	0	0

	Initial Decision					**Expansion Decision - year 2**			
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**
1	0	0	0	1	**1**	0	0	0	0
2	0	0	0	1	**2**	0	0	0	0
3	0	0	1	0	**3**	0	0	0	0
4	0	0	0	1	**4**	0	0	0	0
5	0	0	0	1	**5**	0	0	0	0
6	0	0	1	0	**6**	0	0	0	0
7	0	0	0	1	**7**	0	0	0	0
8	0	0	0	1	**8**	0	0	1	0
9	0	0	0	1	**9**	0	0	0	0
10	0	0	1	0	**10**	0	0	0	0

	Expansion Decision - year 3					**Expansion Decision - year 4**			
Path	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Path**	**Year 1**	**Year 2**	**Year 3**	**Year 4**

1	0	0	0	0	**1**	0	0	0	0
2	0	0	0	0	**2**	0	0	0	0
3	0	0	0	0	**3**	0	0	0	0
4	0	0	0	0	**4**	0	0	0	0
5	0	0	0	0	**5**	0	0	0	0
6	0	0	0	0	**6**	0	0	0	0
7	0	0	0	0	**7**	0	0	0	0
8	0	0	0	0	**8**	0	0	0	0
9	0	0	0	0	**9**	0	0	0	0
10	0	0	0	0	**10**	0	0	0	0

3.7 Conclusion

The work presented in this chapter tackles the problem of optimal incremental investment in energy storage, with the objective of minimizing microgrid demand and energy charges. Treating the incremental option to invest in energy storage as an American-style compound option, makes it possible to find optimal timing of investment, taking into account market uncertainties. Also, by combining the real option investment model with optimal energy storage operation under uncertainty (from Chapter 2), internal sources of uncertainty within a microgrid, i.e. demand and renewable output, are also integrated in the model.

To handle multiple stochastic variables, and to estimate microgrid savings more realistically, a simulation based approach along with least squares regression is used to address more generic assumptions. The impact of annual volatility and annual decline rate of energy storage capital cost are investigated, and the results show that delay in investment becomes more significant as the volatility and decline rate increase. Also, decision strategies based on LSM algorithm are compared to the ones from simple Net

Present Value methodology. Results show that using LSM, yield to more delays in investment for both initial and expansion options, to wait for lower investment costs in the future.

4 ENERGY STORAGE AND MICROGRID MARKET STRATEGY IN AN UNCERTAIN AND DISTRIBUTED ENERGY MARKET

The progressive integration of microgrids into the power grid and their potential participation in the wholesale market makes it necessary for microgrid owners and decision makers to use new business models. In this chapter, we propose necessary tools to optimally strategize microgrids interactions with the power grid, including sale and purchase commitment and bidding price, considering various sources of uncertainty rising from the forecasts of renewable energy resources, electricity demand and day-ahead and spot electricity prices. We treat renewable and conventional generation resources and storage capacity separately. We investigate the impact of energy storage capacity on microgrid market strategies and power reliability in case of power shortage for microgrid internal demand. In this chapter, besides traditional risk-neutral two stage stochastic model, we propose a new model taking into account decision maker's risk attributes. For this purpose, we use Conditional Value at Risk (*CVaR*) as risk measure. We will investigate the impact of storage parameters, i.e. storage capacity and storage cost/production cost ratio, on different elements of microgrid market strategy. We also observe the impact of shortage penalty set by the market operator on microgrid owner's sale commitment decisions and reliability of power provided to the grid.

4.1 Introduction

In this chapter, we present a market strategy model that takes into account the duality of microgrids and optimizes their two-way market interactions. The goal is to provide the

microgrid operator with appropriate tools to strategize on buy, sell or store electricity with the objective of maximizing its profit and power reliability across the network. We also consider maximizing microgrid internal demand reliability in case microgrid has unsatisfied demand and uses storage capacity to fulfill that. The planning and same day operational strategies are computed under both risk neutral and risk-averse conditions. The microgrid is able to participate in price bidding, and it has a portfolio consisting of renewable and conventional generation and storage. The model deals with inherent uncertainties that are commonly attributed to renewable power sources and the demand within the microgrid, as well as the uncertainty in day ahead and spot electricity prices. Per hour excessive capacity probability distribution for the next day is assumed to be given. The model is validated and used to study the following specific problems:

- Economics of storage measured in terms of overall microgrid profit and power reliability
- Microgrid characterization and its relationship to market strategy (presented in Chapter 5)

Our motivation is twofold: (i) Microgrid market in the US is expected to grow rapidly in the near future, with many university campuses, military bases, large manufacturing complexes, and even residential communities and complexes adopting this technology as an alternative source of local, clean and secure energy; (ii) Compared to large macrogrids, microgrids are quite small in size with fewer numbers of generation sources, and are highly volatile due to renewables and unpredictable local demands. Therefore, the traditional planning and operation models within the macrogrid space are far stretch in their assumption of determinism and no uncertainties, and can potentially expose

microgrids to highly volatile spot markets, especially at peak times. This then defeats the whole purpose of microgrids in the first place, which is to provide secure and low emission energy to its owners, and alleviate brownout or blackout risks of the macrogrid, especially at peak times.

4.2 Literature Review

The share of renewable generation in the power systems is an increasingly growing concept due to environmental, economic and technical issues. In [38] the authors focus on the development of an energy management system using Neural Networks, to dispatch generators, on hourly basis, for the purpose of minimizing the global energy costs in a microgrid. The global cost includes the generation, the cost of the energy purchased by the microgrid to supply its loads, and profit from selling energy to the grid. In [39] the authors develop a multi-period optimization model for an interconnected microgrid with hierarchical control that participates in wholesale energy market to maximize its profit. They propose a deterministic model, which includes the operational and technical constraints of distributed energy resources. The authors in [40] address the bidding problem faced by a virtual power plant in a joint market of energy and spinning reserve services. The proposed bidding strategy is a nonlinear mixed-integer programming with inter-temporal constraints based on the deterministic price-based unit commitment. They take into account the supply-demand balancing constraints and also security constraints of virtual power plant. They use genetic algorithm to solve their problem. In [41], the authors present an energy management system for a microgrid optimizing its day-ahead operational plan based on profit maximization while abiding by system constraints and regulatory rules. The microgrid considered in this paper consists of different types of

renewable resources, hydrogen storage and electrical and thermal loads, with the possibility of power exchange with the local grid. Microgrid costs include the operational cost, thermal recovery, power trade with the local grid, and hydrogen production. They use Particle Swarm Optimization for solving the proposed optimization model. In [42], the authors describe the economic scheduling functions of microgrid central controller for the optimization of microgrid operations, i.e. optimizing production of the local resources and power exchanges with the main distribution grid. The authors propose their models based on the application of neural networks dynamic programming. By aggregating the power bids from generators, the proposed controller can participate in the energy market maximizing the revenues of the microgrid. They consider different types of customers with different types of demand. Storage Besides load leveling in the centralized market, energy storage offers additional benefits in utility settings because it can decouple demand from supply, thereby allowing increased asset utilization, facilitating penetration of renewables, and improving the flexibility, reliability, and efficiency of the electrical network [43]. Storage technologies and their applications and benefits in power market have been studied in details in [44]. The authors in [45] present an approximate dynamic programming model to solve storage capacity problems with continuous and convex decision sets.

4.3 Problem Formulation

We use the following vector $T_{s,t}$ to define microgrid market strategy:

$$T_{s,t} = (s_t, p_t, c_t^{sl}, c_t^{pu}, pr_t, sl_{s,t}^{r}, sl_{s,t}^{c}, pu_{s,t}^{st}, pu_{s,t}^{dm}) \tag{4.1}$$

Vector $T_{s,t}$ includes all decision variables which connect the microgrid to the power market, i.e., microgrid's sale and purchase commitment status, sale and purchase commitment levels, bidding price, actual sale from renewable and conventional resources, actual purchase used for storage or satisfying internal demand. Each day, the microgrid forecasts day-ahead and spot market prices for each hour of the next day. Based on these forecasts and also estimated excessive capacity and the corresponding shortage risks, microgrid operator determines optimal bidding price and sale and purchase commitment levels for the next day on an hourly basis. Reduction of shortage risk for all or a portion of its internal demand and alleviating the load are the grid's motivations to buy electricity from the microgrid. The problem of interest here is to compute $T_{s,t}$ day-ahead, and the recourse actions on the next day.

We formulate this problem as a two-stage stochastic optimization model. By discretizing the continuous distributions of the underlying random variables, the problem can be reformulated as the deterministic equivalence of the stochastic model proposed in [46]. The following nomenclature will be used in the formulation of this model. Below, is the description of parameters and variables used in the rest of the paper, followed by problem formulation.

Model Variables

c_t^{sl}	microgrid day-ahead sale commitment
c_t^{pu}	microgrid day-ahead purchase commitment
p_t	binary variable indicating purchase status in day-ahead market
s_t	binary variable indicating sale status in day-ahead market
pr_t	microgrid bidding price

$pu_{s,t}^{st}$	microgrid purchase used for storage
$pu_{s,t}^{dm}$	microgrid purchase used to satisfy internal demand
$pr_{s,t}^{sl,r}$	production level from renewable resources used for sale
$pr_{s,t}^{sl,c}$	production level from conventional resources used for sale
$pr_{s,t}^{st,r}$	production level from renewable resources used for storage
$pr_{s,t}^{st,c}$	production level from conventional resources used for storage
$st_{s,t}$	microgrid storage level
$st_{s,t}^{sl}$	stored energy used for sale
$st_{s,t}^{dm}$	stored energy used for satisfying internal demand

Model Parameters

s	scenario index
t	time index
nsc	number of scenarios generated for two stage stochastic programming
cp^{tr}	transmission/distribution capacity between microgrid and macrogrid
cp^{st}	microgrid's storage capacity
cp^{c}	proportional cost of generation from conventional resources
cp^{r}	proportional cost of generation from renewable resources
cs^{r}	proportional cost of storage from renewable resources
cs^{c}	proportional cost of storage from conventional resources
cu	proportional cost of unsatisfied internal demand
$ex_{s,t}^{r}$	realization of microgrid renewable excessive capacity distribution function

$ex_{s,t}^{c}$ realization of microgrid conventional excessive capacity distribution function

$excess_{s,t}^{r}$ microgrid renewable excessive capacity (processed value)

$excess_{s,t}^{c}$ microgrid conventional excessive capacity (processed value)

$dm_{s,t}$ microgrid internal demand

$dp_{s,t}$ day-ahead market price

l_t electricity load

$\hat{l}_t$ forecast of electricity day ahead price

a_t constant used to obtain the upper bound of the confidence interval

b_t constant used to obtain the lower bound of the confidence interval

$pn_{s,t}^{pu}$ penalty for purchase commitment cancellation

$pn_{s,t}^{sl}$ penalty for sale commitment cancellation

$sp_{s,t}$ market spot price

x_t short term process of the forecasting model

α worst case probability tail

λ risk coefficient

μ_t^{dp} Average value of day-ahead price forecast

σ_t^{dp} standard deviation of day-ahead price forecast

γ_β β-percentage point of the N(0,1) distribution

4.3.1 Discussion on model Variables and Parameters

In the two-stage stochastic programming model, c_t^{sl},c_t^{pu},s_t and p_t are first stage variables, which are determined independent of any scenario realization. All other decision

variables are second-stage variables which depend on the realization of random variables. Each day, microgrid determines how much electricity to commit to buy from the grid, c_t^{pu}, or sell to it, c_t^{sl}, at each time period of the next day. Since microgrid's demand and resources are stochastic, the real sell or purchase levels at period t may be different from the variables committed on the previous day. In this model, we assume that the purchase from the grid is possible, and that the purchased power is either used for storage, or to satisfy internal demand. It is important to mention that in this model we differentiate between renewable and conventional power resources. Microgrid either uses its generation in time period t, $pr_{s,t}^{sl,r}$ or $pr_{s,t}^{sl,c}$, or its storage capacity, $st_{s,t}^{sl}$, to satisfy its sale commitment or internal demand. At the end of each period, the storage level, $st_{s,t}$ is updated using variables $pr_{s,t}^{st,r}$, $pr_{s,t}^{st,c}$ and $pu_{s,t}^{st}$. pr_t is the price which microgrid offers to the grid for its commitment. We assume that at each time period, the microgrid can be either a seller or a buyer. Hence, two binary variables p_t and s_t are used to control the microgrid's status. In case microgrid has unsatisfied internal demand, it can use either the purchased power, $pu_{s,t}^{dm}$ or storage capacity, $st_{s,t}^{dm}$ to satisfy that.

There are internal and environmental parameters which microgrid has to deal with when optimizing its behavior. Microgrid's proportional production cost of conventional power, cp^c is assumed to be constant and averaged over all respective resources. It is assumed that renewable power can be produced at no cost. cs is the proportional storage cost, and we do not differentiate between the stored energy from renewable resources and conventional resources. It is considered as estimation for storage wear and tear per kW usage plus the cost of power generated to be injected in storage. Probability density functions of microgrid's excessive capacity of each type are assumed to be given, and are

controlled by microgrid's internal planning and control system. We approximate the continuous distributions of renewable and conventional excessive capacity and distribution functions of day-ahead and spot price forecasts by a large number ($nsc > 200$) of discrete scenarios assuming the probability of each scenario to be $1/_{nsc}$. This assumption makes it possible to use the deterministic equivalence of the two-stage stochastic model as explained below.

It is assumed that for each committed unit not sold to or purchased from the grid, the microgrid should pay a penalty. The penalty $pn_{s,t}^{sl}$ for the sale commitment is assumed to be the electricity spot price, $sp_{s,t}$, at the time period when the commitment was supposed to be realized. However, we would investigate the impact of other values for not satisfying sale commitment on microgrid behavior. The purchase commitment penalty, $pn_{s,t}^{pu}$, is assumed to be constant. cp^{st} is the maximum storage capacity of the microgrid, and cp^{tr} is the limit capacity of the distribution lines connecting the microgrid to the grid.

Different possible combinations of renewable and conventional excessive capacity and their interpretations are displayed in Figure 4.1. A pre-processing procedure is applied on the values of $ex_{s,t}^{r}$ and $ex_{s,t}^{c}$ before using them in the program.

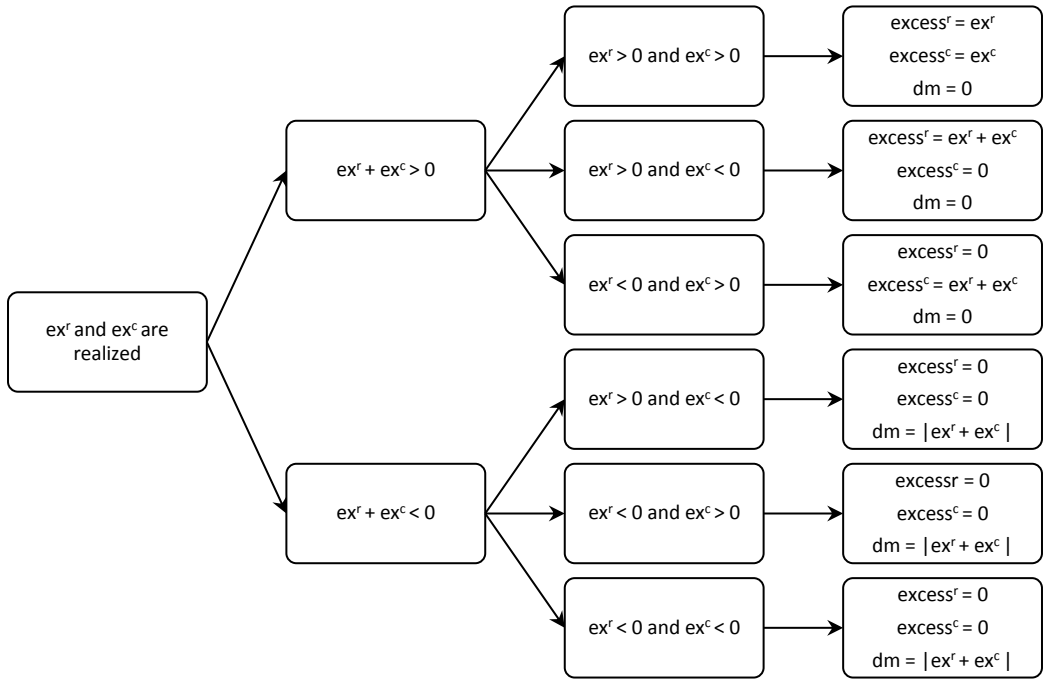

Figure 4.1 Different combinations for renewable and conventional excessive capacities

If $ex_{s,t}^{r} + ex_{s,t}^{c}$ is positive, it means that microgrid has a positive net excessive capacity to commit for sale. In that case, $excess_{s,t}^{r}$ and/or $excess_{s,t}^{c}$ get a positive value equal to $ex_{s,t}^{r}$ and $ex_{s,t}^{c}$, respectively, and internal demand, i.e. $dm_{s,t}$ is set to zero. On the other hand, when $ex_{s,t}^{r} + ex_{s,t}^{c}$ is negative, it means that the net excessive capacity is negative, meaning that the microgrid has some internal demand. Hence, $excess_{s,t}^{r}$ and $excess_{s,t}^{c}$ values are set to zero, and $dm_{s,t}$ gets a positive value equal to the absolute value of net excessive capacity.

4.3.2 Optimization Model

We start with risk-neutral two-stage stochastic formulation of the above problem. We then extend this model to include risk-averse attributes of the decision maker. There are first stage decisions to be made, e.g. sale and purchase commitments. The recourse decisions depend on the realization of the stochastic elements. These recourse decisions

include actual sale or purchase levels, renewable and conventional storage and excessive capacity or storage usage for satisfying sale commitment. The recourse decisions are intended to avoid constraints violation. To take into account microgrid power reliability over time, we define two types of situations; a) when microgrid excessive capacity is positive, i.e. it can sell the excessive amount to the grid, and b) when microgrid excessive capacity is negative, i.e. microgrid has unsatisfied internal demand and can use its storage capacity to satisfy the internal demand and increase its power reliability. In this case, microgrid can sell power to the grid only if it has excessive storage capacity after satisfying its internal demand. To satisfy the non-anticipativity constraint, these two cases should be formulated in a single problem. Model formulations are presented in the following sections.

Objective function

In case 1, where microgrid has excessive capacity and can bid it in the day-ahead market to generate revenue, the objective in this case is to maximize microgrid's expected profit, which is composed of two main elements: expected revenue and expected cost, where cost includes various cost elements, i.e. production cost, shortage cost, cost of purchase cancelation and storage cost.

Microgrid's expected revenue in each scenario at each time period, $rev_{s,t}$, is calculated in Equation (4.2).

$$rev_{s,t} = c_t^{sl} \times dp_{s,t} \quad \forall s, t \tag{4.2}$$

And microgrid's total revenue in scenario, rev_s, is the sum of revenues over 24 hours;

$$rev_s = \sum_{t=1}^{24} rev_{s,t} \quad \forall s \tag{4.3}$$

Cost elements over 24 hours for each scenario are calculated as;

$$co_s^{pr,c} = \sum_{t=1}^{24} cp^c \times pr_{s,t}^{sl,c} \quad \forall s \tag{4.4}$$

$$co_s^{pu} = \sum_{t=1}^{24} dp_{s,t} \times (pu_{s,t}^{st} + pu_{s,t}^{dm}) \quad \forall s \tag{4.5}$$

$$co_s^{sh} = \sum_{t=1}^{24} pn_{s,t}^{sl} \times (c_t^{sl} - pr_{s,t}^{sl,r} - pr_{s,t}^{sl,c} - st_{s,t}^{sl}) \quad \forall s \tag{4.6}$$

$$co_s^{pu,can} = \sum_{t=1}^{24} pn_{s,t}^{pu} \times (c_t^{pu} - pu_{s,t}^{st} - pu_{s,t}^{dm}) \quad \forall s \tag{4.7}$$

$$co_s^{st} = \sum_{t=1}^{24} [cs^r \times pr_{s,t}^{st,r} + cs^c \times pr_{s,t}^{st,c}] \quad \forall s \tag{4.8}$$

$$co_s^{ls} = \sum_{t=1}^{24} c_u \times \left(dm_{s,t} - (st_{s,t}^{dm} + pu_{s,t}^{dm})\right) \quad \forall s \tag{4.9}$$

$co_s^{pr,c}$, co_s^{pu}, co_s^{sh}, $co_s^{pu,can}$, co_s^{st} and co_s^{ls} represent microgrid conventional production cost, purchase cost, shortage cost for external commitment, purchase cancellation cost, storage cost, and cost from lost internal demand, respectively.

Approximating continuous distribution functions with corresponding discrete distribution functions makes it possible to use the linear deterministic version of two-stage stochastic programming [47]. Hence, the final form of the objective function becomes:

$$E[Profit] = \frac{1}{nsc} \sum_{s=1}^{nsc} \left[rev_s - \left(co_s^{pr,c} + co_s^{pu} + co_s^{sh} + co_s^{pu,can} + co_s^{st} + co_s^{ls}\right)\right] \tag{4.10}$$

Constraints

In this section, we describe model constraints. The following set of constraints guarantee the sale commitment level in each time period to be less than or equal to the microgrid's available capacity. When the microgrid has positive excessive capacity, the limit is total excessive capacity plus storage level, during that time period. And when the excessive

capacity is negative, commitment limit is the remaining storage capacity after satisfying internal demand.

$$c_t^{sl} \leq ex_{s,t}^{r} + ex_{s,t}^{c} + st_{s,t-1} - st_{s,t}^{dm} \quad \forall s, t \tag{4.11}$$

The set of constraints in Equation (4.16) control the level of production and storage which is used for sale in each time period to be less than the commitment level for sale in that time period;

$$pr_{s,t}^{sl,r} + pr_{s,t}^{sl,c} + st_{s,t}^{sl} \leq c_t^{sl} \quad \forall s, t \tag{4.12}$$

The following set of constraints guarantee that the real purchase from the grid in each time period is less than or equal to the purchase commitment in that time period.

$$pu_{s,t}^{st} + pu_{s,t}^{dm} \leq c_t^{pu} \quad \forall s, t \tag{4.13}$$

The set of constraints in Equation (4.14) set the limit of production level used for storage, both from renewable and conventional resources, based on microgrid's excessive capacity and the production used for satisfying the sale commitment;

$$pr_{s,t}^{st,r} + pr_{s,t}^{sl,r} \leq ex_{s,t}^{r} \quad \forall s, t \tag{4.14}$$

$$pr_{s,t}^{st,c} + pr_{s,t}^{sl,c} \leq ex_{s,t}^{c} \quad \forall s, t \tag{4.15}$$

The following set of constraints assure that the storage level to be less than or equal to microgrid's storage capacity;

$$st_{s,t} \leq cp^{st} \quad \forall s, t \tag{4.16}$$

The following sets of constraints are used to update the storage level;

$$st_{s,t} = st_{s,t-1} + pr_{s,t}^{st,r} + pr_{s,t}^{st,c} + pu_{s,t}^{st} - st_{s,t}^{sl} - st_{s,t}^{dem} \quad \forall s, t \tag{4.17}$$

The two sets of constraints below assure that the amount of power that microgrid uses for satisfying its sale commitment or internal demand, is less than or equal to its actual storage level;

$$st_{s,t}^{sl} + st_{s,t}^{dem} \leq st_{s,t-1} \quad \forall s, t \tag{4.18}$$

The following constraint guarantees that in each time period, microgrid is either a seller or a buyer of electricity;

$$pu_t + sl_t \leq 1 \quad \forall t \tag{4.19}$$

The constraints below control the power distribution based on microgrid's distribution capacity;

$$c_t^{sl} \leq cp^{tr} \times sl_t \quad \forall t \tag{4.20}$$

$$c_t^{pu} \leq cp^{tr} \times pu_t \quad \forall t \tag{4.21}$$

4.3.3 Microgrid Risk Aversion

Traditional two-stage stochastic programming is risk-neutral; that is, it takes expected value as the preference criterion while comparing the random variables to identify the best decisions. However, in the presence of uncertainty, risk measures should be incorporated into decision making process to account for its effects. The Value at Risk (*VaR*) and the Conditional Value at Risk (*CVaR*) are two commonly used risk measures. In the cost minimization context, VaR_α is the α-quantile of the distribution of the cost and it provides an upper bound that is exceeded only with a small probability of 1- α. This risk measure suffers from being unstable and difficult to work with numerically when costs are not normally distributed-which in fact is often the case, because cost distributions tend to exhibit fat tails or empirical discreteness. Another shortcoming of

VaR, is that it provides no handle on the extent of the costs that might be suffered beyond the threshold amount indicated by this measure. It is incapable of distinguishing between situations where costs that are worse may be deemed only little bit worse and those where they could well be overwhelming. Indeed, it merely provides a highest bound for costs in the tail of the cost distribution and has a bias toward optimism instead of the conservatism that ought to prevail in risk management.

An alternative measure that does quantify the losses that might be encountered in the tail is *CVaR*. *CVaR*, also called Mean Excess Loss or Tail *VaR*, at level α, is the conditional expected value exceeding the *VaR* at the confidence level α. $CVaR_{\alpha}(Z)$ is a measure of severity of the cost if it is more than $VaR_{\alpha}(Z)$. *CVaR*, in a simple way, is defined as follows:

$$CVaR_{\alpha}(Z) = E(Z|Z \geq VaR_{\alpha}(Z)) \tag{4.22}$$

As a tool in optimization modeling, *CVaR* has superior properties in many respects. It maintains consistency with *VaR* by yielding the same results in the limited settings where *VaR* computations are tractable, i.e., for normal distributions. For portfolios blessed with such simple distributions, working with *CVaR* or *VaR* are equivalent. However, computational advantages of *CVaR* over *VaR*, and its capability of measuring cost severity, are turning into a major stimulus for the development of *CVaR* methodology. Figure 4.2 illustrates *VaR* and *CVaR* for a loss distribution.

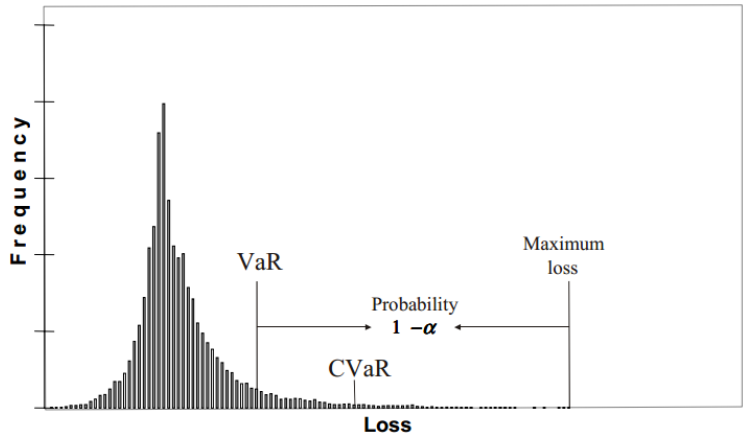

Figure 4.2 *VaR* and *CVaR* illustration

For the case of a finite probability space, where $\Omega = \{\omega_1, \dots, \omega_N\}$ with corresponding probabilities $p_1, \dots, p_N$, we can equivalently reformulate the mean-risk problem

$$\min_{x \in X} \{E[f(x,\omega)] + \lambda CVaR_\alpha\big(f(x,\omega)\big)\}$$

with the following linear programming problem

$$\min \quad (1+\lambda)c^T x + \sum_{i=1}^{N} p_i q_i^T y_i + \lambda(\eta + \frac{1}{1-\alpha}\sum_{i=1}^{N} p_i v_i)$$

$$\text{Subject to} \quad W_i y_i = h_i - T_i x, \qquad i = 1, \dots, N,$$

$$x \in X,$$

$$y_i \geq 0, \qquad i = 1, \dots, N,$$

$$v_i \geq q_i^T y_i - \eta, \qquad i = 1, \dots, N,$$

$$\eta \in R, v_i \geq 0, \qquad i = 1, \dots, N$$

The variable η can be interpreted as a first-stage variable and the excess variables, $v_i, i = 1, \dots, N$, as second-stage variables.

Using the methodology presented in [48], we rewrite our model to take into account the microgrid risk aversion effects. The objective function changes to:

$$\frac{1}{nsc}\sum_{t=1}^{24}\sum_{s=1}^{nsc}\left[\left\{\left[(1+\lambda)\left(rev_s - co_s^{sh} - co_s^{pu,can}\right)\right] - \left(co_s^{pr,c} + co_s^{st} + co_s^{ls}\right)\right\} + \left[(\lambda)\left(\eta + \frac{1}{nsc}\sum_{s=1}^{nsc}\frac{v_s}{(1-\alpha)}\right)\right]\right] \tag{4.23}$$

The following constraint is also added to the set of constraints of original problem presented before. It ensures that the cost corresponding to second stage variables are controlled by variables η and v_i.

$$v_{s,t} \geq \left\{\left[\left(pr_{s,t}^{sl,r}\right)\left(pn_{s,t}^{sl}\right) + \left(pr_{s,t}^{sl,c}\right)\left(pn_{s,t}^{sl} - cp^c\right) + \left(pu_{s,t}^{st}\right)\left(pn_{s,t}^{pu} - dp_{s,t} + c_u\right) + \left(st_{s,t}^{sl}\right)\left(pn_{s,t}^{sl}\right) - \left(pr_{s,t}^{st,r}\right)(cs^r) - \left(pr_{s,t}^{st,c}\right)(cs^c) + \left(st_{s,t}^{dm}\right)(c_u)\right]\right\} - \eta \quad \forall s,t \tag{4.24}$$

4.3.4 Determining Microgrid's Bidding Price

A number of electricity markets in the U.S. work based on single-round auction mechanisms. An auction is a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants. It is an economically efficient mechanism to allocate demand to suppliers. In a single-round auction, market participants submit supply and demand bid curves for the day-ahead and hour-ahead energy markets in sealed bid format. Then, aggregated hourly supply and demand bid curves (considering network and market constraints) are constructed to determine market clearing prices as well as the corresponding supply and demand schedules. A marginal clearing price is set at the intersection point between the aggregated demand and supply curves for each of the 24 scheduling hours. All generators

winning the auction are paid at the uniform clearing price. Those generators bidding above the clearing price are not paid, hence, it is important for generators to have a good forecast of the day-ahead clearing prices and bid strategically. In this paper, we assume that microgrid adopts rules similar to the wholesale market for clearing day-ahead prices. Microgrid's strategy for setting its bidding prices was adopted from the method proposed in [49] for a price-taker generator in the power market where at the time of submitting bids, the values of total demand and day-ahead market price are stochastic to the generator.

We assume that the day-ahead market price at hour *t* is a random variable, and its value has to be forecasted. From a statistical point of view, these random variables are conditioned on the actual price values of the time series used for forecasting. This time series spans from an arbitrary origin up to hour 24 of the day preceding the one whose prices have to be forecasted. There are many forecasting models already existing in the literature, e.g. [50] and [51]. Hence, in this work we do not focus on developing the forecast model for day-ahead market prices. Rather, we assume that the expected value μ_t^{dap} of random variable is the price prediction at hour t. The estimate of the standard deviation of the random variable is also available from the forecasting procedure, and it is denominated σ_t^{dap} [52]. It can be shown that the distribution of random variable dap_t is approximately Lognormal [53], i.e., $dap_t \sim Lognormal(\mu_t^{dap}, \sigma_t^{dap})$.

Upper and lower bounds of the confidence interval are computed respectively as

$$\mu_t^{dap} + a_t \sigma_t^{dap} \tag{4.25}$$

$$\mu_t^{dap} - b_t \sigma_t^{dap} \tag{4.26}$$

It should be noted that parameters a_t and b_t are obtained directly from any forecasting model used, and depend on the level of confidence, e.g., to cover 99% or 95% of the total area under the lognormal distribution. Using results from [49] we compute

$$a_t = \frac{\exp\left(\frac{1}{2}\left(\sigma_t^{dap}\right)^2 + \mu_t^{dap} + \gamma_\beta \sigma_t^{dap}\right) - \mu_t^{dap}}{\sigma_t^{dap}} \tag{4.27}$$

$$b_t = \frac{\mu_t^{dap} - \exp\left(\frac{1}{2}\left(\sigma_t^{dap}\right)^2 + \mu_t^{dap} - \gamma_\beta \sigma_t^{dap}\right)}{\sigma_t^{dap}} \tag{4.28}$$

where γ_β depends on the desired level of confidence.

In [49], thermal generators are assumed to be sources of power, hence the excessive capacity has a deterministic maximum level. Here, we have to modify the results from [49] to include stochastic case. Microgrid should submit a bidding curve for each hour of the market horizon to the market operator. Each one of hourly bidding curves consists of a set of blocks of power and their corresponding increasing prices. A convex bidding curve is required, i.e., prices have to be associated with the power blocks bid. The bidding rule formulated below determines the hourly bidding curve of the microgrid and requires up to two blocks of power and their corresponding prices. The bidding curve for hour t is formulated as a function of the optimal sale commitment production in that hour, $c_t^{sl^*}$. Two cases are possible and are analyzed below. Remember that the stochasticity of excessive capacity was considered in our two stage stochastic program.

Case 1) For $c_t^{sl^*} = 0$, microgrid owner should either not commit to the grid, or, in case there is an obligation to participate in the market due to regulations, commit the

minimum amount allowed by the regulations at price $\mu_t^{dap} + a_t\sigma_t^{dap}$. This bidding price guarantees with a level of confidence of 99% that the power accepted in this situation is 0, which is the optimal self-scheduled power for this case.

Case 2) For $0 < c_t^{sl^*}$, the bidding curve consists of a single block of power $c_t^{sl^*}$ at price $\mu_t^{dap} - b_t\sigma_t^{dap}$. It should be noted that this bidding curve guarantees with a level of confidence of 99% that the power accepted in this situation is $c_t^{sl^*}$, which is the optimal sale commitment for this case.

It should be mentioned that the upper and lower bound of the confidence interval are computed according to the required level of confidence defined by the microgrid owner.

4.4 Validation and Numerical Experimentation

In this section, we investigate the impact of model parameters on different elements of microgrid market strategy. We focus on the impact of storage capacity and storage cost/production cost ratio on microgrid's average daily profit and its average daily sale commitment level. We also observe the impact of shortage penalty set by the market operator as a ratio of day-ahead price on microgrid owner's sale commitment decisions. We define three important elements defining microgrid portfolio and measure the impact of those parameters on microgrid market strategy.

4.4.1 Model Validation

To validate our optimization model, we compare our formulation with other similar works developed for similar objectives. However, since in the previous works, there are not any studies of the exact same objective as this paper, i.e. defining microgrid market strategies under price and resource uncertainty, we validate different parts of the model,

i.e. objective function elements and constraints, separately. Models reviewed in [54] adopt a general form of the objective function used in this paper for generation units and power producers. More specifically, [55] and [56] use the same approach as the one used in this paper to calculate revenue and production cost (Equations (4.2) and (4.4)) for the microgrids. The purchase cost (Equation (4.5)) is also included in the model proposed in [55]. The objective function presented in [39], includes all profit and cost elements included in this paper (Equation (4.2), and Equations (4.4) through (4.9)) for distributed energy resources to bid into low voltage grid.

In [39], the summation of energy storage levels for all electrochemical storage units during each hour is constrained by the installed capacity of electrochemical storage, which is similar to Equation (4.16) in our paper. Similar constraints for transient state variable, i.e. storage level update (Equations (4.17) and (4.18)), can be found in [57]. Transmission line capacity (Equations (4.20) and (4.21)) are modeled the same way as in [57]. The methodology proposed in [58] for applying upper limit to energy discharge from the storage unit is similar to Equations (4.18) and (4.19) of this paper.

Equations (4.11) through (4.15) in this paper, define the limits of decision variables in the two stage stochastic programming, and rise from model assumptions. Equations (4.11) through (4.13) enforce microgrid sale commitment not to exceed the forecast of its excessive capacity, and microgrid real production and purchase to be limited by the corresponding committed amounts. Equations (4.14) and (4.15) refer to the assumption that satisfying sale commitment is preferred over storing. And finally, Equation (4.19) prevents storage unit to be charging and discharging at the same time, an assumption rising from energy storage technological constraints.

4.4.2 Sensitivity Analysis

In this section, we test model validity through some intuitive analyses on model parameters. We do sensitivity analysis on conventional production costs, storage capacity, and excessive capacity. We would investigate the impact of changing these parameters on daily average profit and sale and purchase commitments. We will set two levels for each parameter and run the model for different combinations. Values assumed for each level and sensitivity analysis results are presented in Table 4.1 and Table 4.2. Electricity market price for this analysis follows a typical daily profile, similar to the one shown in Figure 2.7.

Table 4.1 Parameter levels for sensitivity analysis

Parameter	Level	Value
Conventional production cost ($/kW)	1	0.02
Conventional production cost ($/kW)	2	0.1
Storage capacity (kW)	1	50
Storage capacity (kW)	2	100
Excessive capacity	1	base distribution
Excessive capacity	2	base distribution doubled

Table 4.2 Sensitivity analysis results

Case	Conventional production cost level	Storage capacity level	Excessive capacity level	Annual Profit ($)
1	1	1	1	6,748
2	1	1	2	6,902
3	1	2	1	16,242
4	1	2	2	18,308
5	2	1	1	6,304
6	2	1	2	6,752
7	2	2	1	11,789
8	2	2	2	16,731

Sensitivity results show that as excessive capacity and storage capacity increase, microgrid profit also increases, and as conventional production cost increase, microgrid profit decreases. It also shows that excessive capacity has a more significant impact on microgrid profit compared to storage capacity.

4.4.3 Illustrative Examples

In this section, we will present an illustrative example and investigate the impact of model parameters on economics of storage capacity, risk averseness of microgrid owner, and reliability corresponding to microgrid internal demand and sale commitment. We also design an experiment to examine the impact of portfolio of resources in terms of mean and standard deviation and also storage capacity on microgrid market strategy.

Assumptions on parameter values and distributions

Model parameters are presented in Table 4.3 with their corresponding values which are used in the following sections.

Table 4.3 Model parameter values

Parameter	Symbol	Value
Number of scenarios	nsc	100
Transmission/distribution capacity	cp^{tr}	500 kW
Storage capacity (base)	cp^{st}	100 kW
Cost of conventional generation	cp^{c}	0.05 $/kWh
Cost of renewable generation	cp^{r}	0 $/kWh
Cost of conventional storage	cs^{c}	0.06 $/kWh
Cost of renewable storage	cs^{r}	0.01 $/kWh
Cost of unsatisfied demand	cu	1 $/kWh
Purchase commitment cancellation penalty	$pn_{s,t}^{pu}$	0.02 $/kWh
Sale commitment cancellation penalty	$pn_{s,t}^{sl}$	0.02 $/kWh

Economics of Storage Capacity

The impact of storage capacity on microgrid's behavior and its market strategies are observed in this section. The storage capacity was changed from 0 to 250 kWh with the step size of 5 kWh. Microgrid uses storage as a resource to be able to commit for sale at higher levels and generate more revenue. The function shown in Figure 4.3 at any given point determines the increase in profit by adding one unit of storage capacity at the point. This analysis can give us a criteria, shown in Equation (4.29) for incremental investment in energy storage. It implies that investment in more storage capacity is cost-effective only when the marginal profit per unit of storage added to the system exceeds the marginal storage cost.

$$\frac{\Delta(Average\ annual\ profit)}{\Delta(storage\ capacity)} > marginal\ storage\ cost \tag{4.29}$$

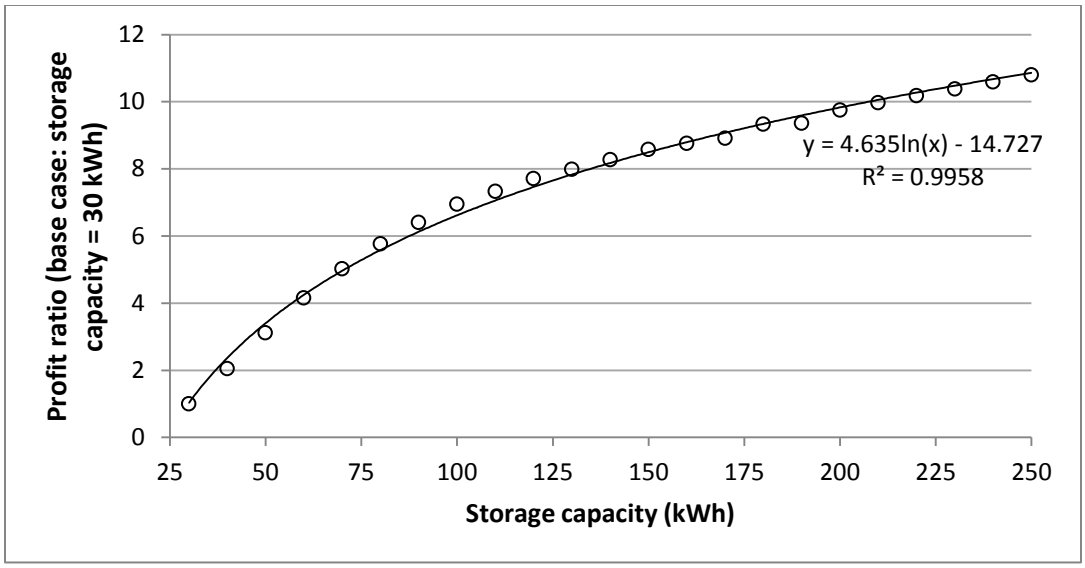

Figure 4.3 Average daily profit by storage capacity levels

The results for the same analysis are presented in Figure 4.4, increasing storage cost and decreasing excessive capacity by 50%. The same behavior can be seen for this configuration.

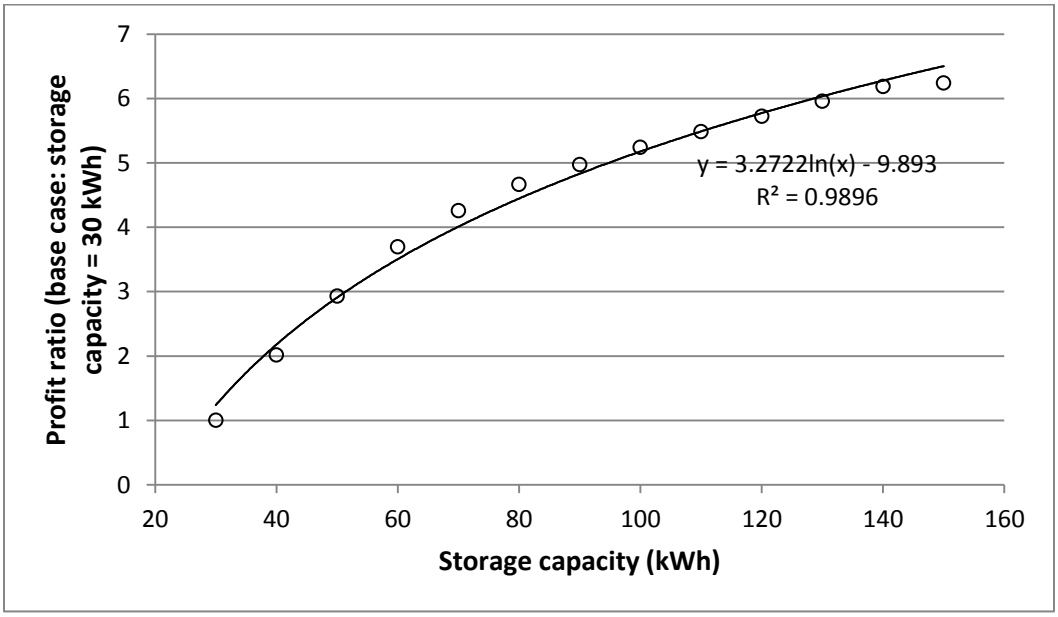

Figure 4.4 Average daily profitby storage capacity - increased storage cost and decreased excessive capacity

The $(\frac{\text{Production cost}}{\text{Storage cost}})$ ratio plays a significant role on the storage economics. Here, storage cost is considered as estimation for cost of battery wear and tear per kW usage plus the production cost of power to be stored. Note that ratio is aggregated over renewables and conventional sources. We change the ratio from 0 to 6 with a step size of 0.25. Figure 4.5 clearly illustrates sensitivity to the ratio of average profit and optimal commitment.

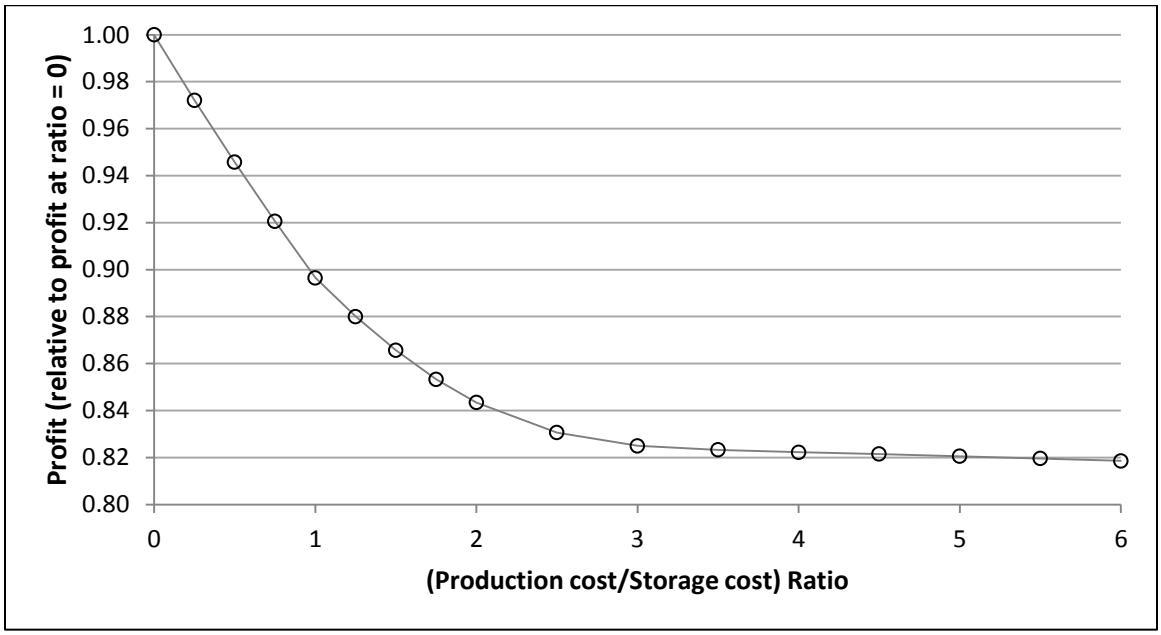

Figure 4.5 Average daily profit and average daily commitment for different Production cost/Storage cost ratios

As it can be seen in Figure 4.5, for cases where ratio < 2, storage cost has a significant value on average daily profit and its impact decreases for values larger than 3.

Power Reliability

<u>Reliability of power satisfying internal demand</u>

Internal demand reliability is defined as the percentage of internal demand which is satisfied. In this paper, microgrid has two sources to supply its internal demand; storage capacity and purchase from grid. Since in each time period, microgrid can be either a

seller or a buyer, and because sale and purchase commitments are first stage decision variables, which are made day-ahead, the use of grid power to satisfy internal demand significantly decreases microgrid's profitability. Thus, in this section, we investigate the impact of storage capacity on internal demand reliability.

The model was tested for different storage capacities ranging from 0 to 65 kWh, and their impact on average percentage of internal satisfied demand presented in Figure 4.6. It is important to notice that because of the relative values of lost demand penalty to microgrid revenue through selling back to the grid, and because the buy or sell status of microgrid are mutually exclusive, microgrid uses its storage capacity to satisfy the internal demand, and sells to the grid at the same time to generate revenue.

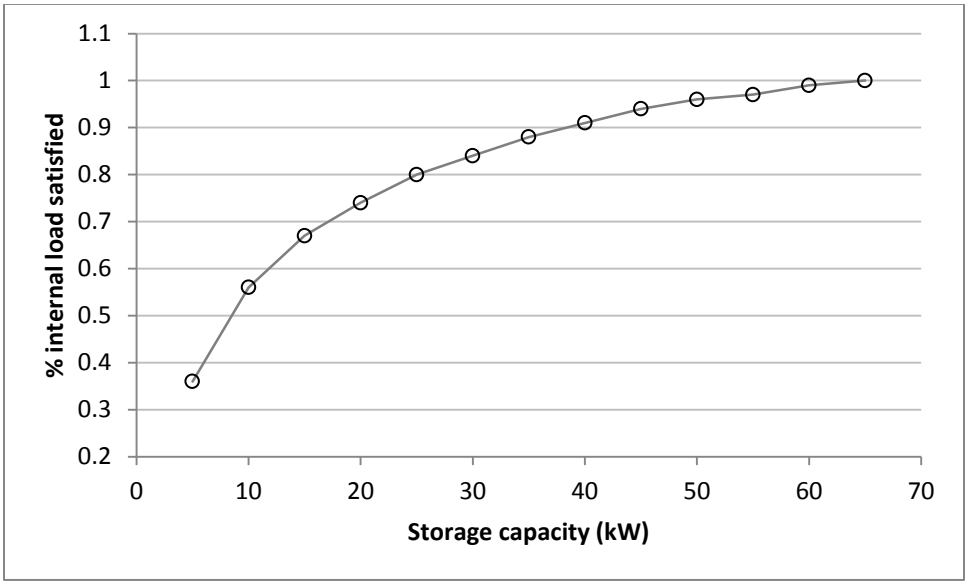

Figure 4.6 Impact of storage capacity on internal demand reliability

<u>Reliability of power provided to market</u>

As stated before, it is assumed that if the microgrid fails to satisfy its sale commitment, it will be charged at a penalty cost. However, for some cases, it may be profitable for the microgrid not to satisfy the commitment when the penalty is less than microgrid's

operational cost. This behavior, when practiced by major players in the market, or by a significant number of microgrids, will have a negative impact on the grid reliability. One strategy to confront such a behavior by market players is to determine the penalty corresponding to failure to satisfy sale commitment independent of electricity spot price. In this section, we investigate the impact of shortage penalty as a fraction of day-ahead price on reliability of the power microgrid provides to the market. Results are shown in

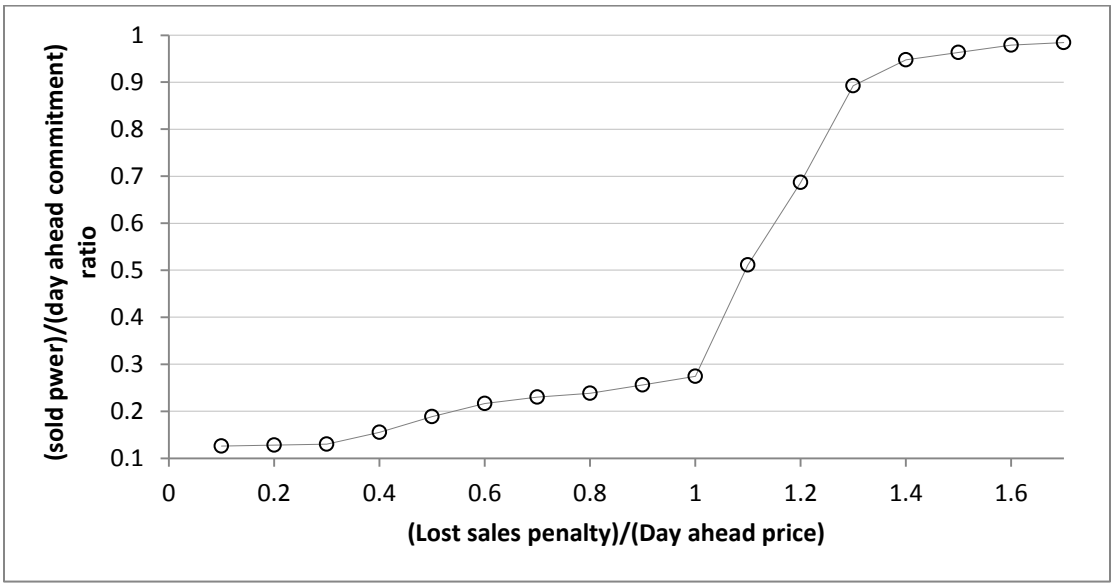

Figure 4.7 Impact of shortage penalty on market power reliability

As shown in Figure 4.7, as shortage penalty increases, the ratio of satisfied day-ahead commitment increases significantly. Based on the parameters we assumed for day-ahead price and corresponding shortage penalty, it seems that when shortage penalty is set to 1.4 times average day ahead price or higher, microgrid is committed to satisfy its sale commitment with a probability of 95% or more. If shortage penalty is set to lower values, then microgrid contribution in power market might result in worsening grid power reliability.

4.5 Conclusion

In this chapter, we propose necessary tools to optimally strategize microgrids interactions with the power grid, including sale and purchase commitment and bidding price, considering various sources of uncertainty rising from the forecasts of renewable energy resources, electricity demand and day-ahead and spot electricity prices. We investigate the impact of energy storage capacity on microgrid market strategies and power reliability in case of power shortage for microgrid internal demand. We formulate and solve the problem as a two stage stochastic model. We investigate the impact of storage parameters, i.e. storage capacity and storage cost/production cost ratio, on microgrid average annual profit, and internal demand reliability. We also observe the impact of shortage penalty set by the market operator on microgrid owner's sale commitment decisions and reliability of power provided to the grid.

5 APPLICATIONS AND FUTURE WORK

The results from the previous three chapters can be integrated into a single framework for investment, market strategy and operational control optimization of storage within microgrids. Here we will only focus on market strategy and present an application where the model of Chapter 4 is used to better understand what factors are significant in microgrid characterization in terms of microgrid profit, sales and purchase commitments, with respect to microgrid renewable and conventional generation capacity, storage capacity and volatility of renewable resources.

5.1 Microgrid Characterization and Market Strategy

Each microgrid has its own internal and environmental characteristics. These characteristics can be defined in terms of specific parameters or functions, and can help the microgrid owner to set market strategies based on a high level understanding of how the microgrid and the market work. Here we will only focus on internal characteristics and examine the impact of the following ratios on market strategies:

- $R_1 = {}^{\text{renewable excessive capacity mean}}/_{\text{conventional excessive capacity mean}}$
- $R_2 = {}^{\text{storage capacity}}/_{\text{total excessive capacity mean averaged over 24 hours}}$
- $R_3 = {}^{\text{renewable excessive capacity standard deviation}}/_{\text{conventional excessive capacity standard deviation}}$

For this purpose, we assign three values to each of the ratios and design the following experiment:

Table 5.1 Design of Experiment for three internal factors

R_1=0.5				R_1=1				R_1=2			
	R_2=0.25	R_2=0.5	R_2=1		R_2=0.25	R_2=0.5	R_2=1		R_2=0.25	R_2=0.5	R_2=1
R_3=1	x_{111}	x_{121}	x_{131}	R_3=1	x_{211}	x_{221}	x_{231}	R_3=1	x_{311}	x_{321}	x_{331}
R_3=2.5	x_{112}	x_{122}	x_{132}	R_3=2.5	x_{212}	x_{222}	x_{232}	R_3=2.5	x_{312}	x_{322}	x_{332}
R_3=5	x_{113}	x_{123}	x_{133}	R_3=5	x_{213}	x_{223}	x_{233}	R_3=5	x_{313}	x_{323}	x_{333}

We recall that vector T was defined in Chapter 4 to characterize market strategy of a microgrid. Our goal is to characterize microgrids interactions with the power grid according to the internal parameters. Here, we examine the impact of the three indices, R_1, R_2 and R_3 on the elements of T. The elements examined in this section are sale commitment, purchase commitment and microgrid profit.

For each of the factors of the market strategy vector, a three-way ANOVA table is presented below. Results presented in Table 5.2 and Table 5.3 show that microgrid's profit and purchase commitment can be characterized by the three factors used for this analysis. All three factors turn out to be significant in explaining the variability of daily average profit and sale commitment. As it can be seen in Table 5.2, the most important factor affecting average profit is renewable excessive capacity mean to conventional excessive capacity mean. One reason can be that this ratio is an indication of the total excessive capacity and hence it is significant. The next important factor is renewable excessive capacity standard deviation to conventional excessive capacity standard deviation ratio. This can be explained by the fact that if renewable excessive capacity has a high standard deviation comparing to conventional excessive capacity, then the part of the commitment planned to be satisfy from renewable resources will be lost with a high probability, and this has a negative impact on the profit. And finally the last significant factor is the ratio of storage capacity to total excessive capacity mean. Obviously when

there is more storage, the microgrid can offer larger sale commitments, and earn more profit.

Table 5.2 Profit ANOVA table

Source of Variation	Degree of Freedom	Sum of Squares	Mean Square	F $F_{2,20,0.05}$= 3.493	P-value
R_1	2	1.85E+09	9.26E+08	110.278	1.578E-11
R_2	2	70813374	35406687	4.218	0.030
R_3	2	3.29E+08	1.65E+08	19.601	1.936E-05
Error	20	2.42E+09	8394456		
Total	26	4.67E+09	1.8E+08		

In explaining the variability of sale commitment, the same order of significance level of factors can also be seen in Table 5.3. The reasons mentioned for average daily profit are valid for this case also.

Table 5.3 Sale commitment ANOVA table

Source of Variation	Degree of Freedom	Sum of Squares	Mean Square	F $F_{2,20,0.05}$= 3.493	P-value
R_1	2	4869.634	2434.817	96.381	5.387E-11
R_2	2	360.721	180.360	7.139	0.004
R_3	2	1785.047	892.523	35.330	2.730E-07
Error	20	7520.652	25.262		
Total	26	14536.054	559.079		

Results presented in Table 5.4 and Table 5.5 show that purchase commitment and actual purchase are highly correlated (in this illustrative example, purchase cancellation did not occur in any of the scenarios) and that R_2 does not play an important role when making decision about buying from the grid. Although R_1 and R_3 are significant factors, but their level of significance is not very high (comparing F-values with F-critical). Hence, other factors should be defined and tested if one is interested in characterizing the behavior of these variables. R_1 is significant, because it is an indication of microgrid's excessive capacity and with higher values of excessive capacity mean, microgrid prefers to store

from its internal resources rather than its purchase from the grid. Dissimilarly, when renewable standard deviation is high comparing the conventional standard deviation, microgrid decides to store using its purchase from the grid, and that is the explanation why R_3 is significant.

Table 5.4 Purchase commitment ANOVA table

Source of Variation	Degree of Freedom	Sum of Squares	Mean Square	F $F_{2,20,0.05}$= 3.493	P-value
R_1	2	5.164	2.582	4.999	0.017
R_2	2	9.421E-05	4.711E-05	9.121E-05	0.999
R_3	2	5.164	2.582	4.999	0.017
Error	20	20.657	0.516		
Total	26	30.986	1.192		

Table 5.5 Actual purchase ANOVA table

Source of Variation	Degree of Freedom	Sum of Squares	Mean Square	F $F_{2,20,0.05}$= 3.493	P-value
R_1	2	5.164	2.582	4.999	0.017
R_2	2	9.421E-05	4.711E-05	9.121E-05	0.999
R_3	2	5.164	2.582	4.999	0.017
Error	20	20.657	0.5164		
Total	26	30.986	1.192		

5.2 Future Work

5.2.1 Enhancement of Investment Model

An extension for the investment model introduced in Chapter 3 is to relax the assumption for parametrically fixed initial and expansion capacities. This would enable investors to make investment decisions based more comprehensive set of investment candidates.

5.2.2 Enhancement of storage control algorithms

Both optimization models introduced in Chapter 2 of this work can be extended to multiple storage units, load buses and generation resources distributed along larger systems. This would make the solution region larger, as charge and discharge controls should be specific for each pair of load-storage, and renewable-storage. Also, additional constraints would be imposed on the model based on locations of different units.

5.2.3 Enhancement of decomposition algorithm (Model II in Chapter 2)

The approximate model can be enhanced and extended in number of ways:

1. Optimization within each zone is enhanced by taking into account price variance within each zone. This will allow us to benefit from arbitrage and also from both charging and discharging within each zone. However, to take advantage of solution space reduction of this model and avoid hourly solutions, a criteria should be defined to identify the zones which are potential candidates for arbitrage, and hourly analysis be done only on zones having the criteria.
2. Model II for control of storage does not account for uncertainty in stochastic parameters. An MPC approach can be beneficial for this problem, so that every time that new observations are received on stochastic parameters, new zones for the remaining hours of the day are constructed and dynamic programming is applied to find new control commands.
3. Considering market and interconnection requirements, excessive renewable output can be sold to the grid, either directly or through storage discharge to increase microgrid profit.

APPENDIX I – PARALLELS BETWEEN SUPPLY CHAIN AND POWER CONCEPTS

Table 0.1 briefly presents some conceptual parallels between supply chain management and power engineering.

Table 0.1 Parallels between supply chain and power concepts

Area	Supply Chain	Power
Demand Management	Kanban	Dispatching
	Line balancing	Energy regulation
	Manufacturing execution system (MES)	Wholesale market design
Demand generation	JIT, push or pull	Used to be JIT, moving towards push+pull
Business risks	Retailer lost business	Load curtailment
Risk and mitigation	Safety stock	Spinning reserve
	Lead time	Delays/lost load sue to wrong renewable forecast
	Inventory/Buffer	Storage
	Dynamic rerouting	Dynamic switching

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