A Game-theoretic Framework to Investigate Conditions for Cooperation between Wind Power Producers and Energy Storage Operators

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ABSTRACT

Game theory has its applications in various domains, but has only recently been applied to study open problems in smart microgrids. A simple microgrid system with a small wind farm, a storage facility and an aggregate load entity is studied here using a non-cooperative game-theoretic framework.

The framework developed is used to study the behavior of rational market participants (players), namely wind power producer and energy storage. The framework is implemented to find the existence of any Nash equilibria and see if cooperation is a natural outcome of the game. If cooperation is not self-enforcing then usefulness of the framework to find the conditions for cooperation is presented. It must be noted that cooperation is not automatically guaranteed as the payoff of the energy storage operator is dependent on the strategy employed by the wind power producer. Similarly, the payoff for the wind power producer is highly intertwined with the strategy employed by the energy storage operator. Historical weather and market data is used to calculate expected payoffs for each possible combination of strategies. The results are presented in the form of payoff matrices and the best response algorithm and/or elimination of dominated strategies is used to find the Nash equilibrium.

Sensitivity of the Nash equilibrium to various storage parameters like storage size, charging/discharging limits, charging/discharging efficiency, and other market parameters like energy imbalance penalties, efficiency of up/down regulation, and electricity market prices is studied and necessary conditions for cooperation are presented.

To My Parents: Dr. Sham Lal Bhela and Dr. Anita Bhela

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List of Abbreviations

AGC	Automatic Generator Control
APS	Arizona Public Service
BPA	Bonneville Power Administration
CAISO	California ISO
DAM	Day-ahead Market Price
DIR	Dispatch-able Intermittent Resources
ERCOT	Electric Reliability Council of Texas
ESO	Electric System Operator
ISO	Independent System Operator
ISO-NE	ISO New England
ITC	Investment Tax Credit
LMP	Location Marginal Pricing
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCPC	Market Clearing Price for Capacity
MCPCRD	Market Clearing Price for Capacity – Regulation Down
MCPCRU	Market Clearing Price for Capacity – Regulation Up
MISO	Mid-west ISO
NYISO	New York ISO
PHEV	Plug-in Hybrid Vehicle
PIRP	Participating Intermittent Resources Program
PJM	Pennsylvania, Jersey, Maryland Power Pool
PPA	Power Purchase Agreement
PSCO	Public Service Company of Colorado
PTC	Production Tax Credit
RD	Regulation Down
REQ.	Required
RTM	Real-Time Market Price
RTO	Regional Transmission Operator
RU	Regulation Up
STWFP	Short-Term Wind Power Forecast
WGRPP	Wind-powered Generation Resource Production Potential
WTG	Wind Turbine Generator

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Chapter 1 – Introduction & Motivation

A microgrid is a distributed level power system that is capable of operating independently from the grid. It is a self-reliant system that has its own renewable and fossil fuel generation, storage, and load, and is connected to the grid through a point of common coupling [1]. It can disassociate itself from the grid and operate in islanding mode or actively export/import power from the grid [1]. The dynamics of a microgrid with considerable renewable energy portfolio is of particular interest as renewable sources of generation are intermittent in nature and hard to forecast accurately. Two commonly proposed ways to deal with the generation-load mismatch in microgrids is to implement a demand response scheme and/or demand side management [2-4]. The other proposed solution is to use energy storage as a device to provide energy smoothing services to better integrate renewables into the grid [4-9]. For the purpose of this study only the energy storage is considered.

1.1 Problem Definition and its Significance

Wind power production has been quickly expanding in the United States in recent years. At the end of 2013 there was 61,108 MW of installed wind capacity in the US, which is exceeded only by China [10]. Texas has one of the largest installed wind capacity in the US with over 12,355 MW installed[10]. It is anticipated that this number will continue to grow in the coming years as product demand increases and prices of Wind Turbine Generators (WTG) decreases.

Due to the highly variable nature of wind, new distributed generation systems cannot be treated as conventional generation sources. Advancement in energy storage technologies (with high round-trip efficiency) has provided the mechanism to absorb the variability (energy imbalance) from wind farms and minimize dependence on expensive generator reserves (ancillary services). With the United States poised to have 20% of its electricity produced from renewable energy sources by the year 2020, there will be a substantial increase in ancillary services, in particular operating and regulation reserves [11].

Integrating these intermittent renewable sources into the power grid, especially microgrids, can be challenging. Power output from renewable sources can be only forecasted with a certain accuracy based on statistical and weather forecast models. Forecasts have improved in recent years, but if the renewable producers don't deliver the scheduled power output based on day-ahead market or hour-ahead market forecasts then there is a mismatch between the generation and load. If left unchecked this can destabilize the power grid. The ancillary services market provides services to stabilize the grid should there be an imbalance. Short-term imbalances are dealt with through frequency regulation and larger imbalances are dealt with through operating reserves [5, 7, 12].

With the increasing penetration of renewable energy sources into the power gird, the present services offered are not sufficient to ensure that the grid is reliable [13]. Sources that can be quickly started and shutdown with flexible ramping capabilities are strongly desired. Hence, it has become imperative to incorporate energy storage units in the power grid especially for providing frequency regulation and energy smoothing/capacity firming services for renewable producers [8, 12, 14]. Lithium-ion batteries are of particular interest as they have high efficiency, low self-discharge rate, high cycling tolerance and high energy density. In addition, their cost is expected to decrease over the next few years as technology improves and they are widely deployed in plug-in electric vehicles.

The social benefit of providing capacity smoothing and regulation service for renewable producers is evident, but is there incentive for energy storage operators to provide such services in a competitive energy market and cooperate with wind power producers? In the current market context (low penetration) wind power producers sell all their energy to the utility and are generally not penalized for deviating from contract, whereas energy storage operators operate independently (unless they are collocated and owned by the wind power producer) by offering their services into the energy and reserves market. The utility takes on the cost of procuring expensive operating reserves to keep the grid stable and reliable, however, as penetration of renewables increases, utilities will want to defer some of these costs onto the wind power producers and have other mechanisms in place to encourage the participation of energy storage operators. One such proposed mechanism is the payment to storage in the form of energy payments or imbalance penalties. This proposed mechanism penalizes wind power producers for deviating from contract and allocates these penalties to energy storage operators.

In markets where imbalance penalties are allowed and variability (energy imbalance) is allocated to storage operators there is a new set of strategies available to the wind power producer: (1) payment of imbalance penalty to utility (2) payment of imbalance penalty to energy storage operators (3) curtailment of output when overproducing. This poses a new challenge as it is not intuitive if wind power producers would consider cooperation with energy storage operators. Similarly, it is not clear whether energy storage operators would want to cooperate with wind power producers and deliver what is promised. A storage operator could operate independently and continue offering its services into the reserve and energy markets without having to ever enter into an agreement with the wind power producer. So the pertinent question is whether these two entities would cooperate in a deregulated microgrid. Here the decision or strategy of one player will affect the outcome of the other player and cooperation is not automatically guaranteed. Payoff of each player involved will be heavily dependent on the amount of wind deviation and the inherent payment mechanism for these deviations, but could also be dependent on other storage and market parameters. Complex interactive problems in which the outcome of a rational agent's action depend on the actions of other rational players are best studied through the setup of a game-theoretic framework. This problem is a multi-agent decision process and as such should not be treated as an optimization problem.

1.2 Goal and Scope of Thesis

The primary goal of the research work presented here is to develop and implement a non-cooperative game-theoretic framework that can be used to study the behavior of wind power producers and energy storage operators in a microgrid. The work presented aims to use the developed framework to find a Nash equilibrium for the game and study if cooperation is the natural outcome regardless of the strategy adopted by either player. Should cooperation not be self-enforcing the framework can be used to explore the conditions under which a unique pure strategy Nash equilibrium exists and it would be rational for both players (renewable producer and storage) to cooperate. As mentioned earlier, cooperation is not automatically guaranteed as the payoff of both players is dependent on the strategy adopted by the other. Additionally, the equilibrium maybe affected by market parameters, such as seasonal variation in market prices and efficiency of up/down regulation or the inherent characteristics of the storage parameters such as charging/discharging limits, storage size and efficiency. This study aims to see if these changing parameters shift the equilibrium of the game to a non-cooperative state. The results presented will be instrumental in helping regulators develop market mechanisms and policies that provide incentive for these two entities to cooperate.

The scope of this thesis will be limited to studying a two-person game (the utility or RTO/ISO sets the rules for the game, but is not considered a player) with the assumption that both players have complete information and act simultaneously. There will be considerable stress on the development of the framework used to calculate the expected payoffs for each combination of strategies available to the wind power producer and the energy storage. The importance of using a game-theoretic framework for the purpose of this study will be highlighted and justified. There is less emphasis on the optimization of the storage parameters itself i.e. the optimal battery size and optimal charging/discharging limits are of little consequence, instead it is of interest to see how sensitive the revenue and ultimately the equilibrium is to these changing parameters.

1.3 Overview of Thesis

The thesis is organized in five chapters followed by a bibliography and an appendix. In Chapter 2 an overview of game theory and its applications in various fields is provided to explain the motivation behind using it as a tool for this study. Chapter 2 also includes a discussion on the different ways in which wind imbalance payments are handled by RTO/ISO's – understanding the current market mechanisms used for handling large wind deviations is instrumental in this study. Chapter 3 introduces the game-theoretic framework used for analysis – details on the wind model and energy storage model used for simulations and calculation of payoffs are presented. Chapter 4 presents the results from the developed framework in the form of payoff matrices. The existence of a Nash equilibrium, necessary conditions for cooperation and sensitivity of the equilibrium to several storage and market parameters is discussed. And finally, Chapter 5 outlines the conclusions drawn from this study and presents ideas for extension of this work.

Chapter 2 – Literature Review

This chapter aims to provide a brief review of game theory, an overview of its recent application in power systems and its importance in the context of the problem defined in this thesis. Additionally, a brief review is presented on the ways in which imbalance penalties are handled by various RTO/ISO's.

2.1 Review of Game Theory

Game theory has been applied to various disciplines from economics to politics [15], but has only recently been used as a tool to study various open problems in smart microgrids [3]. A Game-theoretic framework can be used as a tool to analyze the complex interactions between independent rational players who may have partially or totally conflicting interests [16, 17]. It is a decision making process where the choices or strategies of one player can potentially affect the actions of other players.

Game theory is divided into two main branches: non-cooperative game theory and cooperative game theory [16, 17]. A non-cooperative game captures the decision making process that allows the players to optimize their utilities without communication [16, 17]. The word non-cooperative can be misleading, however. Non-cooperative games do not imply that players cannot and do not cooperate, instead it implies that any cooperation that arises as an outcome of the game is self-enforced [16, 17]. Cooperative games on the other hand assume that communication and co-ordination is possible between players [16, 17]. Cooperative games investigate the possibility of providing incentives to independent decision makers so that they act together and improve their net payoff in the game. These games are further classified under two separate categories: Nash Bargaining and Coalition games [16, 17]. Nash bargaining solutions identify the terms under which a set of players will cooperate, whereas coalition games deal with formation of coalitions – profits from forming such coalitions need to be fairly shared amongst the players and is another topic of research.

Additionally, games can be of the strategic form or the extensive-form [16, 17]. Strategic form games are games in which players make moves simultaneously (time independent) – such games are represented in the form of a table where the payoffs are listed for each strategy combination [16, 17]. Extensive-form games are sequential where the timing of the action and the information available while making a choice is critical to the outcome of the game [16, 17].

There are three main components in a strategic non-cooperative game [16, 17]:

1. A set of players $N = \{1 \ldots n\}$
2. A set of actions/strategies. If each player 'i' has a set of actions, $s_i \in S_i$, then $S = S_1 \times \cdot \cdot \cdot \times S_n$, can be defined as the set of actions/strategies available to all players
3. List of pay-offs/utilities that the players receive $u_i(s)$, where player i's payoff is u_i for the chosen action set 's'

One point to be noted is that the players payoff $u_i(s)$ is dependent both on its own action choice s_i as well as the action choices of all the other players i.e. $u_i(s) = u_i(s_i, s_{-i})$. The work presented in this thesis is studied through the setup of a strategic non-cooperative game framework.

Solution Concept - Solving Strategic Games

Nash equilibrium is the main solution concept behind any game-theoretic framework [16-18]. The Nash equilibrium is a state in the game where no player 'i' can benefit by shifting its strategy unilaterally under the condition that the strategy of all the other players are fixed. It is a vector of actions s^* such that the following condition is true:

$$u_i(s_i^*, s_{-i}^*) \geq u_i(s_i, s_{-i}^*) \qquad \text{for all 'i'}, \forall s_i \in S_i$$

Here each player 'i' is playing their best response s_i^* to the strategies s_{-i}^* that all other players are playing. This is a stable solution in the game – one from which a rational player would not deviate.

To find the equilibrium of strategic games two common methods used are: (1) best response and (2) iterated elimination of dominated strategies [16, 17]. A player's best response is the strategy (or strategies) that generate the greatest payoff for him or her given what the other players are doing [16, 17]. Therefore, strategy s_i^* is said to be a best response to s_{-i}^*, if playing s_i^* always yields at least as good a payoff as playing any other s_i' , given that the opponent always plays s_{-i}^*:

$$\text{Given } s_{-i}^*, \forall s_i' \in S_i, \qquad u_i(s_i^*, s_{-i}^*) \geq u_i(s_i', s_{-i}^*)$$

To find a pure strategy Nash equilibrium, the player's best response to each of the opponent's possible pure strategies can be calculated. Any outcome (if it exists) which is a mutual best response is a pure strategy Nash equilibrium. Best response is one the simplest techniques used to find an equilibrium in a strategic game, however, other techniques such as iterative elimination of dominated strategies can also be used both to simplify the game and to find the equilibrium. Strategic dominance occurs when a player’s strategy is better than another strategy available, no matter what strategy the player's opponents choose to play. It is said that strategy s_i strictly dominates s_i' if playing s_i always yields a higher payoff than playing s_i' no matter what the other players do:

$$\forall\, s_{-i} \in S_{-i}, \qquad u_i(s_i, s_{-i}) > u_i(s_i', s_{-i})$$

Eliminating dominates strategies may be sufficient to arrive at an equilibrium in which case there is dominated strategy equilibrium (which is also the Nash equilibrium for the game) [16, 17]. In other games eliminating dominated strategies may simplify the game, but the best response algorithm may still be needed to find the Nash equilibrium.

For all finite games a Nash equilibrium is guaranteed in mixed strategies i.e. not all games will have pure strategy Nash equilibrium [16, 17]. Mixed strategy Nash equilibrium implies that at least one of players plays multiple strategies with a certain probability. In such a case there will be no pure-strategy Nash equilibrium. It is also possible for games to have multiple equilibria in which case an efficient Nash equilibrium has to be chosen – selecting a desirable Nash equilibrium is difficult and a topic of ongoing research and is not explored further in this thesis.

2.2 Game-theoretic Applications - Wind and Energy Storage

There is not much literature on the application of game theory to study cooperation between wind power producers and energy storage operators. The reason for this is threefold: (1) The focus has been on optimal sizing, placement and scheduling of energy storage to minimize wind power imbalances (in such cases it is often assumed that the wind power producer is also the owner of the storage) [19-22] (2) Most problem formulations don't take into account imbalance penalties imposed on renewable energy producers – without imbalance penalties energy storage operators would operate independently and try to maximize their revenues through participation in the energy and reserves market [23-25] (3) Studies that take into account imbalance penalties are solely concerned with the optimal contracting of wind power to decrease these penalties and maximize the revenues of the wind power producer [26-29]. The work in [30] is one of the few studies that takes a game-theoretic approach to the scheduling problem of both wind power producers (in the presence of imbalance penalties) and energy storage operators. The problem is formulated as a stochastic dynamic optimization, which is simplified through technical mechanisms used in inventory control [31]. Through further approximations of the model it is shown that both the utility functions of the wind power producer and the energy storage are concave (under certain conditions) and a pure Nash equilibrium is guaranteed. Unfortunately, it was determined that a unique equilibrium could not be expected in general, but sufficient conditions could be given for some cases. Another key drawback in this study is that the approximation of the model assumes an infinite horizon policy (all time steps are identical), under the assumption that the storage device is hundred percent efficient and that there are no limits on charging/discharging – this is not a realistic scenario. Although there are some drawbacks to their model, some of the mathematical tools developed, especially the payoff model of both the wind power producer and the energy storage operator has been instrumental in the development of the work in this thesis.

Although the work in [32] is not directly related to the cooperation between wind power producers and energy storage operators, the work presented uses game-theoretic methodology to tackle the planning problem of a hybrid power system comprised of wind, solar and energy storage. Both non-cooperative and cooperative models were used to find a solution to the capacity allocation problem by using the life-cycle income of the three players as payoffs.

2.3 Other Game-theoretic Applications in Microgrids

With the advent of smart microgrids and the increasing penetration of renewable sources of energy there has been a renewed interest in the application of game theory in such systems. This section discusses some of the more recent work in this field. Although very little work has been done in the context of microgrids, the review of these studies shows that game theory (both non-cooperative and cooperative) can be used as an effective tool to analyze the behavior of markets and market participants.

2.3.1 Non-cooperative Games

Energy Trading in Smart Grids

Game theory has been aggressively applied to energy trading in smart grids. In [33], researchers have implemented a new bilateral reserve market that allows trading between wind power producers and conventional power generators. The reserve price is expected to be between day-ahead market price and real-time market price and allows wind power producers to buy cheaper reserve power when they deviate from contract. Conventional generators also benefit from participation in a new market where they can sell energy to maximize their profits. It is shown that in such a competitive market the reserve price can be calculated by solving for the Nash equilibrium [33]. Case studies show that wind power producers will have increased profits with the implementation of such a market model.

Game theory has been used in other studies related to energy trading in smart-grids. In [34] a non-cooperative game theoretic framework is formulated between multiple storage units (PHEV's) looking to trade their stored energy. The amount of energy offered by each storage unit so as to optimize its utility function is found from the solution to the game. A double auction mechanism is used to determine the price for selling.

Demand response/Demand Side Management and Plug-in Electric Vehicles

There have been several applications of game theory related to demand-side management and demand response [25, 35-37]. A recent paper uses a game-theoretic model to automatically schedule appliances of residential customers (assuming they have smart meters) including plug-in electric vehicle batteries that can bilaterally buy/sell energy from the utility [38]. It is shown that a unique Nash equilibrium for the energy management/scheduling game not only exists, but implementing this approach reduces the total energy cost and electricity payment by individual users. This concept was further extended in [39], where a pricing mechanism was implemented to tackle variability due to wind power producers and encourage end users to participate in wind power integration. Each user's payoff is dependent on the pricing model and the energy consumption scheduling vector. The energy consumption and storage game guarantees the existence and uniqueness of a Nash Equilibrium. Additionally, it is shown that the result of the game reduces energy costs to end users while providing benefit to the grid by reducing the generation-load mismatch. These studies mostly focus on the participation of residential users in the microgrid. The work in this thesis is structured more towards the participation of an independent energy storage operator that is interested in maximizing its own revenues. The objective is not to reduce energy costs to users, but to provide backup to renewable sources of energy – although providing such a service that reduces the mismatch may indirectly reduce market prices and ultimately the energy costs to the users.

Game theory has also been applied to other problems related to charging of plug-in electric vehicles. Assuming that an infrastructure of charging stations is laid out in a city and two-way wireless communication is possible between the charging station and the electric vehicle, it is of interest to see how an electric vehicle owner can select the best charging station to recharge its battery [40]. Researchers showed that a non-cooperative oligopoly game can be used to establish the energy price at each charging station, which can be communicated to the electric-vehicle owner and used to make a decision on which charging station to use based on the price and distance to said charging station. The location of the car, its distance to all available charging stations, and the amount of energy requested to recharge the battery are the key decision variables used to find an equilibrium for the game [40].

2.3.2 Cooperative and Coalition Games

Wind Power Producer Coalition

Wind being an intermittent source is hard to predict accurately and wind power producers can be heavily fined for deviating from contract. One way to reduce the power output variability is to have better forecasting methods, the other way is through the formation of sensible coalitions. In a recent study [41] it is shown that independent wind power producers can form coalitions to decrease net power output variability by taking advantage of geographical diversification. Willing wind power producers will have a chance to offer their aggregate output as a single entity in forward markets. Using cooperative game theory researchers showed that a coalition of all or some of the independent wind power producers at a single bus increases the aggregate coalition profit. Further analysis is done to show that the game is stable and balanced and a fair profit sharing mechanism can be implemented amongst the coalition members [41].

Coalition amongst Microgrids

In two other recent studies game-theoretic coalition formulation has also been applied to reduce power losses when power is transferred between microgrids and a macro-station. Their novel algorithms allow microgrids to make decisions on forming coalitions and autonomously cooperate while maximizing their payoffs [42, 43]. The coalitions formed have microgrids that have surplus power available and others that need additional power to meet their load – the algorithms developed allow the microgrids to transfer power between themselves as well as with the macro-station while reducing the total power losses over the distribution lines. Profits produced from forming coalitions are distributed to the players per the Shapley value [42].

Wireless Communication and Networking

There are considerable applications of cooperative game theory that deal with the control and communication aspect of microgrids as well. Game theory has been a hot topic of research in wireless networks which are critical to the infrastructure of the future power grid. The work in [44, 45] was applied to networking problems including flow control, congestion control, routing and pricing of Internet services. More recently, there has been growing interest in adopting game-theoretic methods to model today's leading communications and networking issues, including power control and resource sharing in wireless and peer-to-peer networks.

From the brief review provided in this section it is clear that game-theoretic applications are plenty in the future power grid. The work outlined in [3] and the references therein provide a good review of some current work and ideas for other applications in the future smart grid.

2.4 Wind Integration

Due to the high penetration of renewable energy sources into the power grid different RTO/ISO's handle imbalance payments to the wind power producers differently. A detailed discussion is present in Section 2.4.1 on how some of the major RTO/ISO's handle payments for any deviations from scheduled transactions for wind power producers.

The uncertainty in accurately predicting the wind power output is not a cause of major concern at current penetration levels, but as the renewable portfolio increases there is a need to address the way in which imbalances are handled. The market design needs to be such that it incentivizes wind power producers to use better forecasting methods and schedule their output as close as possible to the actual output.

2.4.1 Imbalance Payments

Imbalance settlements or deviation charges are a topic of ongoing discussion and research – each RTO/ISO uses its own set of market rules to settle imbalances. Following is a discussion on how these rules are implemented in various RTO/ISO's and how curtailments are handled.

Pennsylvania, Jersey, Maryland Power Pool (PJM)

Balancing operating reserve charges are charged to wind power producers for deviating from their day-ahead schedule. However, if wind power producers follow PJM dispatch instructions then they receive balancing operating reserve credit. Imbalance less than 5% or 5MW is not assessed any deviation charges [46]. If a phone call is required to implement manual curtailment (when wind is not following dispatch instructions), then no compensation is provided [47].

New York ISO (NYISO)

Deviations are settled at real-time LMP. No deviation charges are assessed under unconstrained operations (up to 3300 MW of installed capacity) [46].

ISO New England (ISO-NE)

Similar to NYISO, deviations are settled at real-time LMP [46]. Wind power producers face no deviation charges. There is also no compensation for curtailment [47].

Midwest-ISO (MISO)

Intermittent resources receive Revenue Sufficiency Guarantee Charges for negative and positive deviations [46]. This measure guarantees generation units the recovery of production costs i.e. start-up cost, no-load cost and incremental energy offer [48]. Wind power producers that deviate from their schedule are subject to such charges to compensate other generators. Midwest ISO is moving towards dispatch-able intermittent resources (DIR's) where wind generators will be able to receive revenue sufficiency guarantee payments as well if they follow dispatch instructions

[46]. Curtailment is a function of market bids (negative pricing is allowed). If the wind power producer exceeds the market clearing price for energy then it is not dispatched [47].

Electric Reliability Council of Texas (ERCOT)

Wind power producers are instructed to purchase replacement energy for under and overproduction from the dispatch instructions. Wind power producers do not incur any deviation penalty for underproduction, but incur penalties for overproduction. Penalty for overproduction is only applied if the wind power producer is set below its high dispatch limit due to economic dispatch, but is still producing more than 10% above its schedule [46, 49]. It is charged for the overproduced amount based on real-time prices. Compensation for curtailments is built into Power Purchase Agreement (PPA) contracts. Some RTO/ISO's have stipulated hours in a year for which no compensation will be provided for curtailed output [47]. In the ERCOT market wind power producers are not allowed to schedule their own output. ERCOT schedules output for all wind farms based on its own forecasting method. Day-ahead scheduling referred to as the WGRPP (which only affects unit commitment) is based on an 80% exceedance forecast [50, 51] i.e. there is an 80% probability that the forecast will exceed the output scheduled. Hour ahead scheduling referred to as the STPRF is based on a 50% exceedance forecast [50, 51].

California ISO (CAISO)

For generators that are part of the Participating Intermittent Resources Program (PIRP), hourly net deviations are netted at the end of the month and are charged a monthly weighted market clearing price [46]. No compensation is provided for curtailment as existing contracts have provisions for curtailment. To mitigate manual curtailment the CAISO market allows negative bids in its energy markets. Previously the low bid floor was set at -$30/MWh – this was not enough to enforce wind power producers to curtail outputs as the benefit from Production Tax Credits (PTC) exceeded the low bid floor price/MWh. To prevent wind power producers from gaming the system the low bid floor has been set to -$150/MWh – this will discourage wind power producers to oversupply. If bids submitted by the wind power producers are higher than the market clearing price for energy then wind power producers will be forced to curtail their output. This has also extensively been discussed in [52].

Alberta Electric System Operator (Alberta ESO)

No penalties on deviations[46].

Bonneville Power Administration (BPA)

BPA charges wind power producers a balancing service fee of $1.23/kw-month. Penalties are charged on positive and negative deviations that exceed 15% of schedule and 20 MW in an hour for three consecutive hours. Over-deliveries are not paid. Under-deliveries are charged the highest incremental cost for that hour [46]. There is compensation for curtailment under some conditions. Even then wind power producers may have to absorb some of the cost [47].

Public Service Company of Colorado (PSCO)

PSCO follows FERC Order 890 protocols [46]. Wind deviations within $\pm$1.5% (with a minimum of 2MW) of the scheduled transaction are paid 100% of the spot price for both overproduction and underproduction [53]. Due to the high volatility of wind a flexible band around the contracted amount is reasonable. Wind deviations between $\pm$7.5% of the scheduled transaction are paid 90% of the spot price for overproduction and pay 110% of the spot price for underproduction [53]. Wind power producers are exempt from higher penalties for deviations larger than 7.5% [53]. PSCO has made explicit contract clauses in PPA's for compensation of curtailed output. If PSCO curtails for balancing purposes then PSCO will pay wind power producers the value of energy curtailed in addition to the PTC credit. However, PSCO does have a total of 60,000 curtailment hours per year for which it does not need to provide compensation [47].

Arizona Public Service (APS)

APS has take-or-pay contracts and compensates wind power producers for curtailments [46]. However, APS has certain number of emergency curtailment hours built into its contracts just like PSCO [47].

Nordic Market

The Nordic Market runs on a two-price system that is similar to the FERC Order 890 protocol [54, 55].

Other Studies

Some other studies [26, 52] suggest the charging of penalties on both overproduction and underproduction. These models assume that negative deviations are charged at a price $q \in R$ (\$/MWh) and positive deviations are charged at price $\lambda \in R$ (\$/MWh). The imbalance prices can be positive or negative depending on system conditions. Also, the positive imbalance prices and negative imbalance prices are assumed to be asymmetric. Imbalance penalties have also been implemented in several existing markets [24, 27, 28].

Discussion

From the literature review presented it is evident that each RTO/ISO handles imbalances differently. Also, the areas that have high penetration of wind like ERCOT, MISO and CAISO have more advanced techniques of dealing with imbalances. In the context of this study only the following two ways to deal with imbalances are implemented:

1. Imbalance Penalty for both underproduction and overproduction
2. No Penalty

Imposing penalties on wind power producers may seem unfair to wind power producers, particularly because they have little to no control over their output. However, with the increasing penetration of renewables the cost to utilities for procuring generator reserves is going to increase significantly and mechanisms need to be in place to offset some of these costs to the wind power producers. These penalties can be a big driver for innovation of better technology that allow for control of the wind power output from each turbine and enforce the use of better forecasting tools. In the current market context it is difficult for wind power producers to stay profitable even with no penalties imposed on deviations. Wind farms typically come at a high capital cost that is often hard to justify without some government incentive or subsidy. The next section provides a brief overview of the current market scenario and what the government is doing to encourage the participation of renewables. This is important in the context of this thesis as government incentives provide an additional source of revenue and should be considered in order to do a comprehensive study.

2.4.2 Government Incentives and Subsidies

The federal, state and local government initiatives (production and investment tax credits) to reduce our nation's dependence on fossil fuels has made it worthwhile for independent investors to make investments in wind farms.

The most prominent of these tax incentives – Production Tax Credit (PTC) was extended in 2014, as was the ability to take the 30% Investment Tax Credit (ITC) in lieu of the PTC [56, 57]. Wind power projects that begin construction before the end of 2014 are eligible to receive either the PTC or the ITC [56, 57]. The tax credit lasts for 10 years after a project is complete, so most of the wind energy produced in the U.S. will continue to receive federal support for at least a few more years. Any wind farm that was under construction before the end of 2014 will still get a full decade of credits. These provisions have however been discontinued in 2015 and it is not known if they will be reinstated anytime in the near future.

Recently, many environmentalists have begun advocating for energy storage to receive the same investment tax credits that renewable energy technologies have received over the years. Tax credits for energy storage would push these technologies forward and would accelerate the transition to a lower-carbon world.

Chapter 3 – Methodology and Approach

This chapter introduces the game-theoretic framework used for the analysis in this thesis. The setup of the wind and energy storage model that is used to calculate the payoff for each possible combination of strategies is presented in detail. Figure 3.1 shows the design model used in this study for a microgrid community.

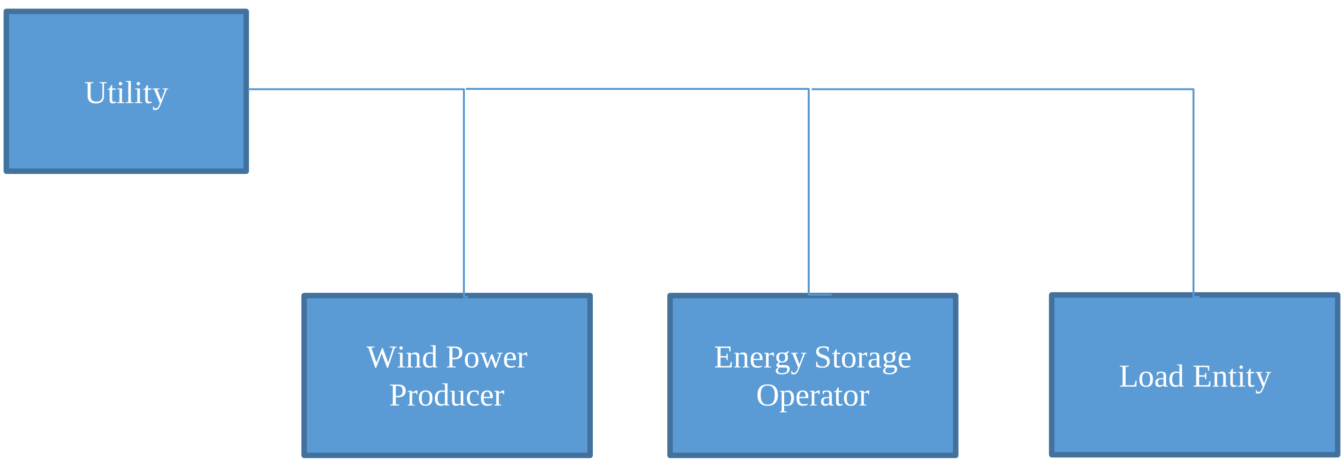

Figure 3.1 – Design Model

3.1 Game-theoretic Framework

The game-theoretic framework developed in this thesis uses a payoff matrix to present the results and identify the Nash Equilibrium. A typical payoff matrix for a two-person game is represented in Table 3.1 below. The columns in the table are the available strategies for the wind power producer and the rows are the available strategies for the energy storage. There are four possible combination of strategies. The net revenues of the wind power producer will be listed in the upper right corner and the net revenues of the energy storage will be listed in the lower left corner of each cell. Details on how the payoffs are calculated are presented in section 3.2.

WIND / STORAGE	**COOPERATION**	**NON-COOPERATION**
COOPERATION	**B** **(Case 1)** **A**	**D** **(Case 2)** **C**
NON-COOPERATION	**F** **(Case 4)** **G**	**D** **(Case 3)** **E**

Table 3.1 – Payoff Table

The following discussion provides a brief overview of the four possible cases in the payoff matrix. These are discussed in further detail in Section 3.2.

Case 1

In this case the wind power producer and the energy storage play cooperative strategies to act as one entity and deliver the promised power output. The energy storage receives imbalance payments (fixed percentage of day-ahead market price) from the wind power producer for giving priority to balancing wind deviations – any remaining capacity is used for arbitrage, regulation service and balancing load deviations and is paid by the utility. In addition to the imbalance payments to the energy storage, the wind power producer may pay additional fines to the utility.

Case 2

In this case the wind power producer chooses a non-cooperative strategy and pays hefty penalties (fixed percentage of day-ahead market price) to the utility. The energy storage indirectly cooperates by balancing wind deviations through the utility, but gives preference to balancing load deviations first – any remaining capacity is used for arbitrage and regulation service. Payment for imbalances (fixed percentage of day-ahead market price) is received through the utility instead of the wind power producer. It is assumed that the penalty charged by the utility is higher than the penalty charged by the energy storage operator.

Case 3

In this case both the wind power producer and the energy storage choose non-cooperative strategies. The wind power producer pays hefty penalties to the utility just like the previous case (case 2). The energy storage chooses to operate independently by providing services to balance net deviations (load + wind deviations) – any remaining capacity is used for arbitrage and regulation service. Storage does not receive imbalance payments in this case.

Case 4

In this case the storage chooses to play a non-cooperative strategy by operating independently like the previous case (case 3). The wind power producer knowing that the storage will choose not to cooperate curtails its output when overproducing to not only increase its revenues, but to reduce the net imbalance on the system.

3.1.1 Wind and Load Model

The wind model used to calculate the expected payoff is relatively simple, the only complexity associated with the model is the way in which imbalance penalties are handled. Various ways in which RTO/ISO's handle wind deviations was explored extensively in Chapter 2 – it is assumed that imbalance payments will be handled similarly in the context of a microgrid. Details on the payment/financial model for the wind power producer are presented in Section 3.2.

As pointed out in the previous chapter the initial capital cost of setting up a wind turbine/farm is very high and needs to be recovered during the operating life of the equipment. Because of the high investment cost and low capacity factors (capacity factor for White Deer, TX was calculated to be 37%) of wind power plants it is important to extract the maximum power available from the wind at any given moment. Power output characteristics of a wind turbine are highly dependent on wind velocity and certain inherit characteristics of the WTG. For this purpose it is customary to study the wind profile of the region of interest and the power curve of the wind turbine being used. The 1.5 MW GE wind turbine which is used for the remainder of this study has a power output curve as shown in Figure 3.2. The cut-in speed of the wind turbine is around 3 m/s and the cut-out speed is around 25 m/s. Cut-in speed is the minimum speed at which the turbine turns to generate power and cut-out speed is the speed beyond which there is no increased power output with further increase in wind speed.

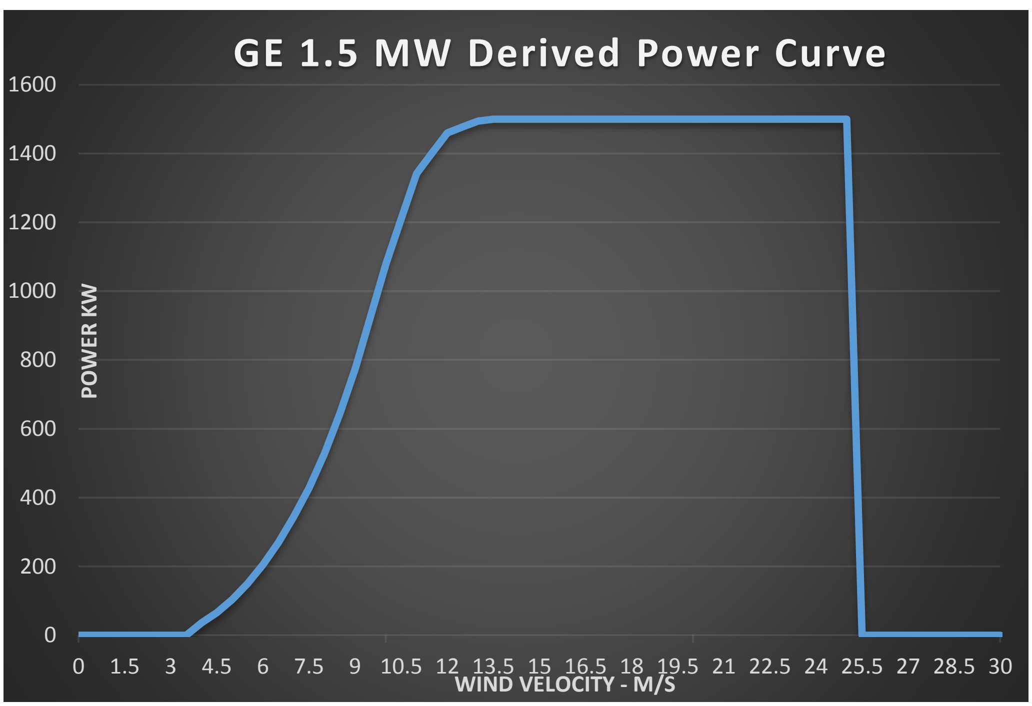

Figure 3.2 – GE 1.5 MW Wind Turbine Power Curve [58]

Finding and Arranging Data

For the purpose of this study publicly available wind speed data from the Alternative Energy Institute was used for a site around White Deer, Texas [59]. Data has been consistently collected for this site since 1995, with monthly averages posted for several years (1995-2009). However, hourly wind speed data is only available for the past four years (2010-2013). Although wind measurements are typically taken at lower heights (10-50 meters above ground), most 1-2 MW wind turbines have a hub height of around 80 meters [60]. Wind speed is known to increase with height, therefore measured data from the past four years was extrapolated from 50m to 80m (hub height of GE 1.5 MW wind turbine) using the wind profile power law [61]:

$$u_x = u_r \left(\frac{z_x}{z_r}\right)^{\alpha} \tag{3.1}$$

Here, u_x is the wind velocity to be estimated at height z_x and u_r is the known velocity at height z_r. The coefficient α , is dependent on the stability of the atmosphere and is estimated to be 1/7 or 0.143 for open land surfaces [61].

Wind data from the year 2013 is used for the remainder of this study. However, there were lots of gaps in the data set – wind velocities were not recorded for certain hours in the year due to malfunctioning anemometers and/or user error. Any day that had missing hourly data (usually spanning a time period of multiple hours) was discarded from the data set. The month of January had two days of missing data and the month of April had four days of missing data. There was no missing data for the months of July and October. Refer to Appendix C.1 for seasonal wind profiles. Seasonal trends suggest that average wind speeds are lower in the summer and higher in the fall, spring and winter. Additionally, wind velocity does not follow the load pattern – velocities are higher during the night and lower during the day. Seasonal Weibull distribution curves (fitted to data from 2010-2013) are also presented in Appendix F.1, which can be used to estimate the total power output and net income from electricity generation per season and per year. This can be useful in determining the profitability of a wind turbine/wind farm installed in this location. The curves can also be used to select a wind turbine with the optimum cut-in speed and optimal cut-out speed.

Load data was obtained from ERCOT for the year 2013 [62]. The data was available in 15 minute intervals, but since all other data used in the study is only available in hourly intervals, the 15 minute load data was converted to averaged hourly values. Load data was also scaled so that 20% of the peak load was equal to the rated capacity of the wind turbine (this will simulate a microgrid that has 20% penetration of wind). Refer to Appendix B.1 for seasonal load profiles. Load is higher in the spring and summer months which is expected due to the hot weather in Texas. The load tends to peak between 2-6 p.m. during the summer and spring and between 6-9 p.m. during the fall and winter months.

Wind Power Output ($\overline{w}_t^1$):

Wind dispatch quantity is typically calculated for a twenty four hour period and is submitted around noon the day before dispatch. This requires really good wind forecasts. Using the GE 1.5 MW wind turbine power curve (Figure 3.2), hourly wind velocity for each month was converted into hourly power output values for the year 2013. The persistence model was used to schedule the wind power producer for the day-ahead market. i.e. if the power output at time ‘t’ hours is 250 kW then the forecasted power output at time ‘t+24’ hours will also be 250 kW.

Modelling Wind Variability ($\Delta\overline{w}_t$)

Forecast uncertainty depends on several factors, the most important of which is the look-ahead time. As the look-ahead time increases the forecast uncertainty increases [63]. Day-ahead forecast values are commonly used but affect only unit-commitment decisions. Hour-ahead forecasts are more reliable and used for dispatch decisions, but have not been modeled in this study. Using a persistence model, forecast error is found by subtracting the actual value from the forecasted value.

$\Delta\overline{w}_t < 0$ – STORAGE DISCHARGING REQ.

$\Delta\overline{w}_t > 0$ – STORAGE CHARGING REQ.

The persistence forecast model is pretty good for the four months considered in this study. This is evidenced through results obtained for the Mean Absolute Error and Mean Absolute Percentage Error, which are both common metrics used to evaluate the accuracy of a forecasting model. The MAE ranges between 0.9 and 1.12. The MAPE ranges between 13.35% and 14.51% – which is pretty consistent with the accuracy of a persistence model. MAE and MAPE values are listed below for each of the four months:

January

MAE	1.01
MAPE	16.13

April

MAE	1.12
MAPE	14.26

July

MAE	0.9
MAPE	13.35

October

MAE	0.98
MAPE	14.51

Modelling Load Variability ($\Delta\bar{l}_t$)

Load forecasts are more reliable than wind forecasts and seasonal load profiles are well known to utilities based on historical data. Load forecast error is modelled by separately creating a typical hourly-weekday and a typical hourly-weekend forecast. Historical weekday values and weekend values are averaged hourly in a given month. The average hourly-weekday values are used as the forecasted value for each weekday that month and the average hourly-weekend values are used as the forecasted value for each weekend in that month. This is a reasonable assumption as weekday and weekend load profiles only change seasonally. $\Delta\bar{l}_t$ is the forecast error i.e. the difference between the actual load and the forecasted load.

$\Delta\bar{l}_t < 0$ – STORAGE CHARGING REQ.

$\Delta\bar{l}_t > 0$ – STORAGE DISCHARGING REQ.

Load and wind forecast errors were found to be weakly correlated. Refer to Appendix E.1 for seasonal correlation of errors.

Modelling net Variability ($\Delta\bar{n}_t$):

Net variability is modeled by taking the difference between the wind and load variability. For a given hour if $\Delta\bar{n}_t$ is positive, then storage charging is required and if $\Delta\bar{n}_t$ negative, then storage discharging is required.

$$\Delta\bar{n}_t = \Delta\bar{w}_t - \Delta\bar{l}_t \tag{3.2}$$

Net system imbalance ($\Delta\bar{n}_t$) = $\Delta\bar{w}_t^+ - \Delta\bar{l}_t^+ < 0$ – STORAGE DISCHARGING REQ.

Net system imbalance ($\Delta\bar{n}_t$) = $\Delta\bar{w}_t^+ - \Delta\bar{l}_t^+ > 0$ – STORAGE CHARGING REQ.

Net system imbalance ($\Delta\bar{n}_t$) = $\Delta\bar{w}_t^- - \Delta\bar{l}_t^- < 0$ – STORAGE DISCHARGING REQ.

Net system imbalance ($\Delta\bar{n}_t$) = $\Delta\bar{w}_t^- - \Delta\bar{l}_t^- > 0$ – STORAGE CHARGING REQ.

Net system imbalance ($\Delta\bar{n}_t$) = $\Delta\bar{w}_t^- - \Delta\bar{l}_t^+ < 0$ – STORAGE DISCHARGING REQ.

Net system imbalance ($\Delta\bar{n}_t$) = $\Delta\bar{w}_t^- - \Delta\bar{l}_t^+ > 0$ – NOT POSSIBLE

Net system imbalance ($\Delta\bar{n}_t$) = $\Delta\bar{w}_t^+ - \Delta\bar{l}_t^- < 0$ – NOT POSSIBLE

Net system imbalance ($\Delta\bar{n}_t$) = $\Delta\bar{w}_t^+ - \Delta\bar{l}_t^- > 0$ – STORAGE CHARGING REQ.

Note that $(.)^+ = \max\{.,0\}$ and is used to specify that the argument in parenthesis is positive or zero otherwise. Similarly, $(.)^- = \min\{.,0\}$ is used to specify that the argument in parenthesis is negative or zero otherwise. No parenthesis are included if there is only one term.

Plots showing the wind, load and net system variability (with and without curtailment) for each of the four months studied is presented in Appendix D.3, D.4, D.7, D.8, D.11, D.12, D.15 and D.16.

3.1.2 Energy Storage Model

During the initial phase of the thesis work a stochastic dynamic programming formulation was considered to calculate the expected payoff of the energy storage operator. There are several advantages of using a dynamic programming formulation: (1) it is easy to implement (2) non-linear equations can be included (3) it is efficient in studying long horizon optimization problems. However, there is at least one major drawback with a dynamic programming formulation – there is a trade-off between number of discretized values of energy storage level and the computational effort required to arrive at an optimal solution. This is often referred to as the curse of dimensionality [64].

Keeping the stochastic element of the problem (i.e. drawing wind and load variability or forecast errors from a known distribution) significantly increases the computational intensity (requires Monte Carlo simulations). Since wind and load variability can be readily modeled from existing data as described in Section 3.1.1, a simpler linear programming problem can be formulated and solved with the help of the Matlab Optimization Toolbox. The analysis is limited to a monthly operation window based on the latest data available for the next day. The Model Parameters used to setup the base case are presented in Table 3.2.

Model Assumptions and Parameters

Variable Name	**Variable Definition**	**Variable Value**
S	Storage Size	4 MWh
$SOCC_{t,}S_t$	State of Charge at time 't'	
γ_c, eff	Charging/Discharging Efficiency of Storage Device	0.9
γ_s	Self-Discharge Rate of Storage Device	1
T	Time Period	1 hour
$\bar{q}^D, Dlim$	Discharge Limit	1MW
$\bar{q}^R, Clim$	Charge Limit	1MW
q_t^R	Quantity purchased through arbitrage at time 't'	
q_t^D	Quantity sold through arbitrage at time 't'	
q_t^{RU}	Quantity of UP regulation offered into the market at time 't'	
q_t^{RD}	Quantity of DOWN regulation offered into the market at time 't'	
P_t	Day-Ahead Electricity Market Price (LMP) at time 't' - \$/MWh	
P_t^{RU}	Market Clearing Price for UP regulation at time 't' - \$/MWh	
P_t^{RD}	Market Clearing Price for DOWN regulation at time 't' - \$/MWh	
C_d	Cost of Discharging at time 't' (\$/MWh)	0

C_r	Cost of Charging at time 't' ($/MWh)	0
$\overline{w}_t^1$	Scheduled wind power output at time 't'	
$\Delta\overline{w}_t^1$	Error in wind power output at time 't' – (Actual - Forecast)	
$\Delta\overline{w}_t^2$	Error in wind power output at time 't' with curtailment – (Actual - Forecast)	
$\Delta\bar{l}_t^1$	Error in load at time 't' – (Actual - Forecast)	
$\Delta\bar{n}_t^1$	Net variability (wind error - load error) at time 't'	
$\Delta\bar{n}_t^2$	Net variability with curtailment (wind error - load error) at time 't'	
∂_1^i	Injection imbalance fee (paid by the wind producer to storage)	190%*P_t
∂_1^e	Extraction imbalance fee (paid by the wind producer to the storage)	10%*P_t
∂_2^i	Injection imbalance fee (paid by the wind producer to the utility)	195%*P_t
∂_2^e	Extraction imbalance fee (paid by wind producer to the utility)	40%*P_t
α_{ruw}	Fraction of time that capacity reserved for Wind UP regulation is called	0.5
α_{rdw}	Fraction of time that capacity reserved for Wind DOWN regulation is called	0.5
μ_{ruw}	Average fraction of wind UP Regulation called when Wind UP regulation is required (30% of installed capacity)	0.45
μ_{rdw}	Average fraction of wind DOWN Regulation called when Wind DOWN regulation is required	0.45
γ_{ruw}	Wind UP regulation efficiency	0.225
γ_{rdw}	Wind DOWN regulation efficiency	0.225
α_{rul}	Fraction of time that capacity reserved for Load UP regulation is called	0.5
α_{rdl}	Fraction of time that capacity reserved for Load DOWN regulation is called	0.5
μ_{rul}	Average fraction of load UP Regulation called when Load UP regulation is required (5% of Peak load)	0.375
μ_{rdl}	Average fraction of load DOWN Regulation called when Load DOWN regulation is required	0.375
γ_{rul}	Load UP regulation efficiency	0.1875
γ_{rdl}	Load DOWN regulation efficiency	0.1875
α_{run}	Fraction of time that capacity reserved for net UP regulation is called	0.5
α_{rdn}	Fraction of time that capacity reserved for net DOWN regulation is called	0.5
μ_{run}	Average fraction of UP Regulation called when net UP regulation is required	0.825
μ_{rdn}	Average fraction of DOWN Regulation called when net DOWN regulation is required	0.825
γ_{run}	Net UP regulation efficiency	0.4125
γ_{rdn}	Net DOWN regulation efficiency	0.4125

Table 3.2 – Model Parameters

Model parameters in the table above are for the base case. This section provides some justification for the numbers used, although as pointed out in the introduction it is not the aim of this study to optimize these parameters. Some recent studies have tried to optimize the storage size and charging/discharging limits to minimize wind power imbalances [65, 66].

The charging and discharging limit determines the ability of the energy storage to provide firm power output when operating in conjunction with the wind power producer. Firm power output can be ensured by setting the charging/discharging limit to the rated capacity of the wind turbine i.e. 1.5 MW, but this will lead to oversizing strictly speaking in terms of providing firm capacity. The remaining capacity can however be used for arbitrage and/or in the ancillary services market to provide frequency regulation or other services. Value of 1 MW both for charging/discharging is chosen so that the storage can handle a majority of the wind deviations based on the persistence model. The storage size is chosen to be 4MWh – it is a common trend to size storage four times the value of the charging/discharging limit, especially in cases where it is used just for arbitrage. This is done so that the storage is able to provide four hours of energy during four consecutive peak hours of the day. Doing so saves the utility money as it is able to offset the cost of starting expensive peaking generating units and benefits the storage as electricity prices are highest during peak hours. The charging/discharging efficiency of the storage is chosen to be 0.9 and is based on the characteristics of energy storage currently available on the market [4].

In addition to the parameters listed in Table 3.2, there are several other assumptions made in this study:

a. There are no constraints on the transmission network and ramp rates are not considered. Although transmission is not constrained, it can be encoded into the model by changing the charging/discharging limits.
b. All quantity offered by wind power producer is accepted for dispatch except where explicitly mentioned that it is curtailed. There is no compensation for curtailment.
c. Wind farm does not participate in ancillary services.
d. Reactive power flow is neglected.
e. The main grid acts as a power source or sink depending on the sign of the net deviation.
f. Wind power producer is not responsible for making payments for frequency regulation service provided by the utility.
g. Estimate of wind variability and load variability are available to both the wind power producer and the energy storage operator.
h. Work done is in anticipation of scenarios in which storage represents less expensive options and is cheaper than generation reserves.
i. All deviations are balanced locally to the extent possible.

Finding and Arranging Data

While the storage, wind and load parameters have been extensively discussed in the previous sections it also important to discuss how the electricity market parameters were obtained. For the purpose of this study data on day-ahead market prices and market clearing prices on up regulation (MCPCRU) and down regulation (MCPCRD) were obtained from ERCOT [67, 68]. Up regulation refers to the ability of a generation resource or storage to increase its output on command and down regulation refers to the ability of the same entity to decrease its output on command.

Refer to Appendix A.1, A.2, A.3, A.4, and A.5 for seasonal variations on these prices. It's difficult to predict a seasonal trend on MCPCRU and MCPRD prices as they are dependent on the load-generation mismatch in the system at the given time – in general, regulation down prices can be expected to be high during the night and lower during the day and regulation up prices can be expected to be high during the day and lower during the night. Electricity prices however show a strong seasonal trend with prices peaking in the afternoon hours during the summer and fall season (this is directly correlated to the increased load during the hotter months). Prices in the winter and spring are relatively flat.

Maximizing Revenue

The problem of maximizing revenue for energy storage through arbitrage and regulation service is formulated as a standard linear optimization problem:

$$\min_{x} f^{T} \text{ such that} \begin{cases} Ax \leq b \\ A_{(eq)}x = b_{eq} \\ lb \leq x \leq ub \end{cases} \tag{3.3}$$

Numerous studies have extensively studied the potential benefits of using storage for arbitrage alone [69, 70]. However, since regulation is considered to be one of the highest revenue services it has also been modelled in this study [71]. Arbitrage involves the practice of buying energy when prices are low (typically at night when demand is low) and selling energy when prices are high (during peak hours when demand is high). Regulation service on the other hand attempts to balance short term deviations (minute-to-minute) to maintain the grid frequency. When the generation exceeds the load, the system frequency increases and when the load exceeds the available generation the system frequency decreases. Generation resources, or in this case the storage operator needs to be flexible enough to be able to respond to control signals and balance these deviations to maintain a stable grid frequency.

The following model describes the behavior of an energy storage device that participates in arbitrage and regulation service – the technical mechanism and mathematical model has been borrowed from the work in [71]:

$$S_t = \gamma_s S_{t-1} + \gamma_c q_t^R - q_t^D / \gamma_c + \gamma_c \gamma_{rd} q_t^{RD} - \gamma_{ru} q_t^{RU} / \gamma_c \tag{3.4}$$

The following constraints restrict the energy charged/discharged and capacity offered into the regulation market to within the charging/discharging limits of the storage device. Additionally, the state of charge is constrained by the physical limits of the storage size.

$$\begin{aligned} &0 \leq q_t^D + q_t^{RU} \leq \bar{q}^D \\ &0 \leq q_t^R + \ q_t^{RD} \leq \bar{q}^R \\ &0 \leq S_t \leq S \end{aligned} \tag{3.5}$$

It is necessary to keep in mind that any capacity that is offered into the regulation market takes away capacity from the amount of energy that can be traded in the market via arbitrage. As is evident from the equation (3.5) the variables we are trying to solve for are q_t^D, q_t^R, q_t^{RU} & q_t^{RD}. Solving for these decision variables provides a solution to the scheduling problem of the energy storage while maximizing its revenue. These decision variables can be grouped together in a vector 'x' as:

$$x = \begin{bmatrix} q_1^D \\ \vdots \\ q_T^D \\ q_1^R \\ \vdots \\ q_T^R \\ q_1^{RU} \\ \vdots \\ q_T^{RU} \\ q_1^{RD} \\ \vdots \\ q_T^{RD} \end{bmatrix} \tag{3.6}$$

Not all of the capacity offered into the market for regulation is accepted, therefore it becomes necessary to define up/down regulation efficiency – this is percentage of up/down regulation offers that are accepted and is mathematically defined as follows:

$$\gamma_{run} = \alpha_{run}\mu_{run}, \quad \gamma_{rdn} = \alpha_{rdn}\mu_{rdn}, \alpha_{run} + \alpha_{rdn} = 1, 0 \leq \mu_{run}, \mu_{rdn} \leq 1 \tag{3.7}$$

Here, α_{run} *and* α_{rdn} is the fraction of time (0.5) in a given time period (1 hour) that capacity is reserved for up regulation and down regulation, respectively. For this study it is assumed that up regulation and down regulation are required for equal amounts of time in a given time period.

$$\alpha_{run} = \frac{\text{number of } RU\ AGC \text{ sample in the period}}{\text{number of } AGC \text{ sample in the period}} \tag{3.8}$$

$$\alpha_{rdn} = \frac{\text{number of } RD\ AGC \text{ sample in the period}}{\text{number of } AGC \text{ sample in the period}} \tag{3.9}$$

$$\mu_{run} = \frac{\sum RU\ \ AGC \text{ sample in the period}}{\text{number of } RU\ AGC \text{ sample in the period}} \left(\frac{\text{one time period}}{q_T^{RU}}\right) \tag{3.10}$$

$$\mu_{rdn} = \frac{\sum RD\ \ AGC \text{ sample in the period}}{\text{number of } RD\ AGC \text{ sample in the period}} \left(\frac{\text{one time period}}{q_T^{RD}}\right) \tag{3.11}$$

Assuming that the initial state of charge of the energy storage is 0, the first few time steps will be as follows:

$t = 1 \quad S_1 = \gamma_c q_1^R - q_1^D / \gamma_c + \gamma_c \gamma_{rd} q_1^{RD} - \gamma_{ru} q_1^{RU} / \gamma_c$

$t = 2 \quad S_2 = \gamma_s(\gamma_c q_1^R - q_1^D/\gamma_c + \gamma_c\gamma_{rd} q_1^{RD} - \gamma_{ru} q_1^{RU}/\gamma_c) + \gamma_c q_2^R - q_2^D/\gamma_c + \gamma_c \gamma_{rd} q_2^{RD} -$

$\gamma_{ru} q_2^{RU}/\gamma_c$

$t = 3 \quad S_3 = \gamma_s[\gamma_s(\gamma_c q_1^R - q_1^D/\gamma_c + \gamma_c\gamma_{rd} q_1^{RD} - \gamma_{ru} q_1^{RU}/\gamma_c) + \gamma_c q_2^R - q_2^D/\gamma_c + \gamma_c\gamma_{rd} q_2^{RD} -$

$\gamma_{ru} q_2^{RU}/\gamma_c] + \gamma_c q_3^R - q_3^D/\gamma_c + \gamma_c\gamma_{rd} q_3^{RD} - \gamma_{ru} q_3^{RU}/\gamma_c$

Since a month long optimization is performed, it is best to put these equations in a matrix format as listed below:

$$A_s x = S, \text{ where } \ A_s = [A_d | A_r | A_{ru} | A_{rd}] \tag{3.12}$$

$$A_d = \begin{bmatrix} -1 & 0 & 0 & 0 & \cdots & 0 \\ -\gamma_s & -1 & 0 & 0 & \cdots & 0 \\ -\gamma_s^2 & -\gamma_s & -1 & 0 & \cdots & 0 \\ -\gamma_s^3 & -\gamma_s^2 & -\gamma_s & -1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ -\gamma_s^{T-1} & -\gamma_s^{T-2} & -\gamma_s^{T-3} & -\gamma_s^{T-4} & \cdots & -1 \end{bmatrix} / \gamma_c \tag{3.13}$$

$$A_r = \begin{bmatrix} \gamma_c & 0 & 0 & 0 & \cdots & 0 \\ \gamma_s\gamma_c & \gamma_c & 0 & 0 & \cdots & 0 \\ \gamma_s^2\gamma_c & \gamma_s\gamma_c & \gamma_c & 0 & \cdots & 0 \\ \gamma_s^3\gamma_c & \gamma_s^2\gamma_c & \gamma_s\gamma_c & \gamma_c & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_s^{T-1}\gamma_c & \gamma_s^{T-2}\gamma_c & \gamma_s^{T-3}\gamma_c & \gamma_s^{T-4}\gamma_c & \cdots & \gamma_c \end{bmatrix} \tag{3.14}$$

$$A_{ru} = \begin{bmatrix} -\gamma_{ru} & 0 & 0 & 0 & \cdots & 0 \\ -\gamma_s\gamma_{ru} & -\gamma_{ru} & 0 & 0 & \cdots & 0 \\ -\gamma_s^2\gamma_{ru} & -\gamma_s\gamma_{ru} & -\gamma_{ru} & 0 & \cdots & 0 \\ -\gamma_s^3\gamma_{ru} & -\gamma_s^2\gamma_{ru} & -\gamma_s\gamma_{ru} & -\gamma_{ru} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ -\gamma_s^{T-1}\gamma_{ru} & -\gamma_s^{T-2}\gamma_{ru} & -\gamma_s^{T-3}\gamma_{ru} & -\gamma_s^{T-4}\gamma_{ru} & \cdots & -\gamma_{ru} \end{bmatrix} / \gamma_c \tag{3.15}$$

$$A_{rd} = \begin{bmatrix} \gamma_c\gamma_{rd} & 0 & 0 & 0 & \cdots & 0 \\ \gamma_s\gamma_c\gamma_{rd} & \gamma_c\gamma_{rd} & 0 & 0 & \cdots & 0 \\ \gamma_s^2\gamma_c\gamma_{rd} & \gamma_s\gamma_c\gamma_{rd} & \gamma_c\gamma_{rd} & 0 & \cdots & 0 \\ \gamma_s^3\gamma_c\gamma_{rd} & -\gamma_s^2\gamma_{ru} & \gamma_s\gamma_c\gamma_{rd} & \gamma_c\gamma_{rd} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \gamma_s^{T-1}\gamma_c\gamma_{rd} & \gamma_s^{T-2}\gamma_c\gamma_{rd} & \gamma_s^{T-3}\gamma_c\gamma_{rd} & \gamma_s^{T-4}\gamma_c\gamma_{rd} & \cdots & \gamma_c\gamma_{rd} \end{bmatrix} \tag{3.16}$$

$$S = [S_1 \quad S_2 \quad S_3 \quad \ldots \quad S_T]^T \tag{3.17}$$

The inequality constraints are as follows:

$$\begin{aligned} &0 \le q_t^D + q_t^{RU} \le \bar{q}^D \\ &0 \le q_t^R + \ q_t^{RD} \le \bar{q}^R \\ &0 \le S_t \le \bar{S} \end{aligned} \tag{3.18}$$

The constraints on the upper and lower bounds of x are listed below ($lb \leq x \leq ub$):

$$lb^{4Tx1} = [0 \quad \dots \quad 0]^T,$$

$$ub^{4Tx1} = [\bar{q}^D \quad \dots \quad \bar{q}^D \quad \bar{q}^R \quad \dots \quad \bar{q}^R \quad \bar{q}^D \quad \dots \quad \bar{q}^D \quad \bar{q}^R \quad \dots \quad \bar{q}^R]^T \tag{3.19}$$

Since the inequality constraints are a function of two parameters in x, the following constraints must also be applied ($Ax \leq b$):

$$0 \leq q_t^D + \gamma_t^{RU} q_t^{RU}, \quad [-I^{TxT} \mid 0^{TxT} \mid -I^{TxT} \mid 0^{TxT}] \; x \leq 0^{Tx1} \tag{3.20}$$

$$q_t^D + \gamma_t^{RU} q_t^{RU} \leq \bar{q}^D, \quad [I^{TxT} \mid 0^{TxT} \mid I^{TxT} \mid 0^{TxT}] \; x \leq [\bar{q}^D]^{Tx1} \tag{3.21}$$

$$0 \leq q_t^D + \gamma_t^{RD} q_t^{RD}, \quad [0^{TxT} \mid -I^{TxT} \mid 0^{TxT} \mid -I^{TxT}] \; x \leq 0^{Tx1} \tag{3.22}$$

$$q_t^D + \gamma_t^{RD} q_t^{RD} \leq \bar{q}^D, \quad [0^{TxT} \mid I^{TxT} \mid 0^{TxT} \mid I^{TxT}] \; x \leq [\bar{q}^R]^{Tx1} \tag{3.23}$$

$$\text{combining } 0 \leq S_t \text{ and } S \leq A_s x \text{ yields } -A_s x \leq 0 \tag{3.24}$$

$$\text{combining } S \leq A_s x \text{ and } S_t \leq \bar{S} \text{ yields } A_s x \leq \bar{S} \tag{3.25}$$

By combining all the inequalities we get the following set of equations in matrix form:

$$Ax \leq b, \text{ where } A = \begin{bmatrix} -A_d & -A_r & -A_{ru} & -A_{rd} \\ A_d & A_r & A_{ru} & A_{rd} \\ -I & 0 & -I & 0 \\ I & 0 & I & 0 \\ 0 & -I & 0 & -I \\ 0 & I & 0 & I \end{bmatrix}, \quad b = \begin{bmatrix} 0 \\ \bar{S} \\ 0 \\ \bar{q}^D \\ 0 \\ \bar{q}^R \end{bmatrix} \tag{3.26}$$

The cost function that is to be maximized is given as follows (cost for charging and cost for discharging are assumed to be zero for this study, but can be modelled if information is available on these parameters):

$$J = \sum_{t=1}^{T}\big[(P_t - C_d)q_t^D + \big(P_t^{RU} + \gamma_{ru}(P_t - C_d)\big)\big]q_t^{RU}$$
$$+\big(P_t^{RD} - \gamma_{rd}(P_t + C_r)\big)q_t^{RD} - (P_t + C_r)q_t^R] \tag{3.27}$$

Although payment for regulation service is typically done at the real-time market price, this study is mostly concerned with day-ahead scheduling and revenues.

$$f = \begin{bmatrix} (P_1 - C_d) \\ (P_2 - C_d) \\ (P_3 - C_d) \\ \vdots \\ (P_T - C_d) \\ -(P_1 + C_d) \\ -(P_2 + C_d) \\ -(P_3 + C_d) \\ \vdots \\ -(P_T + C_d) \\ (P_1^{RU} + \gamma_{ru}(P_1 - C_d)) \\ (P_2^{RU} + \gamma_{ru}(P_2 - C_d)) \\ (P_3^{RU} + \gamma_{ru}(P_3 - C_d)) \\ \vdots \\ (P_T^{RU} + \gamma_{ru}(P_T - C_d)) \\ (P_1^{RD} - \gamma_{rd}(P_1 + C_r)) \\ (P_2^{RD} - \gamma_{rd}(P_2 + C_r)) \\ (P_3^{RD} - \gamma_{rd}(P_3 + C_r)) \\ \vdots \\ (P_T^{RD} - \gamma_{rd}(P_T + C_r)) \end{bmatrix} \tag{3.28}$$

Since the aim is to maximize revenues using the framework of a minimization problem a new variable J^* needs to be defined, which is negative of the cost function defined above. Minimizing J^* will maximize the revenue and profit of the energy storage

$$J^* = -f^T x \tag{3.29}$$

3.2 Payoff Matrix

The optimization process described in the previous section deals with only arbitrage and regulation service. Since our goal is to see if it would be beneficial for the energy storage to support the wind power producer in balancing deviations, some modifications need to be made to the problem defined above. However, this needs to be addressed on a case by case basis and is dependent on the strategy adopted by both the wind power producer and the storage operator. Table 3.3 shows the four possible combination of strategies that can be employed by the players.

WIND **STORAGE**	**COOPERATION**	**NON-COOPERATION**
COOPERATION	**B** **(Case 1)** **A**	**D** **(Case 2)** **C**
NON-COOPERATION	**F** **(Case 4)** **G**	**D** **(Case 3)** **E**

Table 3.3 – Payoff Table

Case 1

In this case both players choose to cooperate and act as one entity to try and provide the scheduled/promised power output by the wind power producer.

- Energy storage has four streams of revenue:

- Revenue from balancing wind deviations ($\Delta\overline{w}_t$) (paid by wind power producer in the form of imbalance payments @ price (∂_1^i, ∂_1^e)). Priority is given to balancing wind deviations before considering the load deviations.
- Revenue from balancing load deviations ($\Delta\overline{l}_t$). (Paid by utility @ price P_t)
- Revenue from arbitrage (paid by utility @ price P_t)
- Revenue from regulation service for net system imbalance (paid by utility in the form of capacity premium and energy payments @ Price P_t).

- The wind power producer schedules power output based on the persistence model. For any deviations from scheduled transactions the wind power producer pays an imbalance fee (∂_1^i, ∂_1^e) to the storage and may also pay penalty (∂_2^i, ∂_2^e) to the utility if the variability exceeds the charge/discharge limits and/or the storage capacity of the storage device. Penalty is paid for both overproduction and underproduction.

Payoff function for storage **(A)** is calculated using the Linear Optimization Approach in Section 3.1.2. However, some modifications are made as described below – the mathematical tool used to absorb imbalances to within the physical limits of the storage device in this case and all subsequent cases is borrowed from the work in [30]:

$$\Delta\overline{w}_t^{1,2} = \frac{\Delta\overline{w}_t^-}{eff} + \Delta\overline{w}_t^+ * eff \qquad (3.30)$$

$$\Delta\overline{l}_t^1 = \frac{\Delta\overline{l}_t^+}{eff} + \Delta\overline{l}_t^- * eff \qquad (3.31)$$

$$\Delta\overline{n}_t^{1,2} = \frac{\Delta\overline{n}_t^-}{eff} + \Delta\overline{n}_t^+ * eff \qquad (3.32)$$

$$N1_t = \max(\min(\Delta\overline{w}_t^1, \min(S - SOCC_t, Clim)), \max(-SOCC_t, -Dlim)) \quad (3.33)$$

$$N1_t = Amt. of\ energy\ charged\ or\ discharged\ by\ the\ storage\ device\ due\ to\ wind\ dev.$$

if $N1_t < 0$

$$N2_t = \max(\min\big(-\Delta\overline{l}_t^1, \min(S - (SOCC_t + N1_t), Clim)\big), \max(-(SOCC_t + N1_t), -Dlim - N1_t)) \quad (3.34)$$

else

$$N2_t = \max(\min\big(-\Delta\overline{l}_t^1, \min(S - (SOCC_t + N1_t), Clim - N1_t)\big), \max(-(SOCC_t + N1_t), -Dlim)) \quad (3.35)$$

$$N2_t = Amt. of\ energy\ charged\ or\ discharged\ by\ the\ storage\ device\ due\ to\ load\ dev.$$

Preference is given to balancing both wind and load deviations (wind first in this case) – the remaining capacity is used for performing arbitrage and regulation service. The constraints in equation 3.18 are modified accordingly (only the upper bounds are modified, as optimization variables cannot take on negative values):

$$\begin{aligned} q_t^D + q_t^{RU} - N1_t^- - N2_t^- &\leq \overline{q}^D \\ q_t^R + q_t^{RD} + N1_t^+ + N2_t^+ &\leq \overline{q}^R \\ S_t + N1_t^- + N1_t^+ + N2_t^- + N2_t^+ &\leq \overline{S} \end{aligned} \quad (3.36)$$

The cost function in equation 3.27 is modified to reflect the additional revenue from imbalances (payoff function for storage **(A)**):

$$J_s = [(P_t)q_t^D - (P_t)q_t^R + \left(P_t^{RU} + \gamma_{run_t}P_t\right)q_t^{RU} + \left(P_t^{RD} - \gamma_{rdn_t}P_t\right)q_t^{RD}]$$

$$[-(\partial_1^i)N1_t^- * eff + (\partial_1^e)N1_t^+/eff] + [P_tN2_t^+ * eff + P_t * N2_t^-/eff] \qquad (3.37)$$

J_s = *First term + second term + third term + fourth term + fifth term + sixth term*

ARBITRAGE

First Term = *Payment for discharging through arbitrage (paid* ***by*** *utility)*

Second Term = *Payment for charging through arbitrage (paid* ***to*** *utility)*

REGULATION

Third Term = *Payment for Regulation UP service*

$P_t^{RU} * q_t^{RU}$ = *Payment for Capacity (paid* ***by*** *utility)*

$(\gamma_{ru} * P_t) * q_t^{RU}$ = *Energy payment (paid* ***by*** *utility)*

Fourth Term = *Payment for Regulation DOWN service*

$P_t^{RD} * q_t^{RD}$ = *Payment for Capacity (paid* ***by*** *utility)*

$(\gamma_{rd} * P_t) * q_t^{RD}$ = *Energy payment (paid* ***to*** *utility)*

BALANCING WIND DEVIATIONS

Fifth Term = *Imbalance Payment (paid* ***by*** *wind power producer)*

Sixth Term = *Imbalance Payment (paid* ***by*** *wind power producer)*

BALANCING LOAD DEVIATIONS

Seventh Term = *Energy Payment (paid* ***by*** *utility)*

Eighth Term = *Energy Payment (paid* ***to*** *utility)*

Payoff function for the wind power producer **(B)** depends on the amount of deviation that is balanced by the energy storage operator. The amount of energy that is not balanced by the storage is subject to heavy penalty from the utility.

$$N3_t = (\Delta\overline{w}_t^- - N1_t^- * eff), N4_t = (\Delta\overline{w}_t^+ - N1_t^+/eff) \tag{3.38}$$

$$N3_t = Energy\ not\ provided\ by\ Storage\ Unit$$

$$N4_t = Energy\ not\ absorbed\ by\ Storage\ Unit$$

The payoff function **(B)** for the wind power producer is as follows:

$$J_w = P_t * (\overline{w}_t^1) + \partial_1^i * N1_t^- * eff - \partial_1^e * N1_t^+/eff + \partial_2^i * N3_t - \partial_2^e * N4_t \tag{3.39}$$

J_w = *First term + second term + third term + fourth term + fifth term*

First Term = *Payment for scheduled transaction (paid* ***by*** *utility)*

Second Term = *Penalty charged for underproduction (paid* ***to*** *Storage)*

Third Term = *Penalty charged for overproduction (paid* ***to*** *Storage)*

Fourth Term = *Penalty charged for underproduction (paid* ***to*** *utility)*

Fifth Term = *Penalty charged for overproduction (paid* ***to*** *utility)*

It must be noted that as evidenced through the mathematical model when the storage is charging there are losses due to conversion efficiency, but the energy storage operator still receives payment from the wind power producer for the true imbalance. Therefore, when charging, the wind power producer bears the losses due to conversion efficiency. When discharging, the energy storage operator needs to provide more energy than the true imbalance to account for the conversion efficiency. Therefore, while discharging, the energy storage operator bears the losses due to conversion efficiency. This is true for the remainder of this study.

It must also be noted that the load deviations balanced by the energy storage operator are not considered an ancillary service and are typically handled through economic dispatch in energy markets, however, it has been modeled in this study as the storage operator is the only other generation source that is able to handle the deviations locally.

Case 2

In this case the wind power producer chooses to not cooperate and pay penalties to the utility, while the storage operator indirectly cooperates by balancing wind deviations through the utility, but gives preference to balancing load deviations first.

- Energy storage has four streams of revenue:
    - Revenue from balancing load deviations ($\Delta\bar{l}_t$). (Paid by utility @ price P_t)
    - Revenue from balancing wind deviations ($\Delta\bar{w}_t$) (paid by utility in the form of imbalance payments @ price (∂_1^i, ∂_1^e)).
    - Revenue from arbitrage (paid by utility @ price P_t)
    - Revenue from regulation service for net system imbalance (paid by utility in the form of capacity premium and energy payments @ Price P_t).

- The wind power producer schedules power output based on the persistence model for the day-ahead market. For any deviations the wind power producer pays penalty ($\partial_2^i, \partial_2^e$) to the utility. Penalty is paid for both overproduction and underproduction.

Payoff function for storage **(C)** is calculated similarly to case 1. The only difference being that imbalance payments in this case come from the utility instead of the wind power producer. Also, priority is given to balancing load deviations. Therefore, the following modifications are necessary:

$$N1_t = \max(\min\left(-\Delta\bar{l}_t^1, \min(S - SOCC_t, Clim)\right), \max(-SOCC_t, -Dlim)) \tag{3.40}$$

$$N1_t = Amount\ of\ energy\ charged/discharged\ by\ the\ storage\ device\ due\ to\ load\ dev.$$

if $N1_t < 0$

$$N2_t = \max(\min(\Delta\bar{w}_t^1, \min(S - (SOCC_t + N1_t), Clim)),$$

$$\max(-(SOCC_t + N1_t), -Dlim - N1_t)) \tag{3.41}$$

else

$$N2_t = \max(\min(\Delta\bar{w}_t^1, \min(S - (SOCC_t + N1_t), Clim - N1_t)),$$

$$\max(-(SOCC_t + N1_t), -Dlim)) \tag{3.42}$$

$$N2_t = Amount\ of\ energy\ charged/discharged\ by\ the\ storage\ device\ due\ to\ wind\ dev.$$

The constraints in equation 3.18 are modified accordingly (only the upper bounds are modified, as optimization variables cannot take on negative values):

$$q_t^D + q_t^{RU} - N1_t^- - N2_t^- \leq \bar{q}^D$$
$$q_t^R + q_t^{RD} + N1_t^+ + N2_t^+ \leq \bar{q}^R \qquad (3.43)$$
$$S_t + N1_t^- + N1_t^+ + N2_t^- + N2_t^+ \leq \bar{S}$$

The cost function in equation 3.27 is modified to reflect the additional revenue from imbalances (payoff function for storage **(C)**):

$$J_s = [(P_t)q_t^D - (P_t)q_t^R + \left(P_t^{RU} + \gamma_{run_t}P_t\right)q_t^{RU} + \left(P_t^{RD} - \gamma_{rdn_t}P_t\right)q_t^{RD}]$$
$$[-\left(\partial_1^i\right)N2_t^- * eff + (\partial_1^e)N2_t^+/eff] + [P_tN1_t^+ * eff + P_t * N1_t^-/eff] \qquad (3.44)$$

Payoff function for **(D),** the wind power producer is pretty straightforward – penalties are paid to the utility for any deviations from schedule.

$$J_w = P_t * (\bar{w}_t^1) + \partial_2^i * \Delta\bar{w}_t^{1-} - \partial_2^e * \Delta\bar{w}_t^{1+} \qquad (3.45)$$

J_w *= First term + second term + third term*

First Term = Payment for scheduled transaction

Second Term = Penalty charged for underproduction (paid ***to*** *utility)*

Third Term = Penalty charged for overproduction (paid ***to*** *utility)*

Case 3

In this case both the wind power producer and the storage operator choose to not cooperate. The wind power producer pays penalties to the utility and the storage operator operates independently and loses out on imbalance payments it could have received from the wind power producer.

- Energy storage has three streams of revenue:
  - Revenue from balancing net deviations ($\Delta\bar{n}_t$) (paid by utility @ price P_t)
  - Revenue from Arbitrage (paid by utility @ price P_t)
  - Revenue from Regulation Service for net system imbalance (paid by utility in the form of capacity premium and energy payment @ price P_t).
- The wind power producer schedules power output based on the persistence model for the day-ahead market. Just like the previous case (case 3) the wind power producer chooses to not cooperate and pays the penalty ($\partial_2^i, \partial_2^e$) to the utility. Penalty is paid for both overproduction and underproduction.

Payoff function for storage **(E)** is slightly different from the previous two cases – storage does not receive imbalance penalties in this case.

$$N3_t = \max(\min(\Delta\bar{n}_t^1\, , \min(S - SOCC_t, Clim))\, , \max(-(SOCC_t, -Dlim)) \tag{3.46}$$

$$N3_t = Amount\ of\ energy\ charged\ or\ discharged\ by\ the\ storage\ device\ due\ to\ net\ dev.$$

The cost function in equation 3.27 is modified to reflect the additional revenue from imbalances (payoff function for storage **(E)**):

$$J_s = [(P_t) * q_t^D - (P_t) * q_t^R + \left(P_t^{RU} + \gamma_{run_t} * P_t\right) * q_t^{RU} + \left(P_t^{RD} - \gamma_{rdn_t} * P_t\right) * q_t^{RD}] - [P_t * N3_t^- * eff + P_t * N3_t^+ / eff] \tag{3.47}$$

Payoff function for wind power producer **(D)** is the same as case 2**:**

$$J_w = P_t * (\overline{w}_t^1) + \partial_2^i * \Delta\overline{w}_t^{1-} - \partial_2^e * \Delta\overline{w}_t^{1+} \quad (3.48)$$

Case 4

In this case the wind power producer chooses to curtail its output knowing that the energy storage will not cooperate – this reduces the positive imbalance on the system and increases the revenue of the wind power producer as it is able to avoid paying fines on overproduction.

- Energy storage has three streams of revenue:
  - Revenue from balancing net deviations ($\Delta\overline{n}_t$) (paid by utility @ price P_t)
  - Revenue from arbitrage (paid by utility @ price P_t)
  - Revenue from regulation service for net system imbalance (paid by utility in the form of capacity premium and energy payment @ price P_t).
- The wind power producer schedules power output based on the persistence model for the day-ahead market. The wind power producer pays the penalties to (∂_2^i, ∂_2^e) to the utility. Penalty is paid only on underproduction.

Payoff function for storage **(G)** is similar to case 3, the only difference being the value of the net system imbalance changes due to the wind power output being curtailed.

$$N3_t = \max(\min(\Delta\overline{n}_t^2, \min(S - SOCC_t, Clim)), \max(-(SOCC_t, -Dlim)) \quad (3.49)$$

$N3_t = Amount\ of\ energy\ charged\ or\ discharged\ by\ the\ storage\ device\ due\ to\ net\ dev.$

Payoff function for the wind power producer **(F)** is also similar to the previous case (note there are no positive wind deviations due to the output being curtailed):

$$J_w = P_t * (\overline{w}_t^1) + \partial_2^i * \Delta\overline{w}_t^{2-} \tag{3.50}$$

First Term = Payment for scheduled transaction

Second Term = Penalty charged for underproduction (paid ***to*** *utility)*

Once the numbers are populated in the payoff matrix using the methodology described in this chapter, the following process is used to arrive at the Nash Equilibrium:

1. Iterative elimination of dominant strategies i.e. Check for strictly dominated strategies and remove them from the game.
2. Check for dominant strategy equilibrium (also the Nash equilibrium)
3. If there is no dominant strategy equilibrium then use the best response algorithm to find the Nash equilibrium of the simplified game.

Chapter 4 – Nash Equilibrium and Conditions for Cooperation

The game-theoretic framework developed in Chapter 3 is implemented in Matlab and the results are presented in this section in the form of payoff matrices. The payoff matrix lists the net revenues for the wind power producer and the energy storage in each cell. Results from the months of January, April, July and October are presented and discussed – these months are assumed to be representative of winter, spring, summer and fall seasons respectively. Additionally, sensitivity of the Nash equilibrium to various storage and market parameters is studied. Since there are only two players in the game, the calculation of the Nash equilibrium (given in bold in each payoff matrix) is fairly simple and is easily calculated using the elimination of dominated strategies and/or best response method. More complex algorithms are required for N-person games and are not discussed in this work. The base case is setup with the assumptions outlined in Chapter 3 and under Table 3.2.

4.1 Payoff Matrix and Nash Equilibrium – January

4.1.1 Base Case

WIND / **STORAGE**	**COOPERATION**	**NON-COOPERATION**
COOPERATION	**$707** **$6,988**	$195 $8,514
NON-COOPERATION	$2,108 $5,422	$195 $4,870

Table 4.1 – Base Case Payoff Matrix

WIND **STORAGE**	**COOPERATION**	**NON-COOPERATION**
COOPERATION	**X=$707** **X=$4,645** **Y=$2,343**	X=$195 X=$8,514 Y=$0
NON-COOPERATION	X=$2,108 X=$5,422 Y=$0	X=$195 X=$4,870 Y=$0

Table 4.2 – Base Case Payoff Matrix

X = Net payment from the utility

Y = Net payment from wind power producer

(X+Y) = Net revenue of energy storage operator

The wind power producer maybe eligible to receive PTC credits in addition to the revenue calculated above. Payment for PTC credits = ($0.023/kwh * Energy output for the month) [56]. This amount is the same for cases 1, 2 and 3, but is different for case 4 as there is no overproduction (output is curtailed). Net wind output for the month will be lower in case 4, therefore it will receive less PTC credits than all the other cases. PTC credits for cases 1, 2 and 3 = $10,870. PTC credits for case 4 = $6,716. In the scenarios where wind output is not curtailed case 4 will be similar to cases 1, 2 and 3. Receiving PTC credits does not alter the equilibrium of the game.

From the outcome of this game it is evident that both players will want to cooperate. Operating independently hurts the payoff of both players. The wind power producer has considerably less revenue if it chooses to operate independently (non-cooperative strategy) as it ends up paying heavy penalties to the utility. By coordinating with the energy storage operator and playing its cooperative strategy the wind power producer can increase its revenues. Similarly, the energy storage operator has significantly higher revenues when it chooses to coordinate with the wind power producer and play its cooperative strategy – this is mostly due to the fact that it is paid both for injection and extraction of power to balance wind deviations. When operating independently (non-cooperative strategy) the storage does not receive imbalance payments and the capacity used to provide the balancing service takes away from capacity that could have been offered into the ancillary services market.

For the base case the Nash equilibrium is case 1 i.e. both players have an incentive to cooperate. Storage revenue in case 1 and 2 exceeds the revenue that would have been obtained had it just performed arbitrage and regulation service – refer to Appendix D.1, D.2. This is possible as the storage is paid both for extraction and injection of power for balancing wind deviations. However, in cases 3 and 4 wind deviations are lumped with the load deviations and the storage operator loses out on imbalance payments it could have received had it chosen to cooperate. Therefore, the storage's cooperative strategy strictly dominates its non-cooperative strategy. Also, since the wind power producer pays higher penalties in cases 2 and 3 compared to cases 1 and 4, its cooperative strategy also strictly dominates its non-cooperative strategy. Therefore, the Nash equilibrium is case 1.

The following four figures show the charging/discharging profile for the storage unit in addition to the electricity market price, market price for up regulation, and market price for regulation down for each of the four cases above.

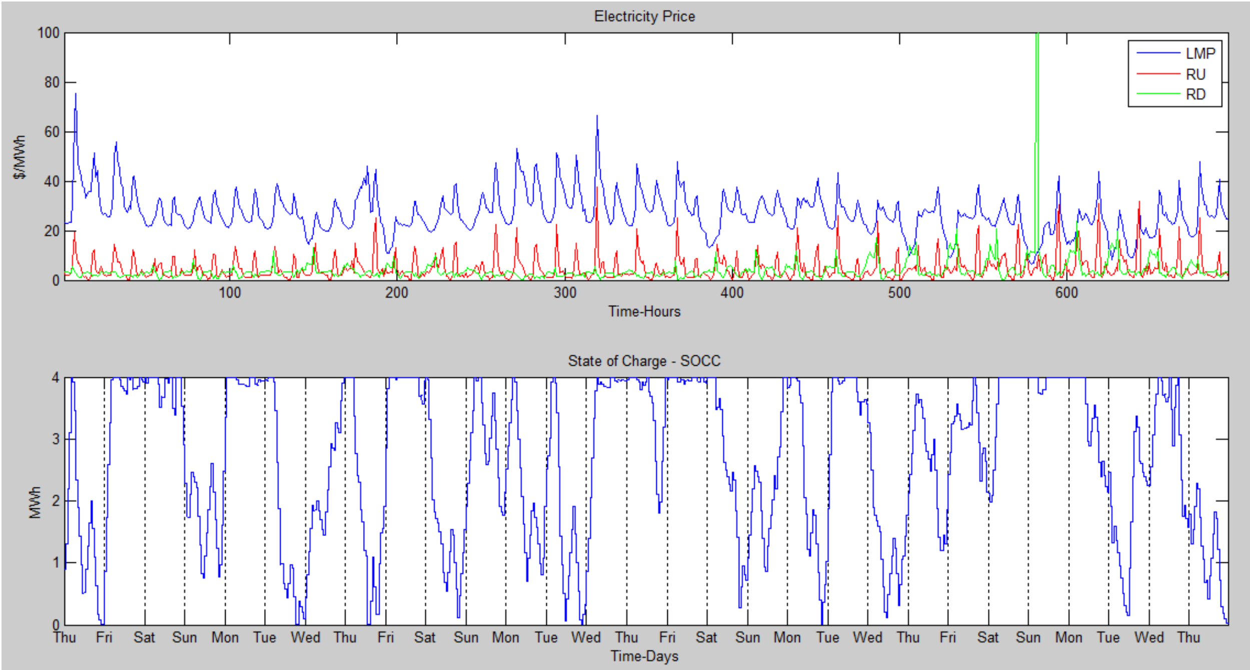

Figure 4.1 – Case 1-Storage Charging/Discharging Profile

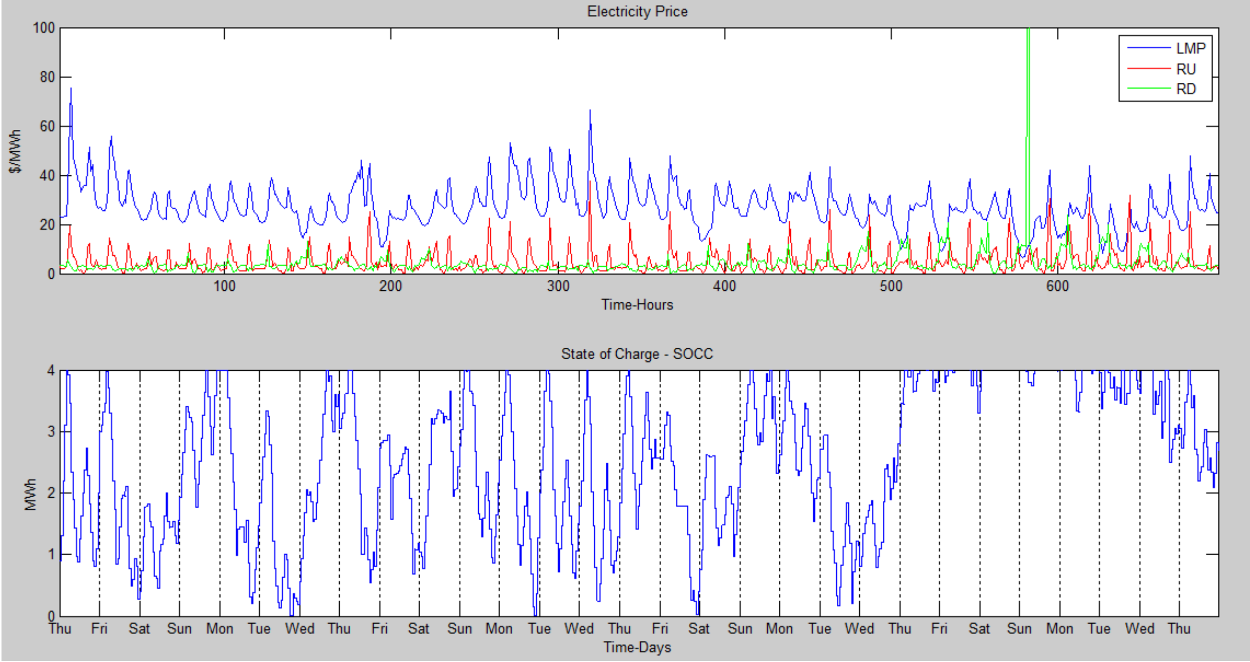

Figure 4.2 – Case 2 - Storage Charging/Discharging Profile

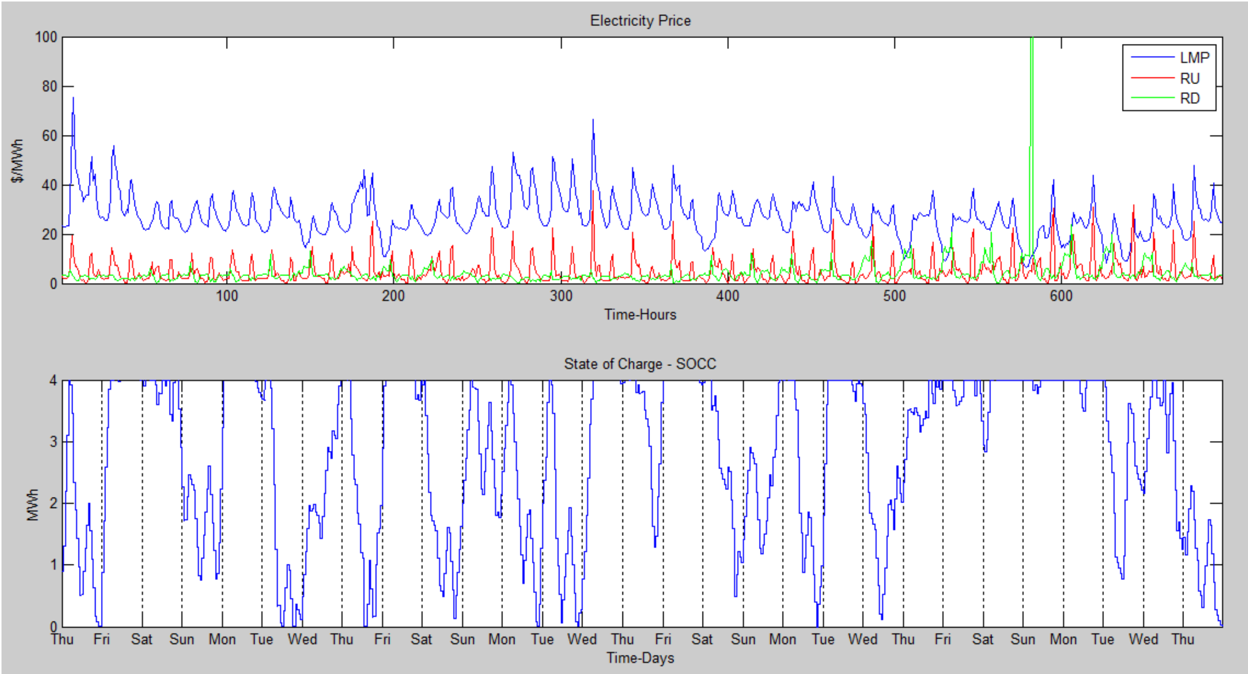

Figure 4.3 – Case 3 - Storage Charging/Discharging Profile

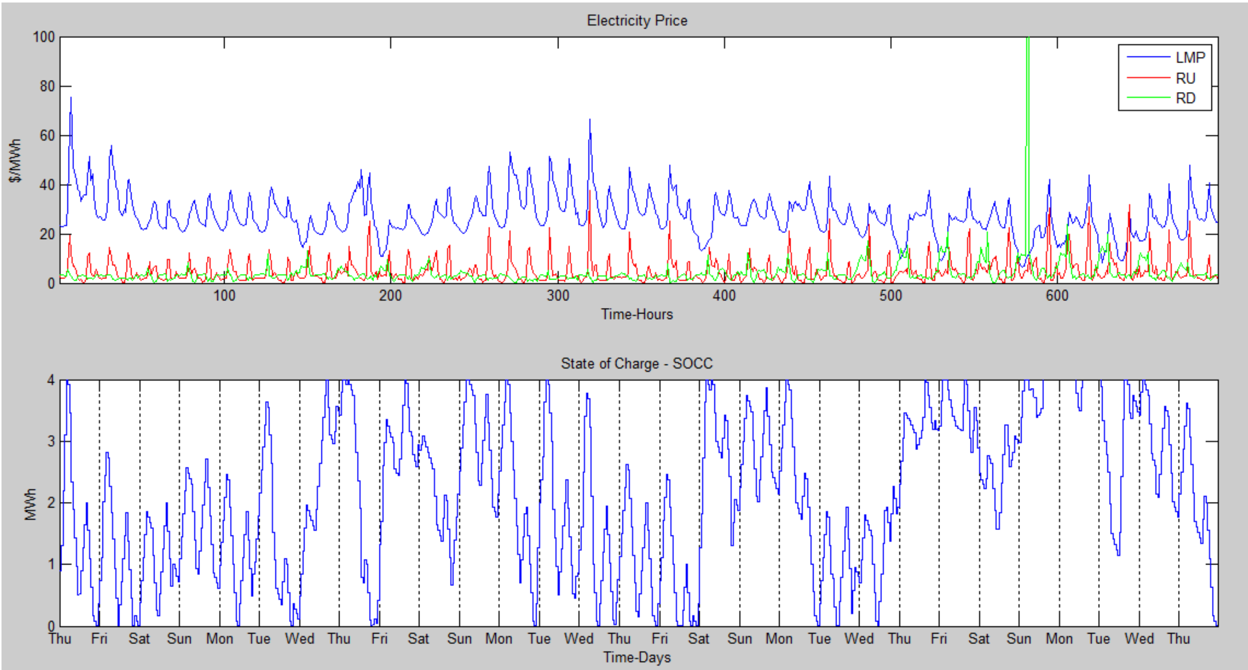

Figure 4.4 – Case 4 - Storage Charging/Discharging Profile

Assuming that there is a penalty paid by the wind power producer for both overproduction and underproduction the following scenarios have been studied to see if there is a shift in the equilibrium (only one parameter is varied at a time, the rest of the model parameters remain untouched and are defaulted to the base values/assumptions outlined in Chapter 3):

1. Sensitivity to up/down regulation efficiency
2. Sensitivity to storage size
3. Sensitivity to charging/discharging limit
4. Sensitivity to efficiency of storage
5. Sensitivity to imbalance penalty

PTC credits, if applicable will be received by the wind power producer in all the five scenarios above. This will be in addition to the net revenue listed in the payoff matrix.

4.1.2 Equilibrium sensitivity to up/down regulation efficiency

$\gamma_{run} = \gamma_{rdn} = 0.5$. Highest possible value for up/down regulation efficiency i.e. all capacity offered into the market is sold/bought.

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**$707** **$6,881**	$195 $8,434
NON-COOPERATION	$2,108 $5,408	$195 $4,744

Table 4.3 – Sensitivity to Regulation Efficiency

WIND **STORAGE**	**COOPERATION**	**NON-COOPERATION**
COOPERATION	**X=$707** **X=$4,538** **Y=$2,343**	X=$195 X=$8,434 Y=$0
NON-COOPERATION	X=$2,108 X=$5,408 Y=$0	X=$195 X=$4,744 Y=$0

Table 4.4 – Sensitivity to Regulation Efficiency

$\gamma_{run} = \gamma_{rdn} = 0.0$. Lowest possible value for up/down regulation efficiency i.e. none of the capacity offered into the market is sold/bought.

WIND **STORAGE**	**COOPERATION**	**NON-COOPERATION**
COOPERATION	**$707** **$7,985**	$195 $9,467
NON-COOPERATION	$2,108 $6,272	$195 $5,936

Table 4.5 – Sensitivity to Regulation Efficiency

WIND **STORAGE**	**COOPERATION**	**NON-COOPERATION**
COOPERATION	**X=$707** **X=$5,642** **Y=$2,343**	X=$195 X=$9,467 Y=$0
NON-COOPERATION	X=$2,108 X=$6,272 Y=$0	X=$195 X=$5,936 Y=$0

Table 4.6 – Sensitivity to Regulation Efficiency

Although the up/down regulation efficiency doesn’t affect the Nash equilibrium it does affect the revenue of the storage operator. Decreasing the efficiency increases the revenue for the storage and vice-versa. The efficiency term depends on the net system frequency regulation required and can vary from area to area. Refer to Appendix G.1 for payoff matrices on some intermediate values for the up/down regulation efficiency.

4.1.3 Equilibrium sensitivity to storage size

$S = 0.1\ MW, \qquad \bar{q}^D = \bar{q}^R = 0.1\ MW$

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**$232** **$596**	$195 $908
NON-COOPERATION	$2,108 $492	$195 $463

Table 4.7 – Sensitivity to Storage Size

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**X=$232** **X=$423** **Y=$173**	X=$195 X=$908 Y=$0
NON-COOPERATION	X=$2,108 X=$492 Y=$0	X=$195 X=$463 Y=$0

Table 4.8 – Sensitivity to Storage Size

$S = 28\ MW,\ \bar{q}^D = \bar{q}^R = 1\ MW$. A 28 MW energy storage unit is the minimum storage size that will balance most of the wind deviations. Increasing storage size beyond this provides no added benefit in terms of its ability to balance wind deviations.

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**$1,717** **$11,313**	$195 $8,208
NON-COOPERATION	$2,108 $5,527	$195 $4,862

Table 4.9 – Sensitivity to Storage Size

WIND / STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**A=$1,717** **X=$4,413** **Y=$6,900**	X=$195 X=$8,208 Y=$0
NON-COOPERATION	X=$2,108 X=$5,527 Y=$0	X=$195 X=$4,862 Y=$0

Table 4.10 – Sensitivity to Storage Size

Storage size has a significant impact on revenues for the wind power producer and the storage operator. However, as expected increasing storage size increased revenues for both players and vice versa. There was no shift in equilibrium.

4.1.4 Equilibrium sensitivity to charging/discharging limit

$\bar{q}^D = \bar{q}^R = 2\ MW$. Since the highest error in forecasted value is equal to the rated capacity of the wind turbine = 1.5 MW, this case adequately covers the worst case scenario.

WIND / STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**$707** **$11,836**	$195 $14,007
NON-COOPERATION	$2,108 $10,604	$195 $9,671

Table 4.11 – Sensitivity to Charging/Discharging Limit

WIND / STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**X=$707** **X=$9,496** **Y=$2,340**	X=$195 X=$14,007 Y=$0
NON-COOPERATION	X=$2,108 X=$10,604 Y=$0	X=$195 X=$9,671 Y=$0

Table 4.12 – Sensitivity to Charging/Discharging Limit

$\bar{q}^D = \bar{q}^R = 0.01\ MW$

WIND / STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**$707** **$191**	$195 $76
NON-COOPERATION	$2,108 $43	$195 $32

Table 4.13 – Sensitivity to Charging/Discharging Limit

WIND / STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**X=$226** **X=$49** **Y=$142**	X=$195 X=$76 Y=$0
NON-COOPERATION	X=$2,108 X=$43 Y=$0	A=$195 A=$32 B=$0

Table 4.14 – Sensitivity to Charging/Discharging Limit

Changing the charging/discharging limit of the storage device significantly impacted revenues for the storage. Increasing the limit allowed the storage unit to increase its revenue through arbitrage, regulation service and imbalance payments. Again, there is no shift in equilibrium.

4.1.5 Equilibrium sensitivity to storage efficiency

$eff = 0.95$

WIND / STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**$685** **$7,761**	$195 $9,265
NON-COOPERATION	$2,108 $6,014	$195 $5,409

Table 4.15 – Sensitivity to Storage Efficiency

WIND / STORAGE	**COOPERATION**	**NON-COOPERATION**
COOPERATION	**X=$685** **X=$5,307** **Y=$2,454**	X=$195 X=$9,265 Y=$0
NON-COOPERATION	X=$2,108 X=$6,014 Y=$0	X=$195 X=$5,409 Y=$0

Table 4.16 – Sensitivity to Storage Efficiency

$eff = 0.7$. Li-ion batteries typically have round trip efficiencies between 0.8 – 0.9. Lead-acid batteries may have lower round trip efficiencies, therefore, the lower limit is set at 0.7.

WIND / STORAGE	**COOPERATION**	**NON-COOPERATION**
COOPERATION	**$822** **$4,304**	$195 $5,620
NON-COOPERATION	$2,108 $3,387	$195 $3,284

Table 4.17 – Sensitivity to Storage Efficiency

WIND / STORAGE	**COOPERATION**	**NON-COOPERATION**
COOPERATION	**X=$822** **X=$2,416** **Y=$1888**	X=$195 X=$5,620 Y=$0
NON-COOPERATION	X=$2,108 X=$3,387 Y=$0	X=$195 X=$3,284 Y=$0

Table 4.18 – Sensitivity to Storage Efficiency

Having a more efficient storage device increases revenues for the storage, but does not cause a shift in equilibrium.

4.1.6 Equilibrium sensitivity to imbalance penalty

$\partial_1^i = 150\% * P_t, \partial_1^e = 10\% * P_t$
$\partial_2^i = 195\% * P_t, \partial_2^e = 40\% * P_t$

Upper Limit on the extraction penalty is set to 40% as increasing the penalty further would make revenues negative for the wind power producer.

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**$1,168** **$6,527**	$195 $7,729
NON-COOPERATION	$2,108 $5,422	$195 $4,870

Table 4.19 – Sensitivity to Imbalance Penalty

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**X=$1,168** **X=$4,645** **Y=$1,882**	X=$195 X=$7,729 Y=$0
NON-COOPERATION	X=$2,108 X=$5,422 Y=$0	X=$195 X=$4,870 Y=$0

Table 4.20 – Sensitivity to Imbalance Penalty

$\partial_1^i = 110\% * P_t, \partial_1^e = 10\% * P_t$
$\partial_2^i = 195\% * P_t, \partial_2^e = 40\% * P_t$

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**$1,630** **$6,065**	$195 $6,945
NON-COOPERATION	$2,108 $5,422	$195 $4,870

Table 4.21 – Sensitivity to Imbalance Penalty

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**X=$1,630** **X=$4,645** **Y=$1,420**	X=$195 X=$6,945 Y=$0
NON-COOPERATION	X=$2,108 X=$5,422 Y=$0	X=$195 X=$4,870 Y=$0

Table 4.22 – Sensitivity to Imbalance Penalty

Reducing the imbalance penalty doesn't affect the Nash equilibrium. However, as expected decreasing the penalty decreases the revenue for the storage and increases the revenue for the wind power producer and vice versa.

No Imbalance Penalty

If there is no imbalance penalty then there is no game to be played between the wind power producer and the storage operator. Both players will operate independently and the storage is not likely to participate in balancing large wind deviations. However, it will still provide value through regulation in the ancillary service market.

4.2 Payoff Matrix and Nash Equilibrium – April

PTC credits if applicable will be as follows: PTC credits for cases 1, 2 and 3 = $13,428. PTC credits for case 4 = $8,709.

Base Case

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**$3,639** **$12,247**	$2,973 $13,623
NON-COOPERATION	$6,255 $10,291	$2,973 $8,950

Table 4.23 – Base Case Payoff Matrix

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**X=$3,639** **X=$9,136** **Y=$3,111**	X=$2,937 X=$13,623 Y=$0
NON-COOPERATION	X=$6,255 X=$10,291 Y=$0	X=$2,937 X=$8,950 Y=$0

Table 4.24 – Base Case Payoff Matrix

Revenues are significantly higher in April (compared to January) for both the wind power producer and the storage unit mostly because average electricity prices are much higher during the spring and summer months, especially during peak hours – refer to Appendix A.1.

4.3 Payoff Matrix and Nash Equilibrium – July

PTC credits if applicable will be as follows: PTC credits for cases 1, 2 and 3 = $12,579. PTC credits for case 4 = $8,896.

Base Case

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**$6,223** **$10,113**	$5,335 $13,495
NON-COOPERATION	$7,956 $8,194	$5,335 $6,988

Table 4.25 – Base Case Payoff Matrix

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**X=$6,223** **X=$5,431** **Y=$4,682**	X=$5,335 X=$13,495 Y=$0
NON-COOPERATION	X=$7,956 X=$8,194 Y=$0	X=$5,335 X=$6,988 Y=$0

Table 4.26 – Base Case Payoff Matrix

Revenues are significantly higher in July (compared to January) for both the wind power producer and the storage unit mostly because average electricity prices are much higher during the spring and summer months – refer to Appendix A.1.

4.4 Payoff Matrix and Nash Equilibrium – October

PTC credits if applicable will be as follows: PTC credits for cases 1, 2 and 3 = $14,796. PTC credits for case 4 = $10,344.

Base Case

WIND / STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**$6,499** **$13,188**	$5,608 $16,997
NON-COOPERATION	$8,368 $11,133	$5,608 $9,762

Table 4.27 – Base Case Payoff Matrix

WIND / STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**X=$6,499** **X=$8,185** **Y=$5,003**	X=$5,608 X=$16,997 Y=$0
NON-COOPERATION	X=$8,368 X=$11,133 Y=$0	X=$5,608 X=$9,762 Y=$0

Table 4.28 – Base Case Payoff Matrix

4.5 Analysis of Results

Wind Power Producer

Through the results presented in the previous section it is evident that the wind power producer's cooperative strategy strictly dominates its non-cooperative strategy. The imbalance penalty mechanism allows storage operators to undercut the utility and give incentive to the wind power producers to cooperate. Therefore, the wind power producer's payoff for case 1 will always be higher than case 2 (storage imbalance penalties < utility imbalance penalties). Similarly, the wind power producer's payoff for case 4 will always be higher than case 3 (in-fact payoff is significantly higher, as, it avoids paying penalties on overproduction by curtailing its output). The wind power producer will always play its cooperative strategy regardless of the strategy adopted by the energy storage operator. Changing the storage or other market parameters does not have an effect on the wind power producer's decision.

Energy Storage Operator

The basic assumption in all four cases is that both wind and load deviations are balanced by the energy storage – any remaining capacity is used for arbitrage and regulation service. The only difference amongst the four cases is the way in which deviations are balanced and paid for. In case 1 wind deviations are given preference over load deviations. In case 2 load deviations are given preference over wind deviations. In both these cases however, the storage operator is paid for providing a capacity firming service to the renewable producer in the form of imbalance payments.

In cases 3 and 4 the wind and load deviations are lumped together into net deviations and these deviations are balanced by the storage – however, no imbalance payments are received. Since the payment for arbitrage and regulation is fairly similar across all cases, the payment for balancing wind and load deviations is a determining factor in the equilibrium of the game. In cases 1 and 2 significant imbalance penalties are received for balancing wind deviations – these overshadow the payments received for balancing net deviations in cases 3 and 4. The storage's cooperative strategy strictly dominates its non-cooperative strategy. It is shown that the equilibrium of the game will always be case 1 regardless of the storage or market parameters.

Discussion

In markets where imbalance penalties are levied on the wind power producers the Nash equilibrium suggests that both players should cooperate. Consequentially, it is evident that imbalance payments are a necessary condition for cooperation between wind power producers and energy storage operators. In markets where no imbalance penalties are charged to the wind power producer there would be no incentive for the energy storage to provide capacity smoothing services. Hence, both wind and energy storage would operate independently.

As evidenced from the results in Sections 4.1, 4.2, 4.3, and 4.4, storage parameters don't have an effect on the equilibrium, even when stretched to their limits. Additionally, there is no change in the equilibrium due to seasonal variation in market prices. However, the size of the storage, efficiency and charging/discharging limits should be chosen wisely as increasing any of these storage parameters comes with an added cost – this added cost must be compared to the increased revenue potential to make a sound investment decision.

High penalties on the wind deviation benefit the storage operator but severely decrease the revenue of the wind power producer, particularly if the wind deviations are high. Using a better forecast than the persistence model would decrease the imbalance payments for the storage and hence its net revenue (revenue would still be higher than the case where it only performs arbitrage + frequency regulation – refer to Appendix D.2, D.6, D.10, D.14), but would increase the revenue for the wind power producer. Although imbalance payments maybe decreased for the energy storage, it is unlikely that it will affect the equilibrium of the game.

Chapter 5 – Conclusion

Through the results presented in this study it was demonstrated that a non-cooperative game theoretic framework can be used as an effective tool to study the behavior of two independent rational players namely, wind power producer and energy storage in a deregulated microgrid. Here are some of the main conclusions drawn from this study:

1. The game-theoretic framework developed in this study was successful in analyzing and evaluating the behavior of wind power producers and energy storage operators in a microgrid community.
2. Imbalance penalties on wind deviations are a necessary condition for cooperation between wind power producers and energy storage operators. Through the case study performed it is shown that the cooperative strategy of the wind power producer strictly dominates its non-cooperative strategy (irrespective of the strategy chosen by the energy storage). Similarly, the cooperative strategy of the energy storage strictly dominates its non-cooperative strategy.
3. The Nash equilibrium is unaffected by the changing storage parameters. The case study shows that both players will always choose to play a cooperative strategy irrespective of the storage size, charging/discharging limits, storage efficiency or up/down regulation efficiency.
4. The equilibrium of the game is unchanged across seasons – winter, spring, summer and fall. Although there is considerable change in seasonal prices of electricity, it does not affect the equilibrium of the game. An energy storage operator would cooperate with a wind power producer irrespective of the time of the year.

5. In a market where there are no imbalance penalties on overproduction and underproduction there is no game to be played between the wind power producer and the energy storage operator. There is no reason a storage operator would want to provide energy balancing services to the wind power producer, especially because the net revenues from providing such a service in the absence of penalties leads to lower revenues when compared to the case where an energy storage operator would only perform arbitrage and regulation service.

Therefore, in markets where imbalance penalties are charged to wind power producers, the energy storage operator would benefit by providing capacity firming services to smooth the power output and deliver what is promised. The wind power producer also benefits as it is able to avoid paying higher penalties to the utility. Overall, a market where the storage severely undercuts the penalties charged by the utility would be the most beneficial and allow for cooperation between wind power producers and energy storage operators.

So, why is cooperation self-enforcing for this game? From the results presented in this study it may seem like the energy storage operator is better off when it chooses to cooperate and the wind power producer chooses to not cooperate. But, a wind power producer could easily deviate from this strategy as it gets a higher payoff by cooperating. Similarly, the wind power producer seems to be better off when it chooses to cooperate and the energy storage operator chooses to not cooperate. But, the energy storage operator could easily deviate from this strategy to receive a higher payoff by cooperating. Although each player would be individually better off if one chose to play its cooperative strategy and the other chose to play its non-cooperative strategy, this is not an equilibrium point in the game, as each player can be better off by unilaterally shifting their strategy. When both players decide to cooperate there is no longer an incentive for either of them to deviate from that strategy. If either of them choose to deviate then depending on the strategy chosen by the other player, at least one player will be worse off than if it had chosen to cooperate.

Let us suppose that the other players' actions were not considered, then the problem would become one of standard decision analysis, and it is unlikely that one will arrive at a strategy that is optimal. For example, a company that reduces prices to increase sales and therefore increase profit may lose money if other players respond with price cuts. In many situations, it is crucial to consider the moves of the other opponents. Game theoretic analysis forces one to consider the range of a rival's responses and allows for the possibility that payoffs depend directly on what other people do.

5.1 Original Contribution

One of the key contributions in this thesis is the development of a game-theoretic framework that can be used to find the Nash equilibrium of the game. Considerable effort and thought was put into the development of the energy storage and wind power producer models to calculate the expected payoffs. Although considerable work has been done in evaluating the benefits of energy storage through arbitrage alone and through arbitrage and regulation service, this is to the best of my knowledge the first study of its kind that also evaluates the benefit of energy storage as an energy smoothing / capacity firming device for renewable energy integration – particularly in markets where there are imbalance penalties. Including this additional stream of revenue in the energy storage model is instrumental in the development of the game-theoretic framework and ultimately the results drawn in this study. The developed framework is used to analyze the market conditions that would be conducive to cooperation between renewable energy producers and storage operators. It is shown that the additional stream of revenue from cooperation (imbalance payments) not only increases the net revenue of the energy storage when compared to a trading strategy where it just performs arbitrage and regulation service, but is also the equilibrium of the game. Sensitivity of this equilibrium to several storage and market parameters is also evaluated.

5.2 Future Work

This work has considerable scope for expansion. Firstly, the study can be replicated for other renewable sources of energy such as Photovoltaics. The current study is restricted to only two players but provides considerable insight into the behavior of the market participants. It would be of interest to explore N-person games (both in a cooperative and non-cooperative framework) in a microgrid setting with multiple renewable energy producers and storage operators.

One area of future research is to model the other streams of revenue for the storage (spinning /non-spinning reserves, voltage support, reactive power support etc.) as discussed in Section 1.1 and study its effect on the equilibrium of the game. Also, with the advent of new wind turbine technology that can actively control the output from the wind turbine [72] it will be interesting to see how allowing wind power producers to participate in the ancillary services market would change the game. Modelling the utility as a player could also change the game – the utilities payoff would involve minimizing the cost for procuring regulation and other reserve services.

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Appendix A

A.1 Average Seasonal Day-Ahead Market Prices

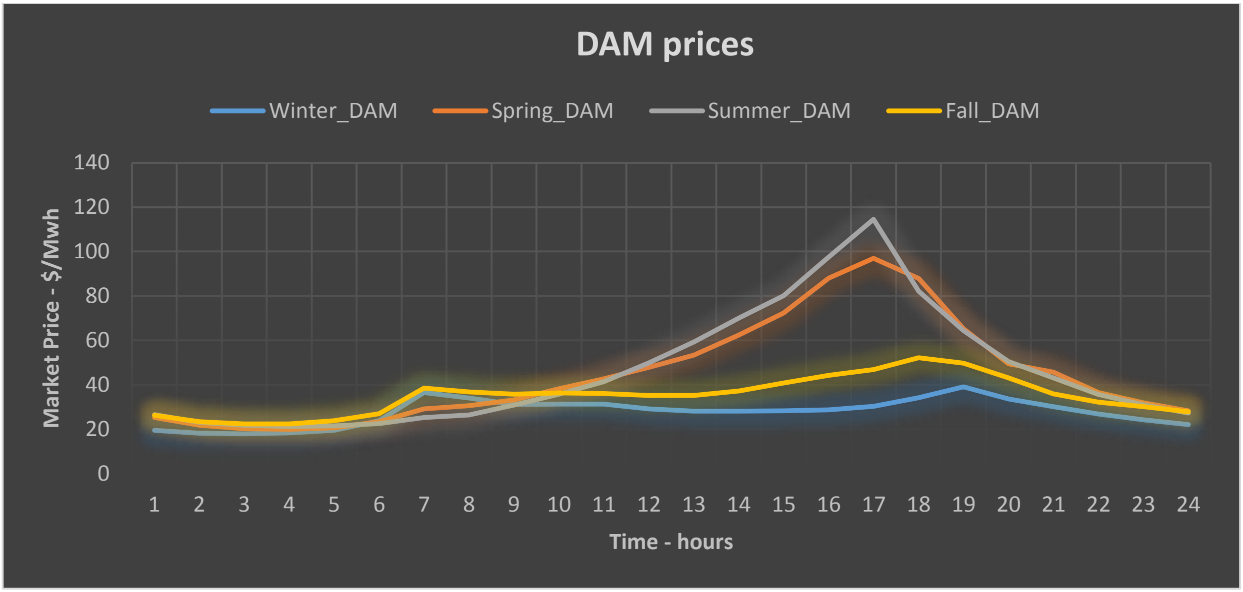

Figure A.1 – Average Seasonal Day-Ahead Market Prices

A.2 Average Seasonal Real-Time Market Prices

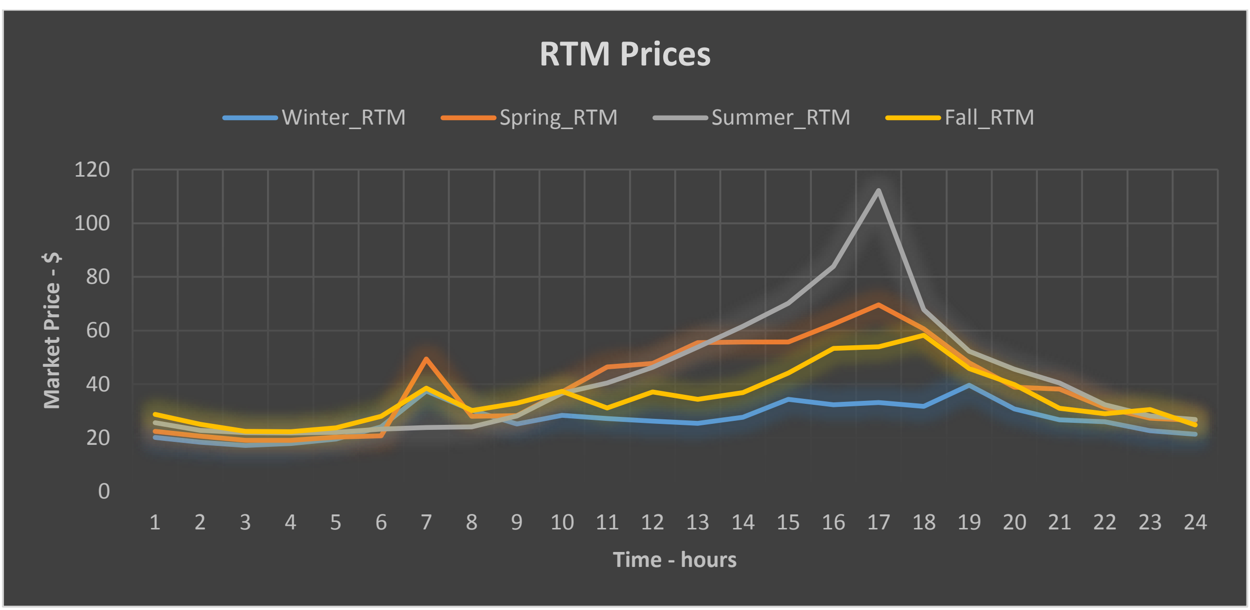

Figure A.2 – Average Seasonal Real-Time Market Prices

A.3 Comparison of average RTM and DAM Prices

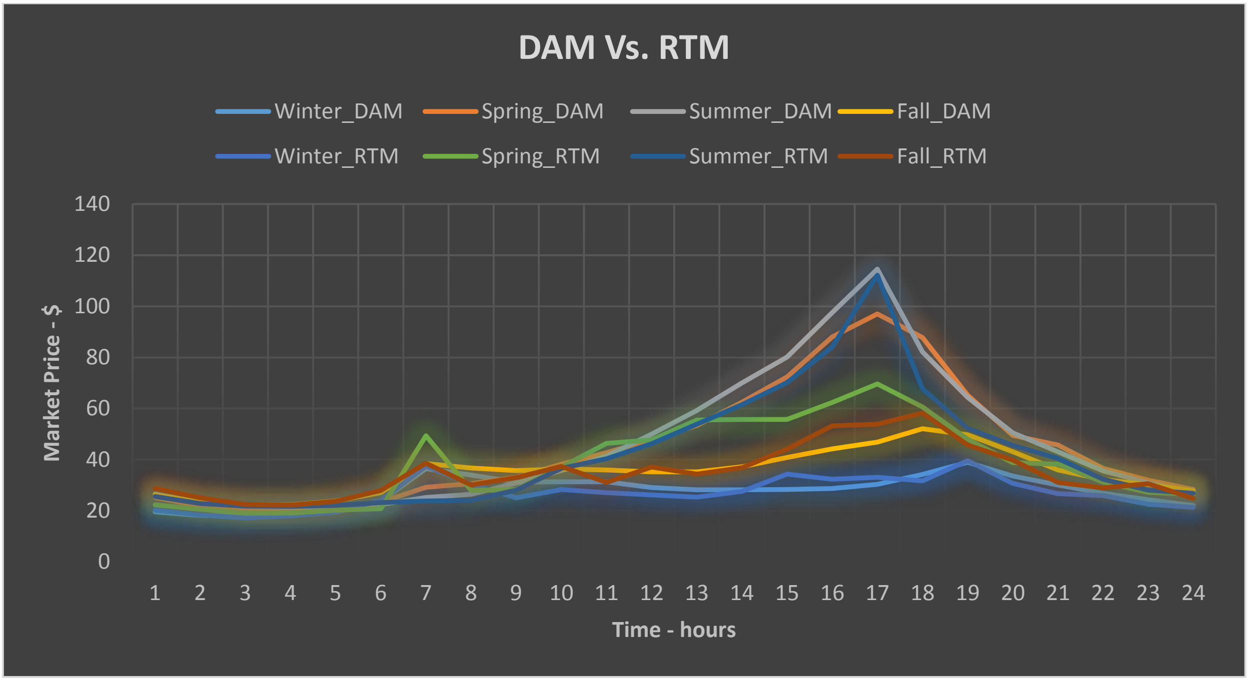

Figure A.3 – Comparison of average RTM and DAM Prices

A.4 Average Seasonal MCPC – Regulation Up

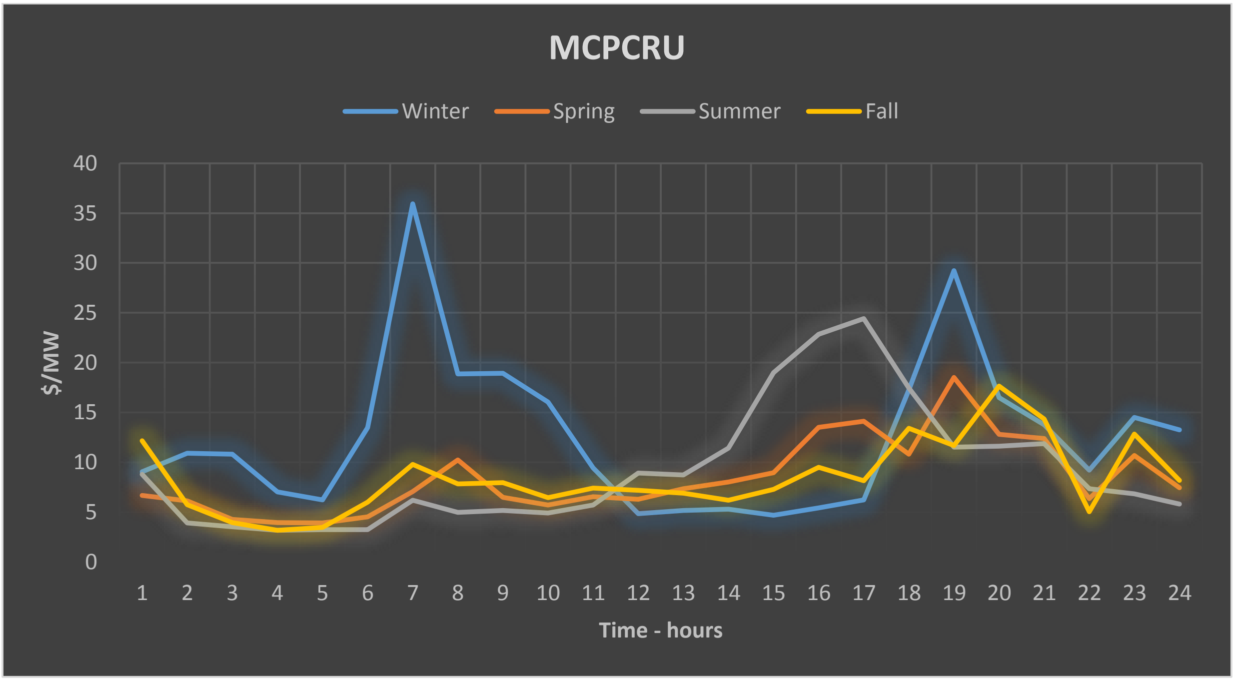

Figure A.4 – Average Seasonal MCPC – Regulation UP

A.5 Average Seasonal MCPC – Regulation Down

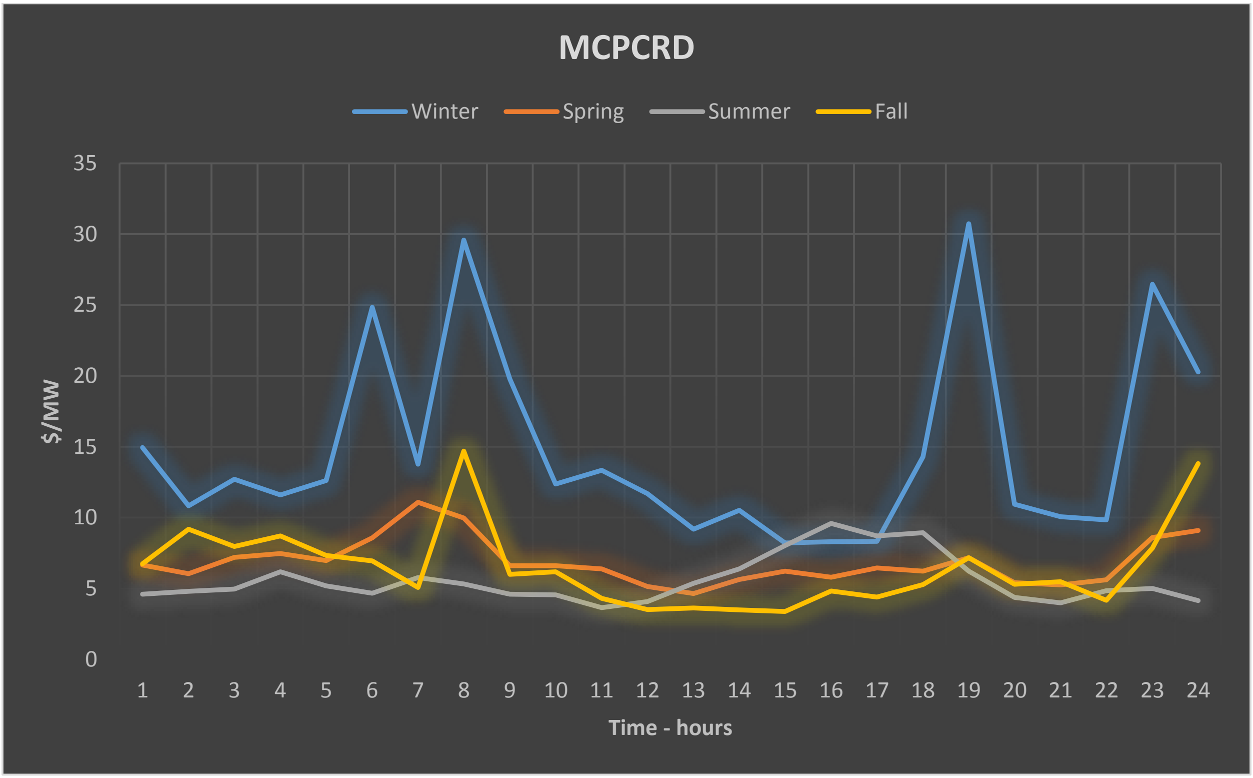

Figure A.5 – Average Seasonal MCPC – Regulation Down

Appendix B

B.1 Average Seasonal Load Profile

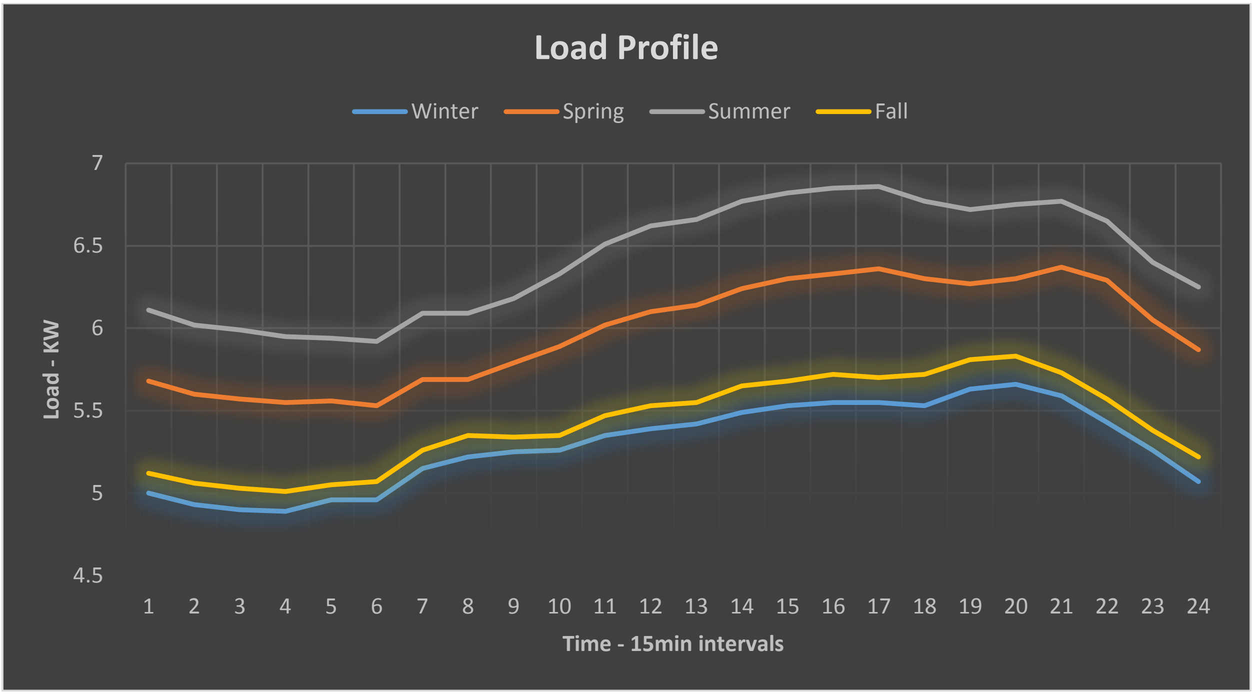

Figure B.1 – Average Seasonal Load Profile

Appendix C

C.1 Average Seasonal Wind Speed

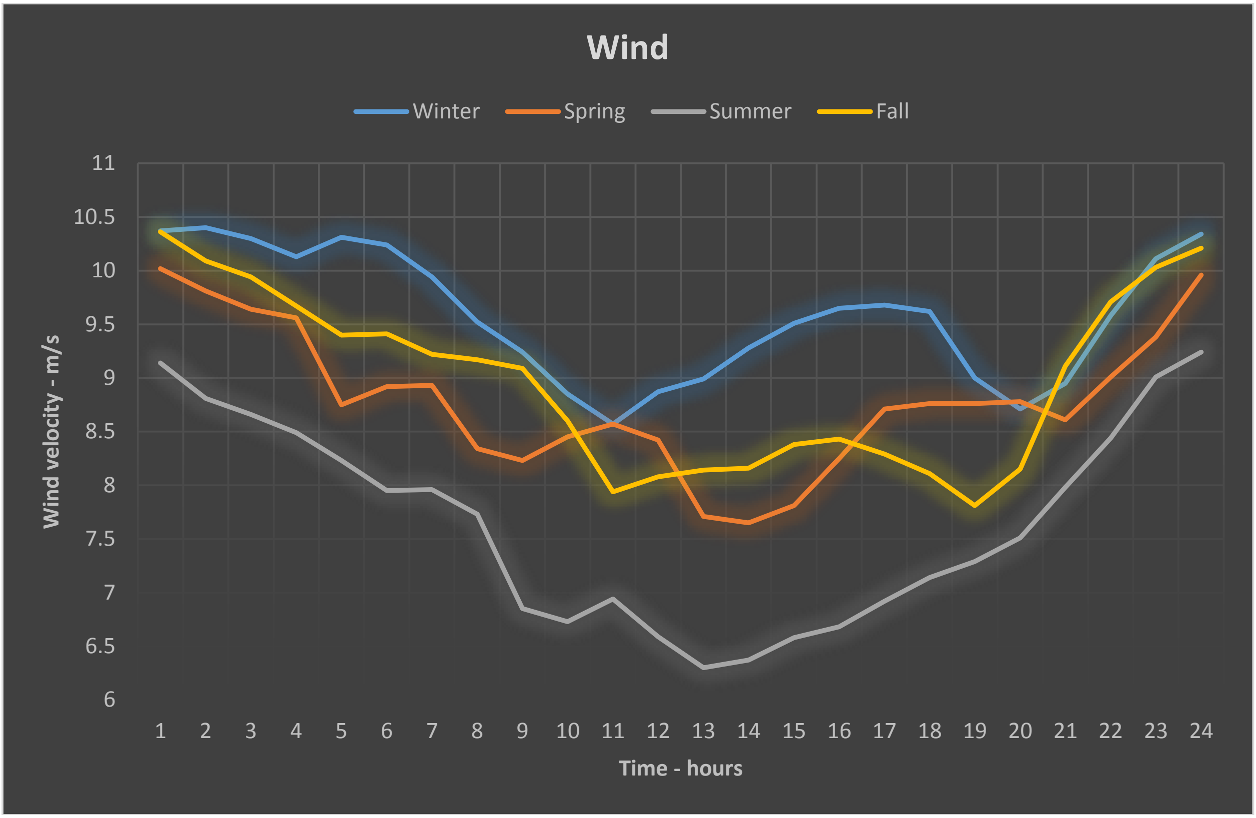

Figure C.1 – Average Seasonal Wind Speed

Appendix D

D.1 Arbitrage Only – January

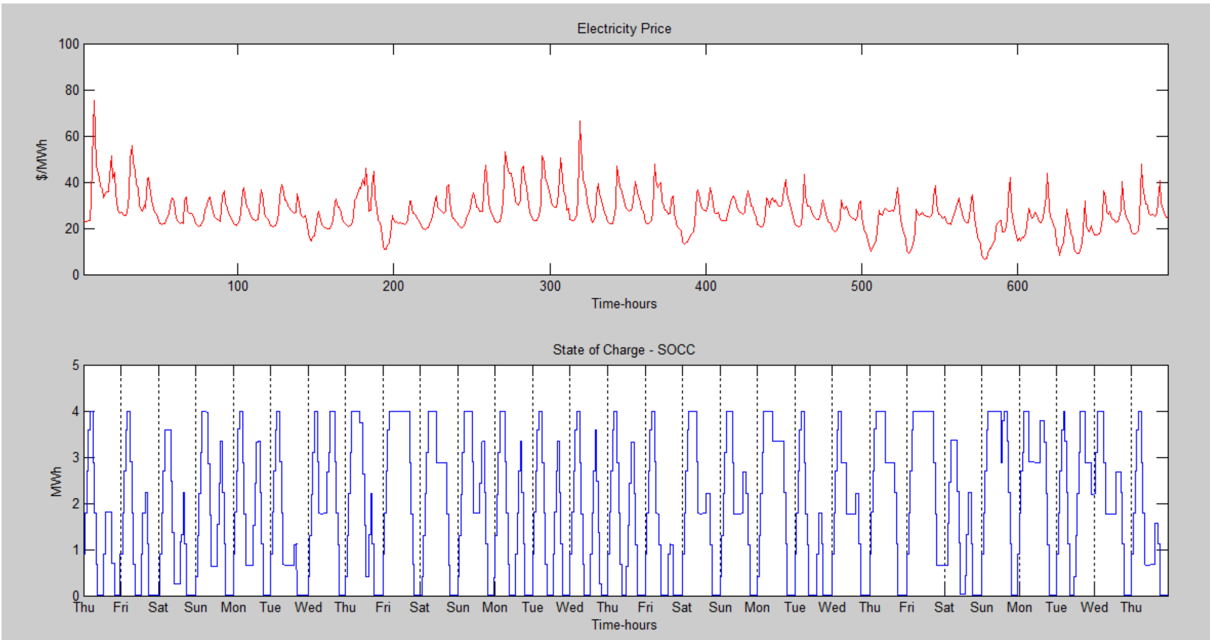

Figure D.1 – Arbitrage Only - January

Revenue from Arbitrage = **$1,690**. As seen here the storage device charges when the prices are low and discharges when the prices are high. Since daily patterns for electricity market prices are pretty similar, the storage device typically charges during off-peak hours and discharges during peak hours.

D.2 Arbitrage + Regulation Service – January

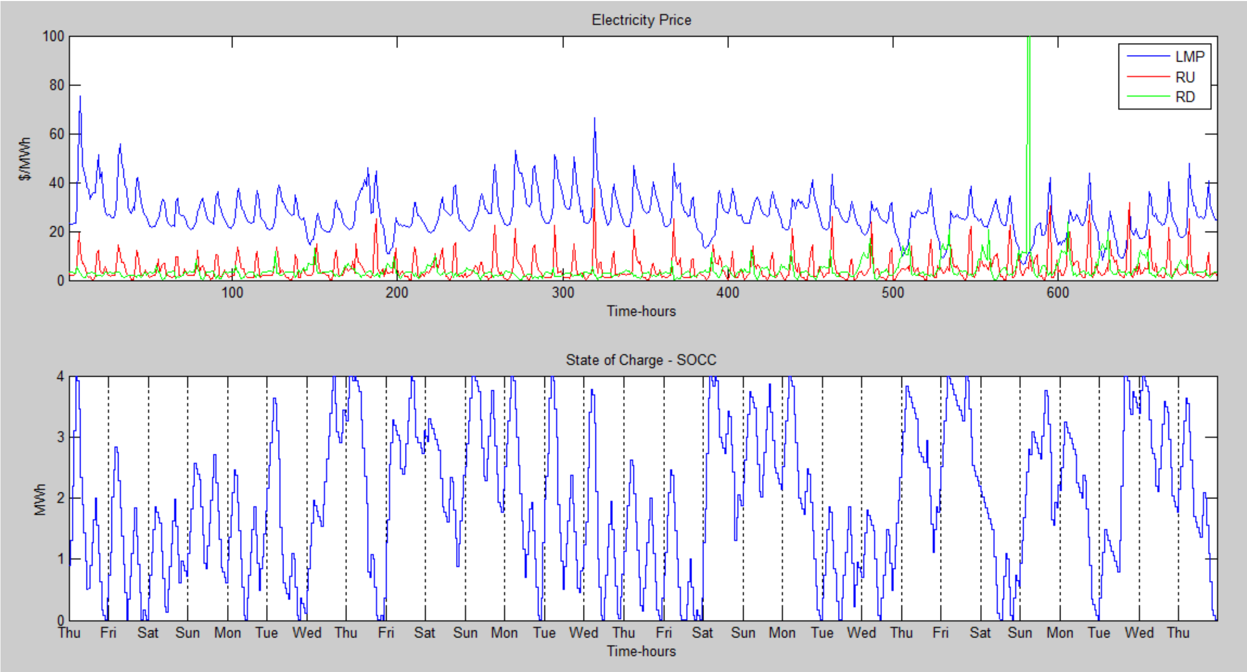

Figure D.2 – Arbitrage + Regulation Service - January

Revenue from Arbitrage + Regulation Service = **$5,586.** Revenue from Arbitrage + Regulation is more than 3 times the revenue from just Arbitrage. As seen above the charging/discharging pattern in this case is significantly different from the arbitrage only case. The storage operator mostly performs regulation service - charging/discharging from arbitrage is done only in a few instances when electricity market prices are either really low or really high.

D.3 Variability without curtailment – January

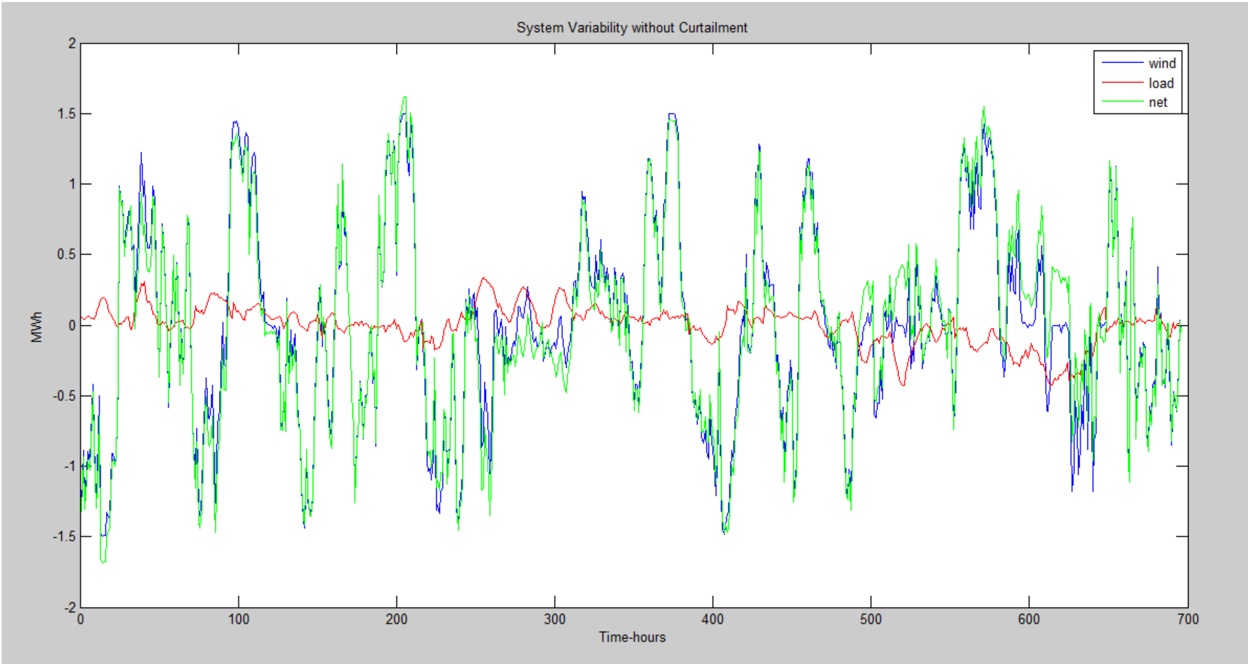

Figure D.3 – Variability without Curtailment - January

Wind deviations are significantly higher than load deviations. This is expected as load patterns are typically well known to utilities. Wind scheduling however is problematic as it is highly dependent on the weather.

D.4 Variability with curtailment – January

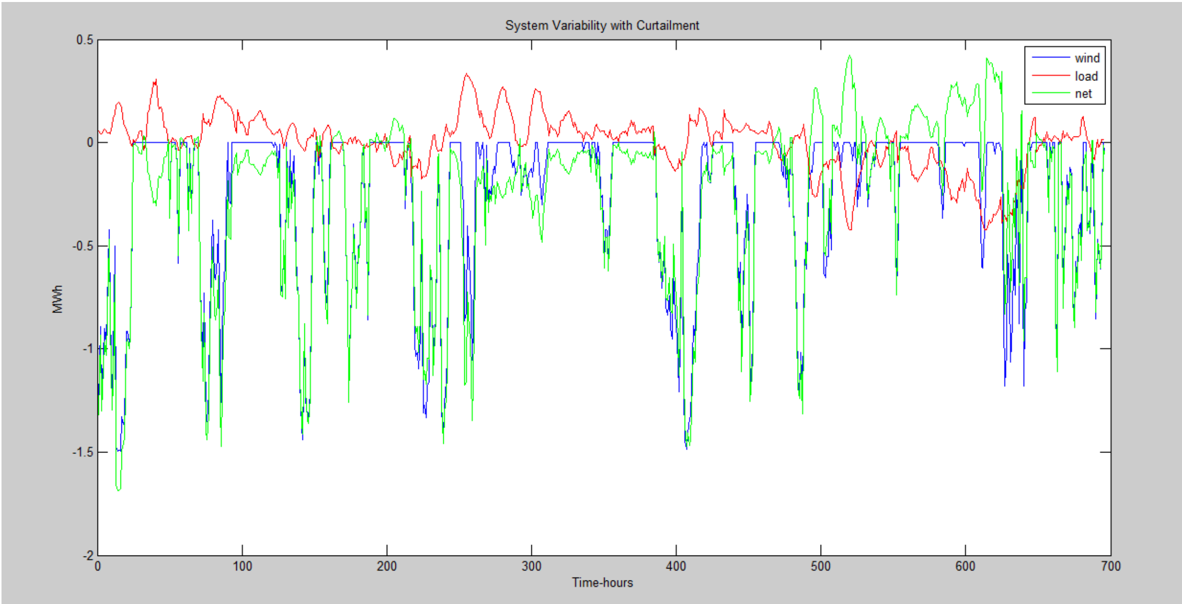

Figure D.4 – Variability with curtailment - January

D.5 Arbitrage Only – April

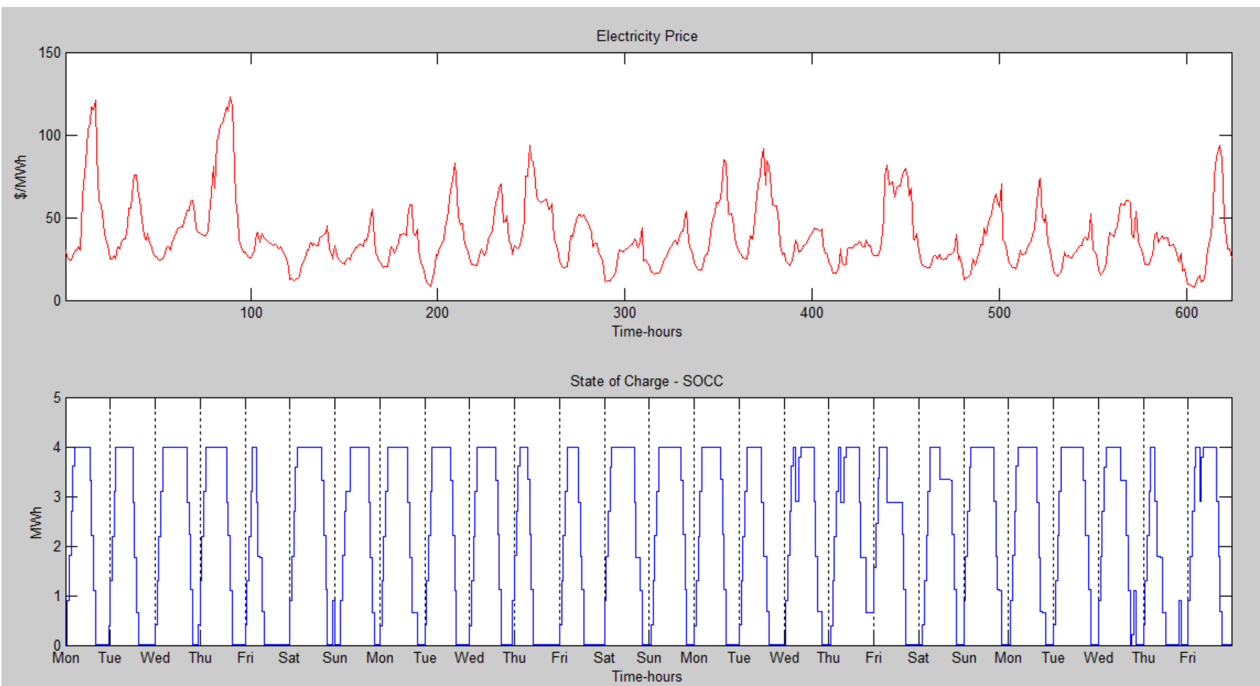

Figure D.5 – Arbitrage Only - April

Revenue from Arbitrage = $3,442.

D.6 Arbitrage + Regulation Service – April

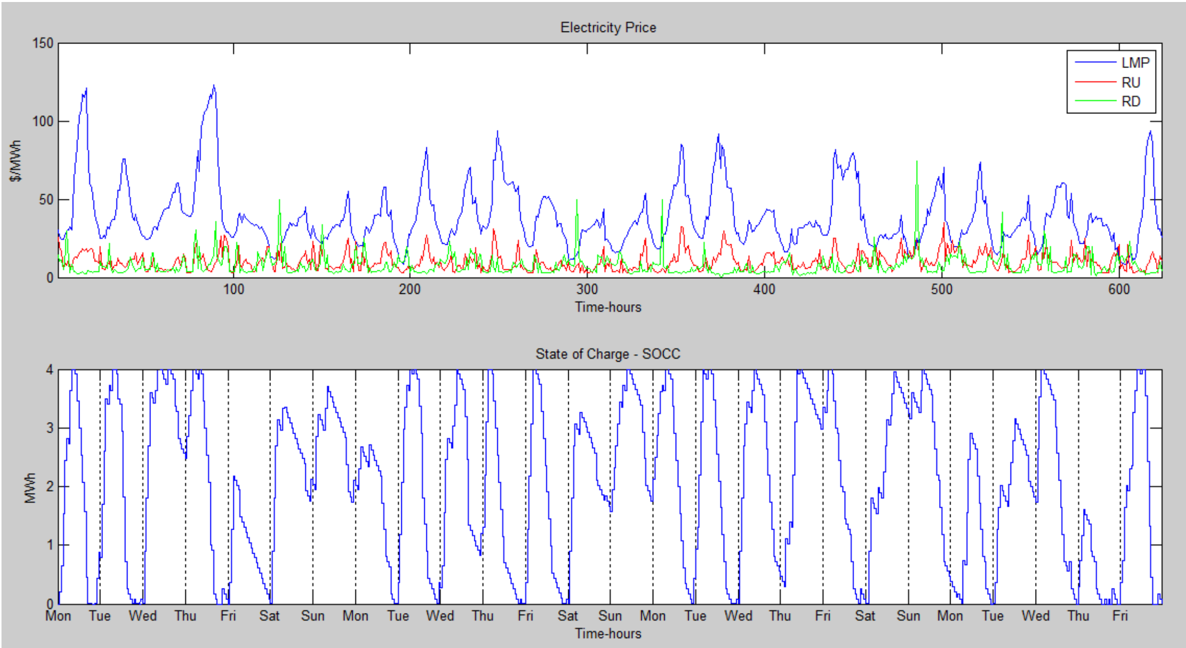

Figure D.6 – Arbitrage + Regulation Service - April

Revenue from Arbitrage + Regulation Service = $10,776. This is more than 2 times Arbitrage.

D.7 Variability without curtailment – April

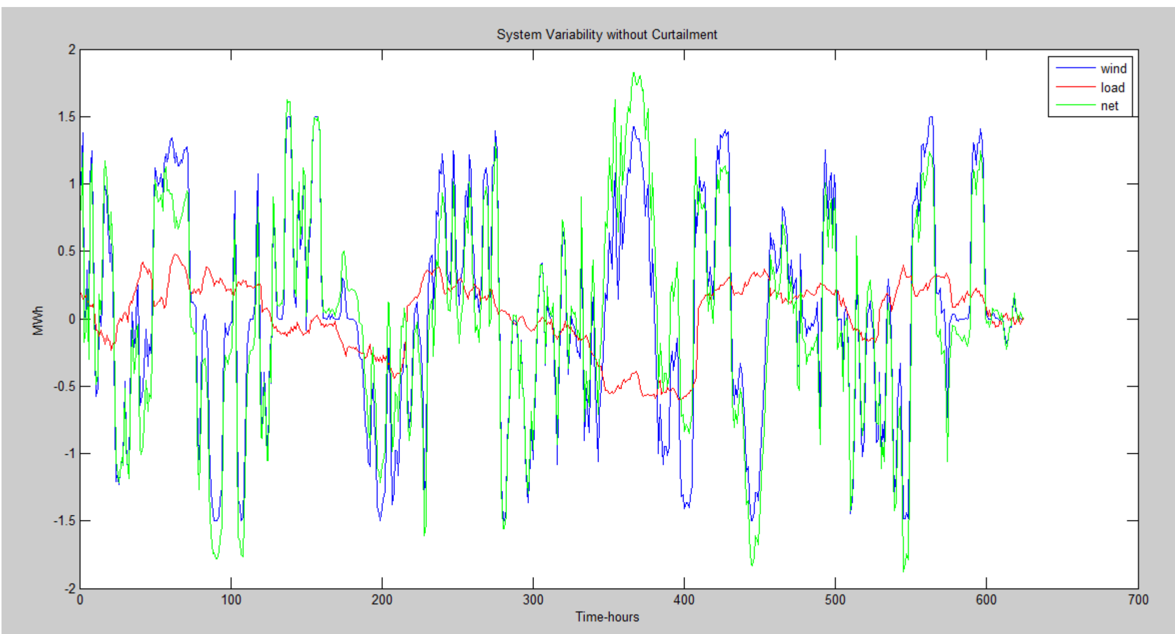

Figure D.7 – Variability without Curtailment - April

D.8 Variability with curtailment – April

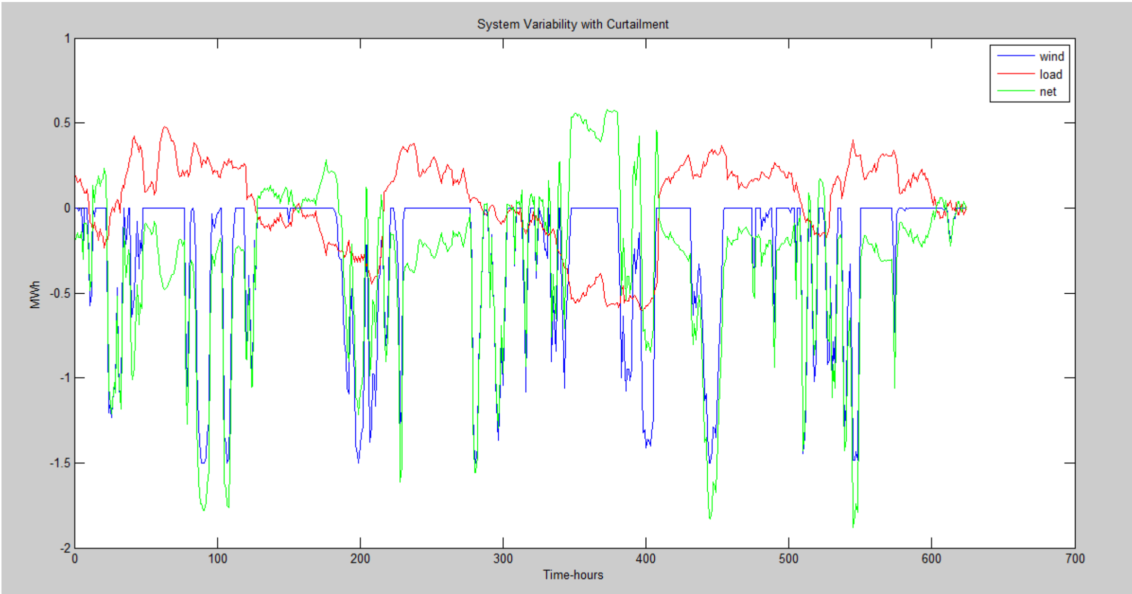

Figure D.8 – Variability with Curtailment - April

D.9 Arbitrage Only – July

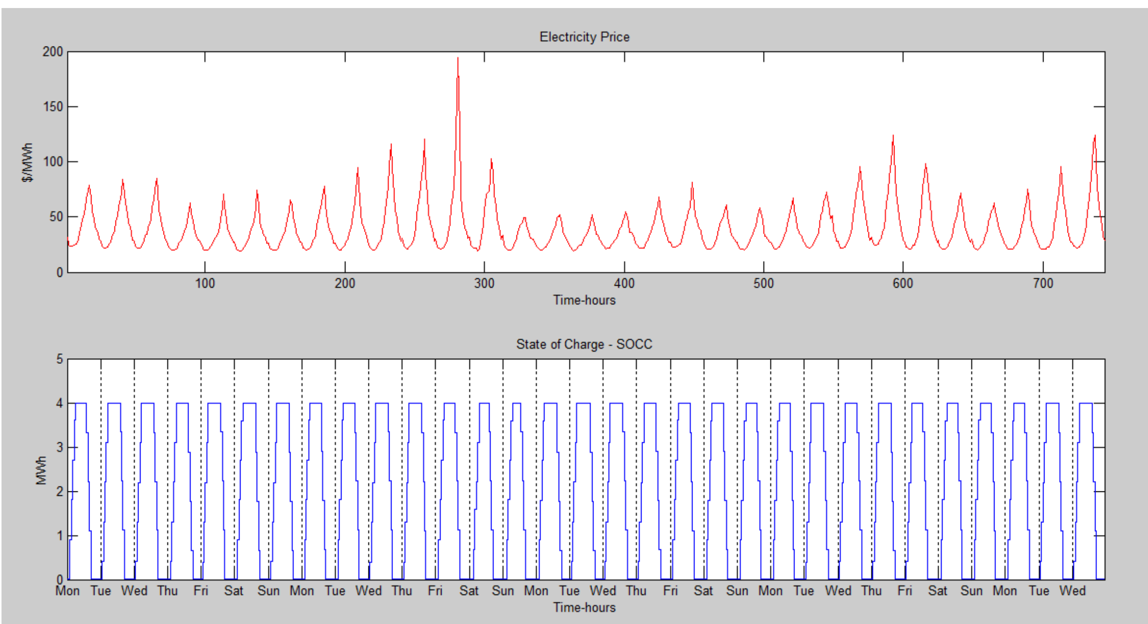

Figure D.9 – Arbitrage Only - July

Revenue from Arbitrage = $5,192

D.10 Arbitrage + Regulation Service – July

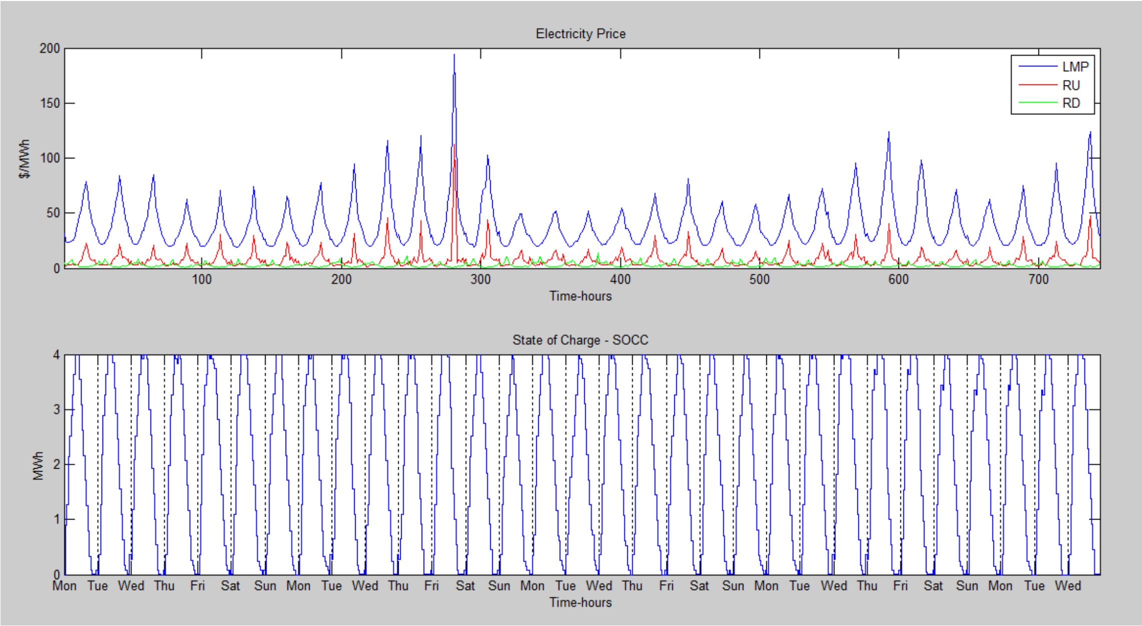

Figure D.10 – Arbitrage + Regulation Service - July

Revenue from Arbitrage + Regulation Service = $9,278. This is less than 2 times Arbitrage.

D.11 Variability without curtailment – July

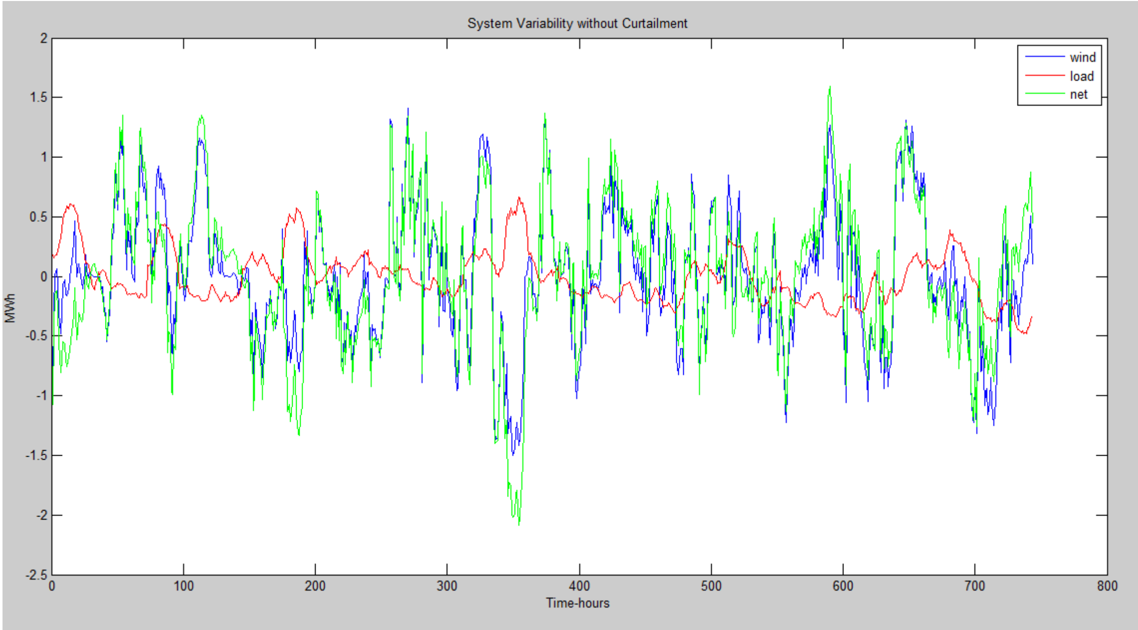

Figure D.11 – Variability without Curtailment - July

D.12 Variability with curtailment – July

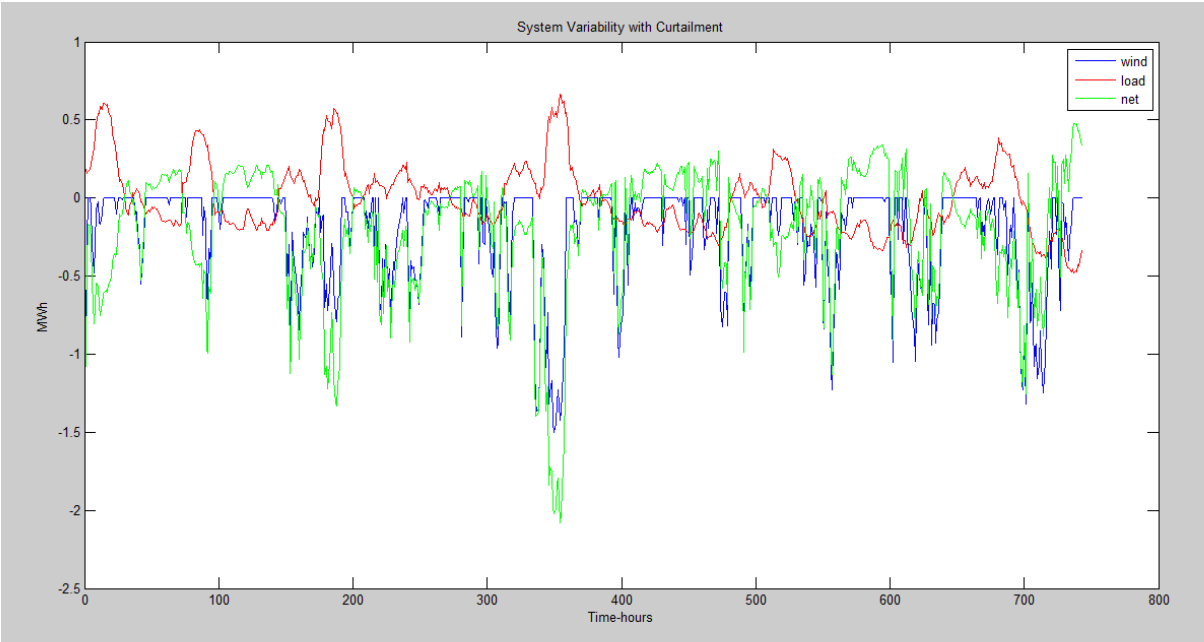

Figure D.12 – Variability with Curtailment - July

D.13 Arbitrage Only – October

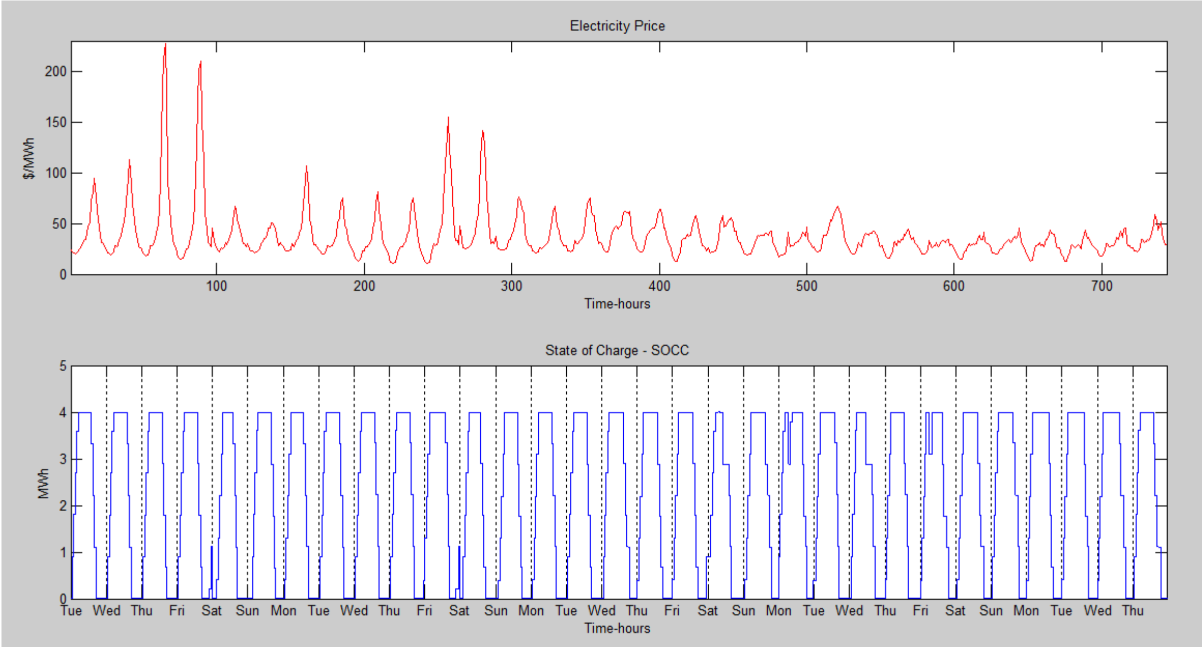

Figure D.13 – Arbitrage Only - October

Revenue from Arbitrage = $5,171

D.14 Arbitrage + Regulation Service – October

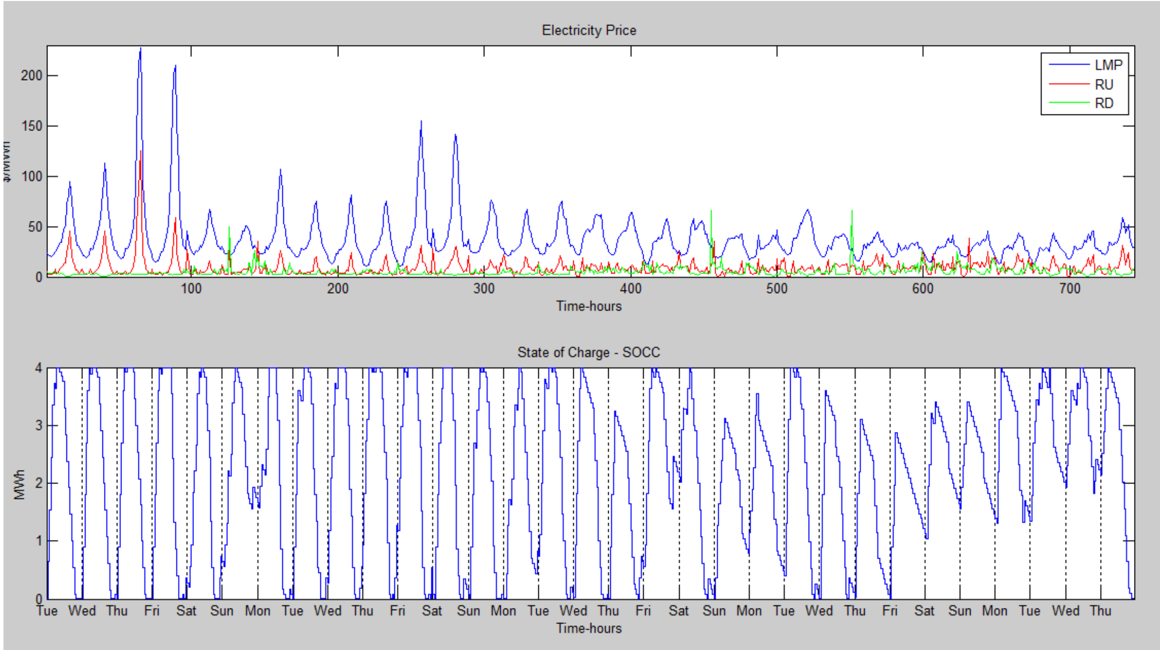

Figure D.14 – Arbitrage + Regulation Service - October

Revenue from Arbitrage + Regulation Service = $11,693. This is more than 2 times Arbitrage.

D.15 Variability without curtailment – October

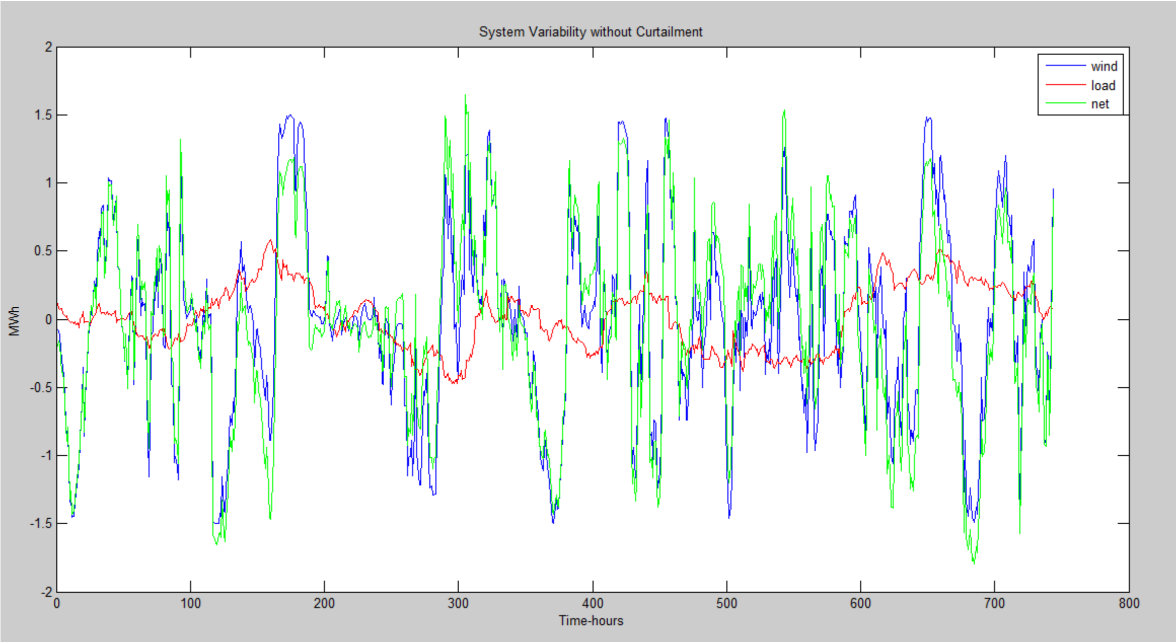

Figure D.15 – Variability without Curtailment - October

D.16 Variability with curtailment – October

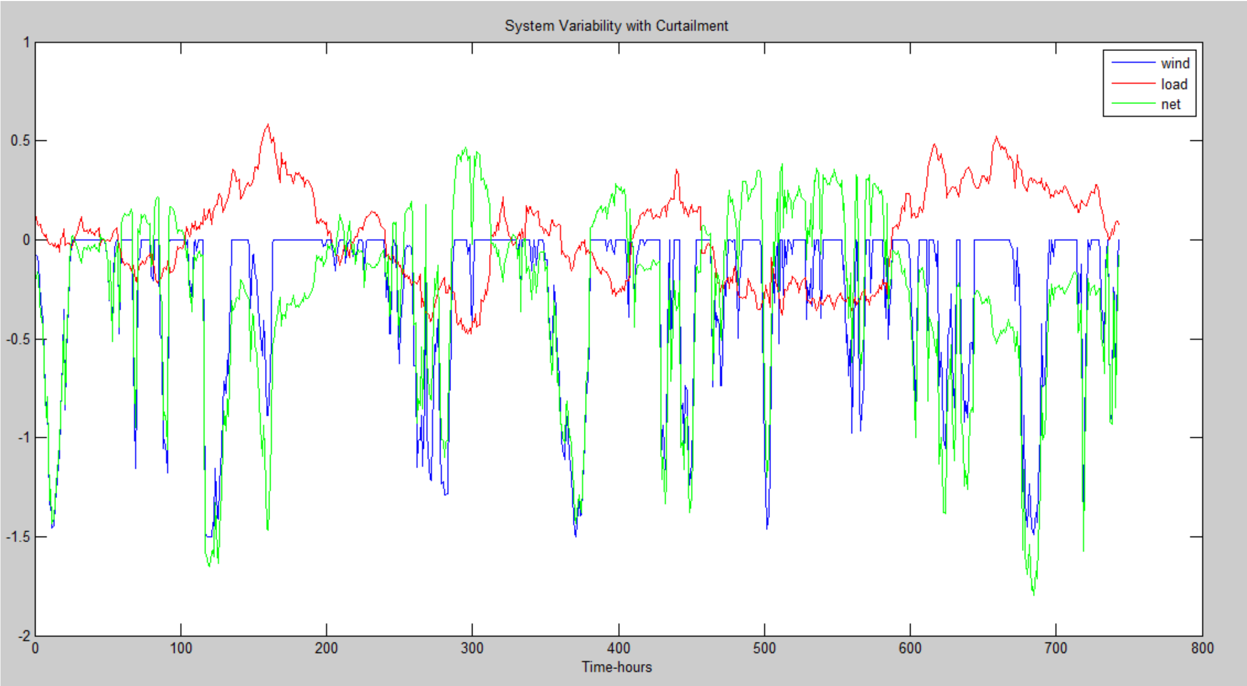

Figure D.16 – Variability with curtailment - October

Appendix E

E.1 Correlation between Wind and Load Deviations

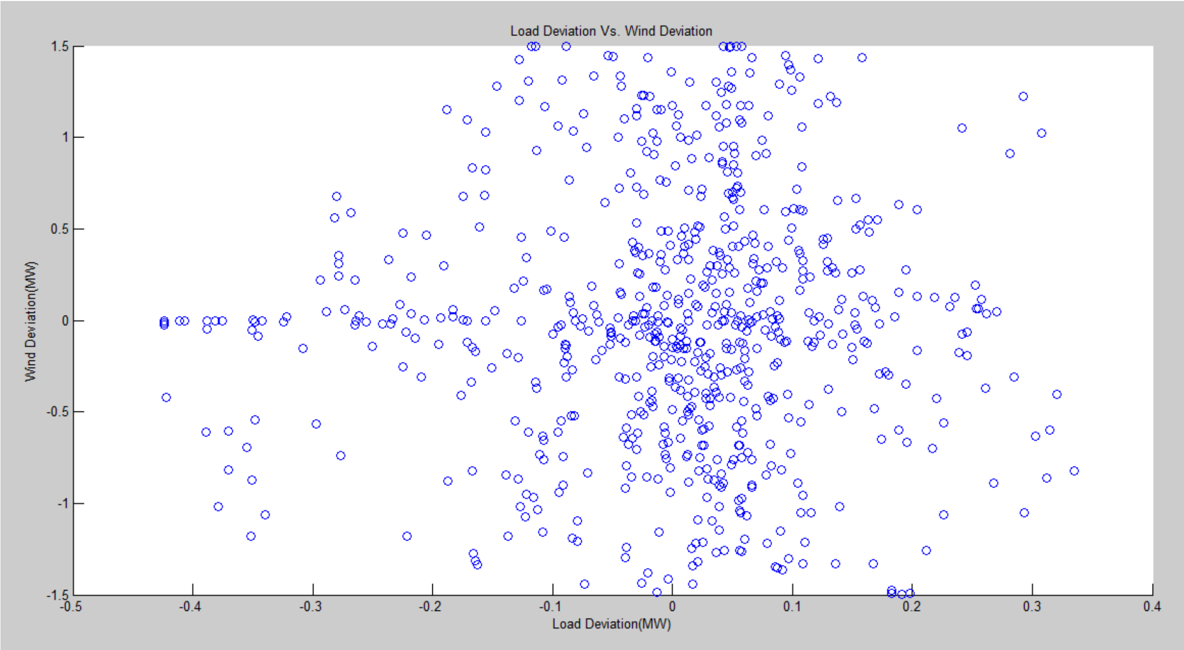

Figure E.1 – Correlation between Wind and Load deviations - January

Correlation coefficient (R) = 0.0174

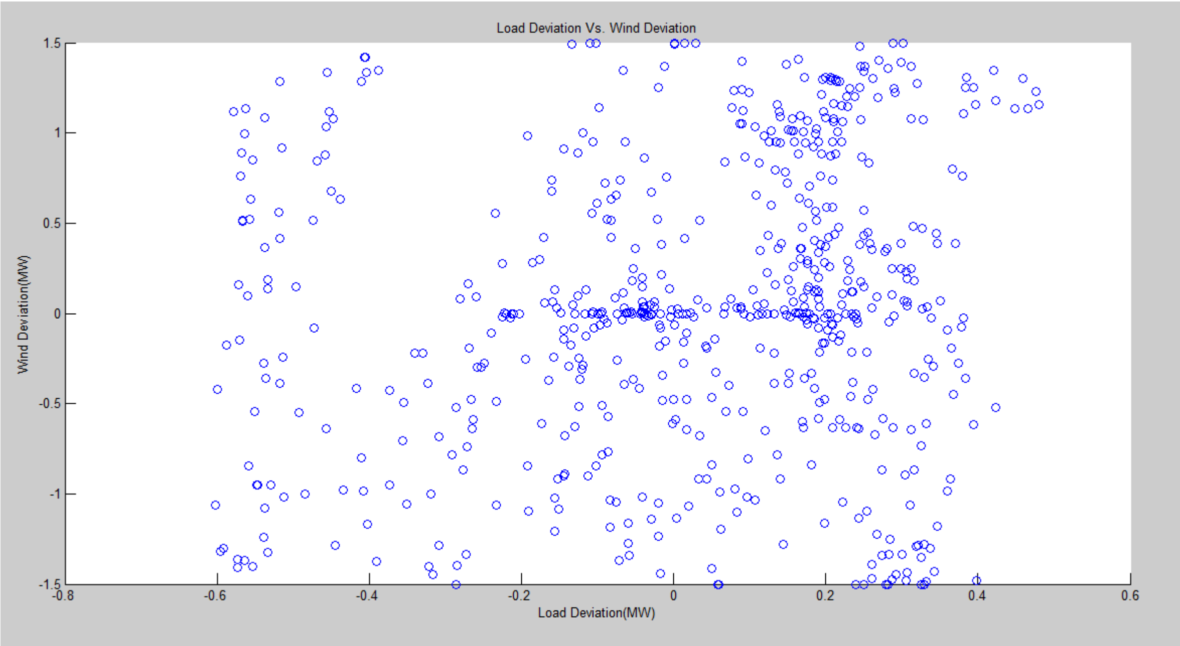

Figure E.2 – Correlation between Wind and Load deviations - April

Correlation coefficient (R) = 0.1494

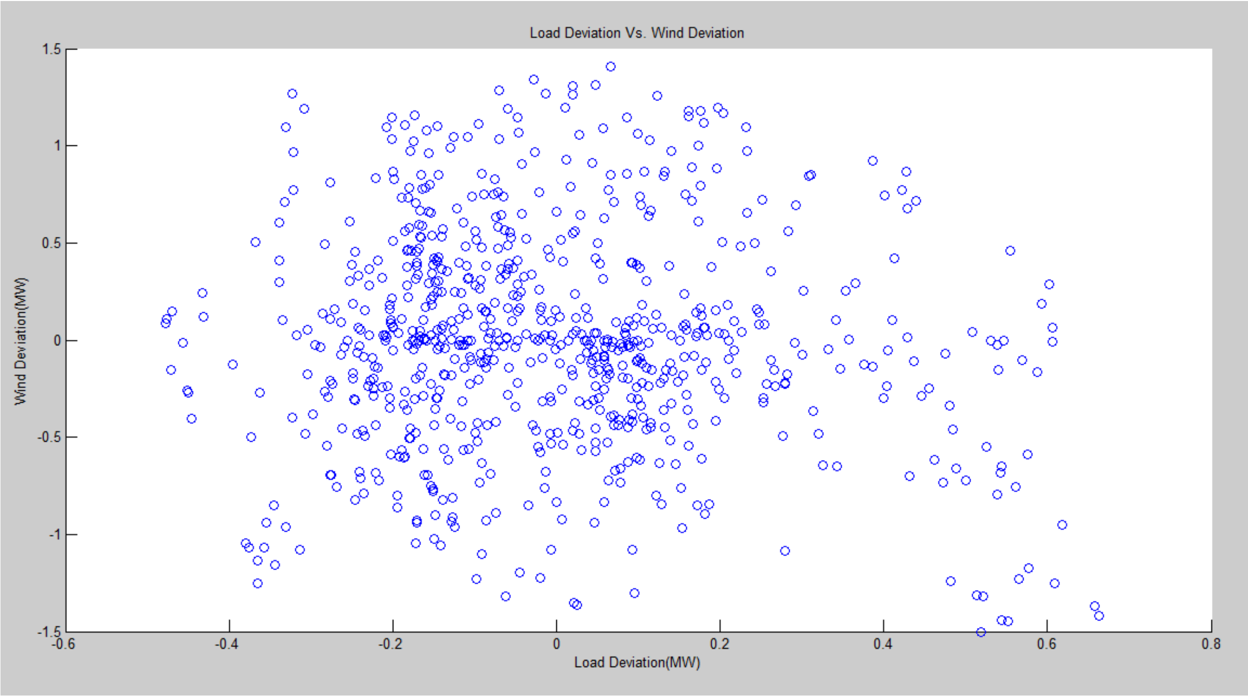

Figure E.3 – Correlation between Wind and Load deviations - July

Correlation coefficient (R) = -0.1018

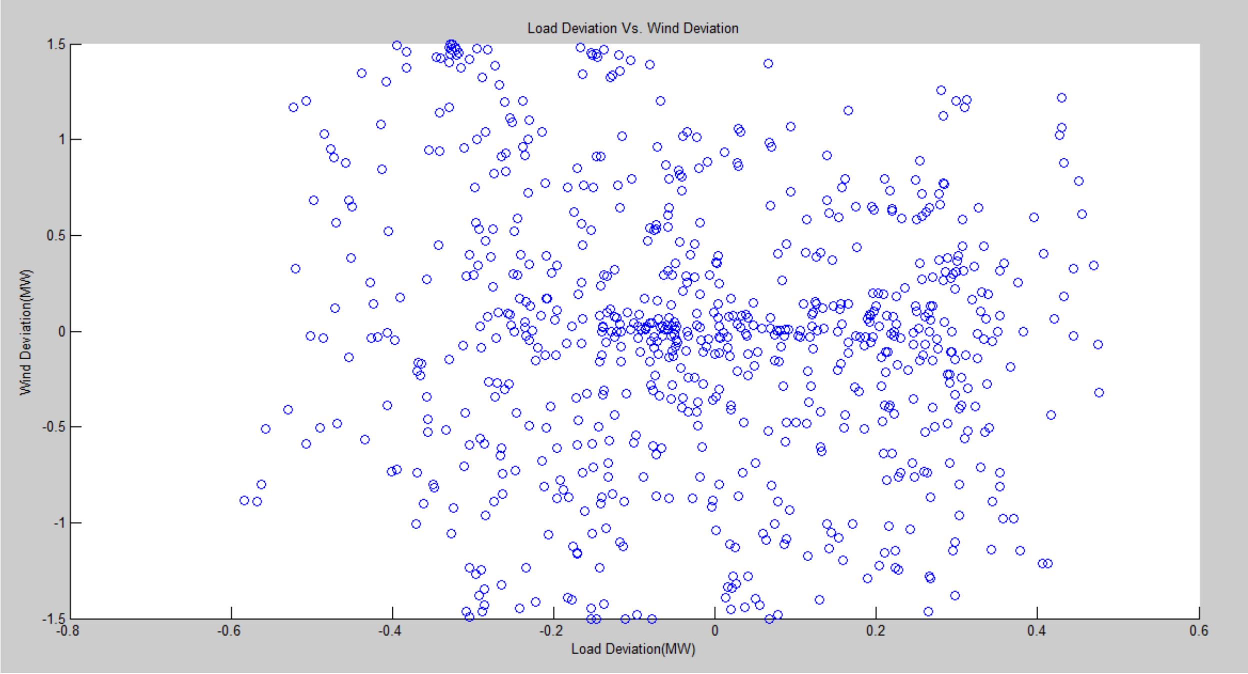

Figure E.4 – Correlation between Wind and Load deviations - October

Correlation coefficient (R) = 0.1123

Appendix F

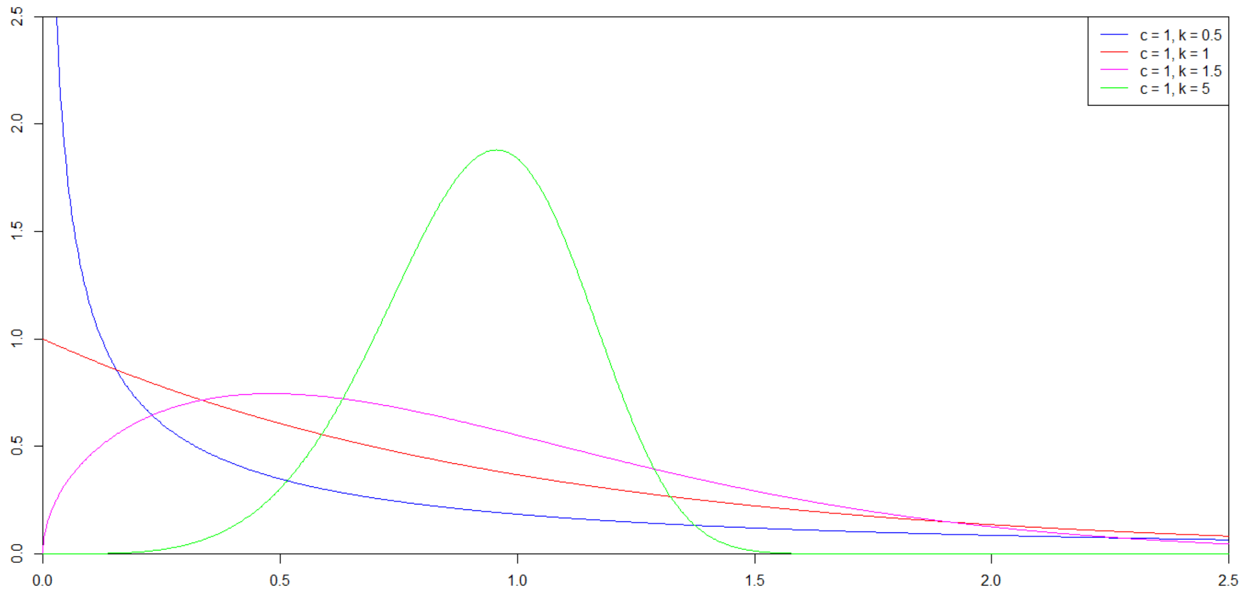

Figure F.1 – Weibull Probability Density Function

Weibull distribution is a continuous probability distribution that is commonly used for wind speed. A Weibull distribution has two parameters ‘k’ and ‘c’. ‘k’ is referred to as the shape parameter and ‘c’ is referred to as the scale parameter. Figure F.1, shows how ‘k’ and ‘c’ affect the shape and scale of the Weibull distribution. As ‘k’ is increased, the maximum of the probability distribution function increases. If ‘k’ is kept constant and ‘c’ is increased the shape of the distribution gets wider and hence, ‘c’ is referred to as the scale parameter. The mean of a Weibull distribution can be estimated as follows:

$$\mu_{Weibull} = \boldsymbol{c}\Gamma\left(\frac{1}{\boldsymbol{k}}+1\right)$$

Here ‘c’ is the scale factor, ‘k’ is the shape factor and ‘ Γ ’is the gamma function.

For this study the mean of wind speed data for all the months is a known quantity. If an estimate is made on the value of ‘k’, then ‘c’ can be calculated from the above equation. However, any number of combinations of ‘k’ and ‘c’ can fit the data. In order to achieve the best Weibull fit the wind power density of the Weibull distribution should match the wind power density of the measured data; adding this constraint solves for a single value of ‘k’ and ‘c’.

Figure F.2, Figure F.3, Figure F.4, and Figure F.5 show a histogram plot of the bin speed vs. frequency, the Weibull distribution that best fits the measured data and the power density for each season.

F.1 Weibull Distributions

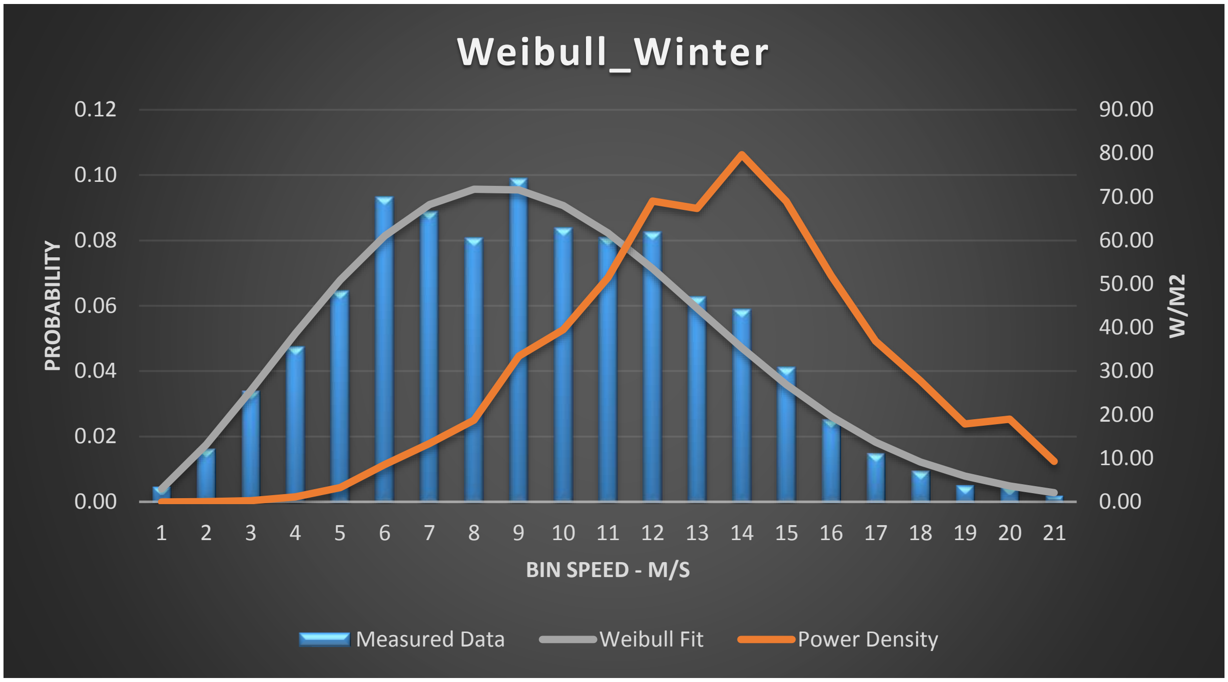

Figure F.2 – Weibull Distribution - Winter

k (shape parameter)	2.36
σ (std. deviation)	1.1
μ (mean)	8.9
c (scale parameter)	10.04

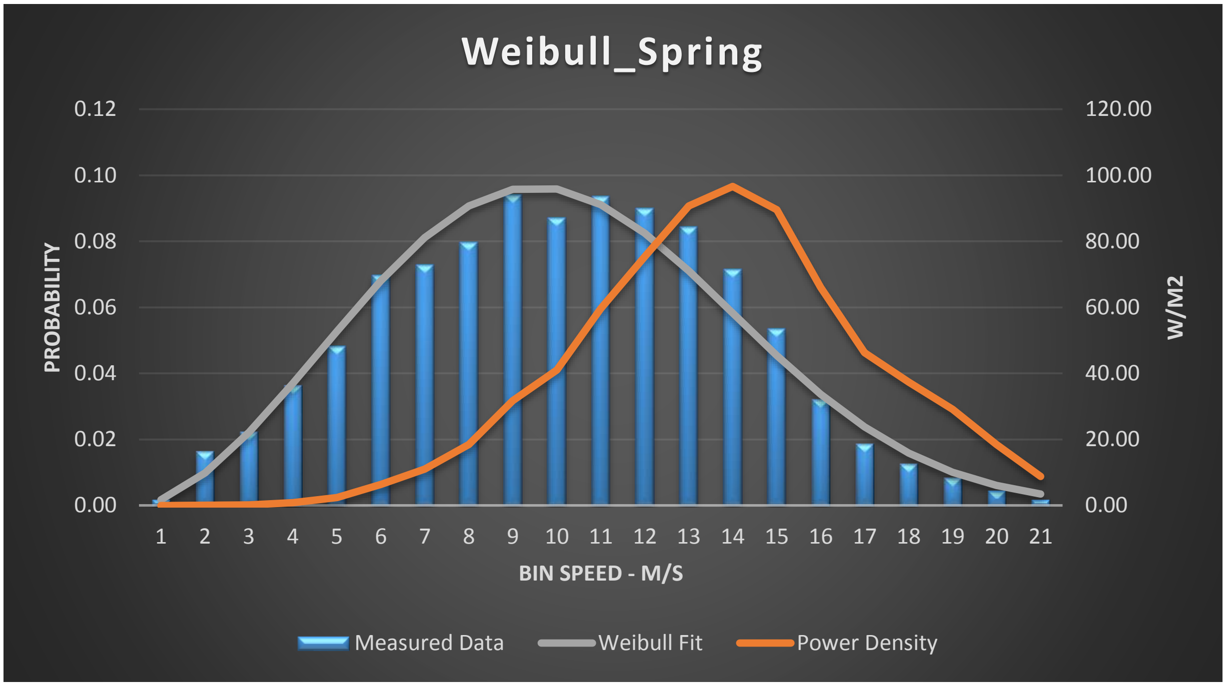

Figure F.3 – Weibull Distribution - Spring

k (shape parameter)	2.61
σ (std. deviation)	1.1
μ (mean)	9.6
c (scale parameter)	10.84

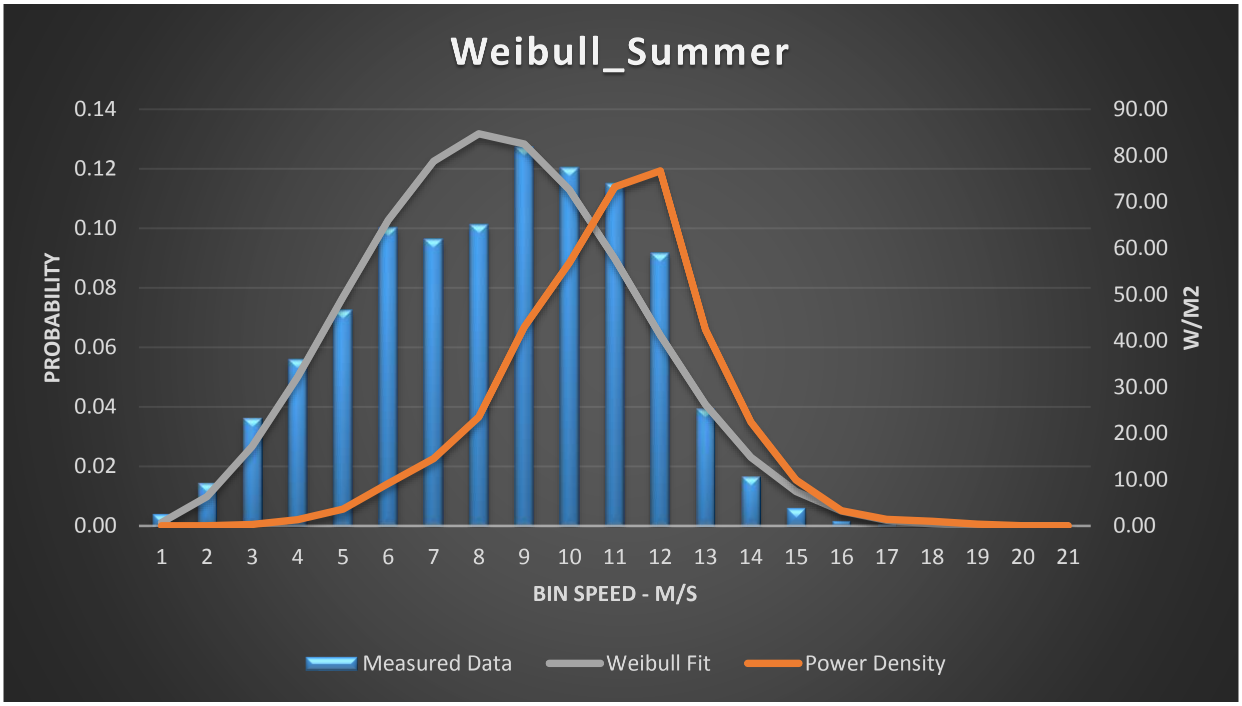

Figure F.4 – Weibull Distribution - Summer

k (shape parameter)	2.98
σ (std. deviation)	1.1
μ (mean)	7.9
c (scale parameter)	8.85

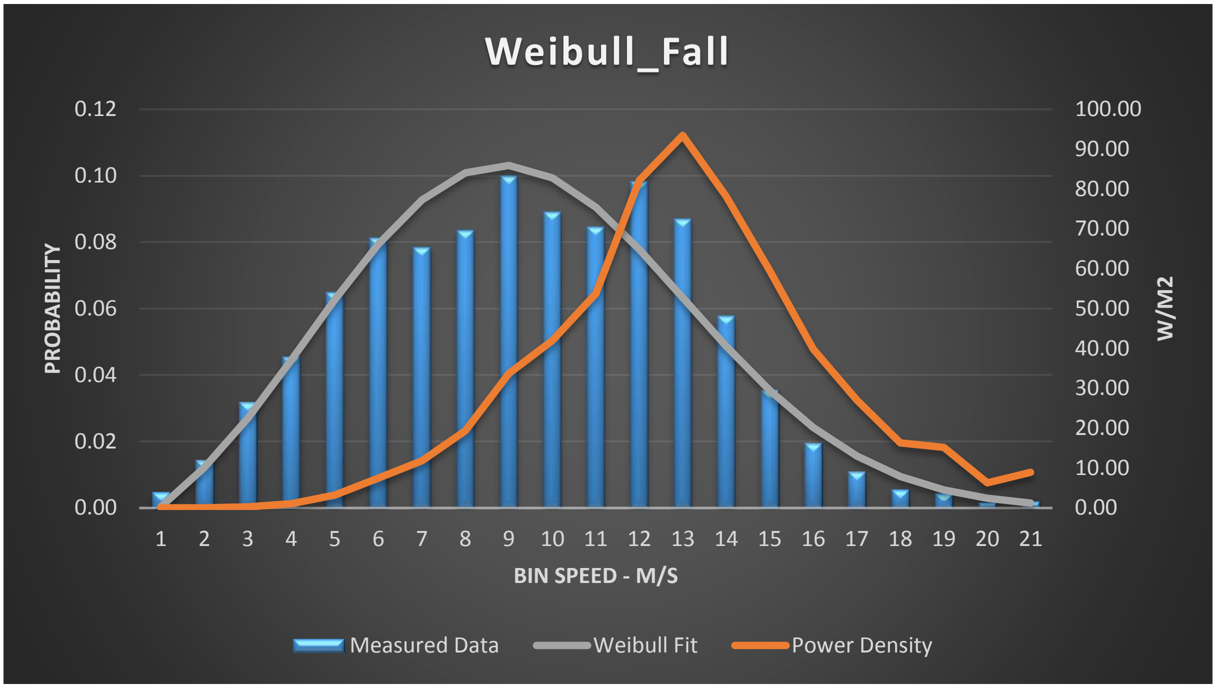

Figure F.5 – Weibull Distribution - Fall

k (shape parameter)	2.59
σ (std. deviation)	1.1
μ (mean)	9.0
c (scale parameter)	10.08

Appendix G

G.1 Sensitivity to Regulation Efficiency

$\gamma_{run} = \gamma_{rdn} = 0.2$

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**\$707** **\$7,328**	\$195 \$8,805
NON-COOPERATION	\$2,108 \$5,605	\$195 \$5,253

Table G.1 – Sensitivity to regulation efficiency

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**X=\$707** **X=\$4,985** **Y=\$2,343**	X=\$195 X=\$4,709 Y=\$4,096
NON-COOPERATION	X=\$2,108 X=\$5,605 Y=\$0	X=\$195 X=\$5,253 Y=\$0

Table G.2 – Sensitivity to regulation efficiency

$\gamma_{run} = \gamma_{rdn} = 0.025$

WIND STORAGE	COOPERATION	NON-COOPERATION
COOPERATION	**\$707** **\$7,889**	\$195 \$9,369
NON-COOPERATION	\$2,108 \$6,168	\$195 \$5,851

Table G.3 – Sensitivity to regulation efficiency

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**X=$707** **X=$5,546** **Y=$2,343**	X=$195 X=$5,273 Y=$4,096
NON-COOPERATION	X=$2,108 X=$6,168 Y=$0	X=$195 X=$5,851 Y=$0

Table G.4 – Sensitivity to regulation efficiency

G.2 Sensitivity to Storage Size

$S = 8$

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**$1012** **$8,321**	$195 $8,499
NON-COOPERATION	$2,108 $5,493	$195 $4,915

Table G.5 – Sensitivity to Storage Size

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**X=$1,012** **X=$4,618** **Y=$3,703**	X=$195 X=$8,499 Y=$0
NON-COOPERATION	X=$2,108 X=$5,493 Y=$0	X=$195 X=$4,915 Y=$0

Table G.6 – Sensitivity to Storage Size

$S = 2$

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**$521** **$6,131**	$195 $8,269
NON-COOPERATION	$2,108 $5,265	$195 $4,796

Table G.7 – Sensitivity to Storage Size

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**X=$521** **X=$4,616** **Y=$1,515**	X=$195 X=$8,269 Y=$0
NON-COOPERATION	X=$2,108 X=$5,265 Y=$0	X=$195 X=$4,796 Y=$0

Table G.8 – Sensitivity to Storage Size

G.3 Sensitivity to Charging/Discharging Limits

$\bar{q}^D = \bar{q}^R = 0.5$

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**$704** **$4,472**	$195 $4,831
NON-COOPERATION	$2,108 $2,717	$195 $2,401

Table G.9 – Sensitivity to Charging/Discharging Limit

STORAGE \ WIND	COOPERATION	NON-COOPERATION
COOPERATION	**X=$704** **X=$2,180** **Y=$2,292**	X=$195 X=$4,831 Y=$0
NON-COOPERATION	X=$2,108 X=$2,717 Y=$0	X=$195 X=$2,401 Y=$0

Table G.10 – Sensitivity to Charging/Discharging Limit