THE WELFARE EFFECTS OF INTEGRATING RENEWABLE ENERGY INTO ELECTRICITY MARKETS

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Alberto J. Lamadrid

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Alberto J. Lamadrid, Ph.D.
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The challenges of deploying more renewable energy sources on an electric grid are caused largely by their inherent variability. In this context, energy storage can help make the electric delivery system more reliable by mitigating this variability. This thesis analyzes a series of models for procuring electricity and ancillary services for both individuals and social planners with high penetrations of stochastic wind energy.

The results obtained for an individual decision maker using stochastic optimization are ambiguous, with closed form solutions dependent on technological parameters, and no consideration of the system reliability.

The social planner models correctly reflect the effect of system reliability, and in the case of a Stochastic, Security Constrained Optimal Power Flow (S-SC-OPF or SuperOPF), determine reserve capacity endogenously so that system reliability is maintained. A single-period SuperOPF shows that including ramping costs in the objective function leads to more wind spilling and increased capacity requirements for reliability. However, this model does not reflect the inter temporal tradeoffs of using Energy Storage Systems (ESS) to improve reliability and mitigate wind variability.

The results with the multiperiod SuperOPF determine the optimum use of storage for a typical day, and compare the effects of collocating ESS at wind sites with the same amount of storage (deferrable demand) located at demand

centers. The collocated ESS has slightly lower operating costs and spills less wind generation compared to deferrable demand, but the total amount of conventional generating capacity needed for system adequacy is higher. In terms of the total system costs, that include the capital cost of conventional generating capacity, the costs with deferrable demand is substantially lower because the daily demand profile is flattened and less conventional generation capacity is then needed for reliability purposes.

The analysis also demonstrates that the optimum daily pattern of dispatch and reserves is seriously distorted if the stochastic characteristics of wind generation are ignored.

BIOGRAPHICAL SKETCH

Alberto J. Lamadrid Luengas was born in Santafe de Bogota, Colombia, on March 11th of 1977. He obtained a Bachelor in Science, with a concentration in Electrical Engineering from the Universidad de los Andes in 1999. In 2004, he earned a Master of Arts with a concentration in Economics from New York University. He worked in London, U.K. with Citibank as Portfolio Manager, and in 2007 he started the Ph.D program at Cornell University. He is expecting to finish his Ph.D studies in 2012. His doctoral research is in Electricity Markets and the adoption of renewables sources of generation . He has accepted an Assistant Professor position in the Department of Economics at Lehigh University starting September 2012.

To my family

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My heart often pilgrimages back home to Colombia and to all my dear friends back there and now in other places, and to my father, my mother, my brother, grandparents, aunts and uncles, cousins and all the people that I am fortunate to have in my life. To them is this work dedicated, because they have made it possible.

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CHAPTER 1

INTRODUCTION

Research in electricity markets is now at a crossroads: the higher penetrations of renewables, either dictated by regulators or requested by consumers due to climate change concerns is creating new challenges for all agents in the system. The reliable operation of the power system can be at odds with the scheduling of resources that are inherently stochastic and can have dramatic swings over the time horizon set by the planner. Given the importance assigned to reliable and adequate management of the bulk power system by regulators and consumers, it is critical to develop methods and technologies that help offset the variability posed by Renewable Energy Sources (RES). In the coming years, the RES that will most likely see significant increases in the U.S. is wind energy [15], followed by solar in certain regions [18]. Availability of wind power is in many cases negatively correlated with the pattern of demand, with high availabilities at night and unreliable supply during the day. Solar on the other hand is positively correlated, but suffers from fast disruptions in output due to atmospheric conditions. Therefore, the balance between generation and load to avoid large mismatches and frequency imbalances becomes more complicated with inclusion of variable resources.

Advancements in storage technology promise to, at least partially, mitigate such problems, while allowing for a reliable operation of the system. Energy Storage Systems (ESS) can be coupled with RES, taking advantage of the high availability of wind at night, charging batteries and then discharging during high demand periods (time arbitration) [73]. However, dedicated storage capacity is likely to be extremely expensive[69], and therefore not preferred. The possible advent of electrified transportation is then a more economical form of providing storage capabilities to the network [67]. The main advantage in this case is that the capital cost of the ESS is divided between the transportation service provided by the vehicle, and the support provided to the grid. Moreover, the economics of capital acquisition for vehicles are based on the much higher prices of gasoline. But the usage of ESS from vehicles is still in need of larger penetrations, technological advancements for the Vehicle-to-Grid (V2G) interface and the proper design of compensation mechanisms. A further and potentially larger source of storage capability can come from the utilization of thermo-storage [16].[1]

From the point of view of the participants in the wholesale market, the decision to provide ancillary services requires proper incentives to match socially desirable outcomes. This is especially important for regulators who need to bear in mind the role of a social planner by maximizing the welfare of all market participants. The availability of ESS and the proper market may allow the owners to 1) lower the cost of purchasing energy through price arbitrage across the day, and 2) be compensated for mitigating the RES variability by selling ancillary services.

From the viewpoint of the social planner, the scheduling of electric generation resources that include some form of ESS should include consideration of the inter-temporal nature of the decision-making process. Since human activity follows a sinusoidal pattern, with increases in demand for electricity in

[1]Pumped storage hydro electric was the first large scale storage application in the United States, with 31 MW power capacity installed in 1929. Lead acid is the most common form of storage used nowadays, specially for backup units for data centers as Uninterruptible Power Supply (UPS). Currently, compressed Air Energy Storage (CAES) is the form of storage receiving the most attention, with potential use of underground formations for storing purposes. Chapter 1 of [17] provides an excellent overview of the technologies available and adoption history of storage for the electric grid.

the morning hours, an important operational issue is the preparedness to cover such expected load surge. Moreover, in an electrical network, the location and amount of generation power available, the technical characteristics of the generation assets available such as ramping capacity, and the transmission network transfer capability all constrain the settlements from Independent System Operators (ISO's).[2] A random component inherent to the operation of the electrical system is also present, such as the unexpected loss of a transmission line, or unforeseen disconnection of generation capacity.

The fundamental quandary is then how to appropriately model the system, taking into account both economic and engineering criteria that accurately reflect the operation of the system.

In the economic field, a wide array of research studies energy and electricity markets, applying tools from dynamic optimization and control, auction theory and industrial organization. Such models, while elegant and computationally tractable, in general, are not appropriate to capture the salient features of electricity markets with high penetration of renewables, with the proper level of nuance necessary for a social planner such as an ISO. The externalities added by the electricity network, which obey physics and not market rules, can lead to flows and outcomes that stylized models do not reflect.

Methodologically, this work is divided into three parts. The first part, discussed in Chapter Two, addresses the individual agent problem. The modeling used is grounded on classical dynamic control and optimization theory. The forms chosen allow for computationally tractable solutions.

[2] A more general label for the social planner is System Operators (SO's), which in this work is used to denote ISO's as well.

The second part, discussed in chapter Three, develops a model for deterministic scheduling of a committed set of generators, taking a systems approach to the problem. The effects of an Alternating Current (AC) transmission network are directly modeled, and the multiperiod nature of the ESS usage decision is discussed. The network model used accurately reflects the physical flows of electricity according to Kirchoff's laws. To incorporate changing information in the system according to system conditions, sequential updates are done in each period. Besides the analytical derivation of the First Order Conditions (FOC's) of the problem, the formulation is tested on a network model.

The third part, discussed in Chapters Four and Five, motivates the use of nuanced models to manage the system, along the lines of work done by faculty and researchers at Cornell as part of a multi-period, stochastic, security constrained AC optimal power flow framework called the SuperOPF. This part relates the work done with single period models and modifications performed to make it dynamic across time, analyzes the problem of determination of reserves for contingency and ramping, and studies the conditioning of the problem and the input information required to run the problem. In Chapter Five, two case studies are done to analyze the usage of this framework for different policy evaluations on the effects of geographical location and congestion.

CHAPTER 2

INDIVIDUAL DECISION MAKING

The individual agent problem formulation leverages models that have been explored in the bio-economic literature for the optimal extraction and management of fisheries and timber (see [60]). The key question is how the valuation and usage of an asset changes over time with uncertainty in the system [12]. [58] applies *Ito*'s Lemma to study investment decisions in a stochastic, continuous time model. The capital replacement model discussed by Rust [62] provides a background to inform the decision-making process for life cycle management of a storage resource.

Three models are presented that analyze the problem from the perspective of a representative consumer. The first two formalize the decision process of a single agent usage of an ESS through dynamic models of the uncertainty faced. The last one represents the operational settlements of a price taker with a finite time horizon.

2.1 Optimal ESS Management, Representative Agent

To study a stylized version of the optimal usage of an ESS with no network, a single agent problem with an ESS endowment is posited. This agent derives utility from consumption of the energy stored in the ESS. This can be thought of as an abstraction of an agent with an electric car that derives utility from the car usage, as well as from consumption of electricity for powering devices (e.g., appliances in the house).

The consumption good (electricity for transportation or for usage in appliances) is homogeneous and denoted by c_t. This can be considered an instantaneous power drain from the battery (e.g., measured in kW). In this case, the period of consideration is averaged over a period of time (e.g., weeks), so that it can be approximated by a continuous-time process.

The energy capacity of the ESS can be modeled by a continuous time stochastic differential equation expressed as:

$$dB = a(B(t), c(t), t)dt + b(B(t), c(t), t)dz \tag{2.1}$$

Equation (2.1) represents an *Ito* process in which $a(\cdot)$ is the drift rate of the process, $b^2(\cdot)$ is the variance rate and dz is the increment of a Wiener process. $B(t)$ is the energy capacity of the ESS (e.g., measured in kWh) and $c(t)$ is the consumption of electricity in period t. For notational simplification, these variables will be denoted by B and c. The agent's problem in this case will be given by:

$$\begin{aligned} &\max_{c} \; W(c) = E_0\Big[\int_{t=0}^{\infty} U(c)e^{-\rho t}dt\Big] \\ &\qquad s.t. \\ &\qquad dB = a(B, c, t)dt + b(B, c, t)dz \\ &\qquad\quad B(0) > 0 \text{ given} \end{aligned} \tag{2.2}$$

Where ρ denotes the discount rate. The utility function is time invariant. The Hamilton-Jacobi-Bellman (HJB) equation and $It\hat{o}'s$ *Lemma* application for this problem is given in (2.3)

$$\begin{aligned}\rho V(B) &= \max_c \left[U(c) + \frac{1}{dt}E_t dV(B)\right], \Rightarrow \\ \rho V(B) &= \max_c \left[U(c) + a(B,c,t)\frac{dV}{dB} + \frac{1}{2}b^2(B,c,t)\frac{d^2V}{dB^2}\right]\end{aligned} \tag{2.3}$$

Assuming that the technologies have discrete-size jumps with arrival times following a Poisson distribution, let q denote a Poisson process, with changes as follows:

$$dq = \begin{cases} 0 & \text{with probability } 1-\lambda dt \\ u & \text{with probability } \lambda\, dt \end{cases}$$

Then, combining both an *Itô* process with a jump process, the change equation can be expressed as:

$$dB = a(B(t), c(t), t)dt + b(B(t), c(t), t)dz + d(B(t), c(t), t)dq \tag{2.4}$$

In equation (2.4), the term $d(\cdot)$ is a known function describing the change that may affect the state variable. In the case of a combined *Itô* and jump process, the HJB equation is given by:

$$\rho V(B) = \max_{c_t}\left[U(c) + a(B,c,t)\frac{dV}{dB} + \frac{1}{2}b^2(B,c,t)\frac{d^2V}{dB^2} + \varepsilon_u[\lambda\{V(B + d(B,c,t)u) - V(B)\}]\right] \tag{2.5}$$

2.1.1 Optimality Conditions

The First Order Conditions (FOC's) with respect to c_t for the *Itô* process problem are shown in equation (2.6)

$$\frac{dU(c)}{dc} + \frac{da(B,c,t)}{dc}\frac{dV}{dB} + b(B,c,t)\frac{db(B,c,t)}{dc}\frac{d^2V}{dB^2} = 0 \tag{2.6}$$

In this case, the marginal utility will depend on the changes of the drift rate, and the associated variance of the process affecting the change in value of the storage resource through time. For the combined *Itô* and jump processes, the FOC's will depend on the relation describing the discrete movement. In situations as the one illustrated here, where the discrete movement does not depend on the control variable but is exogenous (e.g., innovation in batteries does not depend on the charging and discharging regimes adopted), the FOC's will have the form shown in (2.6).

2.1.2 Optimal Feedback Policy

An optimal feedback policy ($c = \phi(B)$) can be obtained according to the functions that describe $U(\cdot), a(\cdot), b(\cdot)$. The optimized HJB equation is shown in (2.7).

$$\rho V(B) = U(\phi(B)) + a(B,\phi(B),t)\frac{dV}{dB} + \frac{1}{2}b^2(B_t,\phi(B),t)\frac{d^2V}{dB^2} \tag{2.7}$$

In the combined *Itô* and jump processes modeling, and assuming that the jump process is independent of the control variable, the optimal feedback policy $c = \phi(B)$ is identical to that obtained in case of an *Itô* process with no jumps. After replacing the optimal feedback policy into equation (2.5), the optimized HJB obtained is shown in (2.8).

$$\rho V(B) = U(\phi(B)) + a(B, \phi(B), t)\frac{dV}{dB} + \frac{1}{2}b^2(B_t, \phi(B), t)\frac{d^2V}{dB^2} + \varepsilon_u[\lambda\{V(B + d(B, c, t)u) - V(B)\}] \tag{2.8}$$

2.1.3 Analytical Solution

Because this model is highly stylized, it allows for a closed form solution, depending on the selection of the functions describing the evolution of the process. Consider logarithmic decay of the capacity of an ESS ($a(B(t), c(t), t) = \left(rB\ln\left[\frac{k}{B}\right] - c_t\right)$, $b(B(t), c(t), t) = \sigma B$), and a logarithmic utility function, as described in (2.9) and (2.10) respectively.

$$dB = \left(rB\ln\left[\frac{k}{B}\right] - c\right)dt + \sigma B dz \tag{2.9}$$

$$U(c_t) = \alpha \ln c - \beta\frac{c}{B} \tag{2.10}$$

The utility function chosen allows for linear utility function, while reflecting the decay observed in the capacity of the battery. In such a case, the optimal feedback policy obtained is $c = \phi(B) = \frac{\alpha B}{\frac{dV}{dB}B+\beta}$. Assuming a logarithmic value function $V(B) = M\ln B + N$, the optimal consumption obtained is given by equation (2.11)

$$c = \phi(B) = \frac{\alpha(\rho + r)B}{\alpha + \beta(\rho + r)} \tag{2.11}$$

For a combined *Itô* and jump process with $d(B(t), c(t), t) = (1 + \gamma_i)B$ and parameters as in the *Itô*-only process, the following solution is obtained:

$$
\begin{aligned}
M &= \frac{\alpha}{\rho + r} \\
N &= \alpha\left[\ln\alpha - \ln\left(\beta + \frac{\alpha}{\rho + r}\right) - 1\right] + \frac{\alpha}{\rho + r}\left(r\ln k - \frac{\sigma^2}{2}\right)\varepsilon_u[\lambda\frac{\alpha}{\rho + r}\ln\{1 + (1 + \gamma_i)u\}]
\end{aligned}
\tag{2.12}
$$

The main implication of equations (2.12), under the assumptions on the model is that usage of the energy in the storage resource for consumption follows a path similar to the degradation observed across time. This result follows the logic of pacing usage according to the technology available. Note that the optimal feedback policy in this case is described by equation (2.11), since the jump process is not affected by the control variable.

2.2 Optimal Replacement

Consider the decision to purchase and replace a capital good with deterministic depreciation. As in section 2.1, this is an abstraction of a user deciding to buy an ESS for use in a house, or a plug-in electric vehicle with a battery that can be used for both transportation and electricity usage, with decisions over a long time horizon. The constant cycling of chemical batteries reduces the usable energy capacity (see e.g. [65]), and hence the degradation assumed. This durable good has a quality level x_t and degrades over time at a rate γ per period. For the sake of simplicity, it is assumed that the number of states is finite. The quality of a new good is denoted by x_0. The utility of using this asset, $U(\cdot)$ depends on the quality level (e.g. less available capacity over time means more frequent charges, and therefore lower utility from the ESS). This good has a replacement cost, $C(\cdot)$ and an associated mapping from monetary cost to utility levels $\phi(\cdot)$. Other goods are ignored here. Let ρ denote the discount rate, and $B(x_t) = \{0, 1\}$ the replacement decision at time t. For this model, a threshold level R will indicate the minimum acceptable quality level (i.e., if $x_t < R$, the good needs to be replaced). The agent's problem in this case will be given by:

$$\begin{aligned} \max_{B(x_t)\in\{0,1\}} u = \sum_{t=0}^{\infty} \rho^t \Big[U\Big(x_t - \phi(C(x_t)) \cdot B(x_t) \Big) \Big] \\ s.t.\ x_{t+1} = &(1 - B(x_t)) \cdot (x_t - \gamma) + B(x_t) \cdot (x_0 - \gamma) \\ x_0\ given \end{aligned} \tag{2.13}$$

The Bellman equation will be given then by:

$$\begin{aligned} V(x_t) = \max_{B(x_t)\in\{0,1\}} \Big[U\Big(x_t - \phi(C(x_t)) \cdot B(x_t) \Big) + \rho \cdot V(x_{t+1}) \Big] \\ s.t.\ x_{t+1} = &(1 - B(x_t)) \cdot (x_t - \gamma) + B(x_t) \cdot (x_0 - \gamma) \\ x_0\ given \end{aligned} \tag{2.14}$$

The problem can then be rewritten as:

$$V(x_t) = \max_{B(x_t)\in\{0,1\}} \Big[U\Big(x_t - \phi(C(x_t)) \cdot B(x_t) \Big) + \rho \cdot V\Big((1 - B(x_t)) \cdot (x_t - \gamma) + B(x_t) \cdot (x_0 - \gamma) \Big) \Big] \tag{2.15}$$

2.2.1 Optimality Conditions

This problem can be numerically solved by fixed point iteration over the possible values of the value function. The level of quality (x_t) is discretized, with 60 periods (e.g. months for five years). The cost of replacement is set as fixed (c \$/unit), and a per-period linear utility function ($a \times x_t$, a set to 2 as the marginal utility of quality). The discount rate (ρ) is set to 0.9, and the marginal utility of money is linear and numeraire ($m = 1$). The degradation rate of the ESS (γ) is considered constant for all periods (γ_0).

For this case, equation (2.15) becomes

$$V(X_t) = \max_{B_t \in \{0,1\}} [ax_t - cmB_t + \rho V((1 - B_t)(x_t - \gamma_0) + B_t(x_0 - \gamma_0))] \tag{2.16}$$

2.2.2 Results and Sensitivity

Given the likely changes to be observed in the ESS technologies [57], a sensitivity analysis of the value of the solution to equation (2.16) is performed. The two parameters analyzed are the cost of replacement, c, and the degradation rate, γ. Figure 2.1 shows the evolution of replacement time as a function of the a) cost of replacement and b) degradation over time, while holding the other parameters constant.

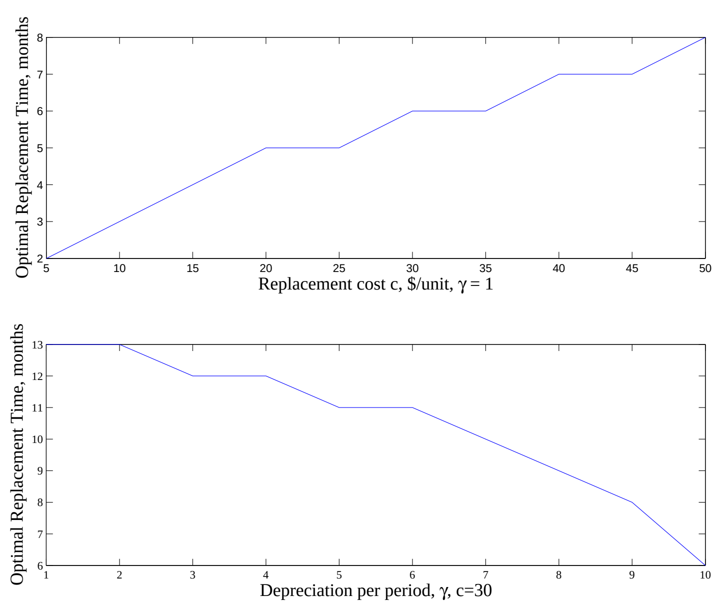

Figure 2.1: Sensitivity to fixed technology parameters

To see how the two studied parameters interact, Figure 2.2 shows contour plots for evolving values of the technology considered. The monetary unit values over which replacement cost vary are from 5 to 50. The variation on degradation are from 1 to 10.

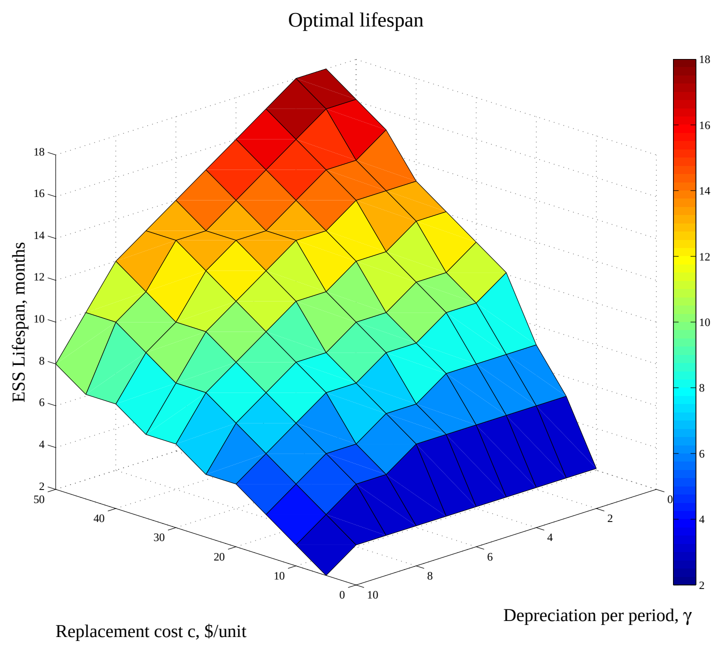

Figure 2.2: Sensitivity to technology parameters

The results show that the model accurately predicts the sensitivity of the mean ESS lifetime to advancements in technology: lower degradation rates and higher replacement costs of the storage sources lead to longer optimal replacement times. This stylized model then formalizes the investment decision for an energy storage, given that time spans are averaging over relatively long periods of time, e.g., months. Hour-to-hour decisions regarding usage will probably be more dependent on the possibility of arbitraging over inter-temporal price differences and the decision to offer ancillary services to the network than on the overall degradation of the ESS.

2.3 Price-taking Operational Consumer Model

A representative agent in a competitive market is posited, facing the decision of timing her energy usage over a day. The agent faces a fixed electricity price (e.g. \$/MWh), which can change for each hour of the day. The objective function is to maximize the net benefits from serving a given load for a given period of time, while not inconveniencing her. The initial energy utilization profile is exogenous, and does not need to be optimal (in fact, it can be random, just following the pattern of activities from the agent, which usually have a sinusoidal form). Additionally, assume the agent has access to an Energy Storage System (ESS). Such device allows usage for both domestic consumption, and energy injections or sales to the network. The timing of charging is a decision variable. The consumer is constrained by the technical characteristics of the ESS, and by her preferences over consumption over the day. The energy to be consumed can be divided into two main types: deferrable demand and non-deferrable demand. While the first one can be serviced at any time of day, the second one is critical, and requires being serviced whenever specified by the agent. Such division is akin to some classifications of load related to temperature sensitivity in temperate countries, where the air conditioning/heating load can be significant (see e.g. [82]). Let t and τ be hourly indices for a day, T the optimization horizon, and Pw_t^{load} the initial demand to be served for period t. Denoting by $e^1_{\tau t}$ the demand to be shifted from hour t to hour τ and $e^2_{\tau t}$ as the energy stored in hour t to be used in hour τ, consider the problem:

$$
\begin{aligned}
\max_{e^{p}_{\tau t},p=1,2} \quad B = & \sum_{\tau}^{T} b_\tau(\sum_{t}^{T} e^1_{\tau t}) + \sum_{\tau=2}^{T} b_\tau(\sum_{t=1}^{\tau-1} e^2_{\tau t}) - \sum_{\tau=2}^{T}\sum_{t=1}^{\tau-1} c^d_t(e^2_{\tau t}) - \sum_{\tau=2}^{T} c^d_\tau[(1-a_\tau)Pw^{load}_\tau] \\
& - \sum_{\tau}^{T}\sum_{t}^{T} c^d_\tau(e^1_{\tau t}) + \sum_{\tau=2}^{T}\sum_{t=1}^{\tau-1} c^d_\tau(e^2_{\tau t}) - \sum_{\tau}^{T}\sum_{t}^{T} c^{s,p}_\tau(e^1_{\tau t}) - \sum_{\tau=2}^{T}\sum_{t=1}^{\tau-1} c^{s,p}_\tau(e^2_{\tau t})
\end{aligned}
$$

$s.t.$

Load Shift constraints

$$\sum_{\tau}^{T} e^1_{\tau t} = a_t Pw^{load}_t, \text{ for } t = 1, \ldots, T.$$

Hourly Limits

$$e^{min}_\tau \leq (1-a_\tau)Pw^{load}_\tau + \sum_{t}^{T} e^1_{\tau t} \leq e^{max}_\tau + \sum_{t}^{T} e^2_{\tau t}, \text{ for } \tau = 1, \ldots, T$$

Energy storage limits

$$ll_\tau \leq \sum_{t}^{\tau-1} e^2_{\tau t} \leq ul_\tau, \text{ for } \tau = 2, \ldots, T \tag{2.17}$$

Table 2.1 has the definition of the each term and variable in equation (2.17).

Table 2.1: Variables and terms for Consumer's problem, adding storage

Variable/Term		Definition
Pw^{load}_t	:	Load to be served for period t.(demand, MW)
$c^d_t(\cdot)$	:	Cost of serving the demand at period t.
$c^{s,p}_t(\cdot)$	:	Cost of shifting load/transferring capacity to period t.
a_t	:	Fraction of load that can be shifted from period t
$e^1_{\tau t}$	:	Load to be shifted from hour t to hour τ.
e^2_{tj}	:	Energy stored in hour t to be used in hour τ.
e^{min}_t	:	Lower limit for load at period t.
e^{max}_t	:	Upper limit for load at period t.
ll_t	:	Lower limit at period t for energy storage.
ul_t	:	Upper limit at period t for energy storage.
$b_t(\cdot)$	:	Personal benefits of moving load/capacity to period t

The technical limits are given by e^{min}_t, e^{max}_t, ll_t and ul_t, which implicitly reflect the efficiency of the ESS, and depend on the technology adopted (see e.g. [65], [69], [6]).

Note that all units used should be consistent, e.g. demand specified in kWh, prices in $/kWh.

The change into the final representative optimized load profile are driven by two main sources: 1) behavioral changes, leading to shifting demand and consumption at different hours of the day, and 2) technological adoption and availability of new energy sources.

In a case where the costs and benefits are linear functions, the problem in (2.17) becomes a linear program (LP). An open question on consumer models that value the potential response to programs using price as a signal is the proper calibration on the willingness of consumers to pay for or change their behavior. This concern has been present for some time (see e.g. [80]) and is the subject of recent experiments analyzing the response to the framing of the policies [2]. The linear model from (2.17) has been implemented and tested in AMPL[21]. The initial calibration used information from Form No. 714 from the Federal Energy Regulatory Commission (Annual Electric Balancing Authority Area and Planning Area Report). The final calibration used data from the NYISO. Assuming a profile of prices similar to those observed for New York City (New York control area J), summer 2008, and assuming demands similar to those for a representative consumer, around 20kWh of daily consumption, the final load profile obtained is flatter than the original (peak shaving valley filling) as suggested by Gellings and Smith [23]. Figure 2.3 shows the change in profiles.

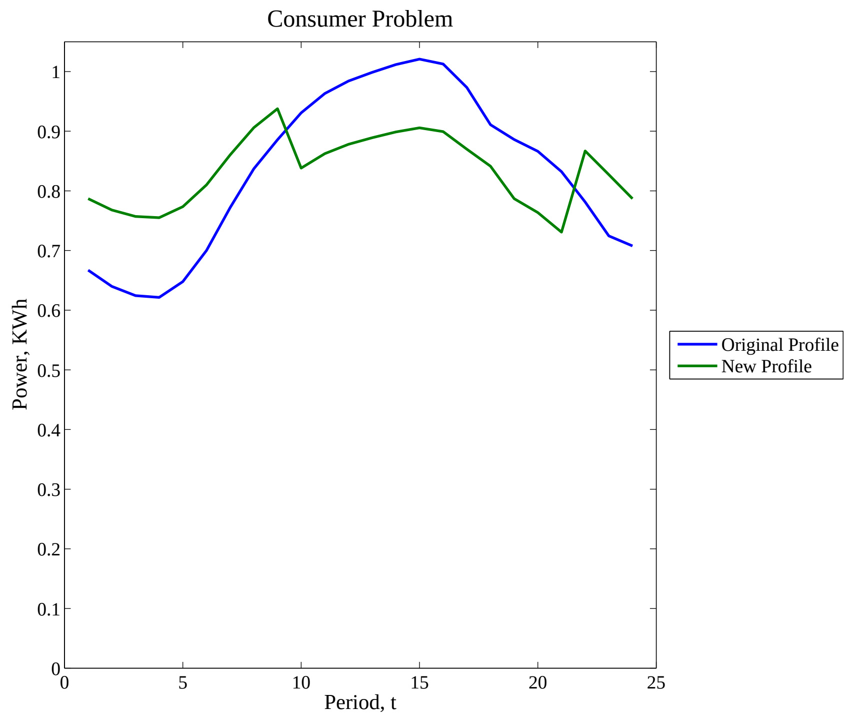

Figure 2.3: Profile for representative consumer

The sensitivity of the model was not formally explored, though modifying the parameters shifted the point of the changes ('kinks') occurring in the day. The solver used in AMPL was CPLEX, with a Dual simplex solved model.

The aggregation of representative consumers in this problem will violate the price-taker assumption. Therefore this model is useful only for partial equilibrium analysis.

2.4 Why Is the Aggregation of Customers an Obstacle

The aggregation of consumers presents two main challenges:

1. The General Equilibrium Effects of price determination
2. The presence of Public goods in the system, such as reliability, that affect the pricing in the system.

To illustrate the difference in valuation with the presence of public goods with a network, assume there is a single resource in the economy, with a given availability M. This resource can be used and transformed into electric power (e.g. MW), which can be instantaneously delivered for consumption as energy (e.g MWh), or left available as a reliability resource in case an unexpected circumstance arises (in power systems parlance, a contingency).

Assume there are $b = 1, \ldots, n_b$ nodes (or buses). Each bus represents a different location with a consumer or a producer (generator), or both. There may be some buses with neither consumption nor production. These buses' function is to connect geographically disparate locations in a real network.

For the buses with generation facilities (injections into the network), it is assumed that there is a single generator.[1] There are $j = 1, \ldots, n_g$ generators. A generator placed in bus i is denoted by g_i. The generation plants have a technology $E_i(\cdot)$ that transforms a portion f_i^c of the resource (M) into electric power p_i as follows $p_i = E_i(f_i^c)$. This same technology function can also transform a portion of the resource f_i^r into electric reliability services r_i as follows $r_i = E_i(f_i^r)$. The technology function does not have to be convex (e.g fixed setup costs), though it will be assumed so for the sake of simplicity of analysis [76]. The quality of power depends on a certain level of quality (or reliability) $Q \geq 0$, obtained from the contributions of each one of the generation plants r_i. Additionally, each

[1] In most systems it is usual to have more buses than generators, though test systems often differ, e.g the modified version of NPCC used in the runs here.

generator has a set of technical characteristics, including the upper and lower production bounds ($P_{max,i}$, $P_{min,i}$)

For the buses with consumption (extractions from the network), the extractions represent the net consumption at that specific location. All consumers in a given location are assumed to have the same reliability[2] The I consumers have extractions from the network $i = 1, \ldots, I$ representing their energy demands. For the sake of simplicity, it can be assumed that there is a single representative consumer at each bus with extractions from the network, representing the aggregate demand at that particular location, i.e. consumers in the distribution network have preferences that can be aggregated, e.g. a Gorman Form [43].

For every node (and hence every consumer) in the network, there is a utility function u_i, dependent on three variables: the consumption of instantaneous power e_i, the quality of the bulk power system Q, and the consumption of other goods c_i, with $\frac{\partial u_i(\cdot)}{\partial e_i}$, $\frac{\partial u_i(\cdot)}{\partial Q}$ and $\frac{\partial u_i(\cdot)}{\partial c_i}$ being nonnegative. The aggregation is done by weighting each individual utility function u_i using a social welfare function W.

The transmission system is modeled as a Direct Current (DC) system. A DC model relates real power to bus voltage angles with linear network equations, assuming the system has no losses. Each transmission line has a maximum rating capacity $r_l \geq 0$, and the overall system bus susceptance matrix is defined by B. Let C define the branch susceptance matrix. The DC power flow solves the set of voltage angles at non-reference buses by solving a set of power flow equations of the form $P_f(\Theta) = B_f\Theta + P_{f,\text{shift}}$. Table 2.2 defines the sets and variables used in this problem.

[2] To be consistent with the overall modeling used in this document, the nodes are in fact buses in a transmission system part of a wholesale market, rather than buses in a distribution network.

2.4.1 Problem Formulation

Table 2.2: Nomenclature for the problem

Variable	Description
$\mathscr{B}$	Set of all buses, n_b elements.
$\mathscr{G}$	Set of generating units, n_g elements.
$\mathscr{I}$	Set of consumers, I elements.
$\mathscr{L}$	Set of connections (transmission lines), n_l elements.
M	Total availability of resources in the economy.
Q	Reliability level in the network.
p_i, r_i	Electric power and electric reliability services provided
e_i, c_i	Consumption of Electric power and other goods in the system

The system characteristics (e.g. generator capabilities, transmission parameters, cost of generation) are exogenous parameters in the optimization. The problem for the social planner will be given by:

$$\max_{e_i,c_i,Q,p_i,r_i,f_i^c,f_i^r} W(u_1(e_1,c_1,Q),\ldots,u_I(e_I,c_I,Q)) \tag{2.18}$$

subject to

$$e_i - p_i = \textstyle\sum_{k\in\mathscr{I}} B_{ik}\theta_k \quad \forall i \in \mathscr{I} \tag{2.19}$$

$$p_i = E_i(f_i^c) \quad \forall i \in \mathscr{I} \tag{2.20}$$

$$r_i = E_i(f_i^r) \quad \forall i \in \mathscr{I} \tag{2.21}$$

$$r_i = Qp_i \quad \forall i \in \mathscr{I} \tag{2.22}$$

$$\textstyle\sum_{k\in\mathscr{I}} f_k^c + \sum_{k\in\mathscr{I}} f_k^r + \sum_{k\in\mathscr{I}} c_k \le M \quad \forall i \in \mathscr{I} \tag{2.23}$$

$$\textstyle\sum_{k\in\mathscr{I}} C_{lk}\theta_k \le |r_l| \quad \forall l \in \mathscr{L} \tag{2.24}$$

$$P_{min,i} \le p_i + r_i \le P_{max,i} \quad \forall i \in \mathscr{I} \tag{2.25}$$

Consistent with the convention used in MATPOWER, positive values of e_i are considered injections. Equation 2.19 states the power balance equation for active power. Equations 2.20 and Equation 2.21 define how the available resource in the economy is transformed by the generators into either energy or reliability services. Equation 2.22 defines the total reliability in the system as a function of the energy generated. Equation 2.22 defines the resource constraint in the economy, while equation 2.25 states the transmission constraints in the network. Finally, equation 2.25 defines the technical constraints in the system for each generator. The Lagrangian for the social planner problem, is then:

$$
\begin{aligned}
\mathcal{L}(\cdot) = & W(u_1(e_1, c_1, Q), \ldots, u_I(e_I, c_I, Q)) + \sum_{i \in \mathcal{I}} \lambda_i (\sum_{k \in \mathcal{I}} B_{ik}\theta_k - e_i + p_i) \\
& + \sum_{i \in \mathcal{I}} \psi_i (r_i - Qp_i) + \gamma(M - \sum_{k \in \mathcal{I}} f_k^c - \sum_{k \in \mathcal{I}} f_k^r - \sum_{k \in \mathcal{I}} c_k) \\
& + \sum_{l \in \mathcal{L}} \tau_l^+ (r_l + \sum_{k \in \mathcal{I}} C_{lk}\theta_k) + \sum_{l \in \mathcal{L}} \tau_l^- (r_l - \sum_{k \in \mathcal{I}} C_{lk}\theta_k) \\
& + \sum_{i \in \mathcal{I}} \mu_i^+ (p_i + r_i - P_{max,i}) + \sum_{i \in \mathcal{I}} \mu_i^- (-p_i - r_i + P_{min,i})
\end{aligned}
\tag{2.26}
$$

The set of $\{\lambda_i\}$ in (2.26) correspond to the Lagrange multipliers for power at each bus of the system. The sets $\{\gamma_i\}$, $\{\tau_l^+\}$, $\{\tau_l^-\}$, $\{\mu_i^+\}$, $\{\mu_i^-\}$ and γ correspond in turn to the multipliers for reliability in the system, transmission limits, the technical limits of the generators and the resource constraint.

Focusing now on the optimization by individual consumers, the problem is as follows:

$$\max_{e_i, c_i, Q} u_i(e_i, c_i, Q) \tag{2.27}$$

subject to

$$\lambda_i e_i + \gamma c_i + \psi_i Q \leq m_i \tag{2.28}$$

The objective function for the individual consumer is defined as above for consumer i. Equation 2.28 is the consumer's budget constraint, with λ_i as the locational marginal price at bus i, γ as the price for the consumption of other goods, and ψ_i as the price for the quality of the energy (reliability) delivered. Each consumer is endowed with a portion of the total resources in the economy m_i. This formulation is similar to [47], although here demand reduction is not a decision variable that can contribute to reliability in the system.

2.4.2 Optimality Conditions

The First Order Conditions for the social planner are as follows:

for e_i

$$\frac{\partial W(\cdot)}{\partial u_i(\cdot)} \frac{\partial u_i(\cdot)}{\partial e_i} = \lambda_i \tag{2.29}$$

for c_i

$$\frac{\partial W(\cdot)}{\partial u_i(\cdot)} \frac{\partial u_i(\cdot)}{\partial c_i} = \gamma \tag{2.30}$$

for Q

$$\sum_{i \in \mathscr{I}} \left[\frac{\partial W(\cdot)}{\partial u_i(\cdot)} \frac{\partial u_i(\cdot)}{\partial Q} \right] = \sum_{i \in \mathscr{I}} \psi_i E_i(f_i^c) \tag{2.31}$$

for f_i^c

$$\lambda_i \frac{\partial E_i(\cdot)}{\partial f_i^c} - \psi_i Q \frac{\partial E_i(\cdot)}{\partial f_i^c} + \mu_i^+ \frac{\partial E_i(\cdot)}{\partial f_i^c} - \mu_i^- \frac{\partial E_i(\cdot)}{\partial f_i^c} = \gamma \tag{2.32}$$

for f_i^r

$$\psi_i \frac{\partial E_i(\cdot)}{\partial f_i^r} + \mu_i^+ \frac{\partial E_i(\cdot)}{\partial f_i^r} - \mu_i^- \frac{\partial E_i(\cdot)}{\partial f_i^r} = \gamma \tag{2.33}$$

for θ_i

$$\sum_{k \in \mathscr{I}} \lambda_k B_{ki} + \sum_{l \in \mathscr{L}} \tau_l^+ C_{li} - \sum_{l \in \mathscr{L}} \tau_l^- C_{li} = 0 \tag{2.34}$$

To analyze some of the tradeoffs, the utility equations can be re-arranged as:

$$\frac{\frac{\partial u_i(\cdot)}{\partial e_i}}{\frac{\partial u_i(\cdot)}{\partial c_i}} = \frac{\lambda_i}{\gamma} \tag{2.35}$$

$$\sum_{k \in \mathscr{I}} \frac{\frac{\partial u_k(\cdot)}{\partial Q}}{\frac{\partial u_k(\cdot)}{\partial c_k}} = \frac{\sum_{k \in \mathscr{I}} \psi_k E_k(f_k^c)}{\gamma} \tag{2.36}$$

$$\sum_{k \in \mathscr{I}} \frac{\frac{\partial u_k(\cdot)}{\partial Q}}{\frac{\partial u_k(\cdot)}{\partial e_k}} = \frac{\sum_{k \in \mathscr{I}} \psi_k E_k(f_k^c)}{\lambda_i} \tag{2.37}$$

The FOC's faced by the individual consumer can be re-arranged as:

$$\frac{\frac{\partial u_i(\cdot)}{\partial e_i}}{\frac{\partial u_i(\cdot)}{\partial c_i}} = \frac{\lambda_i}{\gamma} \tag{2.38}$$

$$\frac{\frac{\partial u_i(\cdot)}{\partial Q}}{\frac{\partial u_i(\cdot)}{\partial c_i}} = \frac{\psi_i}{\gamma} \tag{2.39}$$

$$\frac{\frac{\partial u_i(\cdot)}{\partial Q}}{\frac{\partial u_i(\cdot)}{\partial e_i}} = \frac{\psi_i}{\lambda_i} \tag{2.40}$$

Contrasting the FOC's for the individual with those of the social planner (Equations 2.40 and 2.37 respectively), the marginal rates of substitution between consumption of the public and the private goods differ due to the valuation of all agents included by the public planner. Consequently, solving for the optimal levels of the reliability good and the private consumptions, the solutions will differ. This will lead to an under-provision of the quality of power good for the individual optimizer, due to the marginal valuations given by the agents versus those of the social planner. The electricity market in general is characterized by the presence of public goods. Past research at this group [44] analyzes the presence of public goods in the case of environmental regulation and the effect this has on the operation of socially optimal markets. The under provision of public goods will be below the Pareto Optimal level of provision, a classic economics result, shown by Samuelson [63]. Therefore, the quality needed to sustain the flows in the system (minimum voltage levels and reactive power) is unlikely to be provided at economically efficient levels using a private valuation mechanism. In cases in which the pricing of the public good is set to coincide with the marginal valuation given by the social planner, the problem would be solved, under what is known as a Lindahl Equilibrium. The main implication of Lindahl's equilibrium is that the externality can be corrected, under external pricing (via tax shares) that aligns private and social incentives. However, the main complication of this approach is that it requires revelation of preferences by all agents in the economy [41]. Some experimental work on willingness to pay (WTP) for public goods was done by Bohm [8], but its practical application for reliability in the context of the electricity market is a challenging task. Additionally, the adoption of intermittent sources of energy, such as wind and solar, require more explicit modeling of the probability distribution of these resources and its effects on energy and ancillary services procurement decisions, interacting with the public goods in the network. For this reason, the role of the System Operator as a planner with information of all agents in the system and the transmission constraints allows to operate the system in a more efficient way.[3]

[3] In fact, while there may be some information not known by the system operator, as the cost functions of each generator, the market design can help to make the missing information incentive compatible. In the case of environmental goods, the asymmetries in information make the public valuation more challenging.

2.5 Conclusions

The use of classical dynamic optimization techniques allows partial replication of the decision making of individual consumers, given a set of rather restrictive assumptions. In the case of the optimal management of an ESS resource, the optimal solution shows that the consumer utilization follows the path of degradation of the battery. The use of a logarithmic function that mimics the degradation of certain types of batteries [84, 27], allows for an analytical solution. This parametrization is exogenously determined and therefore negates the possible benefits obtained by extreme operation of the resource. The result comes directly from the assumptions of the model, as quasi steady state behavior is expected, and therefore arbitrage opportunities should not be widely available. The uncertainty modeled is based on the degradation path of the ESS capacity. In the case of the optimal replacement of an ESS source, the results also show a dependence on technology parameters, namely the replacement cost and the degradation of a given technology, modeled by its depreciation. The operational consumer model leads to an optimal policy of arbitration across time, which which would lead to elimination of price differences over the day in a model in which utilization is feedback into consumer electricity prices.

All these models are applications of optimal control policies, to different facets of the consumer decision making. This is an approach favored in many branches of economics including macroeconomic policy. This is a powerful model that has been used for policy formulation. As with any toolset, the usefulness of the results obtained is dependent on the nature of the required simplifying assumptions used in order to make the models analytically tractable. The main issue of such a modeling is that the required detail level cannot possibly be attained without resorting to numerical optimization methods. However, once numerical methods are used, the 'elegance' of the model is discarded, and hence the researcher is faced with the question of the real usefulness of the overall approach to the question at hand. It is my opinion that the strength of this modeling is very limited to answer the kind of questions that arise in modeling the consumer decision making process if we are to limit to analytical solutions of the problem. However, these simplified models provide a formalization on the decisions, and sometimes can be useful to correct the intuition on usage of certain resources.

CHAPTER 3

DETERMINISTIC INTER-TEMPORAL MODEL

This chapter focuses on the solution to a deterministic problem from the point of view of a social planner whose objective is to maximize the welfare of the participants in the energy market (generators and consumers). It utilizes a network wherein the physical flows of power follow Kirchoff's current and voltage laws.

The antecedents to the network problem in engineering models can trace its roots back to the original economic dispatch and Optimal Power Flow (OPF) contributions by Carpentier [10]. Later research has included welfare considerations that allow for optimal load shedding, in the framework of support for ramping service provision [77]. The issue of proper provision of ancillary services is discussed in [56], with special attention paid to the necessity of a clear remuneration structure of these services for adequate quality of service in the Australian New Electricity Market (NEM). Part of the philosophy of NEM is that participants in energy markets should be paid for providing energy services, and pay for the services they use.

The use of RES in the system, specifically wind, is studied in [32] with a wind model that assesses the reliability contribution of a wind farm. The methodology is comprehensive, while recognizing the high level of data requirements for proper calculation. Such high data input requirements are a general problem that can limit the usability of agents with constrained data (ISO's should generally have such information). The study of the capacity contribution of wind is a subject of continued debate. In general terms, the support provided by wind generation is dependent on the characterization of the resource, and its relation to the demand in the system [33].

In the economic literature, Joskow and Tirole [29] study a network-less problem with heterogeneous consumers that could be curtailed in their demand, according to assumed price-sensitivity preferences assigned using a scaling factor. The authors objective is to identify the optimal level of investment to cover the electricity demand, and to calculate the outputs and price schedules expected. Their results provide a limited, stylized benchmark to compare regulatory schemes.

The aim of the model in this chapter is to provide an engineering-economic framework to evaluate the use of storage resources, as optimized by a social planner, in the context of high penetrations of Renewable Energy Sources (RES) in the electricity system. Since the model is deterministic, the uncertainty in the wind is modeled as a gaussian noise in each period that affects the availability of wind.

The main contribution of this work is the use of specific restrictions that reflect the technical (engineering) characteristics of the electricity network, the generating units and the economic and dynamic optimization nature of the energy dispatch for an ESS and for all generating units. Such considerations are necessary to reflect the true benefits (and costs) faced by an ISO, the congestion that can lead up to the formation of load pockets, and the effects that adoption of RES has in the system. This is the first paper to include a complex model of the A.C. characteristics of the network and the inter-temporal tradeoff of using an ESS unit. A complete representation of the characteristics of the generators (e.g. capability curves) is included in the analysis. The problem is solved using lagrangian relaxation, and the optimality conditions for inter-temporal tradeoffs are analyzed. A computational implementation of the problem using MATPOWER [85] is done, with case studies to illustrate the use of the methodology.

The initial model proposed assumes that the unit commitment problem has already been solved, and therefore the set of generating units available is ready to be dispatched without dealing with startup and shutdown decisions (as in [42]). The second part includes the formulation of a multiperiod unit commitment, optimal power flow problem, with minimum up and down times.

3.1 Formulation, Multiperiod OPF Problem

Assume a social planner seeking to maximize social welfare by solving an optimal power flow in an AC network with n_b buses, n_t time periods, n_g generating units and n_e ESS units. Table 3.1 defines the sets and variables used in this problem. The order of the subindices is maintained whenever possible, and no commas are used, unless there is an operation on the index (e.g. $t+1$).

Table 3.1: Nomenclature for the problem

Variable	Description
$\mathscr{T}$	Set of all time periods, n_t elements.
$\mathscr{B}$	Set of all buses, n_b elements.
$\mathscr{G}$	Set of generating units, n_g elements.
$\mathscr{E}$	Set of ESS units, n_e elements.
Θ, V	Vector of n_b bus voltage angles and magnitudes.
P, Q	Vector of n_g active and reactive power injections from generators.
E, F	Vector of n_e active/reactive power injections from ESS units.
$C_{P_i}(\cdot), C_{Q_i}(\cdot)$	Cost for i active and reactive injections from generators.
$C_{E_i}(\cdot), C_{F_i}(\cdot)$	Cost of active and reactive injections for ESS units.
$\pm R_{Xi}^{\text{PHYS}\pm}$	Physical limits for active power ($X = P, E$) for generators and ESS respectively.
$\pm R_{Yi}^{\text{PHYS}\pm}$	Physical limits for reactive power ($Y = Q, F$) for generators and ESS respectively.
ρ^t	Discount factor.

For notational simplification, super indices refer to the set of all variables across that dimension. For example, e^t will refer to all injections from ESS in period t. The problem can be formulated as follows.

$$\min_{\Theta,V,P,Q,E,F} \sum_{t\in\mathcal{T}} \rho^t \sum_{i\in\mathcal{G}^t\cup\mathcal{E}^t} C_{P_i}(p_{it}) + C_{Q_i}(q_{it}) + C_{E_i}(e_{it}) + C_{F_i}(f_{it}) \tag{3.1}$$

subject to

$$g_P^t(\Theta^t, V^t, P^t, Q^t, E^t, F^t) = 0, \quad \forall t \in \mathcal{T} \tag{3.2}$$

$$g_Q^t(\Theta^t, V^t, P^t, Q^t, E^t, F^t) = 0, \quad \forall t \in \mathcal{T} \tag{3.3}$$

$$h^t(\Theta^t, V^t, P^t, Q^t, E^t, F^t) \leq 0, \quad \forall t \in \mathcal{T} \tag{3.4}$$

$$-R_{Pi}^{\text{PHYS}-} \leq p_{it} - p_{i,t-1}^t \leq R_{Pi}^{\text{PHYS}+}, \forall i \in \mathcal{G}, t \in \mathcal{T} \tag{3.5}$$

$$-R_{Qi}^{\text{PHYS}-} \leq q_{it} - q_{i,t-1} \leq R_{Qi}^{\text{PHYS}+}, \forall i \in \mathcal{G}, t \in \mathcal{T} \tag{3.6}$$

$$-R_{Ei}^{\text{PHYS}-} \leq e_{it} - e_{i,t-1}^t \leq R_{Ei}^{\text{PHYS}+}, \forall i \in \mathcal{E}, t \in \mathcal{T} \tag{3.7}$$

$$-R_{Fi}^{\text{PHYS}-} \leq f_{it} - f_{i,t-1} \leq R_{Fi}^{\text{PHYS}+}, \forall i \in \mathcal{E}, t \in \mathcal{T} \tag{3.8}$$

$$u_{\max,ie} \cdot (sc_{i,0} - 1) \leq \textstyle\sum_{\tau<=t} e_{i\tau} \cdot \alpha \leq u_{\max,ie} \cdot sc_{i0}, \forall i \in \mathcal{E}, t \in \mathcal{T} \tag{3.9}$$

$$\textstyle\sum_{t\in\mathcal{T}} e_{it} \cdot t = 0, \forall i \in \mathcal{E} \tag{3.10}$$

Each generator has a capability curve that determines the relation between the active and reactive output it can inject into the network. Since the implementation is done in MATPOWER, these capability curves can be trapezoidal. By convention, positive values of p, q, e and f are considered injections, while negative values are considered demands.

The equality constraints (A.2)-(3.3) are explicitly defined by the power balance equations for active and reactive power.

$$p_{it} - \sum_{j\in\mathcal{B}} |v_{jt}||v_{it}|\Big[G_{ijt}\cos(\theta_i - \theta_j) + B_{ijt}\sin(\theta_i - \theta_j)\Big] = 0, \quad \forall i \in \mathcal{B}, t \in \mathcal{T} \tag{3.11}$$

$$q_{it} - \sum_{j \in \mathscr{B}} |v_{jt}||v_{it}| \Big[G_{ijt} \sin(\theta_i - \theta_j) - B_{ijt} \cos(\theta_i - \theta_j) \Big] = 0, \quad \forall i \in \mathscr{B}, t \in \mathscr{T} \tag{3.12}$$

The inequality constraints defined by (A.3) correspond to two set of branch flow limits as function of the bus voltages and angles, for the *from* and *to* flows on each branch (see [81] and [85] for further detail). Equations (A.9) and (A.10) determine the active ramping constraints for generators and ESS units, according to their physical characteristics. Equations (3.6) and (3.8) are the equivalent conditions to (A.9) and (3.8) for reactive outputs. Equation (A.11) reflects the energy limits on the ESS units, taking into account the initial state of charge. α denotes the time period interval over which a certain power output is needed. Equation (A.12) is a transversality condition, denoting that after all injections and demands into the network are taken into account, the final state of charge of the ESS should be equal to the initial state of charge. For notational purposes, it is assumed that there is only one generator per bus. The Lagrangian for the social planner problem, focusing only in active power, is then:

$$
\begin{aligned}
\mathcal{L}(\Theta, V, P, E, \lambda, \mu) = & \sum_{t \in \mathcal{T}} \rho^t \sum_{i \in \mathcal{G}^t \cup \mathcal{E}^t} C_{P_i}(p_{it}) + C_{E_i}(e_{it}) + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{G}^t \cup \mathcal{E}^t} \lambda_{it}(g_{Pg_{it}} - p_{it}^{net} + P_{Dit}) \\
& + \lambda_{other}^T g_{other} + \mu_{other}^T h_{other} \\
& + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{G}^t} \mu_{\text{PHYS}\ RAMP_{it}^+}(p_{it} - p_{i,t-1} - R_{Pi}^{\text{PHYS+}}) \\
& + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{G}^t} \mu_{\text{PHYS}\ RAMP_{it}^-}(-p_{it} + p_{i,t-1} - R_{Pi}^{\text{PHYS}-}) \\
& + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{E}^t} \mu_{\text{PHYS}\ ERAMP_{it}^+}(e_{it} - e_{i,t-1} - R_{Ei}^{\text{PHYS+}}) \\
& + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{E}^t} \mu_{\text{PHYS}\ ERAMP_{it}^-}(-e_{it} + e_{i,t-1} - R_{Ei}^{\text{PHYS}-}) \\
& + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{E}^t} \mu_{\text{ESS}\ PHYS_{it}^+}(\sum_{\tau \leq t} e_{i\tau} \cdot \alpha - u_{\max,ie} \cdot sc_{i0}) \\
& + \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{E}^t} \mu_{\text{ESS}\ PHYS_{it}^-}(-\sum_{\tau \leq t} e_{i\tau} \cdot \alpha + u_{\max,ie} \cdot (sc_{i0} - 1))
\end{aligned}
\tag{3.13}
$$

The set of $\{\lambda_{it}\}$ in (3.13) corresponds to the sequence of Lagrange multipliers for active power for each bus and time period. The multipliers λ_{other}^T and μ_{other}^T correspond to other equality and inequality constraints not explicitly expressed here (e.g. Maximum power output per generator, $P_{max,i}$). The sets $\{\mu_{\text{PHYS}\ RAMP_{it}^+}\}$, $\{\mu_{\text{PHYS}\ RAMP_{it}^-}\}$, $\{\mu_{\text{PHYS}\ ERAMP_{it}^+}\}$ and $\{\mu_{\text{PHYS}\ ERAMP_{it}^-}\}$ are the Karush-Kuhn-Tucker (KKT) multipliers on the inter-temporal ramping constraints per generator. p_{it}^{net} is defined as $p_{it} + e_{it}$, where negative values of e_{it} correspond to demands from the network, and positive values to injection into the network.

3.1.1 Optimality Conditions

The First Order Conditions (FOC's) with respect to p_{it} and e_{it} can be rearranged to obtain the following:

For p_{it}

$$\rho^t \frac{\partial C_{P_i}(p_{it})}{\partial p_{it}} + (\mu_{\text{PHYS } RAMP^+_{it}} - \mu_{\text{PHYS } RAMP^+_{i,t+1}}) - (\mu_{\text{PHYS } RAMP^-_{it}} - \mu_{\text{PHYS } RAMP^-_{i,t+1}})$$
$$= \lambda_{it} = \frac{\partial \mathcal{L}}{\partial P_{Dit}} \tag{3.14}$$

And for e_{it}:

$$\rho^t \frac{\partial C_{E_i}(e_{it})}{\partial e_{it}} + (\mu_{\text{PHYS } ERAMP^+_{it}} - \mu_{\text{PHYS } ERAMP^+_{i,t+1}}) - (\mu_{\text{PHYS } ERAMP^-_{it}} - \mu_{\text{PHYS } ERAMP^-_{i,t+1}})$$
$$+ \alpha \sum_{\tau \geq t}^{n_t} (\mu_{\text{ESS } PHYS^+_{i\tau}} - \mu_{\text{ESS } PHYS^-_{i\tau}}) = \lambda_{it} = \frac{\partial \mathcal{L}}{\partial P_{Dit}} \tag{3.15}$$

The economic interpretation of the FOC's is that any additional demand can be covered by either moving a generator, (3.14) or moving an ESS, (3.15). For each one, an inter-temporal cost is associated to moving the injection into the network, either as a ramp up, a ramp down or, in the case of ESS units, the availability of energy stored in the system. The λ_{it} in equations (3.14) and (3.15) measure the change in the objective value (cost) by relaxing the constraint for node i and time period t. This shadow price is used for compensation of generators and payments from loads and is identified in the literature as the Locational Marginal Price (LMP). Analyzing the FOC's for (3.15) in two consecutive periods, it can be shown that

$$\rho^{t+1}\frac{\partial C_{E_{i,t+1}}(e_{i,t+1})}{\partial e_{i,t+1}} - \rho^{t}\frac{\partial C_{E_{it}}(e_{it})}{\partial e_{it}} + (-\mu_{\text{PHYS }ERAMP^{+}_{it}} + 2\times\mu_{\text{PHYS }ERAMP^{+}_{i,t+1}} - \mu_{\text{PHYS }ERAMP^{+}_{i,t+2}}) - (-\mu_{\text{PHYS }ERAMP^{-}_{it}} + 2\times\mu_{\text{PHYS }ERAMP^{-}_{i,t+1}} - \mu_{\text{PHYS }ERAMP^{-}_{i,t+2}}) - \alpha(\mu_{\text{ESS }PHYS^{+}_{it}} - \mu_{\text{ESS }PHYS^{-}_{it}}) = \lambda_{i,t+1} - \lambda_{it} \tag{3.16}$$

Therefore, in consecutive periods, the difference in nodal prices is equal to:

- The discounted difference in marginal cost of use of the ESS resource
- The inter-period shadow price differences for increasing the injection from the ESS resource (ramp up)
- The inter-period shadow price differences for increasing the charging of the ESS resource (ramp down)
- The shadow price of using the energy stored in the ESS resource.

Generalizing between periods t and $t+\tau$, the FOC's can be modified to obtain:

$$\rho^{t+\tau}\frac{\partial C_{E_{i,t+\tau}}(e_{i,t+\tau})}{\partial e_{i,t+\tau}} - \rho^{t}\frac{\partial C_{E_{it}}(e_{it})}{\partial e_{it}} + (\mu_{\text{PHYS }ERAMP^{+}_{i,t+\tau}} - \mu_{\text{PHYS }ERAMP^{+}_{i,t+\tau+1}} - \mu_{\text{PHYS }ERAMP^{+}_{it}} + \mu_{\text{PHYS }ERAMP^{+}_{i,t+1}}) - (\mu_{\text{PHYS }ERAMP^{-}_{i,t+\tau}} - \mu_{\text{PHYS }ERAMP^{-}_{i,t+\tau+1}} - \mu_{\text{PHYS }ERAMP^{-}_{it}} + \mu_{\text{PHYS }ERAMP^{-}_{i,t+1}}) - \alpha\sum_{\xi=t}^{t+\tau-1}(\mu_{\text{ESS }PHYS^{+}_{i\xi}} - \mu_{\text{ESS }PHYS^{-}_{i\xi}}) = \lambda_{i,t+\tau} - \lambda_{it} \tag{3.17}$$

The FOC's in (3.17) show the optimal equilibrium condition for any two periods in which energy is to be used. The structure is similar to the aforementioned costs for the consecutive periods case, with additional terms for consecutive ramp costs in periods t and $t+\tau$.

3.1.2 Dynamic Information Updates

To integrate the stochastic changes derived from generation availability and loads in the system, the following algorithm is used.

Algorithm 1 Dynamic Updates

1: $n \leftarrow 0$
2: The optimizer (e.g. social planner) chooses time horizon ($T = n_t$) and number of information updates in which optimization is run (N)
3: **repeat**
4: The best available forecast for wind and load are used in the model (variables with stochastic disturbances)
5: A dynamic optimization is run for the chosen time horizon, starting at time $t + n$ and finishing at time $T + n$
6: In the case of several locations for wind farms, update the forecast for each location
7: $n \leftarrow n + 1$; Go to Step 4
8: **until** $n = N$, Number of user-specified information updates reached

The algorithm re-optimizes on a moving-window time horizon, as more information becomes available. In principle, any variable can be updated, e.g., if a system condition changes for the time horizon considered. However, the most likely variables to be updated correspond to wind information and notification of system outages. This is amenable to updates coming from Phasor Measurement Units (PMU's).

The matrix of information updates for the stochastic variables (wind speed and load forecasts are provided) is shown in (3.18). The optimization horizon (number of periods in each single optimization) is given by T, and the number of specified information updates ('shifts') is given by N.

$$[W_f, L_f] = \begin{bmatrix} f(t) & f(t+1) & \dots & f(t+N) \\ f(t+1) & f(t+2) & \dots & f(t+1+N) \\ \vdots & \vdots & \ddots & \vdots \\ f(t+T) & f(t+T+1) & \dots & f(t+T+N) \end{bmatrix} \tag{3.18}$$

For a single multi-period OPF optimization (i.e., a one time run), only the information in each column is needed. Successive rows have the dynamic information updates. The added value of the information updates is that they allow to optimize in a receding horizon, therefore incorporating better the stochastic changes in the system. This framework is extended in the simulation implemented to allow for several ESS units in the system [36].

3.2 Data and Calibration

The framework from section 3.1 is applied for testing the effects of adding wind as a RES. The calibration of some of the parameters are taken from the literature or from data obtained by members of The Engineering and Economics of Electricity Research Group (E3RG) at Cornell. Parameters like the Value of Lost Load (VOLL) have been studied in the literature (see e.g. [80]). The numbers used were taken from conversations with ISO members, consistent with the social value commonly accepted.

3.2.1 Test Network

The test network used to study the effects of different wind models is a very modified version of the IEEE 30 bus network [4, 20]. This test network has been extensively used for studies at Cornell. It is divided in three areas. Area 1 is considered an urban area with most of the load in the system, a high VOLL (10,000 $/MWh), and limited and expensive sources of generation. Areas 2 and 3 are considered rural, with cheaper sources of generation and overall lower VOLL (5,000$/MWh). The total load of the system is 189MW, while the total generation capacity is 335MW. Therefore, a large amount of excess capacity is available in the system. However, the transmission lines between areas 2 and 3 and area 1 are constrained. Since the generation cost in areas 2 and 3 are lower, in an economic dispatch the local loads and as much as possible of the load in area 1 is covered. Once congestion increases, as demand rises, Area 1 will become a load pocket [39].

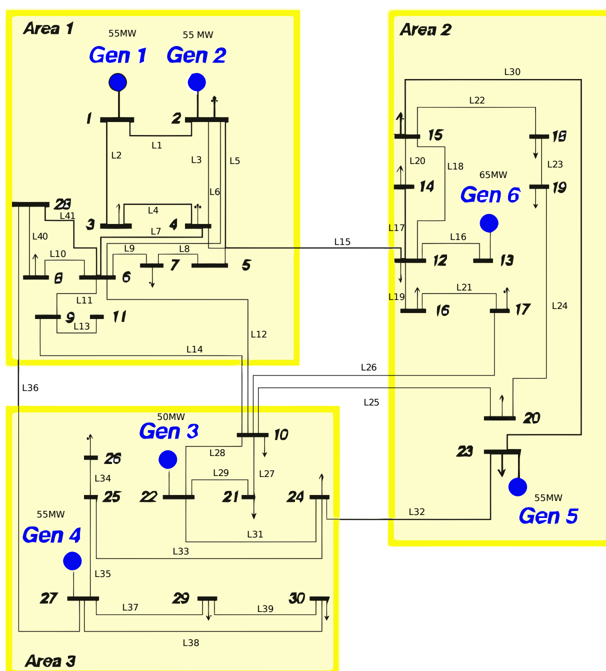

Figure 3.1: A One-Line-Diagram of the 30-Bus Test Network.

Figure 3.1 has the one-line-diagram of the 30-bus network, with the numbering of each area, line and generator. The composition of fuels for this system follows the proportions observed for the Northeastern Power Coordinating

Council as per [3]. Table 3.2 has the summary of the capacity and load in the system used.

Table 3.2: Summary of Generation Capacity and Load, 30 Bus system

	Capacity per Fuel Type (MW)					Total Cap.	Load
Location (area)	coal	cc gas	gct	oil	nhr		
1	0	0	45	65	0	110	84
2	70	0	0	0	50	120	56
3	0	40	0	0	65	105	49
Total	70	40	45	65	115	335	189

[a] Values shown are taken as peak values.

The fuel costs were obtained from PowerWorld and correspond to average prices observed in 2009, as shown in Table 3.3. Area 1 is assigned a high concentration of Gas Combustion Turbines (gct) and oil generation. This allocation corresponds to a stylized case of the generation mix for urban areas with legacy fleets (e.g. the city of New York). Areas 2 and 3 have more efficient, Combined Cycle Gas turbines (cc gas), coal and baseload capacity from Nuclear, Hydro and Refuse plants (nhr).

Table 3.3: Fuel Costs ($/MWh)

	coal	cc gas	gct	oil
Cost	25	55	80	95

3.2.2 Load Modeling

The loads were scaled according to historical data from the NYISO, distinguishing the profile changes between urban and rural. The demands are fixed blocks per time period. They are modeled as negative injections with associated negative costs (the VOLL per load at the substation level). Since this specification allows for outputs smaller than the maximum demand specified per period (both in absolute value), minimizing the expected cost, including load shedding as a cost, corresponds to the maximization of social welfare. The profiles themselves correspond to a day in April 2005 with low variability in intra-day demand from off-peak (night/early morning) and peak (around 5PM for Urban and 8PM for rural and overall system) loads.

3.2.3 Wind Modeling

For wind inputs, the methodology by Anderson and Cardell[5] is followed. Three components are taken into account and implicitly used in the simulation:

1. A set of hourly wind speeds from sites in New England, corresponding to data collected in 2005.
2. An ARMA model for hour-ahead forecasts as ISO's would have had at the decision time
3. A theoretical power curve to convert the forecasts into expected power outputs from the wind farm. The relation between wind speed and expected power output is given by equation (3.19).

$$P_t = c_p \times \frac{1}{2}\rho A_r v^3 \tag{3.19}$$

Where c_p is the wind turbine power coefficient, measuring the mechanical-electrical efficiency for a turbine (in the runs set to $\frac{16}{27}$.); ρ is the air density at standard atmosphere (kg/m^3); v is the wind velocity (m/s); and A_r is the area of the rotor.

Since there is no specific modeling of the stochasticity in inputs, the modeling of wind does not fully represent the behavior of this resource. The proxy modeling of the stochastic component of wind in these runs thus takes the expected available wind as a deterministic input, following the trends observed in historical data from New England regarding the available capacity. For each information update, the expected input was changed by a gaussian noise with zero mean. This update is meant to represent the forecasting errors that can be present as inputs. As the horizon goes further into the future, the variance was increased to represent the added uncertainty.

3.3 Case Study

The objective of this case study is to use the formulation in Section 3.1 to analyze the effects of geographical averaging for both wind and ESS, and price arbitrage over a day. The set of cases is limited to simple changes in the layout of the wind capacity and the ESS location. For this purpose, the following cases are considered:

1. Single ESS (40MWh capacity) in urban center (bus 8), single wind farm (50 MW capacity) in rural location (bus 13).
2. Single urban ESS, two wind farms in rural locations (buses 13 and 27), each one with a 25MW capacity and positively correlated wind patterns.
3. Two ESS units, one urban (bus 8, capacity 20 MWh) and one collocated with the wind farm (bus 13, capacity 20 MWh). Single wind farm with 50 MW capacity.
4. Two ESS units as Case 3, two wind farms as Case 2.

The marginal cost for the ESS is set to zero, as is the marginal cost of the wind generation units. This corresponds to a case in which the degradation of the ESS resource is negligible, for operating purposes. The ramping capacity of the ESS units is set equal to one-tenth of the energy capacity for the urban unit when individual, and to 4MW in Cases 3 and 4. The ramping power capacity of the rural ESS is one fourth of the energy capacity. Charging and discharging rates are set equal; therefore, in cases with a single wind farm, a full roundtrip charge-discharge cycle can be completed. No minimum charge constraints were included. The ESS usage here is subordinated to the network usage. It does not represent the battery of, e.g., a car, since transportation usage constraints are not included.

The wind forecasts for each location in Cases 2 and 4 are set as independent, but correlated, with a random noise component added. This modeling corresponds to a lower bound on the capacity of geographical averaging [32]. In such a case, the main advantages are the location in terms of network effects and congestion, rather than the potential gains due to complementary characteristics of the wind resource. The wind information is updated for each one of the N hourly displacements. Load profiles are also adjusted, following the matrix shown in equation (3.18).

$$[W_{fcst}, L_{fcst}] = \begin{bmatrix} f(7) & f(8) & \dots & f(13) \\ f(8) & f(9) & \dots & f(14) \\ \vdots & \vdots & \ddots & \vdots \\ f(6) & f(7) & \dots & f(12) \end{bmatrix} \tag{3.20}$$

The time steps used are hours, the optimization horizon (N) is 24 and the number of information updates is set to seven. The matrix of information updates follows the structure shown in equation (3.20). No contingent state is realized, and therefore it is expected that dispatches should closely follow the load profile, with small deviations due to the added random noise.

3.3.1 Results

Figure 3.2 shows the usage of the ESS units hour to hour for cases 1 and 2. Case 1 (left figure) can be considered the base case (Single Wind Farm, Single ESS in urban location). Each line corresponds to one of the information updates ('shifts'), with a small random noise added. The shift to the left corresponds to an hour advance. The horizontal axis shows the hour according to the shift considered. So for example the hour marked as 1 for n = 6 corresponds to 7AM ($t_s = 1 = 7 - 6 = t - n$). The ESS dispatch shows the usage of this resource as an arbitrage mechanism, charging in low demand periods (and therefore periods with cheap energy prices, like 1-6AM). For the last shift simulated ($t_s = 1$), starting at 1PM ($t = 13$), the energy available in the ESS is completely used, completing a full roundtrip for the battery (from fully charged to fully discharged and charged again). Due to the gaussian noise added, each information update is not an exact displacement to the left of the curve.

The distribution of the wind capacity (Figure 3.2, right pane) leads to a different usage of the ESS's available. By virtue of the increased availability of the wind resource, thanks to its geographical distribution, the ESS capacity is not fully required. This applies to all information updates. Additionally, for the ini-

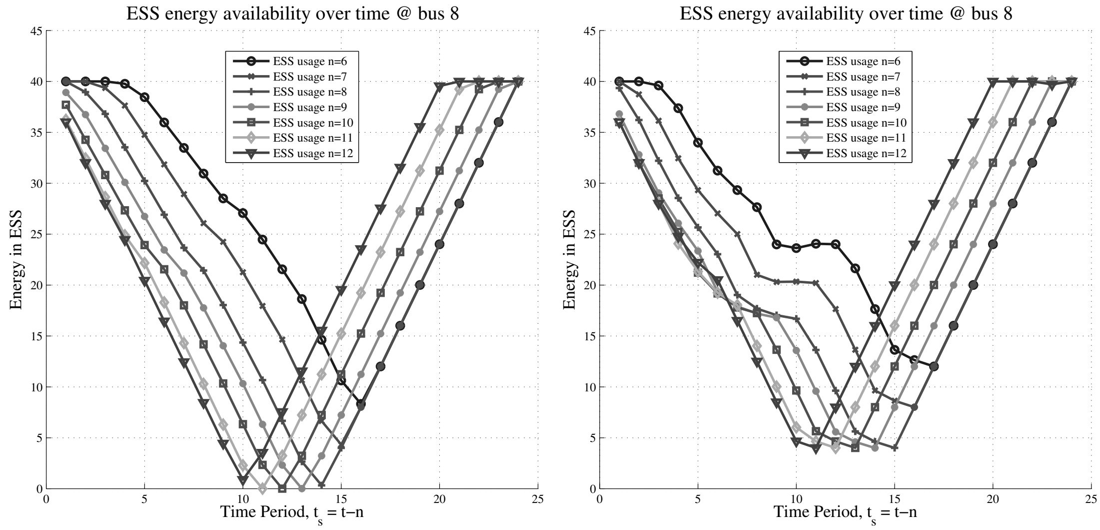

Figure 3.2: Energy Available from ESS units (MWh), Case 1 and 2

tial runs (e.g. starting at t = 7AM, t_s = 1), there is some idle time during certain relatively high demand periods (4PM, t = 16, t_s = 10). This situation occurs due to the limited time available to use the energy available in the ESS, given the ramping constraints on the battery. In such a case, it is not optimal to deplete it, as the control given by equation (A.12) establishes that the final state of charge should be equal to the initial one.

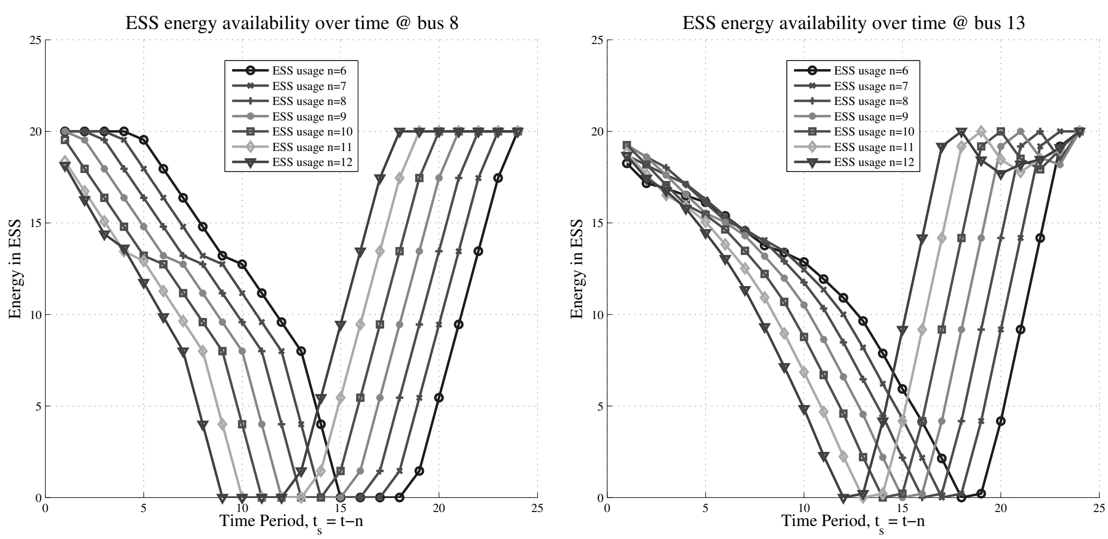

Figure 3.3: Energy Available from ESS units (MWh), Case 3

Figure 3.3 has the ESS usage for Case 3. The distribution of the ESS capacity, while maintaining a single wind farm, leads to slightly higher usage of an equivalent capacity of energy storage to that available in Case 1 (Sum of outputs shown in Figure 3.3). The location of the ESS units shapes the utilization curve, but overall the pattern of price arbitraging is maintained. Since the second ESS is placed in the same bus where the wind farm is, it can potentially help offset the variability of the wind resource.

Figure 3.4 shows the joint effect of distributing wind and energy storage capacity (Case 4). In this case, an effect that is observed in Case 2 is amplified: the ESS located in the urban area is charged in periods with shoulder demand (not very high, not very low load periods). This ESS is fully used (i.e., it completes a full discharge cycle, as shown in the curves). The dispatches of the wind farms have contrasting patterns: While the unit at bus 13 is fully used at all hours, the wind farm at bus 27 ramps up with the same rate of change as the charging of the the ESS placed in bus 8. While this is not a direct coupling, the ESS and the RES are complementary.

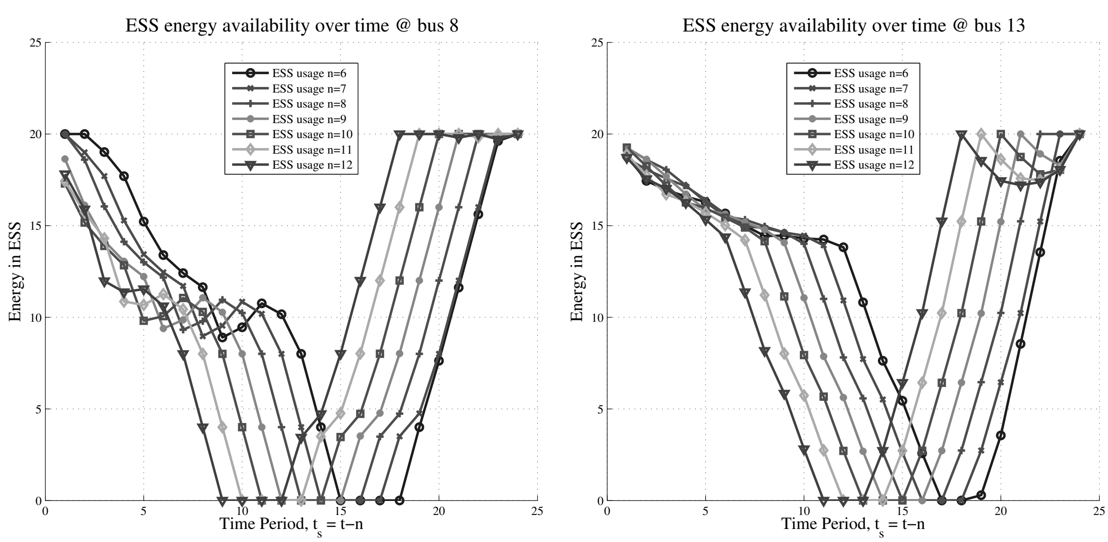

Figure 3.4: Energy Available from ESS units, Case 4

3.3.2 Payments in the Wholesale Market

Table 3.4 summarizes some key results over the 24 hour cycle, as an average of the correspondent hour for the seven information updates done. The variance is shown in parentheses. The Load Paid row shows the disbursements made by customers. The benefits of wind distribution are clear (comparing Case 1 to Case 2), while distributing the ESS capacity actually leads to higher load payments (Case 1 to Case 3). This result is due to the congestion in the system. It highlights the importance of the network topology. The average energy needed to cover the load of the day has a similar characterization as the customer payments. The distribution of wind capacity allows for lower energy needed (from a generation point of view), while the distribution of the ESS creates congestion in the system. The average amount of wind dispatched demonstrates the implicit coupling of wind resources with ESS. The distribution of ESS leads to a 6% decrease in the amount of wind used, again due to congestion. The conventional generation used shows the replacement observed in the generation fleet. Load Not Served is not included in Table 3.4, as no load is shed observed in any of the cases, for all the information updates. The energy provided by ESS units row shows a substitution away from ESS units when the wind capacity is distributed. This result may seem counterintuitive, as it would be expected that placing ESS capacity close to the wind farm would allow for coupling of both resources, and therefore higher overall ESS usage. But the non-linear effects created by the AC network leads to congestion that may in fact limit the total flow of wind energy from the (electrically) far location to the load center. Figure 3.5 summarizes the average payments over 24 hours for the seven information updates. In all cases, the operating costs are close in magnitude (though Case 4 has a clear advantage). However, the main difference lies in the difference

Table 3.4: Summary of Key Results

	Case 1	Case 2	Case 3	Case 4
Operating Costs ($1,000/day)	32.81	32.23	32.50	25.85
	(13.67)	(0.11)	(1.40)	(0.10)
Load Paid ($1,000/day)	146.29	90.62	147.77	86.76
	(9.66)	(0.08)	(0.01)	(0.00)
Energy Needed to cover load of day (MWh)	4,049.30	4,038.80	4,050.17	4,037.70
	(0.28)	(0.08)	(0.01)	(0.01)
Wind Energy Dispatched (MWh)	638.69	639.25	600.00	919.85
	(0.12)	(0.14)	(0.00)	(0.04)
Conventional Generation (%)	84.23	84.17	85.19	77.22
	(0.00)	(0.00)	(0.00)	(0.00)
Energy provided by ESS Unit(s) (MWh)	20.96	19.78	20.21	12.57
	(74.16)	(81.74)	(199.48)	(358.59)

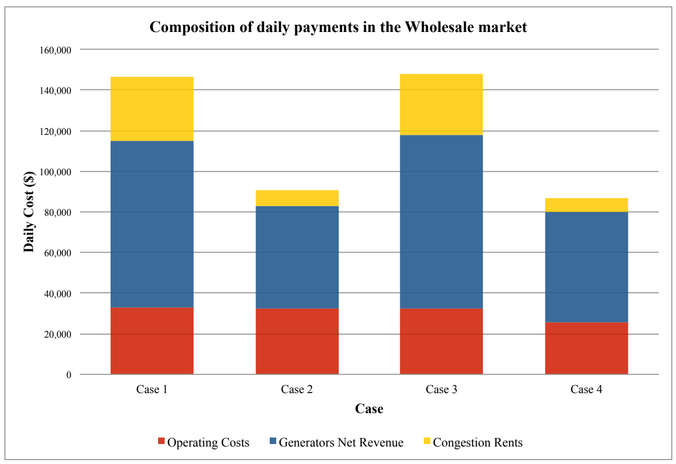

Figure 3.5: Composition of Payments in the Wholesale Market

in payments from loads, due to the separation of prices induced by congestion. The congestion rents are proportional to the generators net revenue, with ranges around 36% for Cases 1 and 3, and 12% for Cases 2 and 4. The detachment seen here is due to the large effect that wind distribution has on the congestion in the network.

Comparison of fuel dispatches

An advantage provided by the use of ESS is the possibility to service additional loads in periods of low demand, and therefore lower congestion in the network. Figure 3.6 shows the mean fuel composition used to service the same load profile in Cases 1 to 4. The dispatches shown correspond to the average dispatch observed over the 7 information updates simulated. In all cases, Gas Combustion Turbines (gct) and oil are not used for covering the load. This is due to the availability of cheaper sources of generation (including wind), lack of congestion in the network and overall low demand level.

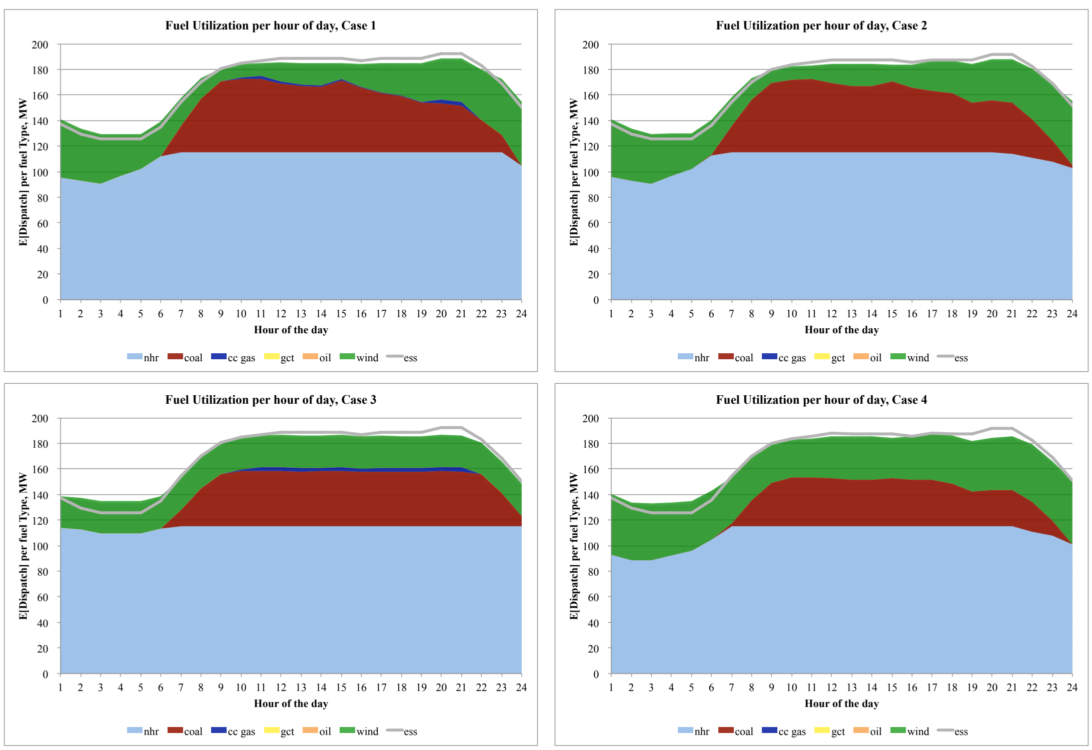

Figure 3.6: Generation Dispatch by Fuel Type

The main fuels used are Nuclear, Hydro and refuse (nhr, as baseload), coal (for load following) and wind. In Cases 1 and 3, the Combined Cycle (cc) gas capacity is sparely utilized, while Cases 2 and 4 replace this fuel away completely. ESS usage is shown as a thick line in the plots. In cases where this line is below the area indicating all generation, the difference between the upper area limit and the line correspond to charging periods for the ESS unit. Analogously, cases in which the 'ess' line is above the total fuel area correspond to network injections from the ESS units. ESS units are used to cover part of the peak demand in all cases, while charging is done at low demand periods, as expected.

The composition of the three main fuels is close in percent participation in the four cases. Case 3 is the only situation in which nhr participation is 3% higher than average nhr participation of the three remaining cases. On the other hand, coal has the lowest participation in the generation portfolio for Case 3 (distributed ESS, single wind) and Case 4 (Distributed ESS and wind). It is remarkable the extent to which distributing ESS units in the system (Case 3) leads to a very smooth operation of the baseload units ('nhr'). In fact, for both Cases 3 and 4, the operation of all the generation fleet does not witness sudden changes hour to hour (in average). Taking into account that no ramping costs are included in the objective function, this is an interesting result from the point of view of the usage of ESS units. It means that the wear-and-tear cost of the conventional generation fleet can be decreased by using these resources. Such investments will then have implications from the policy standpoint if explicit ramping markets are developed as another ancillary service.

To what extent the ESS units in the network provide support as grid resources is not clear cut in the simulated cases. Figure 3.7 compares the total dispatches net of wind for all cases. The distribution of wind in the system (comparing Case to 1 to Case 2) does not lead to adjustments of the conventional generation schedule, with almost overlapping total dispatch. The distribution of the ESS capacity (Case 3) however leads to overall higher dispatches at low demand periods (e.g. early hours of the day), and lower dispatches at peak periods. Distributing the wind capacity, joint with the ESS capacity (Case 4) shifts down the total dispatch from conventional sources due to the aforementioned increase on the usable wind capacity. This outcome, from the perspective of increasing usage of RES, is a positive, if anticipated outcome: the distribution of the wind resource, and the usage of storage mechanisms (both close to where the load is and coupled with the wind farms) are supporting mechanisms for better renewable utilization.

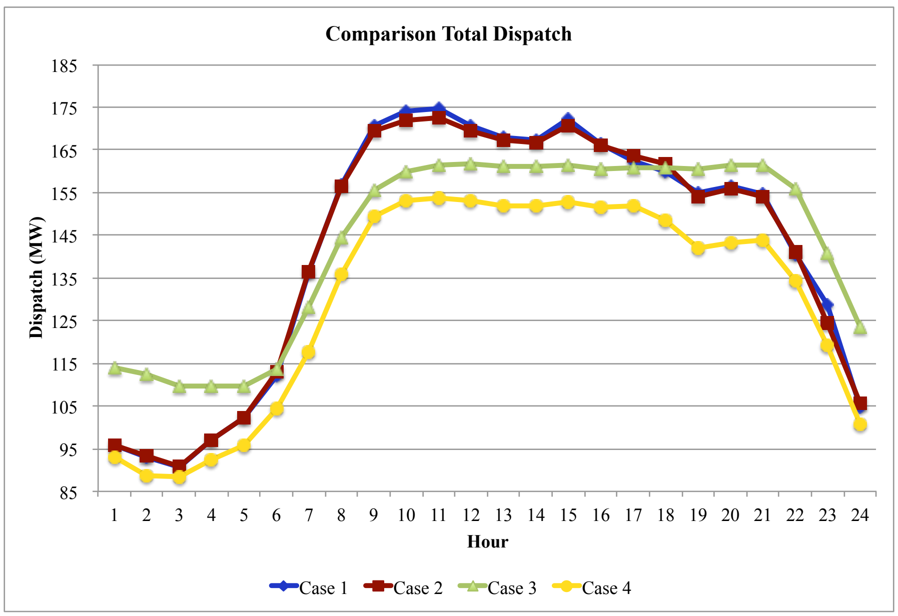

Figure 3.7: Comparison of Dispatches

The effect on prices is very dependent on location. In the 30-bus network, there are potentially 30 different prices. In the simulations performed, approximately 10 clusters of prices are observed during the day, with some separation as demand increases over the day. To simplify the analysis of prices, the simple arithmetic mean of prices over the 30 buses is calculated for the four cases simulated. Figure 3.8 plots the average price for all cases, giving an equal weight to all 30 buses in the system. The distribution of the wind capacity leads to lower average prices on the system, with average prices in the neighborhood of the cost of coal generation (Cases 2 and 4). The average prices for the other cases at peak hours are close to the marginal cost of combined cycle gas turbines (55$/MW).

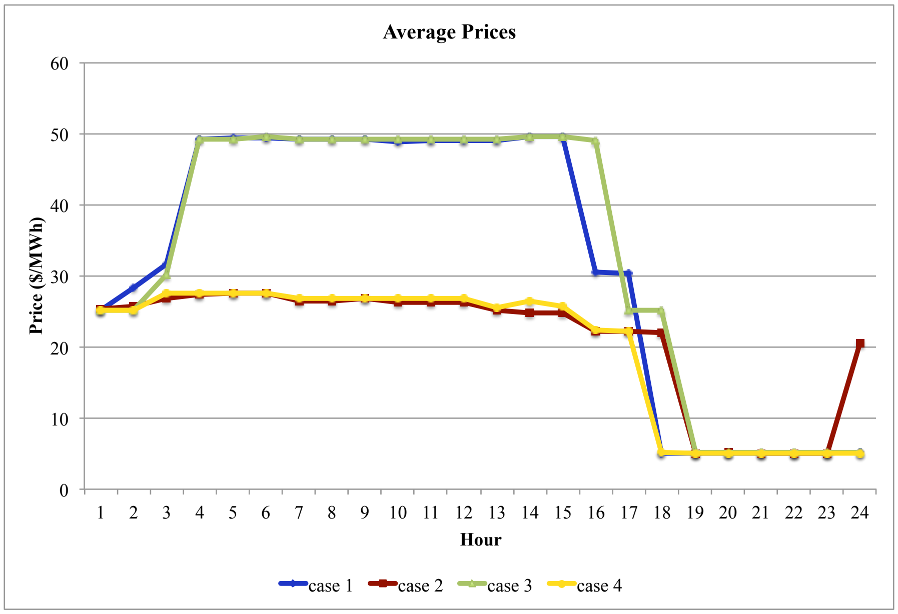

Figure 3.8: Average Prices Over a Day

It is important to note that this analysis is based on short run cost for generators. Therefore, it does not include considerations regarding the adequacy of prices to recover the cost of capital of the generating companies.

An extension that provides a tool for researchers interested in combining optimal power flow analysis and unit commitment was implemented using MATPOWER. (See Murillo-Sanchez [49])

The details of this model are included in Appendix A.

CHAPTER 4

THE MULTIPERIOD SUPEROPF

The modeling of the uncertainty in the system is a problem that requires consideration of the sources of stochastic behavior, and its effects on the management of the available generation fleet in a system.

This chapter discusses the motivation for the development of a Multiperiod Super OPF as part of the efforts of a group of researchers at Cornell, the Engineering and Economics of Electricity Research Group (E3RG).

The antecedents to this work are common in part to the literature presented in Chapter 3. An comprehensive overview of the organization of electricity markets was presented at the presidential address to the econometric society by Robert Wilson [78]. This article describes the overall organization of the electricity systems in different countries, from energy-only markets like Australia to more complex systems with ancillary services such as the New York System Operator (NYISO). Extending from that background, most of the economic literature has been concerned with strategic bidding behavior in the electricity market and its consequences for exercising market power. Harvey and Hogan [26] perform a Monte Carlo simulation for a single market for electricity to study the California and New England (NEPOOL) systems during the crisis that occurred in 2002. The results obtained follow observed trends in the market. However, due to lack of detail in the modeling, its usage and comparison is not possible without knowing the assumptions they made, which are not explicit. Kamat and Oren [31] study the characteristics of a two settlement market as the one in the U.S., and its consequences on contract formation and capacity withholding. Their findings show the importance of accounting for unforeseen circumstances in the transmission system (i.e. contingencies in the system), especially the impact of lines subject to congestion at peak times. Wolak [79] analyzes complex bids in the market, taking into account dynamic costs that may be incurred (e.g., ramping costs). The effect of dynamic costs of operation are studied by Mansur [42], abstracting from the unit commitment problem (UC) and taking a revealed preference approach (i.e., assuming generators have already solved the UC problem or somehow decided to self commit).

The issue of strategic behavior and self-commitment has been analyzed from different perspectives. Zhang et al.[83] study the provision of energy services, taking into account ramping constraints, using Lagrangian relaxation, with reaction models for both individual agents and the social planner (ISO). They find consistent higher cost savings when using a stochastic version of the model. Shrestha et al.[66] study strategic behavior of generators and considerations on how to use ramping rates in energy bidding operating under market conditions. Their model assumes cost minimization by the social planner and also assumes that the bidding agent uses the ramping capability of the generating units as a source of additional revenue. Additionally, the physical characteristics of the units are taken into account (e.g. economic valuation of rotor life).

In Bouffard et al. [9], a security-constrained OPF (SC-OPF) model for energy is proposed. The system is constrained to have a single contingency for the optimization, and a probability is associated to the occurrence of the contingency in the system. Reserve prices are determined by the cost of load shedding in post-contingency states. In Chen et al. [11], the objective function is modified to include the cost of energy and reserves in a co-optimization framework (CO-OPT), with a base case and a set of credible contingencies with associated probabilities of occurrence for each one.

In Condren et al. [13], the problem of dealing with expected post-contingency flows in including ramping is studied in what the authors call an Expected Security-Cost OPF (ESCOPF). The transition from pre- to post-contingency states is valued with functions reflecting the ramping cost per generator to deal with the change in operating points for a single time period.

The framework for what is called the Cornell SUPEROPF was introduced in [70]. This is a stochastic, security constrained AC OPF with endogenous reserves. Following CO-OPT, energy and reserves (positive and negative) are solved simultaneously, taking into account the social cost of Load Not Served (LNS), priced at the Value of Lost Load (VOLL). In this context, the contingencies are included as economic constraints, allowing for a better accommodation of the stress induced in the network (e.g. the inclusion of non-dispatchable sources). Models along a similar philosophy include [72], who use a Monte Carlo simulation approach in a Mixed Integer Program (MIP), modeling transitions from period to period as the physical ramping constraints for a Direct Current (DC) Network.

From the regulatory standpoint for the US, the Energy Policy Act of 2005 [74] and the "Electricity Modernization Act of 2005" recognize the importance of reliability standards for the "Bulk Power System." By this act, the Federal Energy Regulatory Commission (FERC) was given the authority to enforce reliability standards. The North American Reliability Corporation (NERC) was in turn appointed by FERC as the Electric Reliability Organization (ERO), with the responsibility of specifying reliability standards. The set of reliability standards [51] is a comprehensive document, with a lot of detail in a variety of topics.

Overall, for reliability, at least two main dimensions are used for evaluation:

1. *Operating Reliability (security): the ability of the bulk power system to withstand sudden, unexpected disturbances such as short circuits or unanticipated loss of system elements due to natural or man-made causes.*
2. *Resource Adequacy (adequacy): the ability of supply-side and demand-side resources to meet the aggregate electrical demand (including losses).*

A number of different techniques are used to measure both of these dimensions above. Loss of Load Expectation (LOLE) and Loss of Load Probability (LOLP) are examples of adequacy metrics, while the $n-1$ is an example of a security one.[1] LOLE calculations include load forecast uncertainty (due to economic and weather conditions), as well as generating resources information. The information for generation covers number of units with respective sizes, maintenance schedule and seasonal derates, as well as emergency operating procedures. The available injections and exports to other systems also have information, given a transmission interconnection. Usually LOLE calculations do not include transmission design, only the planning for generation expansion, due to its long look ahead planning horizon for optimization.

Security, on the other hand, is an operating reliability criterion that takes into account serviceable reserves needed to cover contingencies. The perspective for optimization in this case tends to be a short term, deterministic requirement.

The issue of measuring the welfare effects of the adoption of RES has been studied by Newbery and Pollitt [52], in the context of the benefits of privatization, with appraisal of welfare from the perspective of consumer and producer

[1] $n-1$ means that the system will be able to withstand the loss of any network element and continue operating.

surplus. Such calculations require a counterfactual for what the situation would have been without privatization. [30] does an assessment of the benefits of privatization for the US case, without building a counterfactual, but by looking at different measures of adequacy and security.

The main contribution of this chapter is to motivate the reasons for better models with specific restrictions that reflect the technical (engineering) characteristics of the electricity network, the generating units and the economic and dynamic optimization nature of the energy dispatch for an ESS and for all generating units. Such considerations are necessary to reflect the true benefits (and costs) faced by an ISO, the congestion that can lead up to the formation of load pockets, and the effects that adoption of RES has in the system.

This is the first analysis to include a complex model of the A.C. characteristics of the network, the inter-temporal tradeoff of using ESS units, the uncertainty in the system due to adoption of renewables, and the security necessary to comply with reliability requirements. The program is implemented by Carlos Murillo and Ray Zimmerman as part of a project with the Consortium for Electric Reliability Technology Solutions (CERTS).

The current implementation assumes that the unit commitment problem has already been solved. Though a deterministic UC-OPF problem as specified in Section **??**, the stochastic UC problem is currently undergoing testing.

4.1 Variability in Markets with High Penetration of Non-dispatchable Sources of Generation

Renewable Energy Sources (RES) are likely to continue the upward trend observed in the past decade. The change from using dispatchable generation to an environment in which Independent System Operators (ISO's), Regional Transmission Operators (RTO's), Load Serving Entities (LSE's) and consumers dynamically respond to the conditions in the system and help to alleviate the uncertainty linked to RES requires appropriate tools to evaluate the social benefits and costs of different policies implemented.

In the first approximation to this problem, a security constrained, single period OPF with two settlements derived from the first generation of the SuperOPF is used to study the operations on a test network to simulate a typical day. The objective is to compare the effects of 1) controllable demand, 2) on-site storage, and 3) upgrading transmission capacity on metrics that reflect true system costs. The different scenarios are evaluated in terms of 1) the percentage of potential wind generation spilled, 2) the total operating cost of production, and 3) the amount of installed capacity needed to maintain operating reliability. A simplified formulation of the objective function for the problem solved is shown in (4.1).

$$
\begin{aligned}
\min_{G_{ik},R_{ik},\mathrm{LNS}_{jk}} \sum_{k=0}^{K} p_k \Bigg\{ \sum_{i=1}^{I} \Big[& C_{G_i}(G_{ik}) + \mathrm{INC}_i(G_{ik} - G_{i0})^+ \\
& + \mathrm{DEC}_i(G_{i0} - G_{ik})^+ \Big] + \sum_{j=1}^{J} \mathrm{VOLL}_j \mathrm{LNS}(G_k, R_k)_{jk} \Bigg\} \\
& + \sum_{i=1}^{I} [C_{R_i}(R_i^+) + C_{R_i}(R_i^-)]
\end{aligned} \tag{4.1}
$$

Subject to meeting Load and all of the nonlinear AC constraints of the network.

Table 4.1: Variables

Name	Description
$k = 0, 1, \ldots, K$	Contingencies in the system
$i = 0, 1, \ldots, I$	Generators
$j = 0, 1, \ldots, J$	Loads
p_k	Probability of contingency k occurring
G_i	Quantity of apparent power generated (MVA)
$C_G(G_i)$	Cost of generating G_i MVAs
$\mathrm{INC}_i(G_{ik} - G_{i0})^+$	Cost of increasing generation from the base case
$\mathrm{DEC}_i(G_{i0} - G_{ik})^+$	Cost of decreasing generation from the base case
VOLL_j	Value of Lost Load, (\$)
$\mathrm{LNS}(G, R)_{jk}$	Load Not Served (MWh)
$R_i^+ < \mathrm{Ramp}_i$	$(max(G_{ik}) - G_{i0}))^+$, up reserves quantity (MW)
$C_R(R_i^+)$	Cost of providing R_i^+ MW of up reserves
$R_i^- < \mathrm{Ramp}_i$	$(G_{i0} - min(G_{ik})^+$, down reserves quantity (MW)
$C_R(R_i^-)$	Cost of providing R_i^- MW of down reserves

The modeling of the storage in this study was approximated by the characterization of the wind capacity availability at any point in time. Therefore, periods with high wind outputs were used to charge the ESS available. Analogously, periods with low wind outputs were served by available stored capacity. This behavior was not endogenous to the model, but rather derived from smaller models with no contingencies, as the ones described in Chapter 3.

4.1.1 Limits and Inter-temporal Constraints, Single Period Model

Computationally, the first and second settlements (stages) are similar in this formulation. However, stage-specific constraints are applied to each stage to differentiate the specific information conditions, in order to properly reflect the RES usage.

First Settlement

For the first stage, the maximum and minimum power outputs are constrained by 1) the power output obtained with the maximum load and the lowest forecast for the RES for the day sets the maximum.[2] 2) The power output obtained with the minimum load observed and the maximum forecast for the RES over the day sets the minimum bound.

Second Settlement

In the case of the second stage, the aforementioned limits are tighter, as they will come from the reserves contracted in the first stage. Also, in the first stage the contracted amounts are not specified. The initial condition at time t for the first stage is established as the output from the second stage dispatches in the previous hour ($t-1$). The RES is modeled as a discrete scenario with an associated power output and probability of occurrence. The reserves are obtained endogenously from the first stage as the maximum deviations up and down from the

[2] This case requires other generators to ramp up to compensate for the low output from the RES.

contracted amount.[3] After the first stage is determined, the optimal contracts are set, and the outcome from the RES is observed. The steady state conditions for the system are obtained by running the simulation over identical days, until outputs (dispatches, voltages, etc) stabilize.

4.1.2 The Determination of Reserves

This initial approach provided valuable insights to some of the problems faced in the operation of the system. One of the most salient challenges faced by SO's is the possibility of sudden changes in output from stochastic generators, leaving the system out of the expected state of operation. In fact, historically this has been one of the lessons learned by operators in Texas in which sudden changes in wind output left the system stressed [7]. Central to resolving this question is the determination of the appropriate amount of reserves needed to reliably operate the system, and therefore being able to withstand these situations.

A proposition coming from the research done at E3RG at Cornell is to solve for the amount of reserves needed to operate the system by explicitly including a set of credible contingencies that reflect the possible modes of operation of the system. Hence, reserves will be calculated from the optimal set of dispatches observed, as the maximum upward and downward deviations from a contracted, or most probable case [46]. A central question then is what is the value of determining the reserves endogenously, as opposed to using a criterion or set of rules based on heuristics and management of the system?. In this context, contingency reserve is the amount of power that can be available in a short period of time to cover unforeseen circumstances.

[3] In this calculation, an outage is not considered a downward deviation.

In order to evaluate the advantages of using endogenous reserves to securely operate the system, Case 1 in the article [37] is used as a benchmark for comparison. This case is a no wind scenario, in which a sequential optimization as described in section 4.1.1 is performed over a 72 hour horizon. The reserves are optimally solved using the modified sequential optimization and then used in a case with fixed reserves set as a reliability case.

The objective of this example is to be able to compare the dispatch done using a modified SuperOPF model and a model in which reserves are determined exogenously.

Figure 4.1 shows the setup used as input for one of the hours in the horizon, with equal reserves in both cases. In the case of a fixed reserves dispatch, the objective is to minimize the cost of energy and reserves in the system, a similar objective to that of the modified SuperOPF. The crucial difference is that, while the latter takes into account the locational aspect of the reserves, the former does not. Hence, a fixed reserves model does not elicit the contracting of reserves needed according to the possible operational states of the system. It will rather contract the cheapest available reserves offered by generators.

In normal operating conditions, and absent the congestion that can build up in the system, these reserves will be available and usable. However, as illustrated in Figure 4.1, with exactly the same amount of reserves, not all operating conditions will be served at the same level. In this case, the outage of a generator in Area 2 can lead to load shedding. The locational aspect of reserves in the SuperOPF allows for survival in this condition without recurring to load shedding.

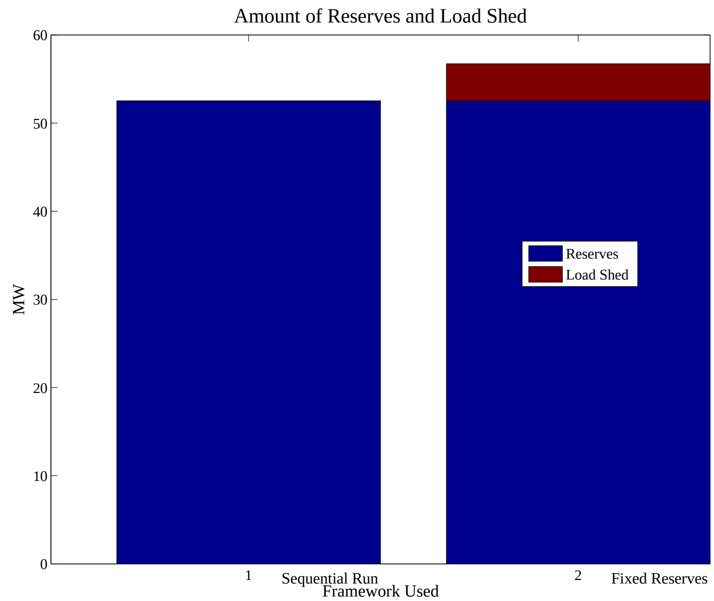

Figure 4.1: Comparison of Reserves and Load Shed

The management of the system without specific reserves for generators is problematic in terms of cost, as illustrated in Figure 4.2. While the cost of energy and reserves is higher in the modified SuperOPF, the total cost of operating the system with fixed reserves far exceeds the cost paid in the modified SuperOPF. This effect is due to contracting of more expensive generation due to locational considerations, when adding the cost of load shed valued at the Value of Lost Load (VOLL).

This is an instance in which the endogenous determination of reserves leads to a more economically efficient dispatch of the system. As the uncertainty in the output from generators increases, especially due to RES adoption, the contracting of reserves to offset variability will become an increasingly important issue.

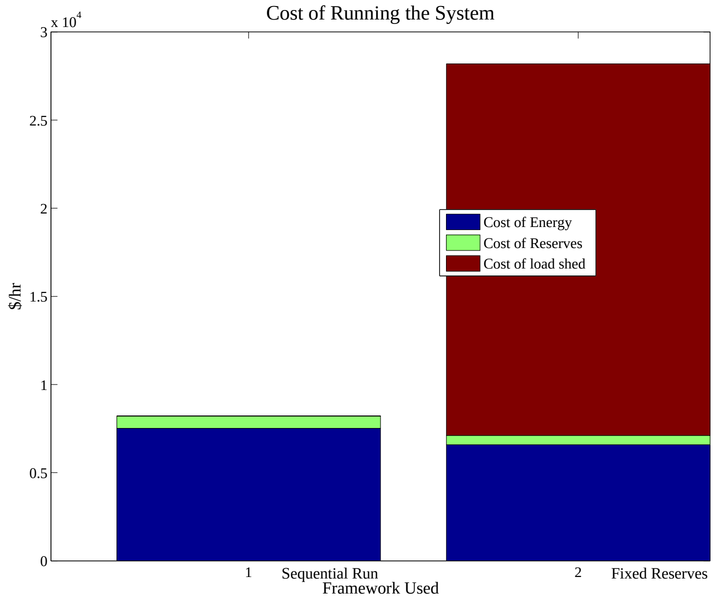

Figure 4.2: Comparison of Reserves and Load Shed

4.1.3 The cost of cycling in the system: Ramping Costs

The main result of this preliminary study, submitted to the journal *Energy Economics*, shows that the use of ramping costs in the decision making process plays a significant role in the way the system is operated, and particularly, how the wind capacity available in the system is dispatched. The most important implication of ramping costs is the fact that these are real costs incurred by the generating units that provide reserve capacity to mitigate the variability of wind. Thus, excluding ramping costs from the least-cost optimization has distributional effects that tend to over-commit the wind generation while maintaining the security of the system. In addition, ignoring the ramping costs affects the financial viability of the generators that provide ramping services because they are not compensated for their extra costs. The rationale then for adding ramping costs is that they signal the social planner (System Operator, SO's) the costs faced by conventional generators when they need to move from their operating point. While the SO's take into account the cost of energy, there are sources of costs not included in the objective function when moving a generator's dispatch:

1. The loss of efficiency and potential higher heat rates for the generators incurring the ramp.
2. The increased maintenance costs derived from ramping generators
3. The increased probability of an outage derived from the fatigue of ramping up and down the generators.

This last item seems to be one of the main sources of costs for producers. In a study for the Ontario producers [25], the aggregated cost due to loss of efficiency, maintenance costs and probability of forced outages is estimated at around 28 \$-hr/MW. Note that the range of costs for coal fired units vary widely (see e.g. [1, 77, 28] for other estimates on the cost of ramping for some coal units).

The simulated cases in [37] show consistently lower levels of wind dispatches in all cases in which ramping is endogenized. The cause of the apparent waste of a zero-cost resource is the penalty imposed in the event of a wind cutout. In such instances, other available generating units have to rapidly adjust their dispatches to compensate for the sudden, unexpected loss of available power, therefore incurring the cost of ramping up. A related dual situation can occur when unexpectedly high RES power becomes available. This is hardly surprising, given the inherent uncertainty associated with the wind resource. Therefore, mechanisms that facilitate hedging this uncertainty will witness higher utilizations of the stochastic resource.

Overall, the recent evidence on the exploration of ramping costs is that its real cost for generators is likely being undervalued [71]. Besides the importance of ramping cost, this paper showed that controllable demand improves (reduces) operating costs, improves generation capacity needed for reliability and increases the amount of wind taken, by alleviating congestion and mitigating wind variability. In contrast, the beneficial effects are smaller for on-site storage, because on-site storage does not shift load to off-peak periods or reduce congestion, and for upgrading transmission, because upgrading transmission does not shift load to off-peak periods or mitigate wind variability.

An important feature of market design for ancillary services is the fact that offers for capacity should be incentive compatible, and therefore cost reflective. If such is the case, income from ancillary services will be used to offset possible costs (e.g. wear-and-tear and ramping costs) additional to the fuel costs (heretofore operating costs) and therefore affect the generators net revenue. This point gains relevance when considering different ancillary services, such as contingency reserve and load following reserve.

Load following reserves are the amount of power per unit of time (e.g. MW/hour) required from each generator to be able to follow the changes in load from period to period. This contrasts with contingency reserve, in which the unit of time considered is shorter or instantaneous. With the addition of renewable energy sources, besides the period-to-period uncertainty in load changes, the changes in wind availability will presumably increase the amount of load following reserve needed.

In the specific case of load following reserve, it is expected that the income from selling this service will be used to offset the cost of ramping incurred by the peaking and shoulder units in the system, following the incentive compatibility rational in well designed markets.

In the initial approach to this problem, the use of single period-OPF's, though concatenated one period at a time, did not reflect the tradeoffs in longer horizons faced by energy units like ESS's and conventional generators with technical capability constraints. The scheduling of units with start up and shutdown costs, and the minimum run times these units require for technical reasons, or in general, the constraints of the unit commitment (UC) problem, go beyond the two-period analysis. This is one of the main motivators for the second generation SuperOPF.

The formulation with multiple periods combines the OPF and UC problem, and reflects the uncertainty in the system that is characteristic of the decisions made when the share of uncertain resources is increased in the electricity system, by assuming the wind is Markovian. Since this problem has a finite horizon, but the scheduling process is continuously repeated, the final set of states can be determined by imposing a transversality condition on the residual value of variables that can be used in subsequent periods after the horizon.

A simplified formulation of the objective function for the problem is shown in (4.2) and the notation is defined in Table 4.2.

$$
\begin{aligned}
\min_{G_{itsk},R_{itsk},\mathrm{LNS}_{jtsk}} & \sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}^t}\sum_{k\in\mathcal{K}}\pi_{tsk}\Big\{\sum_{i\in\mathcal{I}}\Big[C_{G_i}(G_{itsk})+ \\
& \mathrm{Inc}^{+}_{its}(G_{itsk}-G_{itc})^{+}+\mathrm{Dec}^{-}_{its}(G_{itc}-G_{itsk})^{+}\Big] \\
& \sum_{j\in\mathcal{J}}\mathrm{VOLL}_j\mathrm{LNS}(G_{tsk},R_{tsk})_{jtsk}\Big\}+ \\
& \sum_{t\in\mathcal{T}}\rho_t\sum_{i\in\mathcal{I}}[C^{+}_{R_{it}}(R^{+}_{it})+C^{-}_{R_{it}}(R^{-}_{it})+C^{+}_{L_{it}}(L^{+}_{it})+ \\
& C^{-}_{L_{it}}(L^{-}_{it})]+\sum_{t\in\mathcal{T}}\rho_t\sum_{s_2\in\mathcal{S}^t}\sum_{s_1\in\mathcal{S}^{t-1}}\sum_{i\in\mathcal{I}^{ts_2 0}} \\
& [\mathrm{Rp}^{+}_{it}(G_{its_2}-G_{its_1})^{+}+\mathrm{Rp}^{-}_{it}(G_{its_2}-G_{its_1})^{+}]
\end{aligned}
\tag{4.2}
$$

Subject to meeting Load and all of the nonlinear AC constraints of the network.

The formulation is flexible regarding the length of the individual period of analysis, as long as the problem is not in a transient state. For all the analysis done with the policy case studies, the individual period of analysis is set to hours. It follows the logic of optimization used in regulated markets for load following products. Smaller time periods are associated with other ancillary services, such as frequency regulation. For even shorter scales of time, the automatic controls from generation units (Automated Generation Control or AGC) take care of the balance of supply and demand in a pre-established algorithm, taking into account the normal characteristics of the generator fleet. The use of hours as basic period of analysis for determination of energy and reserves will then be a limiting conditions for some special units. Chief amongst them is the proper scheduling of units designed to provide services in longer horizons, such as ESS unit. Therefore, in order to solve for an optimal set of contracts of a predefined set of committed conventional units in a correct manner, it is important to include the interaction with inter temporal resources such as the

Table 4.2: Definition of Variables, simplified Formulation

$\mathcal{T}$	Set of time periods considered, n_t elements indexed by t.
$\mathcal{S}^t$	Set of scenarios in the system in period t, n_s elements indexed by s.
$\mathcal{K}$	Set of contingencies in the system, n_c elements indexed by k.
$\mathcal{I}$	Set of generators in the system, n_g elements indexed by i.
$\mathcal{J}$	Set of loads in the system, n_l elements indexed by j.
π_{tsk}	Probability of contingency k occurring, in scenario s, period t.
ρ_t	Probability of reaching period t.
G_{itsk}	Quantity of apparent power generated (MVA).
G_{itc}	Optimal contracted apparent power generated (MVA).
$C_G(\cdot)$	Cost of generating $(\cdot)$ MVA of apparent power.
$\text{Inc}^+_{its}(\cdot)^+$	Cost of increasing generation from contracted amount.
$\text{Dec}^-_{it}(\cdot)^+$	Cost of decreasing generation from contracted amount.
VOLL_j	Value of Lost Load, (\$).
$\text{LNS}(\cdot)_{jtsk}$	Load Not Served (MWh).
$R^+_{it} < \text{Ramp}_i$	$(max(G_{itsk}) - G_{itc})^+$, up reserves quantity (MW) in period t.
$C^+_R(\cdot)$	Cost of providing $(\cdot)$ MW of upward reserves.
$R^-_{it} < \text{Ramp}_i$	$(G_{itc} - min(G_{itsk}))^+$, down reserves quantity (MW).
$C_R(\cdot)$	Cost of providing $(\cdot)$ MW of downward reserves.
$L^+_{it} < \text{Ramp}_i$	$(max(G_{i,t+1,s}) - min(G_{its}))^+$, load follow up (MW) t to $t+1$.
$C^+_L(\cdot)$	Cost of providing $(\cdot)$ MW of load follow up.
$L^-_{it} < \text{Ramp}_i$	$(max(G_{its}) - min(G_{i,t+1,s}))^+$, load follow down (MW).
$C_L(\cdot)$	Cost of providing $(\cdot)$ MW of load follow down.
$\text{Rp}^+_{it}(\cdot)^+$	Cost of increasing generation from previous time period.
$\text{Rp}^-_{it}(\cdot)^+$	Cost of decreasing generation from previous time period.

aforementioned ESS, and hence the necessity to include several periods in the optimization horizon. This multiperiod problem has the possibility of properly following the dispatch of ESS units reflecting on the stochastic nature of the decisions taken. Furthermore, the proper determination of contracts for these units will depend on the nature of the utilization of the resource. For security of the system, there are cases in which the stored energy provides support in low probability cases. Since tracking the level of energy of the storage may limit the capability of using ESS units in low probability cases, the modeling implemented tracks the maximum and minimum levels of stored energy at each period of time for high probability cases. The formulation models the tradeoffs between the mitigation of uncertainty in a give period (due to extreme conditions or contingencies) and the time arbitrage of the stored energy.

Additional to the inter temporal constraints for energy units, and the associated power constraints in each period, the System Operator (SO) needs to include the physical capability to ramp up or down, and the economic cost of this ramping performed in a period to period basis. The negligence to include these technical constraints can result in deviations from real optimal conditions and even situations in which the optimized initial contracts in the solved solution is not implementable, due to physical limitations in the characteristics of the generators in the control area.

To illustrate the effect of ramping costs on metrics that reflect the true system costs, an example is borrowed and extended from the policy study in Chapter 5. Suppose a system operator faces the conditions outlined in Section 5.2. In those cases, the generators have a cost of ramping related to the individual transitions between scenarios, as well as offers for load following reserves. The value of the ramp reserve is set to 10$hr/MW for peaking units, 30$hr/MW for shoulder units and 60$hr/MW for base load units, following the aforementioned logic. For the sake of simplicity, we will only illustrate in cases that have either deferrable demand (Case 3) or utility-scale storage (Case 4). The ramping costs are then scaled up proportionately, up to twice the initial value considered, and down to zero from this base case. Figure 4.3 shows the expected wind dispatched in the system for each one of the cases.

The increase in ramp reserve cost decreases the amount of wind dispatched, thanks to the internalization of these costs, and in line with the expected direction of changes. The relationship however is not linear for Case 3. This is

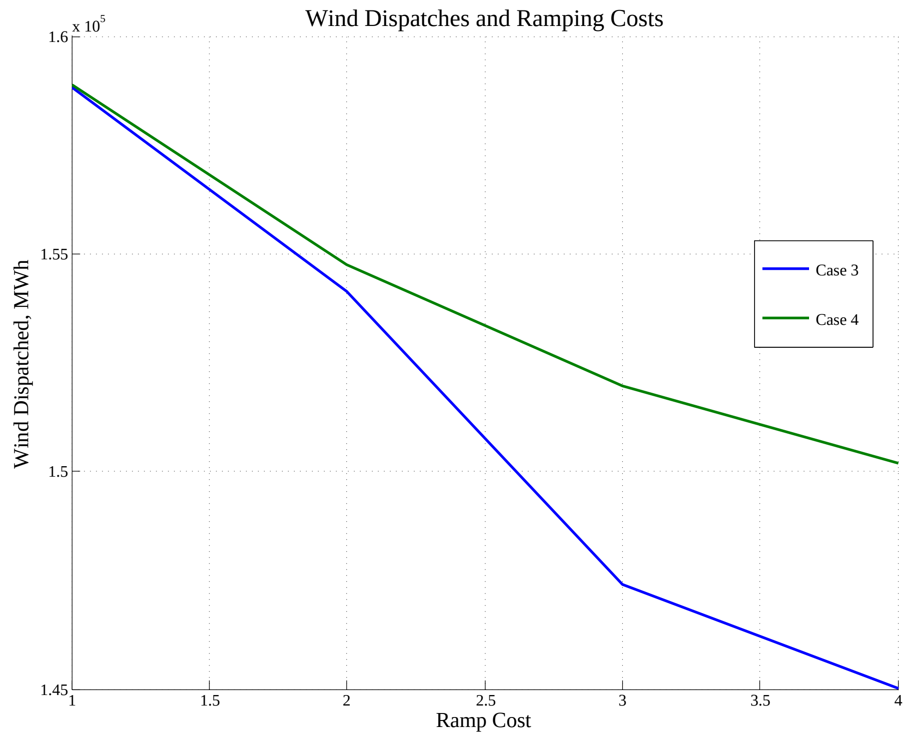

Figure 4.3: Wind Dispatches, Sensitivity to Ramping

due to the nonlinear changes that occur when increasing the ramp rates and the congestion that builds up in the network, specifically the Leeds-Pleasant Valley branch in the NPCC system.

From the social point of view of compensating generators for ramps mandated by the ISO, this case clearly internalizes the costs of moving the conventional generation. This is a desirable policy to avoid the fallacy of believing that having more wind dispatched is desirable without accounting for effects like the ramp necessary from the current generation fleet to support the uncertain resource. The loss of efficiency and increased heat rates, and the potential emissions that are incurred by moving plants from their optimal operating point need to be accounted to have a full picture of the benefits of the adoption of renewables.

Figure 4.4 shows the capacity requirements as the ramp reserve cost increases. In this case, as with the wind dispatches, the maximum capacity at peak required to cover the load is negatively related to the cost of the load following reserve. This relation is related to the decreased wind dispatched, and hence the need to use less capacity to cover the possible changes in generation from stochastic sources in the system.

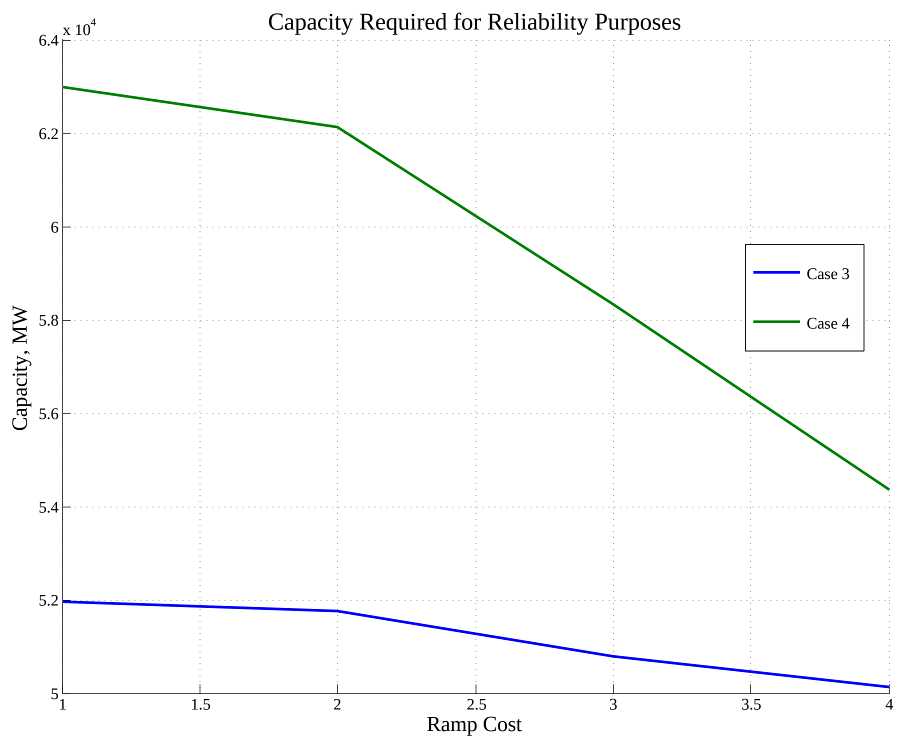

Figure 4.4: Capacity Needed, Sensitivity to Ramping

This implies that, if the cost of capacity required for reliability is monetized, there would be systemic benefits in including the cost of ramping reserves. Not all markets have ancillary services markets, and a ramping reserve product is still an proposal being discussed in some ISO's [50]. Therefore the cost of capacity is not always valued in monetary terms, so the comparison of benefits will depend on the market on which this policy is implemented.

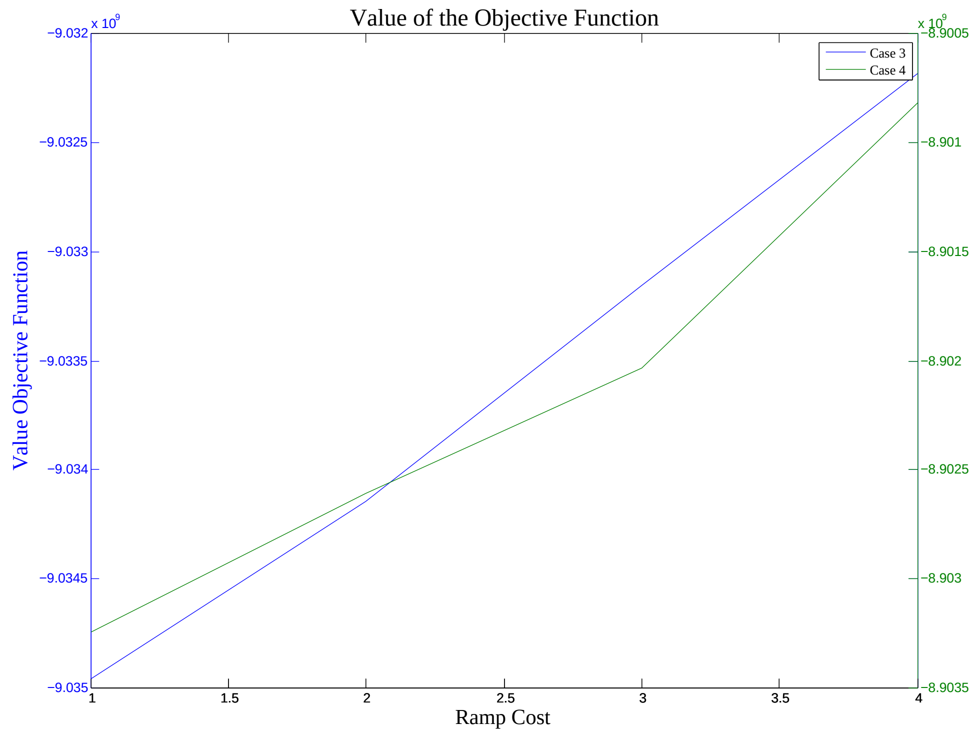

Figure 4.5: Capacity Needed, Sensitivity to Ramping

In order to study the overall costs implied by ramping, including fuel and operational, and from the contracting of reserves in the system, the comparison of the value of the objective function for cases 3 and 4 is shown in Figure 4.5. The results are consistent with the effects observed in the capacity needed for reliability purposes: the increase in the ramp reserve cost leads to an increase in the value of the objective function. In this case again the driver is the spilling of wind capacity that, althought it has a zero cost of production, would require more conventional capacity to be properly accommodated into the system.

Overall, the results are consistent in the multiperiod framework with what the concatenated single period problems would prescribe in terms of the effect of ramping for system measures. The main advantage of the new modeling is the rigorous treatment of the ESS units, as opposed to the reduced modeling done in the previous runs. This allows to study better the technology that will provide the proper service needed according to the network topology studied.

4.2 Comparison to Simplified Modeling Methods

This section evaluates the merits of solving an stochastic network model compared to simplified approaches to this problem. The simplifications commonly range from ignoring the uncertainty in the system by using deterministic inputs, to using models without networks that solve the problem ignoring the transmission constraints. To evaluate these two simplifications, the following cases are represented: 1) No Network: consider a case where all generators and loads are placed in a single node in the system. This is equivalent to ignoring all the thermo transmission ratings in the system. 2) Deterministic Renewables: consider a case where the inputs representing the main sources of uncertainty (i.e. the variable generation) do not have variation in each period considered. This representation uses the expected value of the variable resource, determined from historical information, with variation from period to period (inter period), but no intra period variation. In the context of the cases analyzed in this thesis, the variable resource considered is wind, with characteristics as discussed in Chapter 5. Figure 4.6 left pane shows the potential wind generation in each one of the four scenarios discussed in Chapter 5, representing stochastic wind, while the right pane shows the expected values for deterministic wind. The x-axes for both figures show the hours of the optimization horizon, indicating a decrease in the amount of wind during peak demand times and high availability in low demand periods.

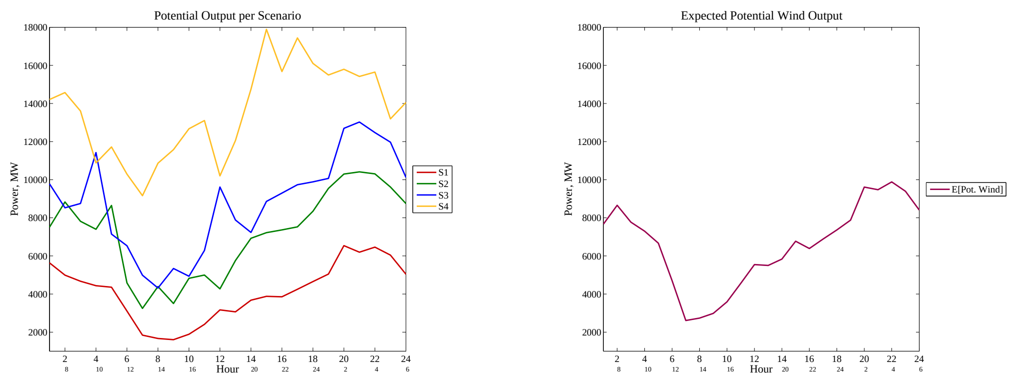

Figure 4.6: Available and Expected Wind

The cases considered for this comparison are:

1. Case 2, Wind, 29 GW of wind capacity at 16 locations added.
2. Case 2up, Wind + Upgrade of the transmission system.
3. Case 2e[w], Case 2 with deterministic wind.
4. Case 2e[w]up, Case 2u with deterministic wind.

The first two cases, representing stochastic wind, serve to compare the effect of removing transmission constraints with uncertainty. The last two cases are identical except that deterministic wind replaces stochastic wind.

The results are summarized in Table 4.3, reporting the three system criteria and the value of the objective function for the four cases.

The cases are identical in their specifications, including characteristics of the

Table 4.3: Summary of the Daily Results for Stochastic and Deterministic Wind

	Case 2	Case 2up	Case 2e[w]	Case 2e[w]up
Operating Costs (k$/day)	41,932	41,469	36,692	35,252
GenCap (MW)	57,004	56,977	55,668	55,567
Wind Energy (MWh)	137,517	147,346	155,565	158,907
Objective Function (k)	-8,896,185	-8,897,412	-8,897,935	-8,899,321

generation fleet, demand patterns and topology of the problem.[4] The elimination of transmission constraints (Case 2up) enables an economic order dispatch, therefore increases the amount of wind dispatched in the system by 10GWh. This contributes to a reduction of the operating costs, thanks to the zero marginal cost of wind. In determining the optimal amount of wind dispatched, the optimization trades off the zero energy cost of wind with the cost of providing reserves by conventional generators. The relaxation of transmission constraints implies that less capacity is optimally required in each possible scenario to cover the wind uncertainty. Nevertheless, the procurement of these reserves will be below the levels actually needed in the system to operate securely in a real system, because in fact the real system does have the physical constraints.[5]

The comparison between a full model (Case 2) and a reduced form model with no stochastic behavior included (Case 2e[w]) reveals changes similar to those of Case 2up, but the magnitudes of the changes are much larger. By ignoring the stochastic characteristics of wind, the amount of additional wind energy dispatched is almost double the change observed when network constraints are neglected (18GWh in Case 2e[w] vs. 10GWh in Case 2Up). The additional wind capacity also reduces the operating costs with respect to Case 2 by 5 million

[4]The location of the generators, dispatchable and variable, are irrelevant for the upgrade transmission system cases, as transmission constraints will never bind.

[5]This bias is introduced by the researcher or operator due to the modeling performed.

$/day, compared to a 0.5 million $/day reduction in Case 2up. It is especially notable that the amount of reserves required for operating reliability is reduced, with 1.3GW less capacity needed. The combination of no wind transmissions and deterministic wind allows the utilization of all the potential wind energy, without spillage.

The expected optimum amounts of wind dispatched in the four cases are shown in Figure 4.7. The lowest amount of wind dispatched occurs in Case 2 with stochastic wind and the initial network, and the highest occurs in Case 2e[w]up (Case 2eu in the Figure) with deterministic wind and no network constraints. It is interesting to note that most of the wind spilled occurs towards the end of the planning horizon. As a result, mechanisms that use the available and spilled wind capacity at night could provide system benefits, depending on the economic costs of adoption of this technology.

Therefore, the biases introduced by modeling without stochastic consideration of the wind resource are much larger that those observed when the transmission constraints are ignored. Alternatively, the consequential policy recommendation is that the benefits of mechanisms that allow to reduce the uncertainty in the output from renewables provide larger economic benefits that the implementation of policies that aim at increasing the transmission capacity of the system. It must be highlighted that this recommendation is specific to the topology studied under the wind characteristics modeled.

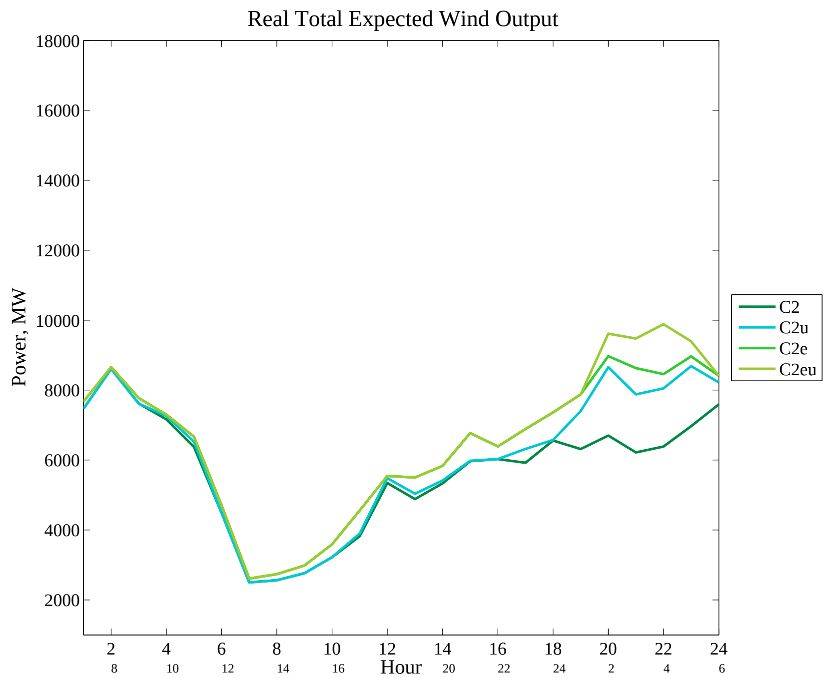

Figure 4.7: Expected Wind Dispatched per Case

4.3 The Value of the Stochastic Solution for Renewable Resources

This section analyzes the value of having a stochastic program to determine the dispatches of all generators and energy sources. The objective is to compare how uncertainty affects the physical metrics adopted to measure the performance of the system. In the policy cases studied here, the source of uncertainty comes from the wind availability in each scenario considered. In the context of the organization of this thesis, this section contrasts models similar to the one presented in Chapter 3 with contingency reserve in each period, to the multiperiod SuperOPF. This comparison is based on the policy cases analyzed in Chapter 5, focusing on the cases with deferrable demand and storage collocated with wind farms.

The removal of uncertainty in wind is performed in two ways: 1) by removing the variability in the maximum available wind across scenarios. 2) by modifying the maximum output available to make it identical in all cases to the expected wind available (E[W]). While the first method has a numerically close to zero probability of reaching a different state, the second one will have the same output no matter which path is taken, by design of the setup.

In addition, a benchmark is done by removing the transmission system (marked with a suffix 'Up'). The motivation in this case is to have a base for comparison of the uncertainty in wind dispatches, versus the limitations due to geographical constraints.

Figure 4.8 shows the information for operating costs, wind compensation and wind dispatches (secondary axis) in the system for the base cases (Cases 3 and 4), the cases without uncertainty in wind scenarios (Cases 'E[W]'), and the case with no constraints in transmission (Cases 'Up').

The removal of uncertainty in wind greatly decreases the operating costs, due to a significant increase in the amount of wind dispatched at the maximum potential wind level in the system. The compensation to wind also increases, driven by the dispatched amount change. Removing the transmission constraints moves the system in the same direction as the removal of the uncertainty in the system, with two main differences: 1) the magnitudes of changes are smaller than in the E[W] cases and 2), the amount of wind taken increases with respect to the base cases, but is still below the level observed in the E[W] cases. This is indicative of the impact that the wind uncertainty has on the optimal level dispatched (or conversely spilt).

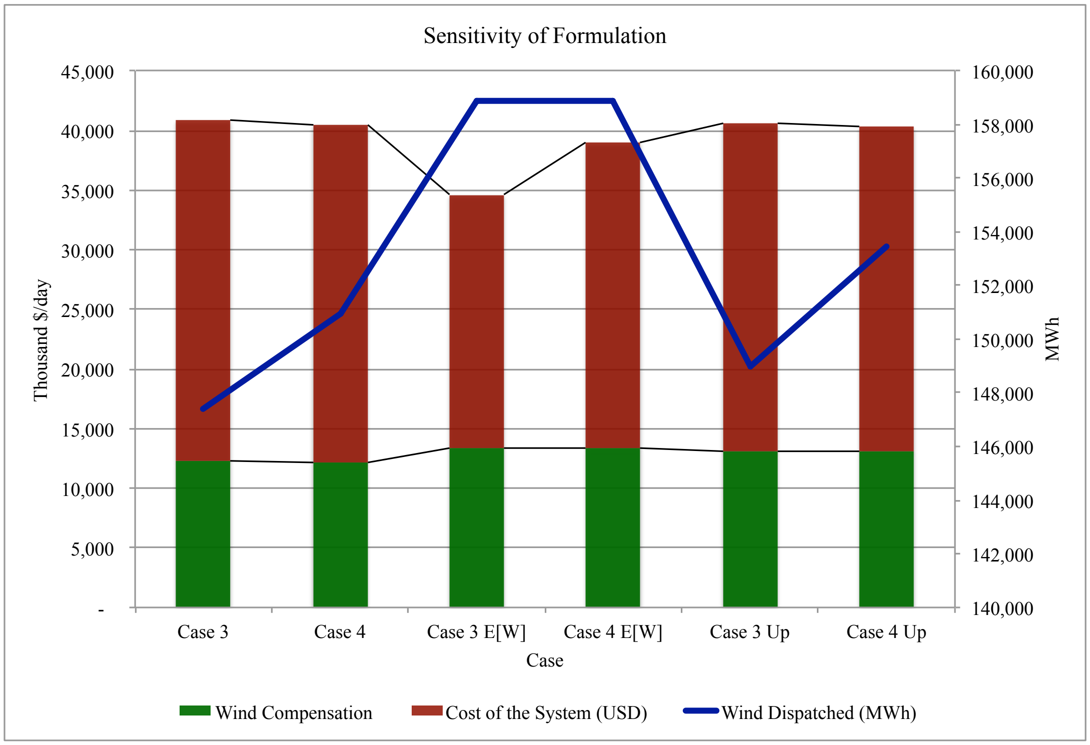

Figure 4.8: Wind Compensation, Dispatches and System Operating Costs

In terms of the generation capacity needed, both the E[W] cases and the 'Up' cases underestimate the reliability requirements needed, with the former one being the worst offender in both cases (See Figure 4.9).

The underestimation of the capacity requirements is especially important for the SO, given the compliance with reliability mandates. This capacity has a network placement (or geographical placement) component. For this reason, the capacity requirements are lower with no network constraints in place.

In the stochastic programming literature [14], a metric for comparison along the kind of models here outlined is the value of the stochastic solution (VSS), defined as shown in (4.3)

$$VSS = z^S - z^D \tag{4.3}$$

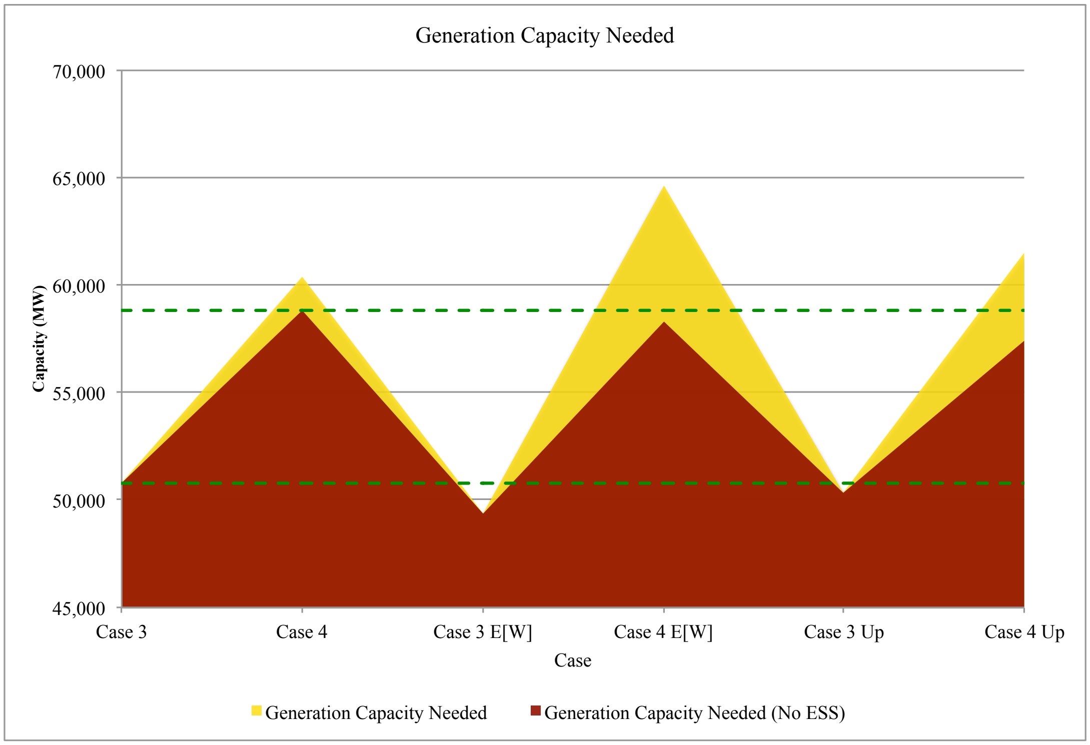

Figure 4.9: Capacity Required for Reliability Purposes

Where z^S is the objective function for the stochastic solution, and z^D is the objective function for the deterministic solution of a problem. Figure 4.10 shows the negative of the values of the objective functions obtained for cases 3 and 4. To appreciate the differences in each case, the negatives of the values of the objective function for Case 3 are plotted on the left vertical axis, while those for Case 4 are plotted in the right vertical axis. The main gains between the base cases and the expected wind (E[W]) cases comes for the deferrable demand cases (Case 3), tolling at 2,093,964, compared to 610,959 in the collocated storage cases (Case 4). The largest percentage gain in the case of deferrable demand is due to the possibility of dispatching the wind generation available at the potential level. As shown in Figure 4.8, the difference between the wind dispatched in the base case and the wind dispatched in the expected wind case is much larger for deferrable demand than for the collocated utility scale storage.

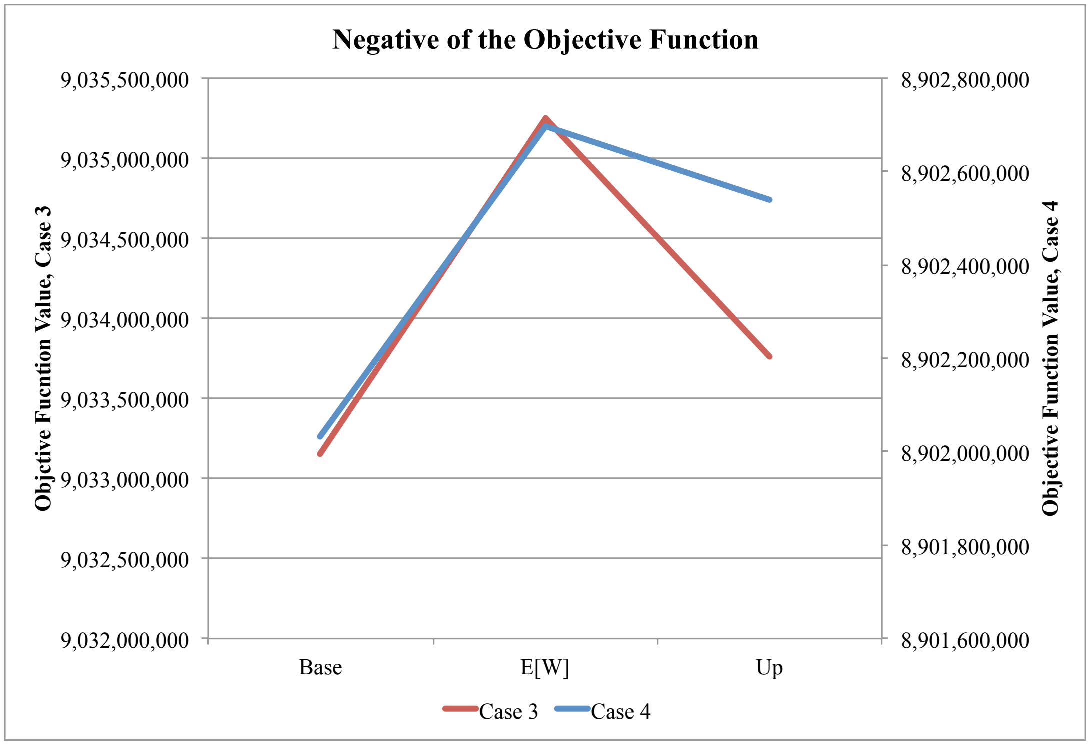

Figure 4.10: Comparison of Objective Function Values

In the models compared here, a stochastic component is still present, derived from the use of contingencies in each time period. However, the comparison in the differences of the objective function provides a valuation on all of the total expected costs of energy and reserves as presented in (4.2).

In all cases, the higher compensation to wind generators in Case 3 compared to Case 4 is maintained (see Section 5.2.2).

4.4 The Modeling of Transitions Across Time

The unfolding of uncertainty across time in the Multiperiod SuperOPF is modeled by a *Markovian* transition probability matrix. In this modeling, the stochastic process $\{x_t\}$ evolves according to a probability matrix P [68].

This matrix relates the I states in period t to the J states in period $t+1$, and can be denoted by $p_{j,i} = Prob(x_{t+1} = s_j | x_t = s_i)$

$$\mathbf{P} = \begin{pmatrix} p_{11} & p_{12} & \cdots \\ p_{21} & p_{22} & \cdots \\ \vdots & \vdots & \ddots \\ p_{t1} & \cdots & p_{j,i} \end{pmatrix}$$

This transition probability matrix must satisfy the following assumption:

$$\sum_{j=1}^{J} p_{j,i} = 1 \tag{4.4}$$

In the multiperiod SuperOPF, the states are denoted as scenarios, and characterize high probability realizations - as opposed to low probability contingencies. In the policy case studies, Lindsay Anderson perform a scenario selection and construction of the transition probability matrices for 24 hours. The scenarios were determined using a center-based k-means clustering algorithm, as described in [24]. For this, let D be data set with n instances, and let $C_1 \ldots C_k$ be the k disjoint clusters of D. The macro algorithm for categorization is described in Algorithm 2.

The k-means algorithm can be treated as an optimization problem, with the objective function defined in (4.5)

$$p(W, Q) = \sum_{l=1}^{k} \sum_{i=1}^{n} w_{il} d_{euc}(\boldsymbol{x}_i \boldsymbol{q}_l) \tag{4.5}$$

Where $Q = \{\boldsymbol{q}_l, l = 1, 2, \ldots, k\}$ is a set of objects, d_{euc} is the Euclidean distance, and W is an $n \times k$ matrix that satisfies the following conditions:

Algorithm 2 $k - means$

Require: Data set D, Number of clusters k, Dimensions d

{C_i is the ith cluster}
{1. Initialization Phase}
$(C_1, \ldots C_i)$ = Initial Partition of D
{2. Iteration Phase}
repeat
    d_{ij} = distance between case i and cluster j
    $n_i = \arg\min_{1 \le j \le k} d_{ij}$
    Assign case i to cluster n_i
    Recompute the cluster means of any changed clusters above
until no further changes of cluster membership occur in a complete iteration
Output results.

- $w_{il} \in \{0, 1\}$ for $i = 1, 2, \ldots, n, \ l = 1, 2, \ldots, k$
- $\sum_{l=1}^{k} w_{il} = 1$ for $i = 1, 2, \ldots, n$

In the studies here included with the multiperiod SuperOPF, the number of clusters selected was set to four, for computational ease.

4.5 The Initial Conditioning

The determination of initial conditions for storage units will affect the dispatches of both these as well as conventional and wind generators. In order to control for the changes in these parameters, algorithm 3 was implemented.

With this method, the conditions of the system are assumed to be in steady state. However, the necessary ramp between the last period of the horizon and the first one will not be included, and there is no guarantee that it will be physically feasible to make such transition. The reason for this is because the ramp constraints are only enforced in high probability cases. Hence, and everything

Algorithm 3 ESS conditions

Require: Case Information C, Set of ESS prices for charge $\mathscr{L}^c$, Set of ESS prices for discharge $\mathscr{L}^d$, Dispatches of ESS units $\mathscr{P}$, Stored Energy in ESS units $\mathscr{E}$

{1. Initialization Phase}
Run Simple OPF with C
Obtain $(L_1^{m1}, \ldots L_n^{m1})$ = Initial Prices of $\mathscr{L}^m, m = \{c, d\}$
Obtain $(P_1^1, \ldots P_n^1)$ = Initial Dispatches of $\mathscr{P}$
Obtain $(E_1^1, \ldots E_n^1)$ = Initial Energy Stored of $\mathscr{E}$
{2. Iteration Phase}
repeat
    Run Multiperiod SuperOPF
    d_{ij}^m = difference between prices in iteration i and iteration $j = i - 1$
    d_{ij}^e = difference between energy stored in ESS units in iteration i and iteration $j = i - 1$
    d_{ij}^p = difference between dispatches of ESS units in iteration i and iteration $j = i - 1$
    Assign to $(P_1^j, \ldots P_i^j) = (P_1^i, \ldots P_n^i) = \forall$ ESS dispatches $\in \mathscr{P}$
    Assign to $(E_1^j, \ldots E_i^j) = (E_1^i, \ldots E_n^i) = \forall$ ESS stored energy $\in \mathscr{E}$
    Recompute the distances obtained
until distances below tolerance levels set
Run full problem with established starting conditions

else being equal, in cases in which the probability of occurrence of contingencies increases, the possibility of making this transition decreases. This design decision is part of the tradeoff between attaining security in the system, and maintaining the number of possible trajectories without increasing them in an exponential way. The motivation for the initialization of the storage and wind units was to start from steady state conditions. However, in the testing and verification of this process, it was noted a sensitivity to the starting point of the solution, as it is often the case in optimal control problems [35]. The verification of this hypothesis implies running different initial conditions for each case of study. This entails having longer horizons with identical days that reflect the state of the system. As the horizon is extended however, the ability to accurately forecast distant periods of time is reduced, and therefore this strategy does not provide for an improved solution for the system planner. The experience from industry and System Operators with increased levels of renewable generation suggests that, besides the solution of the optimal control problem, a new generation of models will benefit from the constant update of information reflecting the current state of the system. Another important difference that may not be corrected by the algorithm suggested is the effect that a higher availability of the stochastic resource ramping up in early morning hours (1AM to 5AM) can have on the initial stored energy for the horizon, compared to the ramp down typical of later morning hours (7AM to 10AM). Section 5.2.4 explores these consequences and discusses the findings on this ongoing research.

4.6 Final Remarks

The operation of the electrical system requires the use of methods that reflect the transitions across time for the set of control variables, including its physical constraints and an explicit modeling of the uncertainty that is inherent to this decision making process. With the addition of renewable generation, additional to the uncertainty derived from sudden changes of topology and other contingencies, comes the variability in injections from resources with zero marginal costs. This chapter motivates the need for these models, and illustrates some of the important considerations in terms of the boundary conditions of the problem, the determination of reserves necessary for reliability, the inter temporal problem of ramping and the value of an stochastic program to solve this problem. For boundary conditions, given the nature of the problem, it is necessary to determine the situation in which transitions between successive optimization horizons are done without violating the fundamental properties of the system.

The determination of reserves has been an essential question in the research done at Cornell, to calculate the optimal level of capacity that needs to be contracted, according to the possible states of operation of the system. In terms of ramping, a proper model of the system must include constraints that indicate the physical ramping capacity of the available units across time, as this will limit the feasible region for this optimization. In such a situation, the underlying economic problem is to determine whether it is less expensive to mitigate this variability of renewables using units that have high fuel costs and low ramping costs or units that have low fuel costs and high ramping costs. The value of an stochastic program to solve this problem lies in the interaction of the aforementioned factors to obtain the operation of a system not only is a secure way, but also in an economically efficient way.

CHAPTER 5

POLICY IMPLICATIONS

The transition to a low carbon economy requires changes in the electricity system that encompass most of its constituents. Different states in the US and around the world have looked at different options in terms of investment in new generation sources, implementation of new management methods and consumer response to this challenge. From the viewpoint of investment in new generation sources, one of the most widespread policies adopted to encourage renewable energy sources has been the establishment of Renewable Portfolio Standards (RPS) and feed-in tariffs (FIT) for Renewable Energy Sources (RES). For implementation of new management methods, [75] and [50] propose frameworks that change the prototypes used by Independent System Operators (ISO's). The consumer response arena has been one of the most productive areas of focus, analyzing the electrification of transportation, changes in demand response and usage of Energy Storage Sources (ESS) (See [45, 59, 34] for a small sample of some of the research on this area).

In this chapter, the comparison of location decisions for storage to improve the management of uncertainty derived from usage of renewables on the system, and the effects of wind and storage decisions on a set of measures reflective of the system operation are analyzed. The management of a representative generation fleet on a reduced network of the Northeastern Power Coordinating Council is analyzed, with the underlying assumption that increased amounts of renewable generation will enter into the system, in line with RPS objectives. A set of technical and economical metrics is used and discussed in Section 5.2.1 to evaluate the merits of each proposed mechanism based on the direct performance of the system, such as operating costs and needed installed capacity for reliability purposes.

5.1 Data and Calibration

The calibration of input data was done using publicly available sources, and it encompasses the modification of the test network and the modeling of wind and Energy Storage Systems (ESS).

5.1.1 Test Network

Figure 5.1 has a one-line diagram of the network used in the case study. This is a New York and New England centric network reduction of the North Eastern Power Coordination Council- NPCC, [3], that has been modified to include very detailed information of the generating units at each bus. The generation information was obtained from PowerWorld Corporation.

The total load of the system is around 138 GW, and the generation capacity available is 143 GW [3]. The generation and load of the system corresponds to the information in [3] and was calibrated to represent the demand for a summer day.

Table 5.1 has a summary of the generation capacities and loads for each Regional Transmission Organization (RTO) considered.

The average fuel cost varies by location as shown in Table 5.2, with high coal and oil average costs in New England, and high average natural gas prices in

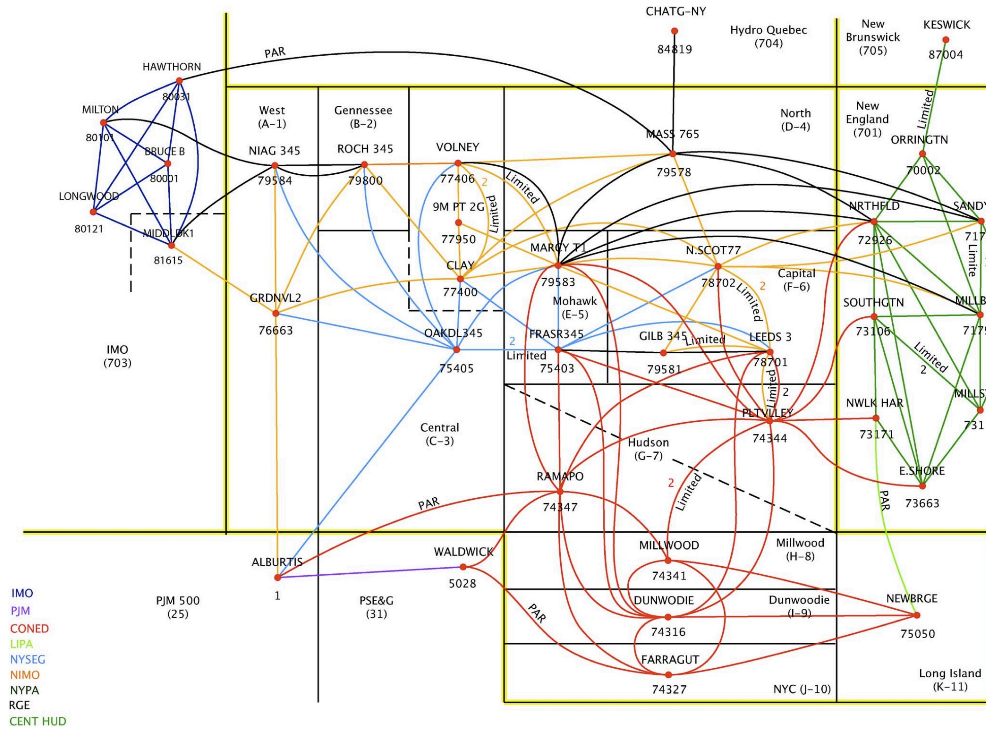

Figure 5.1: A One-Line-Diagram of the 36-Bus Test Network.

Table 5.1: Summary of Generation Capacity and Load

	Capacity per Fuel Type (MW)							Total Cap.	Load
RTO	coal	ng	oil	hydro	nuclear	wind	refuse	(GW)	(GW)
isone	1,840	9,219	4,327	1,878	5,698	0	0	22.9	23.8
marit.	2,424	1,072	22	641	641	0	0	4.8	3.5
nyiso	4,557	18,185	5,265	7,345	4,714	30	55	40.1	38.2
ont.	5,287	3,594	0	779	12,249	0	0	21.9	21.1
pjm	14,453	14,611	8,915	2,604	12,500	0	0	53.1	51,6
quebec	0	0	0	800	0	0	0	0.8	0
Total	28,562	46,681	18,530	14,048	35,802	30	55	143.7	138.4
Total NYNE	6,397	27,404	9,592	9,223	10,412	30	55	63	62
Rp.C.[b]	30	10	10	60	60	0	60		

[a] Values shown are taken as peak values.
[b] Ramping costs in ($.t/MW).

New York, PJM and Ontario.

The prices of natural gas (ng) in this analysis correspond to 2008, with a value of around \$7.50/MMBTU. This is much higher than the current prices

Table 5.2: Summary of Average Fuel Cost per region, 2008

	Cost ($/MW)		
Location (RTO)	coal	ng	oil
isone	27	78	224
maritimes	27	84	234
nyiso	25	94	201
ontario	25	112	146
pjm	27	101	213
Average Total	26	91	202

[a] Values shown are taken as peak values.

in the system at around 2.5$/MMBTU. With current natural gas prices, a displacement of the coal capacity is expected for future analysis, depending on the location of the generation infrastructure.

5.1.2 Load Modeling

For the simulation, a day in a high demand period was calibrated (following historical load information from August 2008), distinguishing the profiles between urban and rural demand profiles. Each one of the areas has a different profile over the day, with more pronounced variation for the urban loads and lower rates of load change per hour for rural loads. The changes observed over one day were replicated from 2008 historical data available for the study area, allowing for different changes in hour to hour demand according to the location of the load. Accordingly, the Value of Lost Load (VOLL) also depended on location, with a value of $10,000/MWh for urban areas and $5,000/MWh for rural areas.

The coincident peak system demand occurs at 3PM, caused mainly by urban demand. Demand was calibrated according to historical data from the New York Independent System Operator (NY-ISO) and the New England ISO (NE-ISO).

5.1.3 Wind Modeling

This study analyzes a case with a wind penetration close to 20% of the total system load. The setup of the wind specification is divided in two main tasks: finding the location of the wind sites that reflects the real characteristics of the system, and characterizing the variability of the wind resource.

The location of the wind farms is derived from the National Renewable Energy Laboratory (NREL) Eastern Wind and Transmission Study (EWITS) data [54]). To match the data from NREL to the available buses in the NPCC network, a principal component analysis (PCA) is performed by Wooyoung Jeon, leading to nine sites in New York and seven sites in New England.

The location of the wind farms are in the following buses: Orrington, Sandy Pond, Millbury, Northfield, Southington, Millstone, Norwalk harbor, Millwod, Newbridge, 9Mile Point, Leeds, Massena, Gilboa, Marcy, Niagara and Rochester.

To characterize the variability in spatial and geographical terms, a cluster analysis by Lindsay Anderson is implemented using a *k-means* methodology for scenario reduction [24]. The determination of the clusters for the transition probability matrix was done using the wind speeds from the NREL dataset, and then the wind speeds are converted to available wind power using a multi-turbine modeling approach [53]. The wind scenarios are then reduced to four, with the probability of occurrence of each one accordant to the historical data from NREL. In this setup, a 'high wind', a 'low wind' and two intermediate scenarios are modeled, with different spatial patterns for each site. The transition matrices are assumed to be Markovian, allowing for determination of the wind output and state at different hours of the day. The input data used the available information on days with similar characteristics in terms of wind speed.

5.1.4 Storage Specifications

To model Energy Storage Systems (ESS), special generators were specified, with the possibility of having different charging and discharging efficiencies, according to the physical properties of the ESS. The energy available in any ESS can be used to provide energy in a base case, or to help support the grid in contingencies. The optimal use of storage is dependent therefore on the value of the stored energy. To determine this value, a run with no ESS in the system was done, and the maximum price observed across time was chosen as the starting transversality condition. Then the algorithm suggested in Section 4.5 was implemented. This modeling allows determination of the opportunity cost of stored energy at the end of the horizon period, avoiding the bias of using all of the stored energy by the end of the optimization period or when contingencies occur (i.e. a transversality condition for this resource).

The ESS are located in the same buses where wind is placed for the relevant case. The capacity of the energy storage resources consider a case with high penetration, with total energy capacity equal to the amount of deferrable demand. This specification makes comparisons between cases easier. The maximum hourly power available per ESS was set to be one sixth of the energy capacity (i.e. it would take six hours to completely deplete a fully charged ESS, if the discharging efficiency is set to 100%).

5.2 Case Study, NPCC Network

The objective of this case study is to analyze different mechanisms for integration of RES into the system, specifically wind. The case study will examine two main mechanisms, a supply side one and a demand side one. The mechanisms studied analyze the conjoint effects of adding wind into the system, plus storage, either placed close to demand centers as deferrable demand, or co-located with the storage. The time steps considered are hours.

All cases include both wear and tear costs (often referred to here as ramping costs) and load following reserve. The purpose is to internalize costs that are now privately faced by generators but not compensated in the market. While the SO's take into account the cost of energy, there are sources of costs not included in the objective function when moving a generator's dispatch as discussed in section 4.1.3.

The value of the ramp reserve is idiosyncratic to the specific fleet considered, given the three aforementioned sources of costs. For example, while newer coal plants are more flexible in their operation range without affecting their heat rates, in areas where the majority of the fleet is composed of legacy generators the efficiencies of coal plants tend to be negatively affected when required to ramp up or down.

In the case of a base load unit, due to the preferred operating regime of these generators, the cost of ramping is difficult to determine, as no data is available. In such a case, the best proxy for the cost of ramping is the price a base load unit would be willing to pay to avoid being moved. Assuming a nuclear plant is asked to reduce their output in response to network conditions, the opportunity cost for such plant would be the price of energy. In [61], the cost of energy is assumed to be around 0.05 $/kWh for their calculation of total losses per shutdown, which will be taken as a guideline.

The case for deferrable demand, on the other hand, is engaging demand side resources - as opposed to supply side mechanisms like storage co-located with wind farms. In this case, loads broadly defined (consumers, industrial loads, etc) specify a certain portion of their demand that can be covered at any time of the optimization horizon. Presumably, these loads will be served in periods when the costs of serving them are lower (time arbitrage). In a case where enough deferrable demand is available in the system, the hourly price should converge to a narrow band of values, where the width of the band will depend on the supply demand variability (e.g., intermittency from stochastic resources). Research done at this group suggests that around 25% of the total summer load in New York can be considered deferrable. In this context, deferrable is the demand that is temperature sensitive, and that therefore can be served using devices that perform time arbitration. A case in point are the so called 'ice batteries', which produce ice at low price periods and then melt it to cater for the air-conditioning (a-c) demand. The implementation uses an ESS that can be serviced at any time period, but does not provide injections into the system.

5.2.1 Results

The results here presented summarize the cost of serving a given demand profile for a 24-hour period for four cases. The analysis assumes that the bulk power is allocated through a wholesale market. The injections and exports from outside of the New York and New England regions (NYNE) are fixed, to focus on this region. For this reason, the results include information only for the NYNE region, and the wind farm and storage placement is focused on this region. Many studies on the effects of renewable integration focus on the payments made by customers thanks to decreased energy prices. This research group (E3RG) has argued before that this emphasis ignores the financial adequacy issue for conventional generators [46]. Because of the zero marginal cost offers from renewable resources, conventional generation will see a decreased energy income, and therefore less resources to cover the capital expenses they have. In this situation, and according to the reliability contribution of the generators, generators can be compensated in the capacity market, therefore cover some of their decreased income. To avoid then the distortions from evaluating a policy based on the payments from customers, the different cases are evaluated using a measure reflective of the system operation and performance. The measures used are:

1. The expected operating costs, including reserve payments, to reliably cover the load of the day.
2. The amount of renewable energy accommodated and dispatched in the system. This presumes that the social planner is interested in the increase of wind energy dispatched.
3. The total generation capacity needed from conventional generators for re-

liability purposes. This generation capacity may have a low probability of use, but are contracted for reserves, and hence needed in contingency cases.

The simulation starts at 7AM and finishes the next day at 6AM. To obtain parameters for the final value of storage, the initial conditions in dispatch for generators and the initial storage amount, an iterative process is implemented in which the system is simulated several times, until the differences in the three aforementioned initial conditions are stable and below a threshold. The obtained initial conditions can be considered therefore a steady state situation.

Four main cases are specified, with incremental modifications to the system.

- Case 1: No Wind: System with status quo.
- Case 2: Wind: 29 GW of wind capacity added.
- Case 3: Wind + Deferrable Load, 22GW of energy deliverable per hour.
- Case 4: Wind + Storage collocated with wind, 22GW of energy deliverable per hour.

In all cases, the cost of ramping and the determination of load following reserve is included as part of the optimization. The operational reliability in the system is evaluated by generator outages in Northfield (Bus 72926) and East Shore (Bus 73663), that provided ramping and base load capacity in the system, and are electrically close to the load centers in the system.

Table 5.3 summarizes the main results for the cases simulated. The first row shows the operating costs for each case, with sequential reductions thanks to adoption of wind (Case 2), use of deferrable demand in urban sites and wind

Table 5.3: Summary of Key Results

	Case 1	Case 2	Case 3	Case 4
1. E[Operating Costs] (k$/day)	50,279	41,932	40,908	40,513
2. E[Ramp Payments] (k$/day)	499	1,385	1,080	1,166
3. E[Gen. Net Revenue] (k$/day)	77,182	52,488	53,377	52,665
4. E[ISO Surplus] (k$/day)	8,477	8,851	-5,124	7,956
5. E[Payments Loads] (k$/day)	135,939	113,385	101,423	113,229
6. GenCap (MW)	58,550	57,004	50,778	60,360
7. E[Wind Energy] (MWh)	718	137,517	147,401	150,957
8. LOLE (hours/year)	0	1.76	0.17	0.37
9. E[Amount Shed] (MWh/year)	0	1,543	81	275
10. Objective Function (k)	-8,885,102	-8,895,685	-8,957,600	-8,902,580
11. E[Wind Revenue] (k$/day)	NA	10,112	12,262	12,094

(Case 3), and co-location of storage in the wind farm sites (Case 4). This reduction in operating costs is driven by adoption of zero short run marginal cost wind, and better utilization of the installed wind capacity (Row 'Wind Energy').

The conventional generators net revenue (row 3) is decreased by the adoption of wind that displaces some of the units used in the no wind case (Case 1). In both the base wind case and the storage case (Cases 2 and 4), the net revenue for generators, while smaller than Case 1, are higher than when deferrable demand resources are available in the system. The explanation for this lies in the changes that the wind resource creates: the adoption of wind increases the congestion in the network, unless this change is mitigated by controllable demand. The congestion payments, the difference between what the loads pay and what the generators get paid, are higher in Cases 2 and 4 than in Cases 1 and 3, causing higher net revenues compared to Case 3, and congestion payments. This difference indicates more price segregation and locational differences in prices when the storage is collocated with wind. The wind revenue (row 11) are the payments for energy valued at the locational marginal price. The main finding in this case is that, tough Case 3 dispatches less wind than Case 4, the revenue in this case is higher. This is later discussed in further detail. The ISO surplus (row 4) is calculated as the difference between the payments from loads (row 5) and the income that generators receive (sum of rows 1, 3 and 11). Assuming that the ISO's surplus (or congestion rents) sustain the operating costs of the system operator, and any surplus is allocated for transmission infrastructure projects, the lower payments seen in the deferrable demand case mean less resources for this purpose. The reason for this outcome is due to the more uniform usage over the optimization horizon of the transmission assets, relieving pressure at peak periods of time and therefore leading to a reduced segmentation of the market. Collocating storage with the wind farm on the other hand increases the congestion payments with respect to the base wind case (Case 2), because the higher wind availability now has to be shipped at peak hours of the day to the demand centers in downstate New York and the Boston area. These areas have a constrained transmission capacity, and as such, can become load pockets at peak period times. Such a situation would provide local generators with market power that could further increase the payments from loads. The negative value observed in the deferrable demand case is due to the relative low payments by loads in this case. This low payment is achieved thanks to more stable energy purchases over the day, leading to a flattened profile for the prices observed in the system.

While payments from loads (row 5) are not indicative of the benefits in the system due to the problem of depression of energy prices, all wind cases clearly help to decrease these payments when compared to the no wind case. The use of deferrable demand in fact leads to the lowest payments from loads, derived from the elimination of the congestion before discussed. Therefore, if the objective is to increase the benefits for consumers in the form of reduced payments from loads, which for certain constituencies may be a selling point to adopt new policies, deferrable demand measures deliver the highest benefits.[1]

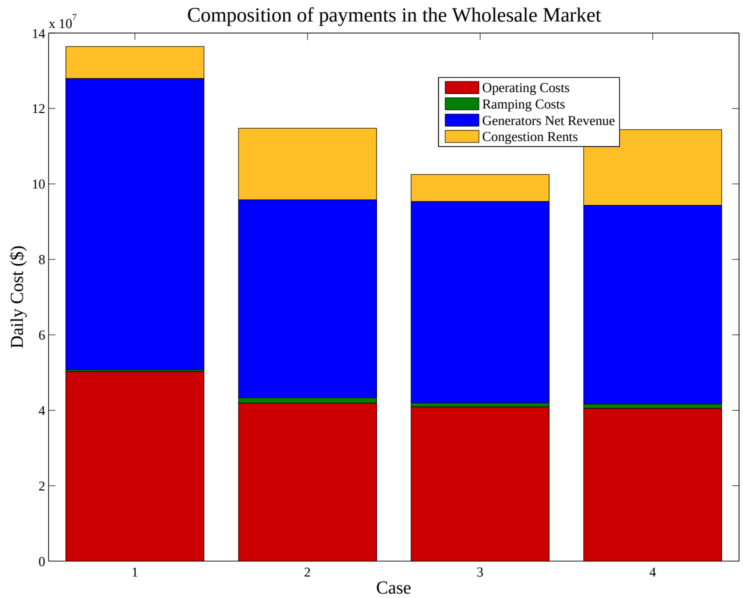

Figure 5.2: Expected Payments in the Wholesale Market

A further symptom of the system benefits of placing storage close to demand centers, though operational costs are not decreased, is manifested in the conventional generation capacity needed for reliability purposes (row 6), which is decreased with deferrable demand (Case 3), but increases in the utility storage case (Case 4). This increase with respect to the base wind case (Case 2), at almost the level of the No wind case (Case 1) indicates the need to dispatch the available fleet in a manner that supports the flows of power available from the wind buses. In our previous research we generally found that the conventional gen-

[1]The reduction in prices observed can lead to more “missing money” for conventional generators that are needed for reliability purposes, and then would have to be compensated in a capacity market. For this reason, focusing on prices is not a preferred metric of the real performance of the system.

eration capacity needed was increased as wind was adopted. In these cases, the use of 16 wind sites in the system and the geographical averaging that this distribution achieves gives wind a capacity contribution that allows less conventional generation needed for reliability purposes. The contribution of capacity from wind depends on the underlying characteristics of the resource, according to location, and its interaction with the other factors in the system, including load patterns, and the maintenance and availability of the conventional generation fleet (which is not modeled in this study). This is an area of active research [33], and while the results obtained here are in part derived from the network reduction characteristics, the evidence suggests that these results are also driven by the scenario specification, and the offsetting effects of using a typical day in the load duration curve to calculate the transition probability matrices.

In Cases 3 and 4, the further use of storage and deferrable demand increases the utilization of wind (row 7), by avoiding spillage caused by the uncertainty of this intermittent resource. Given the characteristics of the network, the use of utility scale energy storage systems (ESS) enables the highest utilization of the installed renewable capacity observed, even higher than placing the same amount of storage close to the demand centers of the system. The Loss of Load Expectation (LOLE, row 8) measures the number of hours that are expected to be shed during a determined period. According to the reliability standards established by NERC (page 48, [51]), the planning authority has the responsibility to: *Calculate a planning reserve margin that will result in the sum of the probabilities for loss of Load for the integrated peak hour for all days of each planning year analyzed (per R1.2) being equal to 0.1. (This is comparable to a "one day in 10 year" criterion).* For the purpose of this calculation, it is assumed that if some load is shed in a period, the full hour is added.[2] In all cases, the LOLE is below the maximum established by reliability standards, 2.4 hours per year. However, the superiority of Case 3 (deferrable demand) is clear, with less than half the value compared to utility storage (Case 4), and one tenth of the value in the unmitigated wind case (Case 2). As an additional measure, the quantity of load shed expected is reported in row 9. For the cases considered, the order observed in the LOLE analysis of the cases is maintained. However the magnitudes show very small amounts of load shed in case 3, compared to the other two cases. This provides information for planners useful for evaluating each case, in addition to the probability reflected in the LOLE calculation, and reflects the importance of considering both dimensions, given the inherent limitations in the calculation of LOLE.

Figure 5.2 summarizes the expected costs in the system excluding ramping costs.

5.2.2 Discussion

The expected dispatch of the generators varies according to the uncertainty in the availability of resources, the use of the storage resources and the response from the demand side. Figure 5.3 shows the expected dispatch for Cases 1 and 2. For the no wind case (left pane Figure 5.3) the base load generators (Nuclear, Hydro, refuse) and the Coal generators are managed steadily, with no ramping. The ramping for load following is performed by natural gas units, and some oil generators close to demand centers.

[2] This is a conservative way of calculating the amount shed, as the fault is likely to be shorter than the full length of the individual periods of analysis.

The addition of wind generation (right pane, Figure 5.3) replaces 25%, 16% and 7% of the daily energy of the day provided by gas, oil and coal generators respectively. This replacement by zero short run marginal cost wind takes into account the necessary ramping payments to be paid to conventional generation to compensate them for the added fatigue incurred in the accommodation of the uncertainty of wind.

The use of deferrable demand (left pane, Figure 5.4) changes the overall load profile, increasing the conventional generation dispatched at low demand periods (for example from 8PM to 7AM, right side of the figure), and decreasing the amount of generation needed to cover the peak demand of the day. The reason for this change is because the demand to be deferred, around 25% of the total demand, can be serviced at any time, and as noted in the profile, leads to load shifting. This is achievable by using thermal energy storage, like ice batteries and other devices that are readily available and whose cost is relatively affordable, around 40$/kWh [16].

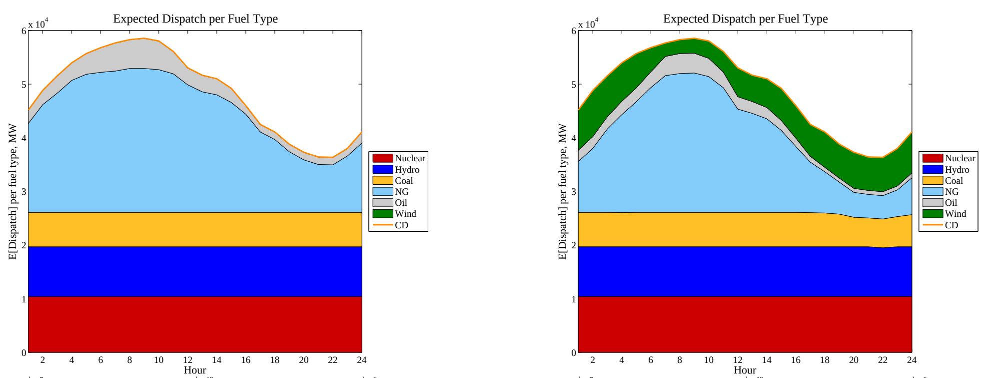

Figure 5.3: Expected Daily Composition of Generation, No Wind and Basic Wind.

This modification of the load also has advantages from the point of view of the use of the available assets in the electricity system, since the peak is clipped and less of the capacity in the load pocket is necessary for covering the highest demand of the day. Therefore, reductions of 15% in the energy used from oil generators close to demand centers are achieved, compared to Case 2. While the difference between day and night is not totally suppressed, the overall fleet management has ramping excursions with lower magnitudes than those observed in cases 1 and 2 for the ramping fuels (natural gas and oil). The coal fleet is managed with less expected ramping than any of the other wind cases, accruing environmental benefits due to avoided emissions incurred in ramping.[3] The hour-to-hour movements are optimal because the independent system operator internalizes the cost of ramping in all cases.

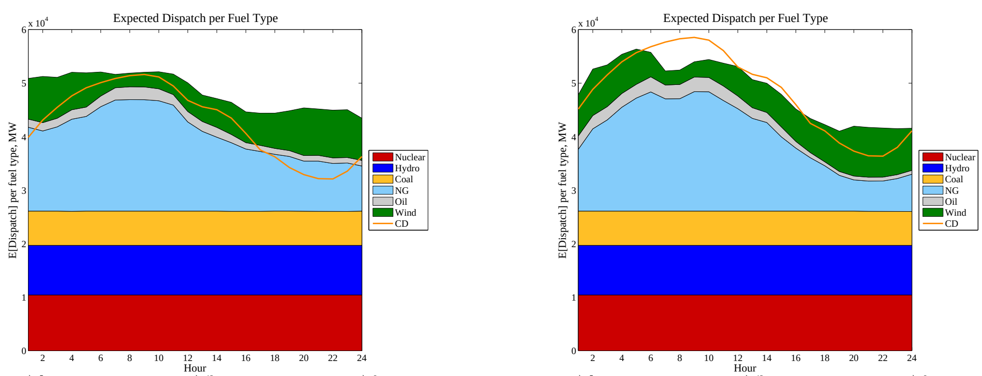

Figure 5.4: Expected Daily Composition of Generation, Deferrable Demand and Storage.

The placement of storage at the buses where the wind is placed (Case 4, Figure 5.4) achieves a milder reduction of the total system peak, around 6%, and as previously noted, causes the highest wind utilizations of the four cases considered. This additional use of the wind capacity available comes at the expense of natural gas usage, which is reduced around 8% compared to Case 3 and 5% compared to case 2. However, the increased congestion observed in this case marginally increases the use of oil generators in load pockets in urban

[3]The magnitude of these benefits is not calculated here and will be subject of future research.

centers by 6% with respect to Case 3.

In this analysis, the cost of deployment of either alternative (storage and deferrable demand) is not considered, just the operational management. While not trivial in nature, these costs are witnessing steady reductions [17] and the savings obtained from their usage can be used to amortize the capital costs incurred during the installation phase, as well as offset the aforementioned costs of the smart grid.

Figure 5.5 summarizes the overall expected energy used per fuel type in each case. The nuclear and base load capacity remains virtually constant in all cases, with the main substitution of fuels occurring in gas, oil and to a lesser, proportional, extent coal.

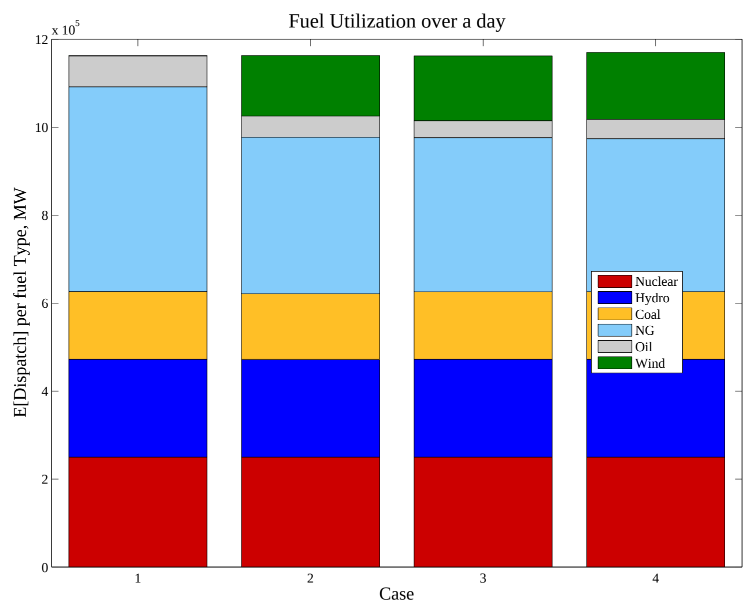

Figure 5.5: Total Expected Energy for the day

The comparisons, while harder to observe due to the magnitudes of energy used during the day, indicate the tradeoffs in different fuel types discussed in the commentary to Figures 5.3 and 5.4.

To analyze the financial viability of wind operators, a metric of interest is the compensation these generators receive for the electricity generated. In the wind cases, wind generators are placed in buses with other sources of generations, typically with higher marginal costs. Therefore, these generators are rarely marginal in the system. Table 5.4 summarizes the total payments made to wind operators in each one of the cases studied. The most important characteristic is the fact that, though less wind is dispatched in Case 3 compared to Case 4 (Table 5.3), the payments to wind farms for the energy generated is higher. To understand the reason for this situation, refer to Figure 5.6. Here, the hourly expected payments are plotted for each one of the cases, with the x-axis indicating time (the lower marking indicates the hours of the day). In the simulated days, two periods are characterized by decline in the income for Case 2 (unmitigated wind): around 1PM and around 4AM. The first one of these low revenue periods is caused by lower wind availability, reflective of the historical information of the day used to calibrate the model. The overall period from 11AM to 6PM is nonetheless characterized by the highest prices in the system, given to conventional generation in urban areas.

The second decrease in income is due mainly to the opposite effect in wind patterns: high wind availability, coupled with low demand, leads the prices in the system to be close to zero, making wind generators the marginal units in certain buses. Contrasting this situation to the base wind case (Case 2), the shift of demand to these hours of the day in Case 3 requires the utilization of additional resources besides wind, therefore increasing prices and the payments received by the wind generators. Utility storage, while avoiding zero prices in the system at low demand periods due to accumulation of the available energy, is not as effective as Deferrable Demand in raising the income of wind generators. This is due to the fact that Case 4 does not increase demand at these hours, it just uses whatever capacity is available to charge the storage units.

Table 5.4: Payments to Wind farms (USD Millions)

Case 2	Case 3	Case 4
10.112	12.262	12.094

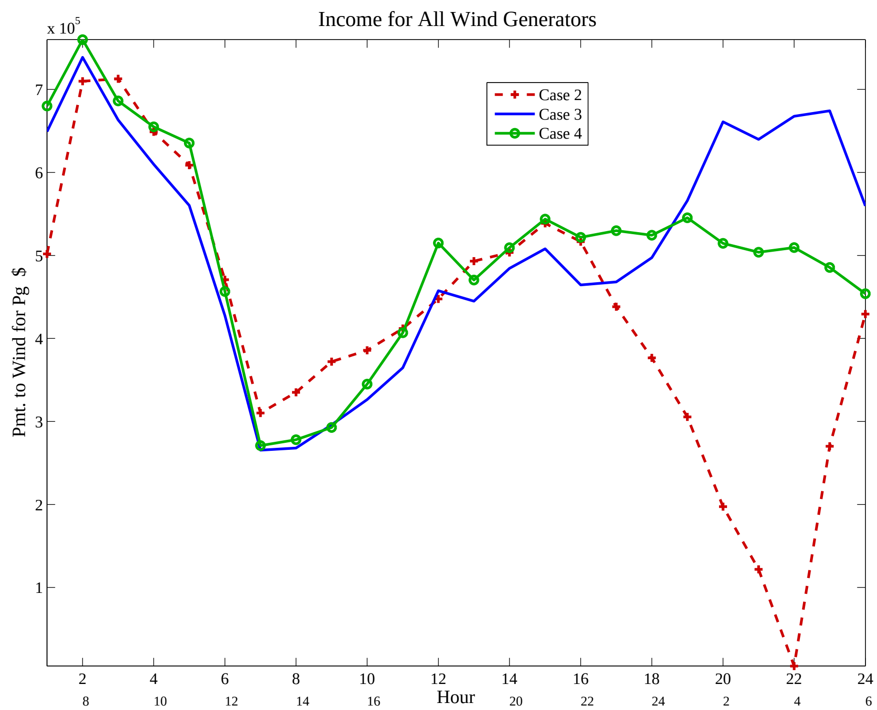

Figure 5.6: Hourly Compensation for Wind Farms

Table 5.5 shows the geographical decomposition of these payments in the New York and New England regions, which in both areas are increased under the Deferrable Demand case.

Figure 5.7 compares the expected incomes for each one of the wind farms in

Table 5.5: Geographical Composition of Wind Payments (USD Millions)

	Case 3	Case 4
NE	5.0562	4.9658
NY	7.2058	7.1282

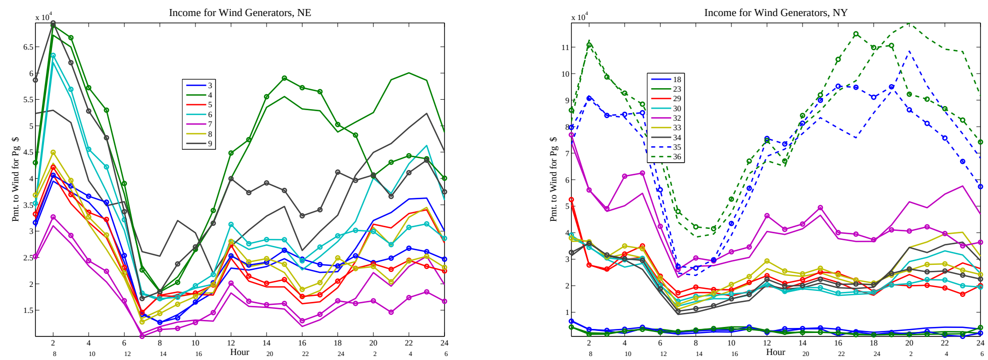

Figure 5.7: Expected Income for Wind Generators per Region

the NY and NE regions. The lines with a marker correspond to Case 4, as in Figure 5.6. The wind generators most affected by the use of Deferrable Demand are those with the highest capacities in the system, generally placed far from the main urban areas of the system. Therefore, the wind farms in Sandy Pond and Norwalk Harbor in New England (buses 4 and 9), and those in Niagara and Rochester (buses 35 and 36) have the highest payments. This is an important feature for policy making, as it is not necessary to put storage in the production buses to create more favorable conditions for these generators, which was the theoretical motivation behind the formulation of the deferrable demand case.

This geographical effect is further illustrated in Figure 5.8. The four maps show the expected prices in the system at 1AM. The map in the upper left corner corresponds to the distribution of prices in case 1, with relatively high prices in the 86 to 89 \$/MWh range. Unmitigated wind capacity helps to greatly reduce these energy prices, now moving in the 45 to 66$/MWh range, due to the additional generation placed in the system.[4] Utility storage (lower right corner) increases the prices in some of the buses, but the extent of its effectiveness is muted compared to the deferrable demand case (lower left corner). In this latter case, the higher demand from urban centers avoids the low prices at low demand periods, while avoiding very high prices in high demand periods, thanks to a more uniform demand management over the optimization horizon.

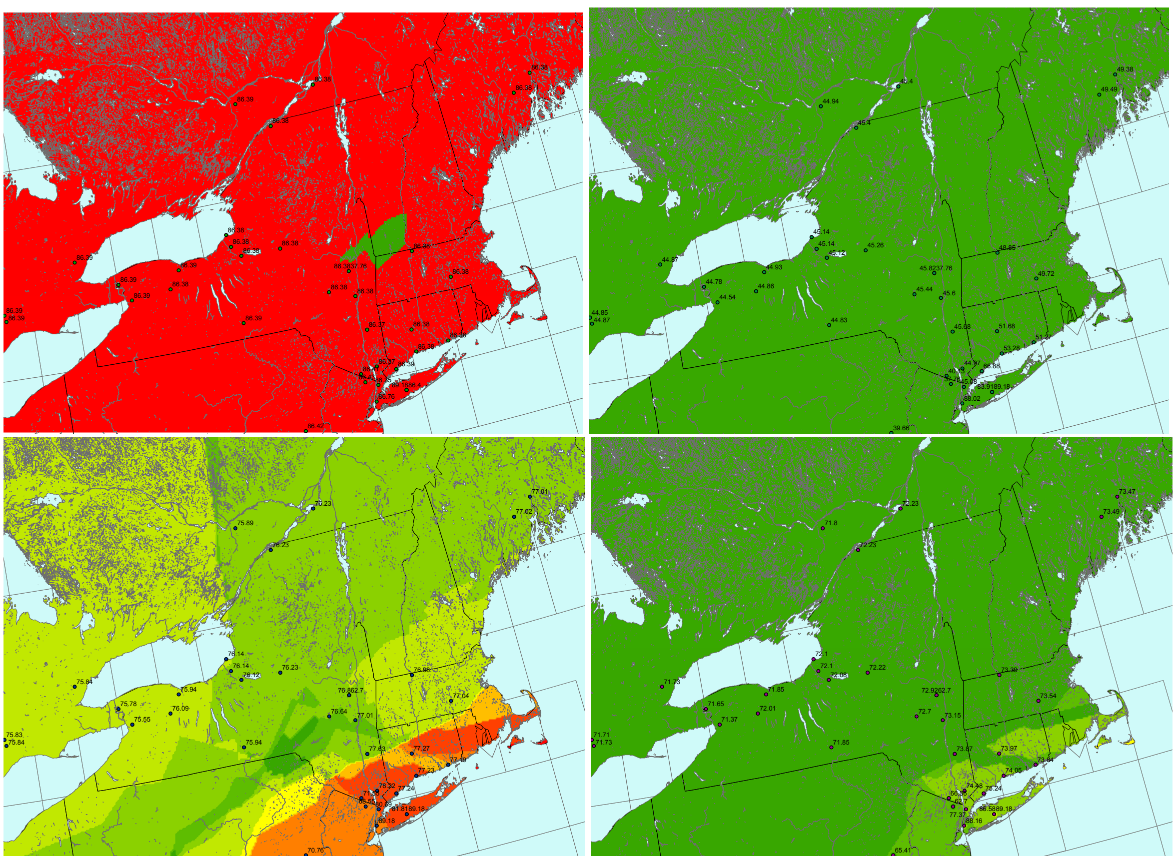

Figure 5.8: Prices in the system, Low Demand Period

The choice between deferrable demand and storage collocated with the wind farm will then depend on the objective sought with each measure, as none of them Pareto dominates the other. If the objective is to maximize the amount of

[4]Wind is not marginal at this hour, but in the 2AM to 5AM period sets the price in certain buses

wind used, the collocation of the storage is more effective for two main reasons: first, as long as the energy capacity of the storage is comparable to the wind capacity installed, the production surpluses obtained at low demand periods can be used instead of spilled if no additional support from the conventional generation is available to facilitate the flows from the wind buses. This facilitates the deferring of consumption decisions regarding the wind resource. Second, the use of storage makes the wind resource amenable to a conventional generator, that can be dispatched at will, within its technical constraints. This management would partly eliminate the uncertainty of wind, hence facilitating its optimal scheduling and usage by the system operator and the loads in the system. Additionally, the operating costs would be lower, given the zero marginal cost of wind.

If on the other hand the purpose is to reduce congestion and eliminate load pockets in the system, to reduce the generation capacity needed for reliability purposes or to increase the payments to wind generators (not necessarily the dispatched amount), the use of deferrable demand is more effective than collocating storage. This is due to the possibility of serving demand in periods that are characterized by low transmission usage and high availability of the wind resource. Since load and wind availability are in certain cases almost negatively correlated, the change in the timing of the demand decreases the variability in use of the transmission system, with a more constant delivery of energy occurring at all hours. This management avoids the congestion that occurs at peak hours of the day, which in a transmission constrained system as the NPCC one can limit the transfer capacity to the demand centers in urban areas. A collateral benefit of this operation is observed in the decreased generation capacity required to cover the contingencies considered in the optimization horizon. This is a direct consequence of the load shifting that deferrable demand facilitates. The load that was previously served at peak times can now be served at low demand periods, relieving conventional generation that was needed to cover the energy for high demand periods. Since the amount of generation necessary to reliably cover the load is dictated by the peak over the horizon considered, the “shaving” of this peak contributes to the reduced capacity needs. While deferrable demand is only used for energy purposes, the extend of its usage takes into account the possible occurrence of contingencies. Then, the liberated conventional resources from peak hours are available to serve energy in both high and low probability cases, and hence the reduced generation required for reliability purposes.

5.2.3 Environmental and Capital Costs

To compare all the costs in a common basis, the total operating costs accrued over the horizon were divided over the total load served.

In the case of capital costs, the annual cost of replacement of the conventional fleet used was calculated per fuel type, and divided by the equivalent total load of the system over a year [48]. All peaking units are treated with a

Table 5.6: Expected Annualized Capital Costs ($/MWh)

	Case 1	**Case 2**	**Case 3**	**Case 4**
Operating Costs	43.23	36.06	35.20	34.63
Capital Cost	33.43	33.02	31.37	35.13
Total Operating+Capital Costs	76.67	69.08	66.57	69.75
Environmental Costs	11.96	11.01	11.01	11.04
Grand total	88.63	80.09	77.58	80.79

similar capital cost. This calculation assumes that every day of the year is similar - or more accurately, that the used day is representative of the average day of the year. In the case of the environmental costs, all damages are divided by the total energy delivered over the day. The capital costs of wind and transmission are not included.

The average operating costs are sequentially reduced in the cases considered: the adoption of wind (Case 1 to Case 2), decreases the operating costs, ramping costs included, due to the displacement of more expensive sources of generation. The use of deferrable demand (Case 2 to Case 3) further reduces the operational costs, in part thanks to the optimized used of the available generation capacity and a more uniform operation of the fleet over the horizon considered. The placement of storage resources close to the wind production buses (Case 2 to case 4) increases the overall wind utilization, displaces non-renewable generators and consequently reduces the average operational costs. The reductions in operational costs from less spillage of the wind capacity thanks to storage are in fact larger that those observed with deferrable demand (Case 4 and Case 3), because the former substitutes away more conventional capacity than the latter.

On the capital costs, a similar sequence is observed, but due to different causes: The adoption of wind that, thanks to its relation to load helps to provide some capacity value into the system, reducing the average capital costs in the system (Case 1 to Case 2). The use of deferrable demand reduces the cost of capital of the used generation fleet, as well as does the utilization of storage. Deferrable demand (Case 3) has the lowest generation capacity needed of all cases considered, and the resulting cost of capital is lower than the observed in the storage collocated with wind case (Case 4).

The operational management of the generation fleet is likely to affect the airborne emissions and hence the marginal damages caused by the ramping (up and down) of the conventional generators. One of the reasons for the ramping of generators from hour to hour is to accommodate the wind in the system and its volatility.

To estimate the environmental effects of the management of the fleet, the marginal cost per MWh of expected energy delivered per fuel type is calculated. Table 5.7 shows the the marginal damages per fuel type (See [64]) in the areas where the dispatch of the generators is an endogenous variable (New York and New England).

Table 5.7: Summary of Average Marginal Damages per Region

	Cost ($/MWh)		
Location (RTO)	coal	ng	oil
isone	77.00	0.48	9.42
nyiso	82.90	3.22	22.78
Average Total	81.20	2.32	14.70

The data on marginal damages corresponds to a monetization of the cost of emissions of fine particulates of SO_2 and NO_x for each one of the 693 generators included in the original dataset.

The total damages expected are then calculated ex-post for all the expected dispatches observed in the system. Figure 5.9 summarizes the expected damages for each one of the four cases considered. Given the high marginal damages for coal generation, it is not surprising that in all cases, this fuel type has the largest effect, even though in absolute terms coal provides only in average 13% of the energy needed to cover the load of the day (see Figure 5.5).

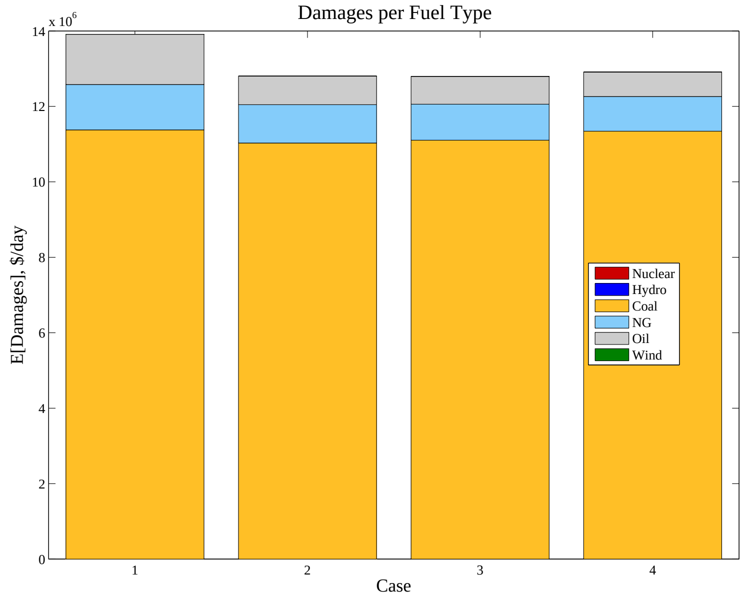

Figure 5.9: Expected Damages per Operational Management

The addition of wind into the system substantially reduces the environmental damages observed, thanks to the displacement of coal capacity, the major contributor of emission damages, and oil generators. The environmental damages in the Wind and Deferrable Demand case are very close, with less damages from oil in the Deferrable Demand case (Case 3) than in Case 2, due to displacement of this capacity in urban locations. This comes at the expense of higher damages from natural gas. However, due to the fact that the lion's share of damages comes from coal generation, and in both cases the utilization of coal is virtually identical, the overall value of marginal damages in both cases is also approximately equal (1% lower in Case 3 with respect to Case 2).

While non-mitigated wind and deferrable demand both reduce the environmental damages with respect to the no wind case, the placement of storage in the same buses where the wind farms are located requires the support of coal generation in load pockets at high demand hours, increasing the total cost of damages.

In the case study, the cost of ramping is included as a factor affecting the decision to move the generators. For this reason, the emissions observed are likely to be below the expected levels observed if this externality was not taken into account.

Including the environmental costs in each one of the cases considered reflects some of the tradeoffs incurred in the final generation portfolio. Both unmitigated wind and deferrable demand (Cases 2 and 3) have the lowest environmental damages, and after accounting for all costs in the system (operational, capital and environmental), the use of deferrable loads is the policy that provides the largest system wide benefits.

An alternative way to study the operating and capital system costs is to analyze them as total values over the period of analysis (in this case a day), and calculate the equivalent capital costs correspondent to this period of analysis. In this calculation has implicit assumptions regarding the generating units affected and the duration of the peaking spell. The motivation for this alternative calculation is to harmonize with the way in which capital costs are calculated in a case without a network. The overall results are rank consistent.

The price of capacity for peaking units is the same used in the prorated calculation [48], using a replacement capital cost of 88 Thousand $/MW-Year for all generating capacity. This valuation assumes that the peak generation capacity is primarily affected by the changes in peaking units, not baseload. In order to focus on the operation time of the peaking units, it is assumed that these are

Table 5.8: Total Expected Costs for the NYNE Region

	Case 1	**Case 2**	**Case 3**	**Case 4**
1. Operating Costs (k$/day)	50,279	41,932	40,908	40,513
2. Ramping Costs (k$/day)	499	1,385	1,080	1,166
3. Capital Cost (k$/day)	103,048	100,328	89,370	106,235
4. Total Costs (k$/day)	153,828	143,646	131,359	147,915
5. % Change from Case 1	-	-6.62	-14.61	-3.84

used only for 100 hours in the summer peaking load, of which two hours are part of the representative day chosen. In the case of utility storage (Case 4), this calculation will be a lower bound in the likely case that these units are used to provide peaking capacity. For deferrable demand, since the capital cost is shared by the provision of thermo services, these costs are neglected. Table 5.8 summarizes the overall costs for the new calculation. Rows 1 and 2 are identical to the results shown in table 5.3 for operating costs and ramping payments. The addition of wind capacity into the system (Case 2) lowers the total system costs by 6.5% compared to Case 1, and adding utility storage lowers these costs by 3.9%. The most dramatic reduction occurs when adding deferrable demand, with a 14.3% reduction in the total system costs, driven by the capital cost reduction, thanks to the decreased conventional generation capacity required for reserves to cover contingencies and mitigate wind variability. This is consistent with the former calculation of capital costs.

To analyze part of the geographical diversity component in the system, Tables 5.9 and 5.10 divide the results for buses with and without deferrable demand. The deferrable demand buses chosen are urban centers with the highest demands in the system, corresponding to the New York and Boston areas (eastern part of the system). These customers have reductions in capital costs of 24.3% compared to case 1, supporting the initiative to provide this capability for urban demand centers.

Table 5.9: Total Expected Costs for the Deferrable Demand Buses

	Case 1	Case 2	Case 2u	Case 3	Case 4
1. Operating Costs (k$/day)	23,122	18,653	17,323	17,416	19,152
2. Ramping Costs (k$/day)	285	452	561	275	434
3. Capital Cost (k$/day)	53,251	51,845	51,820	40,294	54,898
4. Total Costs (k$/day)	76,658	70,950	69,704	57,985	74,484
5. % Change from Case 1	-	-7.45	-9.07	-24.36	-2.84

Table 5.10: Total Expected Costs for the Other Buses

	Case 1	Case 2	Case 2u	Case 3	Case 4
1. Operating Costs (k$/day)	27,158	23,280	24,145	23,492	21,362
2. Ramping Costs (k$/day)	215	934	1,010	806	733
3. Capital Cost (k$/day)	49,797	48,482	48,459	49,076	51,337
4. Total Costs (k$/day)	77,170	72,697	73,614	73,373	73,431
5. % Change from Case 1	-	-5.80	-4.61	-4.92	-4.84

5.2.4 The Initial Conditioning

To analyze and compare the influence of the starting point as part of the initialization process, the case study presented in section 5.2 was modified. Therefore, instead of starting the optimization horizon at 7AM, the initial period was set to coincide with the beginning of the day (midnight).

Table 5.11 shows the metrics for system performance in the case of a midnight horizon start. These cases are identical to those reported in section 5.2.1, with different starting hours for the system, denoted by a suffix 'm'. Due to the initial conditions of the problem, the values for all metrics change, however maintaining ordinality in general. Following will be an analysis of the main differences observed in Table 5.11 compared to the cases in Table 5.3. By design, the

Table 5.11: Summary of Key Results, Midnight Start

	Case 1m	Case 2m	Case 3m	Case 4m
1. E[Operating Costs] (k$/day)	50,304	41,857	40,741	35,710
2. E[Ramping Costs] (k$/day)	524	1,640	1,595	1,239
3. E[Gen. Net Revenue] (k$/day)	76,570	49,938	50,591	55,913
4. E[ISO Surplus] (k$/day)	8,467	8,857	-4,894	8,246
5. E[Payments Loads] (k$/day)	135,340	110,824	99,395	114,008
6. GenCap (MW)	58,550	56,947	50,579	63,762
7. E[Wind Energy] (MWh)	718	145,024	159,660	169,966
8. LOLE (hours/year)	-	1.60	1.03	0.51
9. E[Amount Shed] (MWh/year)	-	1,465	917	42
10. E[Wind Revenue] (k$/day)	-	10,173	12,957	14,139

reason for the changes is due to the modification of the initial period considered. The operating costs (row 1) maintain the same order, with significant decreases in operating costs for Case 4 (Wind and storage), driven in turn by an increase in the wind dispatched (Row 7). In fact, the total amount of wind dispatched is higher than the potential wind available when starting the optimization at 7AM. The reason for this is partly due to the higher wind availability in the initial period, and the accumulation of probabilities through the transition probability matrix. Figure 5.10 shows the expected wind comparing to the values in Case 2 starting at 7AM. This fact will shift all results according to the initial point used.

The higher wind usage leads to an increase in the ramping payments made over the day (row 2), with large values in Cases 2 and 3. The Generators Net Revenue is similar in order to the observed results using a 7AM starting point, with significantly lower values in all wind cases compared to Case 1m due to displacement of the conventional capacity. The ISO surplus (row 4) is the difference between payments to generators (the sum of rows 1, 3 and 10) and the payments by loads (row 5). This coarse measure of the congestion in the system behaves similarly to the results in Section 5.2.1, as does the payment to loads

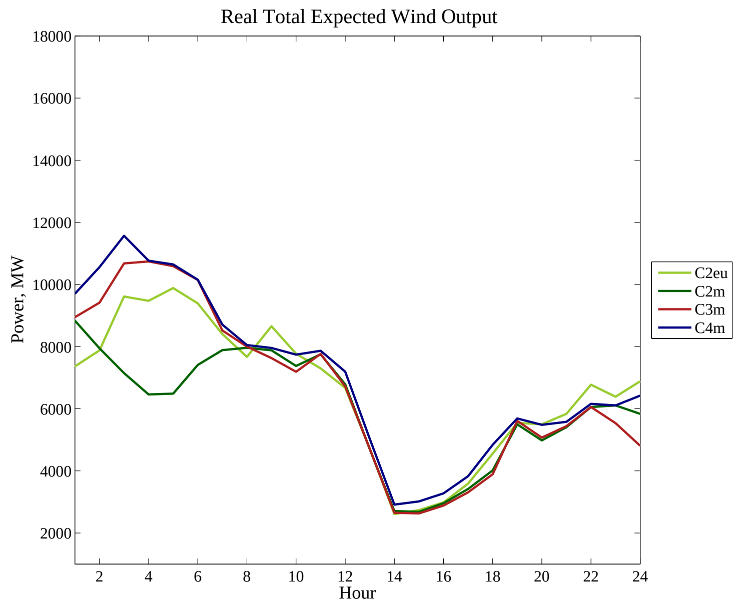

Figure 5.10: Expected Wind Dispatched, Midnight Start

(row 5) and the generation capacity needed (row 6).

The loss of load expectation (row 8) complies with the reliability standards, with an interesting decrease in case 4 (utility storage). The reason in this case is that the initial energy stored at high availability periods of the horizon, when the uncertainty is lower, helps to decrease the low occurrence of cases in which load has to be shed due to the variability of the wind resource. This also affects the wind compensation, which now improves with the utility storage case and maintains a higher price at low demand periods thanks to better utilization of the storage capacity.

The main conclusion of this part is that, though conditioning the system to start with better initial and final constraints for storage and generators dispatches seemed like a sensible way of removing the possible bias problems, it is not enough to counteract them. The implementation of a receding horizon scheme similar to that suggested in Section 3.1.2, and additional constraints that reflect the settlement of contracts for ancillary services (reserves for contingency and inter-temporal imbalances) can help to obtain closer to optimal conditions and improve the performance of the market, both for planning and real time reconciliation. This is a future research direction.

5.2.5 Final Remarks

This section presents the analysis of a demand side and a supply mechanism germane to integration of renewable energy sources (RES). On the demand side, deferrable demand is studied as a mean to increase the usage of renewable resources, by accounting for the availability and uncertainty of theses sources of generation. On the supply side, the use of storage in the same bus as the wind generators are placed is considered. While none of these proposals will strike one as new, the main contribution of this study is the use of a rigorous stochastic optimization model that extends the dispatch models used by ISO's. Some differences specifically studied here are the addition of terms in the objective function to account for load following reserves. This framework also allows for a nuanced representation of the variability of renewable energy sources (RES), and the usage of Energy Storage Systems (ESS) and processes to defer load that go beyond the time arbitrage aspect traditionally considered. We find significant benefits in the use of controllable demand, both from the fleet operation point of view and from the perspective of welfare and payments in the system for reliability purposes. One of the premises of ESS adoption is that time arbitrage will make storage sources more economically viable. Charging an ESS when is cheap and discharging it at expensive hours is not enough to justify the investment costs given the current technology. Moreover, such an approach ignores the general equilibrium effects that will eliminate price differences over the day. The case illustrated in this section is a point in case, in which establishing a procedure to defer load (e.g. a contract, or the use of novel devices to cover the temperature sensitive demand) achieves less congestion in the system, better utilization of the RES available in the system and decrease in spatial and temporal price differences. In all measures used (but operating costs), the demand side mechanism is clearly superior. The main advantage from the operational point of view is the reduction of congestion observed, leading to substantial savings to consumers, and the improved usage of the generation assets available. From the planning point of view, the total generation capacity needed is significantly decreased.

5.3 Case Study, 30-Bus Network

The objectives of this case study are two principal ones: (1) to analyze the geographical effects of wind and placement of storage in the system in a test system (the 30-bus network). (2) To quantify the benefits of using a nuanced model of the electricity system, with a full network. Additionally, another objective is to understand the reliability contribution of storage resources for operation of the system. The cases used here are an extension of those considered in Section 3.3. However, instead of the deterministic multiperiod OPF from Chapter 3, the second generation Multiperiod SuperOPF is used (see Chapter 4). For this purpose a number of low probability possible scenarios (contingencies) are included, simulating a variety of operational conditions in the system that can deviate from the high probability scenario. The characteristics of the 15 contingencies include:

- Full outages of generation at any given bus in the system, for all the generation buses (six contingencies).
- Loss of transmission tie lines between areas, linking urban and rural areas, one line at a time (four contingencies).
- Loss of intra region lines, providing reliability services in the urban area, one line at a time (five contingencies).

5.3.1 A Test Network for Reliability Purposes

The network used is the 30-bus test system (see Section 3.2.1), which due to its construction and characteristics, enables reliability analysis in a wide range of operation without violating voltage limits or threatening the feasibility of the problem. The following cases are considered:

1. No Wind, base case for comparison
2. Wind in a single rural location (bus 13), 50MW power capacity.
3. ESS in a single urban location (bus 8), with 80 MWh energy capacity.
4. Wind in a single rural location (bus 13), 50MW power capacity. ESS in a single urban location (bus 8), 80 MWh energy capacity.
5. Wind in two rural locations (buses 13 and 27), each one with a 25MW power capacity. ESS in a single urban location (bus 8), 80 MWh of energy capacity.

6. Wind in a single rural location (bus 13), 50MW power capacity. ESS in two locations, one urban (bus 8, energy capacity 40MWh) and one co-located with the wind farm (bus 13, energy capacity 40MWh).
7. Wind in two rural locations (buses 13 and 27), each one with a 25MW power capacity. ESS in two locations, one urban (bus 8, energy capacity 40MWh) and one co-located with one of the wind farms (bus 13, energy capacity 40MWh).
8. Wind in two rural locations (buses 13 and 27), each one with a 25MW power capacity.

The rationale for the setup of these cases is to isolate individual changes, and perform pair-wise comparisons. For example, to analyze the effect of the distribution of wind capacity, Cases 1 and 7 can be compared. All cases were simulated with and without a network, to analyze the effects of congestion in the system, and the differences in using a simplified single bus model versus an engineering model. The cases with no network are denoted by a suffix 'u' (e.g., Case 1u). A further case could be analyzed, by distributing the capacity of the ESS resource, without having external sources of uncertainty. This case was simulated, but results are omitted here for the sake of brevity. The overall ESS modeling characteristics are similar to those used in Section 5.1.4.

5.3.2 Calibration

For this study, the wind information corresponds to data from the National Renewable Energy Laboratory [54]. The characterization of wind corresponds to the potential output (in MW) observed in wind site 11, Massena. This wind site is chosen because of the maximum range between high and low availabilities. For this site, the available capacity is among the highest across all the sites in New York in high wind availability periods, but also among the lowest in low wind periods (from 4% to 70%). Therefore, the variability of the resource will stress the system and require more compensation from conventional generation.

The first hour of the simulation corresponds to the 7AM load, and the last hour is 6AM of the next day. In the figures here included, the axis was not modified to start at 1AM and finish at midnight. The reason for this is to maintain the sequence solved in the simulation. The transitions from period to period are governed by the Markov transition matrices (se Section 5.1.3). While the periods close to the beginning of the horizon have relatively low uncertainty, thanks to better forecasting of the uncertainty in closer periods, towards the end of the horizon there is a higher inherent uncertainty in the forecasts used. This is particularly important in the plots of ESS usage, for cases in which storage helps to reduce the volatility in the system.

The data used for load calibration corresponds to historical data from the NYISO [55].

5.3.3 Results

The analysis of results is organized as follows. The first part analyzes the ESS usage for some selected cases, and the contribution this resource has for system operations. Then, an explanation of the differences between a case that includes a network and a single node study is done. Illustrative figures are used to analyze the salient features of chosen cases. Lastly, the comparison of all cases in terms of system benefits is done.

ESS Usage

For the first part of the evaluation of results, one of the considerations when adopting utility scale energy storage or a surrogate form of ESS controlled by a system planner is the management that can be given to this resource. The most straightforward usage of a storage resource is to provide the service of deferring energy consumption decisions across time. Nowadays, the available storage capability is very reduced, and therefore the supply and demand of power at each instant of time needs to be in balance in order to avoid deviations in the frequency of the system.[5] ESS capabilities allows storage of energy when more supply than demand is available in the system, and then manage the electricity system as other goods and services systems, with inventories that provide additional support in unforeseen circumstances.[6] This is especially important for the adoption of RES like wind. The capacity contribution of renewables and specifically wind is dependent on its interaction with load and other parameters in the system, as well as the inherent characteristics of the resource in spatial terms [33]. Wind in certain locations exhibits an almost negatively correlated pattern with load, with high availabilities at times when demand is typically low (e.g., 2AM in the morning) and low availabilities at high demand periods (e.g., 3PM in a hot summer afternoon). This inherent behavior limits the amount of usable wind, and is responsible for the typical capacity factors observed around 25% for the North Eastern US.

[5] In cases in which the demand is higher than the supply, the frequency will drop below 60 cycles per second, the level which is maintained in the US and in most of the Americas.

[6] Certain supply chains are managed with almost instant matching between supply and demand decisions, or Just in Time (JIT), as is the case for most of the electricity system at present.

The use of ESS then provides a symbiotic role with wind, supporting the increased amounts of wind taken into the system and improving the utilization of the RES installed capacity. However, the value of storage, besides time arbitrage, lies in the possibility of using this resource for reliability purposes to mitigate the uncertainty that occurs in the system. This uncertainty is ever present, but becomes more relevant with the adoption of wind, with several high probability states of nature that can be realized depending on the nature of the wind in the analyzed area.

Figures 5.11 and 5.12 illustrate this situation, by contrasting the scheduling given to an ESS in a case with no wind and contingencies occurring three percent of the time, to a case in which both wind and ESS resources are available in the system.

In Figure 5.12 in the upper pane, a separation is observed between on the one hand the expected dispatch and the base cases, and on the other hand the contingency cases. In the first case, the dispatches are always below the maximum available capacity per time period, with charging occurring at low demand periods and discharging mostly in the afternoon peak and some in the early hours of the day due to variability in wind outputs. Contingency cases on the other hand are grouped at the upper power limit of the ESS. This implies the use of the energy in the ESS for support in some low probability cases. The decreased demand at early hours of the morning requires less capacity from conventional generation. Is at these hours that ESS plays a more active role in supporting the reliability of the system.

The lower pane shows the reserves provided by the ESS, both for contingency and load following. In the contingency cases, the reserve provided is mostly upward contingency reserve, in line with the outputs observed in the upper pane at the maximum of the power delivery capacity and above the contract and dispatch. In the case of load following, most reserves are for ramp up capacity provided, partly following the profile of the day.

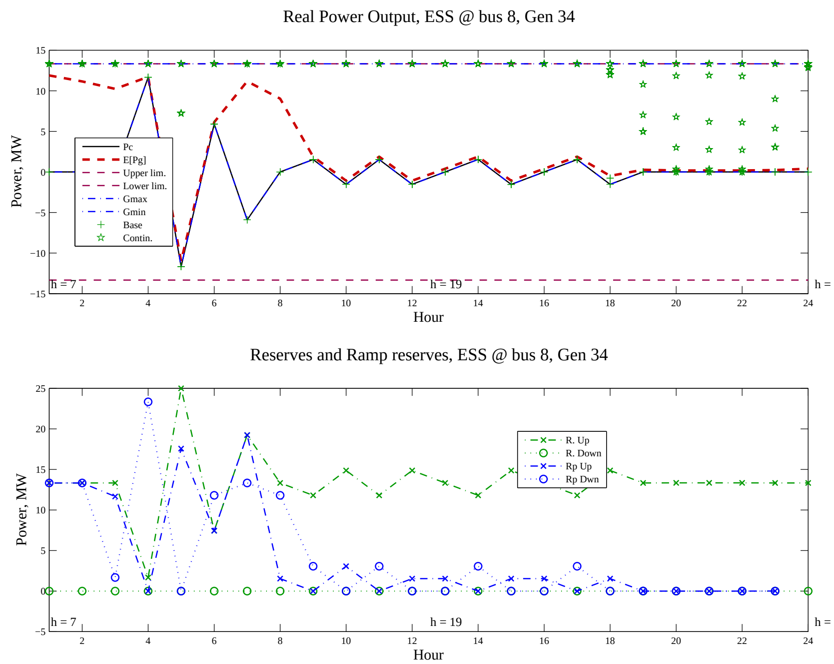

Figure 5.11: Expected ESS Management, Case 3, Single ESS

Adding wind into the system magnifies the reliability contribution of the ESS resource, as shown in Figure 5.12. In the upper pane, a trace of the expected dispatches observed in figure 5.11 is maintained, with the contracted amount following the minimum availability of the ESS across scenarios. Since the contracted amounts is an endogenous variable that minimizes the cost of ramping up and down, this indicates a downward bias in dispatches, happening at early hours of the horizon.

The differences observed between the expected dispatch/contracted amounts and the maximum availability of the day correspond to contingency cases in which the variability of wind, interacting with the outages, drive the contingency dispatches, and the range of possible dispatches observed. This pattern differentiates the ESS usage when wind becomes a resource in the system. Additionally, some contingency dispatches are observed in the peak hours (hours six to 12, corresponding to noon to 6PM).

The utilization of the ESS resource to counteract the uncertainty in the system is also present in the reserves provided in the system (lower pane, Figure 5.12).

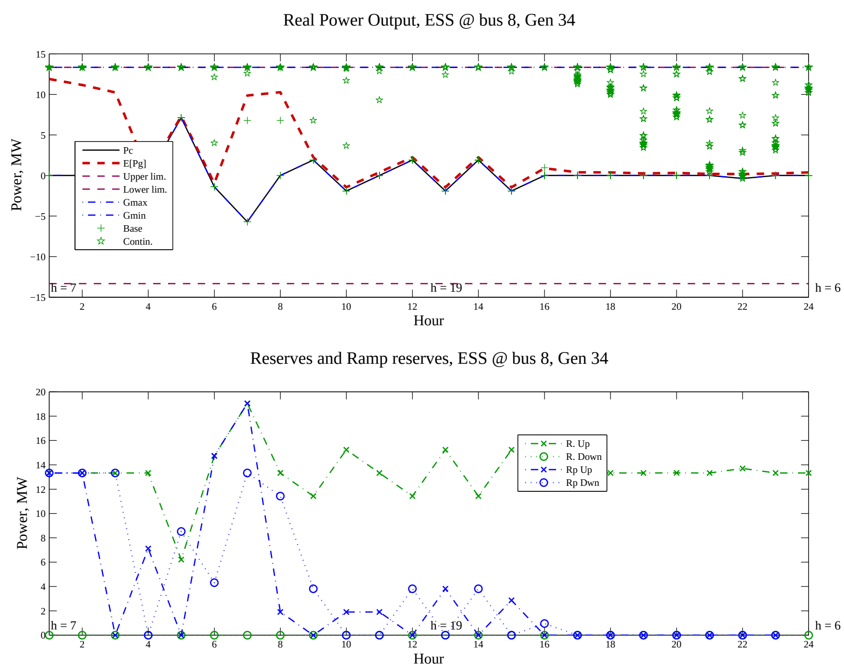

Figure 5.12: Expected ESS Management, Case 4, Single ESS and Wind

Locational Aspects

For the second part of the evaluation of results, a comparison between a network model and a network less analysis is performed.

The main consequence of using a network-less system is that the dispatch will be merit ordered, with cheaper generators being dispatched first, according to their technical characteristics. All generators and loads behave as if they were located in a single node, and the service constraint just becomes a single one: the sum of all injections from the available generators should be equal to the sum of all loads and all the losses in the system. The losses tend to be negligible in such a system, so in fact it is a balance between supply and demand of energy without limitation in the transfer capability. There will be a single price in the system, which is paid to all generators, and is the same price that all loads pay. Figure 5.13 shows the expected prices at the generator buses in a case with no wind and no network (NN).

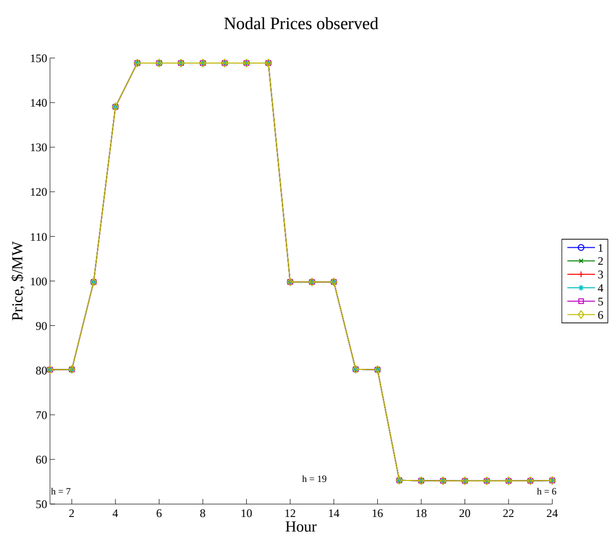

Figure 5.13: Expected Nodal Prices Generator Buses, Case 1, No Network

The addition of network constraints introduces the locational aspect of generation and the multiplication of constraints in the system, with a balance between generator supply on the one hand and loads and losses on the other being maintained in every bus of the system. Other operating constraints include the line limits for active and reactive power, limiting the amount of instant power that can be exchanged between buses and areas. The cost of congestion in electricity transmission is significant in certain areas, and creates challenges for the operation of competitive markets[38].

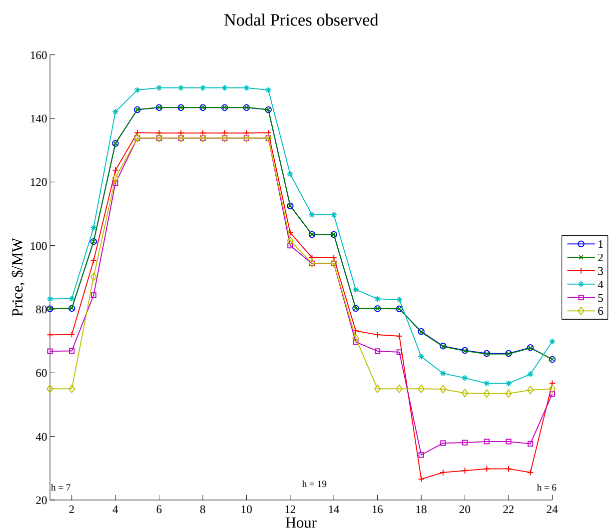

Figure 5.14: Nodal Prices Generator Buses, Case 1, Network

In extreme cases, when enough congestion builds up in the system, generators may be dispatched out of merit order from the system point of view, due to its electrical proximity to load that needs to be serviced, creating what is called load pockets [39].

Figure 5.14 shows the expected prices observed in generator buses when transmission constraints are added into the system. Comparing to the NN case, a separation in the prices is observed at peak hours between between areas (5 to

11 in the Figure, corresponding to 11AM to 5PM).

The generators in Area 1 ('1' and '2' in the figure, for buses 1 and 2) have the highest prices due to servicing of the load using local expensive gas combustion turbine (gct) generation. The buses in area 2 have the lowest prices ('3' and '5' in the figure, for buses 13 and 23) thanks to cheap coal generation; and the buses in Area 3 have intermediate prices at those hours ('4' and '6', corresponding to buses 22 and 27), due to the available combined cycle gas turbines (cc gas) in those buses.

Figure 5.15 shows the normalized utilization of the tie-lines linking each one of the areas, for both maximum and expected utilization. The maximum utilization indicates the flow that can occur when at least one of the contingencies considered realizes.

The separation in prices observed occurs due to the congestion observed between areas, mostly in transmission lines 15, linking areas 1 and 2, and line 32, linking areas 2 and 3. In limiting cases, the KKT multipliers will be greater than zero for the highlighted lines.

In terms of fleet management, the most important feature of including network constraints is the fact that generators assets that are needed in the network case are completely ignored in a network-less one. To illustrate this, consider Case 2 with no network (Case 2u), and the oil generator in bus 2 (generator 4). This generator provides energy for peak hours of the day in very small amounts (between 1.93 and 7.73 MWh out of 30MW installed capacity) in the No Network case, mainly due to its high fuel costs and easy substitutability with other, cheaper and readily available sources of both energy and reserves.

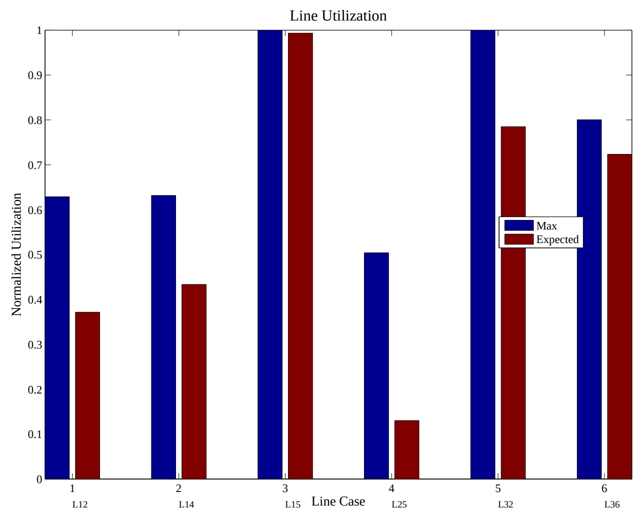

Figure 5.15: Maximum and Average Line Utilization, Case 1, 3PM

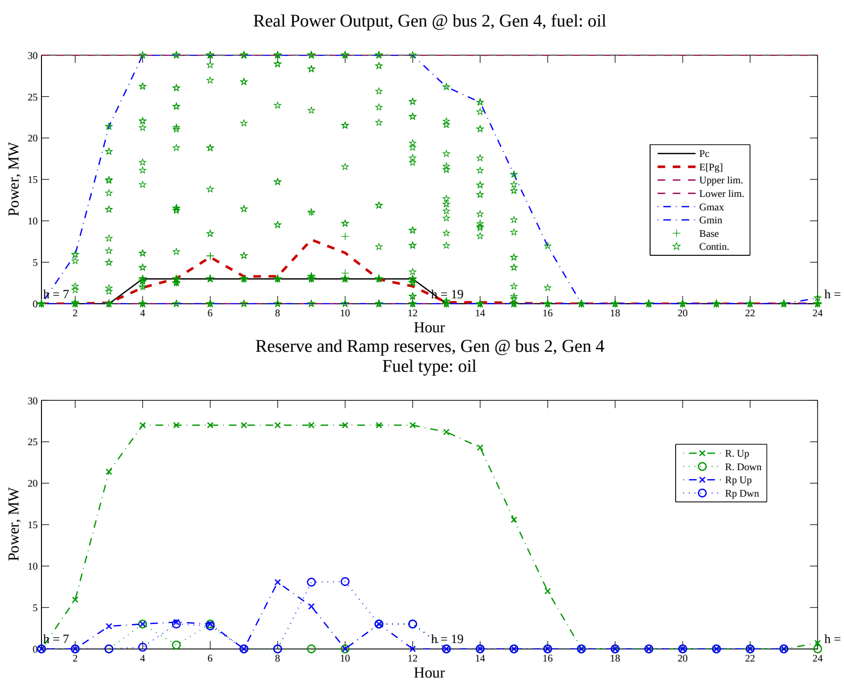

Figure 5.16: Oil usage Case 2, No Network

In the analogous case with a network (Case 2), due to the congestion observed in the system, the oil generator placed in bus 2 is expected to provide between 2.16 and 24.03 MWh. Moreover, when a contingency is realized in the system, this generator is needed, and hence it provides reserves for safe and reliable operation in all hours of the day, compared to 17 hours in the NN case (Figure 5.17).

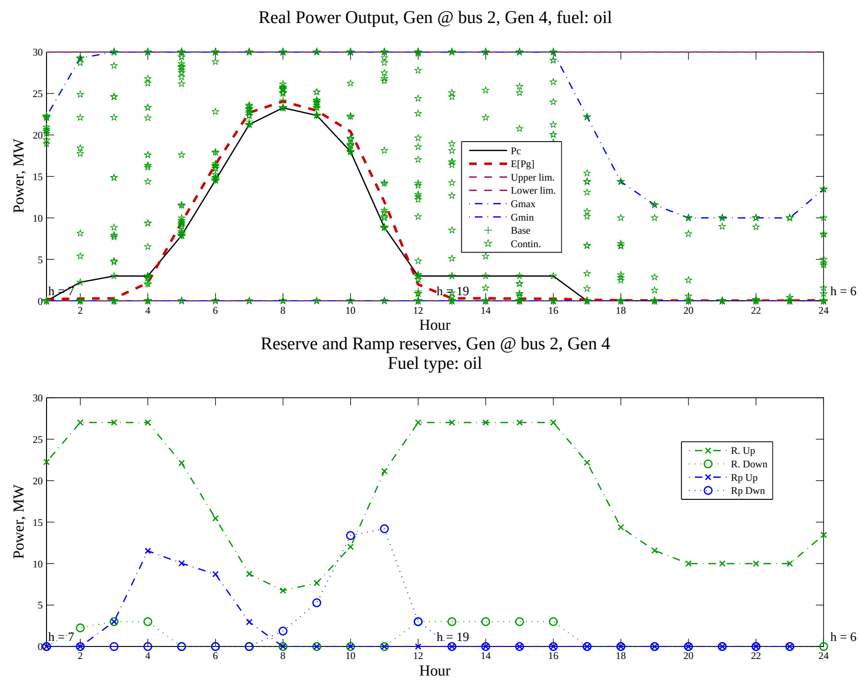

Figure 5.17: Oil usage Case 2, Network

The management of generator 6 in Case 1 provides a further example of the differences in fleet dispatch due to the network restrictions. This combined cycle gas (cc gas) generator placed in bus 22 is dispatched for energy in Case 1u for all hours of the optimization horizon, with a decrease in dispatch at low demand hours (hours 19 to 24, corresponding to 1AM to 6AM). Once network constraints are added, this generator is expected to provide 5% more energy for all hours of the horizon considered, serving as a base load generator most of the day. In addition to energy, this generators is dispatched for reserves at all hours of the horizon (Figure 5.18).

The illustrative cases are instances in the no wind case and base wind case. As noticed, once wind is adopted into the system, the uncertainty is increased due to the stochastic nature of wind. Consequently, the contracting of reserves for reliability purposes increase and the effects of the network constraints become more important.

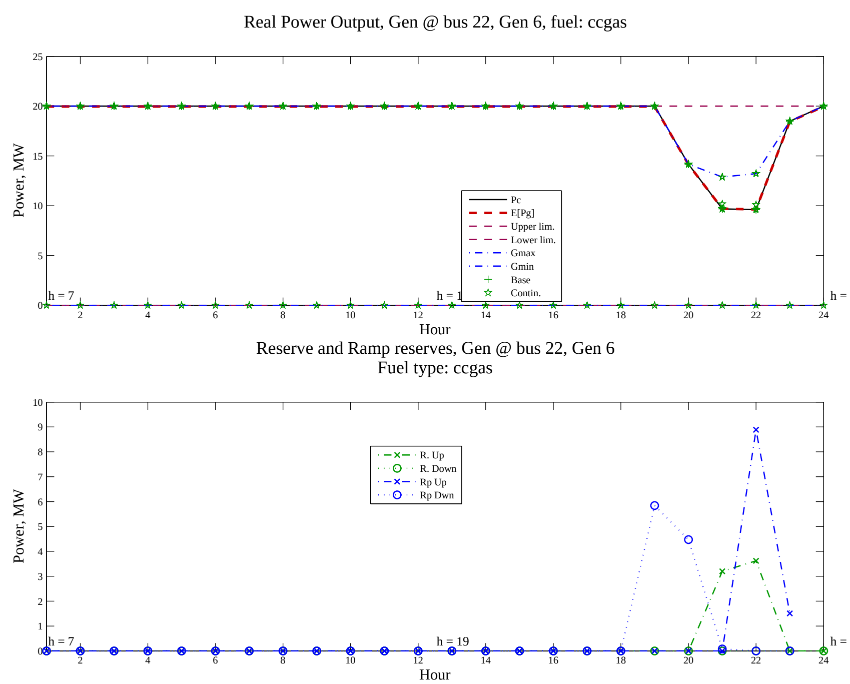

Figure 5.18: Expected CC gas usage Case 1, Network

Generally, the use of a network will affect the choice of generators as illustrated with the examples above. The choice of the portfolio of generators used has system consequences as will be illustrated in the last part of this analysis.

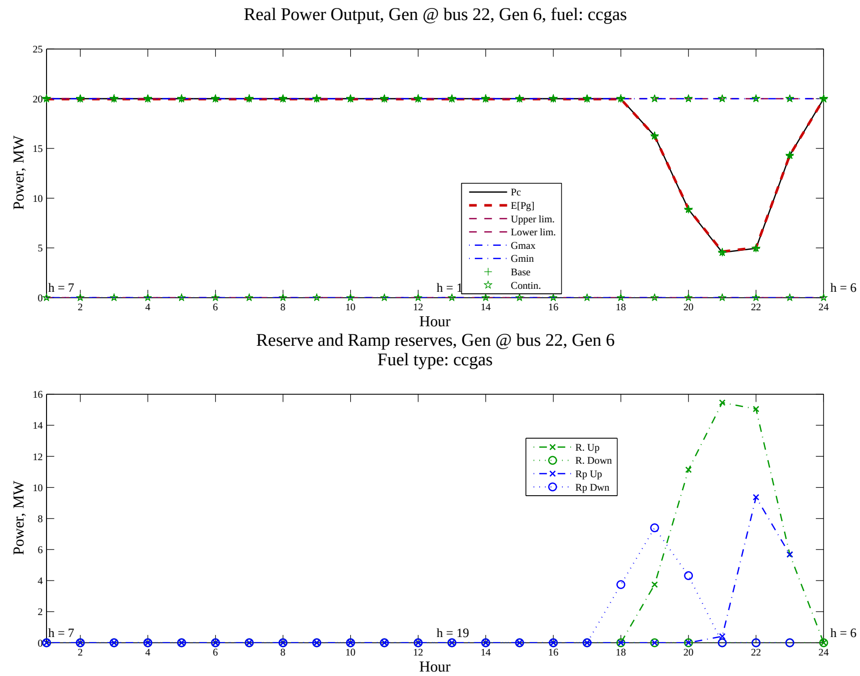

Figure 5.19: CC gas usage Case 1, No Network

System Results

The final part of this analysis studies each one of the cases and overall trends observed in the system. While information for both cases with and without a network are included (for the sake of completeness) the analysis is focused on the network cases, given the importance that the network constrains impose on conventional generation capacity needed for reliability. To evaluate the cases considered, the metrics used will focus on physical measures of interest. The metrics considered are the same ones considered in section 5.2.1

Table 5.12 summarizes the main results on the cases considered. Case 1 is considered the base case for comparison (No Wind). Cases 2 and 3 are considered base cases for wind adoption and ESS adoption respectively.

An overall observation is that, no matter what the regime is, the amount of wind dispatched over the day remains relatively constant, indicating that the main benefits will be coming from better utilization of the conventional generation fleet available. The amounts of wind energy dispatch move in two levels, one for the network case and one for the no network case.

The adoption of 50MW of wind (Case 1 to Case 2) and 80 MWh of ESS capacity (Case 1 to Case 3) both reduce the operating costs in the system. In the wind case, the reduction is due to the adoption of zero short run marginal cost into the system. In the ESS adoption case, the reduction is due to the time arbitrage possibility offered by the ESS placed in the bus with the largest load, in the transmission constrained area with the highest fuel costs. This ESS resource allows the use of cheaper generation sources at low demand periods, displacing more expensive generation sources at times of high congestion in the network. While both cases reduce operating costs, compared to the No Wind case (Case 1), the unmitigated wind has a larger effect (3.15 percent reduction in Case 2 vs. 1.95 percent in case 3).

To analyze the characteristics of distributing geographically the wind capacity, Case 8 provides a lower bound on the possible achievable benefits. In this modeling, the underlying wind process is assumed to be identical across the geographical areas. For cases in which the characteristics of the wind resource varies across the geographical area considered, the distribution of the wind capacity installed brings benefits for operation.[54, 22]. Nevertheless, the distribution of the wind capacity (Case 2 to Case 8) further decreases the operating costs observed in the wind case, thanks to the better accommodation of the available wind in the system and supporting flows in the network from cheaper sources.

The distribution of the ESS capacity also help to reduce the operating costs of the conventional generation fleet by 1.1%.

Combining both wind in a rural area with an ESS in an urban area (Case 4) further decreases the operating costs, due to better use of the available generation fleet. In this case, the congestion observed in the tie-lines at peak times is reduced for most lines, and specifically for line 15 at peak hours, linking Area 2 (where the wind is located) and Area 1 (where the demand is located). See Figure 5.20

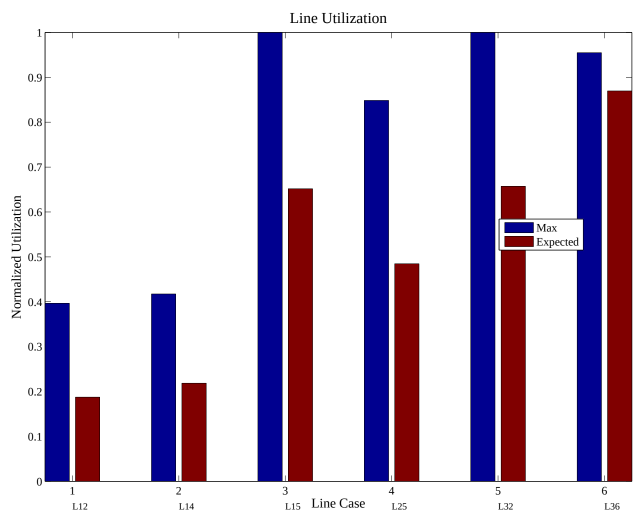

Figure 5.20: Congestion at 2PM, case 4

Dividing the wind capacity while maintaining the ESS in an urban area (Case 5) reduces the cost compared to Case 4. Interestingly, given the wind characterization used, the reduction in operating costs is larger when distributing the ESS capacity (Case 6) than when distributing the wind installed capacity. This is an idiosyncratic result derived from the wind modeling. In cases in which wind is modeled to be more complementary across sites in the network, the effect on system costs is likely to be different.

The distribution of both wind and ESS capacity installed helps to decrease even more the operating costs with respect to the base wind case (Case 2). This is again due to the reduced congestion in the system, hence allowing for a dispatch closer to economic merit order. Note that in most cases, the reduction in costs do not come from the increased amounts of wind in the system, but rather from dispatches that are closer to economic merit order, due to congestion relief in the network.

The generators net revenues behave with a pattern close to the operating costs, with the exception of Case 5. While the distribution of the wind capacity helps to reduce the operating costs, the payments to generators (their generation multiplied by the locational marginal prices, λ_i) are increased in this case. The reason for this is because locational marginal prices will tend to move closer together, due to congestion dissipation. With prices moving in a closer range, the payments to generators that were previously paid small amounts will tend to increase, leading to this phenomenon.

The congestion rents, the difference between the payments from loads and the payments disbursed to generators, are an indication of the cost of transferring the energy from sources to sinks [38]. The location of wind in a single location increases the congestion in the network, as the energy from the wind farm will have economic priority, leading the other generators to respond to this availability (comparing Case 1 to Case 2). Increasing demand, by placing an ESS in the load pocket also increases the congestion in the system, (Case 1 to Case 3), in a much smaller scale. This reflects the amount of extra energy required to cover that demand of the storage device, given the spatial characteristics of the system. While ESS is expected to provide support for peak times, and this

ESS does in fact provide energy at peak time (in expectation) the larger congestion payments differences between Case 3 and Case 1 come from low demand periods with more separation of prices in the system.

Due to this behavior, the combination of ESS and a wind farm follows a similar direction, with a small increase in congestion rents with respect to the base wind case (Case 1 to Case 4). Such behavior is related to the congestion of Line 15 in the system, which limits the transfers between the wind production buses and the ESS consumptions nodes. The distribution of the wind capacity provides alleviation of the observed congestion, with a reduction in payments for congestion (comparison Case 4 and Case 5).

The distribution of the ESS capacity between the urban area and the wind bus does not help to alleviate congestion (Case 6). This surprising results stems from the fact that the ESS's are heavily used as an uncertainty management resource, as opposed to a time arbitrage resource (see Figure 5.21).

The more realistic case of distribution of ESS capacity and Wind Capacity (Case 7) is similar in interpretation to Case 6: the reduction of the congestion payments is mainly driven by the geographical averaging conducted with the wind farm in different areas of the system. The ESS is utilized mostly to reduce the variability of the wind farm, hence reducing the operating costs to the lowest levels observed in the system.

The comparison of congestion rents between Case 2 and Case 8 can be used to isolate the contribution of distributing the wind resource alone. This clearly indicates the benefits that geographical averaging have for system purposes.

The energy payments from loads are the sum of the operating costs, the gen-

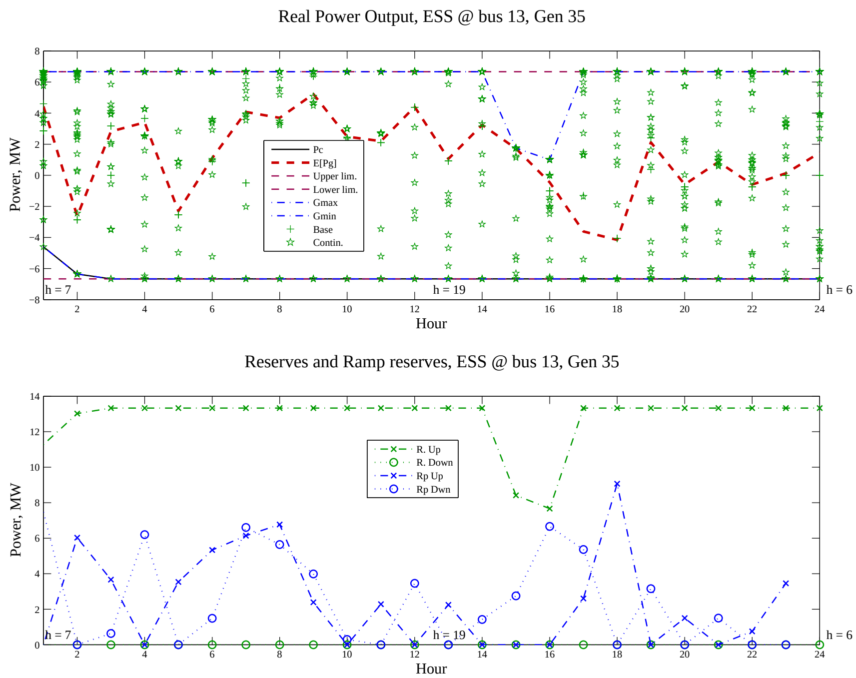

Figure 5.21: ESS collocated with Wind Farm Power Delivery in Case 4

erators net revenue and the congestion rents. Since these were already discussed by component, no further analysis is done here. However, a more interesting question opens up. In the calculation of payments from loads, the monetary disbursements from loads correspond to their demand multiplied by their LMP's. The operating costs are directly calculated from the fuel costs, and the payments to generators for energy are the multiplication of their production by the LMP's, analogous to the payments from loads. The way congestion rents are calculated here is the difference between energy payments from loads and energy payments to generators. However, in the total compensation to generators, both energy and capacity payments are provided. Since the loads do not have a specific charge for capacity levied on them, the total availability of resources for the Independent System Operator to pay for energy and capacity comes from this pool of resources. Let the difference between total payments from loads and total payments to generators be denoted as the ISO surplus, as it is commonly referred in the literature (see [40]). Due to capacity payments, the congestion rents, as defined above, will be greater than or equal to the ISO surplus. This presumes that ancillary services are additional income to generators.

Focusing on physical measures of performance in the system, the generation capacity (GenCap) needed for capacity adequacy is the maximum amount of conventional generation required at any moment of the horizon to reliably cover the load of the day. As more intermittent sources of generation are included, it is expected that an increased amount of dispatchable resources will be required. The 30-bus system used has a total installed capacity of 335 MW. While under normal operating conditions the system has spare capacity to cover the peak load, with maximum demand reaching 302.72 MW at 3PM, the relatively large generator contingencies require all available capacity at peak hours. Consequently, GenCap in the cases simulated will not measure the change in capacity driven by intermittency of renewable resources, but rather by the contingencies in the system. Interestingly, the system has flexibility enough to accommodate 50MW of wind without creating load shedding. Figure 5.22 illustrates the hourly change in generation capacity needed and demand in the system.

The amount of wind dispatched, on the other hand, moves in a bimodal range, with 260MWh dispatched when transmission constraints are included in the system, and 250MWh when the optimization is done without a network. Figure 5.23 shows the dispatches of wind for cases 7 and 7u.

The amount of wind spilt is higher in the no network case, though the minimum dispatches amount observed are lower in the network case. This phe-

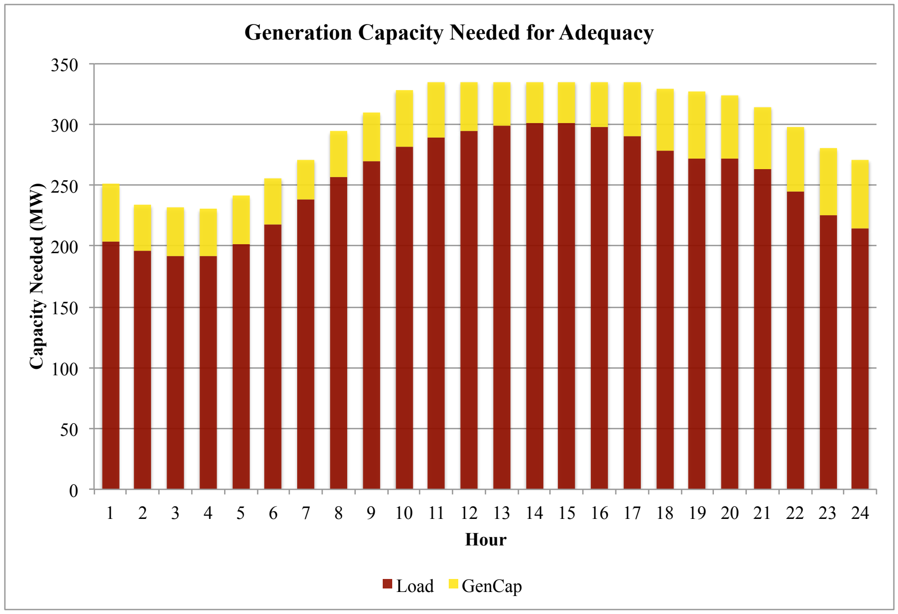

Figure 5.22: Generation Capacity Needed across hours

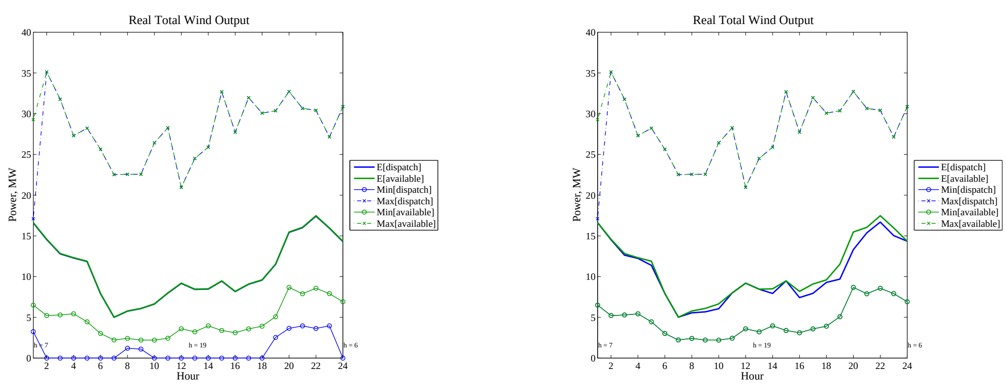

Figure 5.23: Wind Energy Dispatched, Cases 7 and 7u

nomenon is due to the relatively low probability weight of the contingencies where the spillage of wind occurs for Case 7. This contrasts with the cases where wind is spilt in case 7u, which occurs in high probability scenarios. The tradeoff in generation occurs with the NHR unit placed at bus 27, which in case 7u is dispatched completely flat, while in case 7 has a decreased output at low demand periods, displaced by the wind generator. Since the no-network case is devoid of locational effects, the tradeoff occurs due to the load following reserve included in each one of the cases.

5.3.4 Final Remarks and Further Research Directions

The location of storage to support adoption of renewables is heralded to increase the usable installed capacity of variables sources of generation. The cases here included show that, while location is important, the main benefits come not from increased wind dispatched, but from dispatches that are closer to merit order. The solution is very sensitive to the initial conditions, which lead to an algorithm to calibrate the initial values of storage and the final values of storage considered. The contrast between a system without constrained transmission capacity (no network run) and the systems with constraints is lower operating costs, thanks to the lack of separation of areas due to congestion. The generation capacity needed is not useful as a discriminant criteria, due to the high load levels and the relative impact of the contingencies considered. The results here included are useful as an intermediate analysis of similar cases with modified parameters. For future cases, the capacity of the wind farm should be higher, and the load levels considered lower. This will allow analysis of the effect of wind on generation capacity needed for reliability purposes, as well as observe larger discrimination in utilizations of wind in the system.

5.4 Concluding Policy Recommendations

The use of the multiperiod SuperOPF helps to elucidate the policy implications of the decisions made in the electricity system. The following recommendations in some cases resonate on the body of work done at Cornell by faculty, researchers and students. Firstly, the importance of the topology of the system is crucial to understand the effect of the penetration of renewables on the economics of the system considered. In this work two networks are analyzed and contrasted with the network less problems, and the under provision of capacity for reliability purposes is shown. In the 30 bus system, the use of the network is also shown to affect the effectiveness of the storage systems placed and the utilization of the wind resource. While the importance of the network is a known fact, it will condition the extent to which the other policy recommendations can be generalized, as all results are dependent on the specific topology studied. Secondly, the effects of the uncertainty in the wind resource are shown to be larger than the effects of the network constraints in the case of the NPCC system studied here. This is a complement to the mainstream view that in order to provide further integration of renewables an upgraded transmission system is required. The main reason for this is the elimination of network constraints, which allows for more wind use, but also requires more offsetting of the changing conditions in the system by conventional generators, making them incur the cost of ramping up and down. Once this cost of ramping is included, in many cases it is optimal to spill wind capacity instead of contracting additional stand-by resources. The NPCC system is a reduction of a highly interconnected system, with generation placed relatively close (electrically speaking) to the demand centers. In other systems such as the western interconnection, with a more radial layout, this recommendation is to be tested but it is less likely to hold.

Thirdly, in the NPCC system studied, the most economically effective policies are those aimed at diminishing wind variability (for example deferrable demand). This is consistent with the previous recommendation, with large gains obtained by the use of utility scale storage systems and modifications of the demand profiles with deferrable demand. The reductions in energy purchases at peak demand periods with deferrable demand are especially beneficial because they help decrease the requirements for conventional generation capacity to reliably ($n-1$) operate, and cover both demand and unforeseen circumstances, as discussed in Section 5.2.1. This policy will support the structural decrease of operating and capital costs of the system. This is an important feature of this demand oriented policy, because the peaking demand hours are negatively correlated with the availability of the intermittent resources for the geographical area and historical time period considered. However, in other regions this negative correlation may not hold [19]. While the most effective mitigation mechanism at utilizing more of the installed variable generation capacity is collocated storage, the revenue streams in the studied case are slightly larger in the deferrable demand case. This is achieved thanks to the increased prices at traditionally low demand periods obtained by separating the time of purchase of the energy from the time of the provision of the energy service.

The fourth recommendation, and a part of future work, is the implementation of a receding horizon scheme to better include the information available from the variable sources of generation, and control for the varying initial and transversality conditions of the system. Even though the iteration to try to find steady state conditions would work for hypothetical situations in which the horizon is exactly repeated in one time tests, the realm of application is extremely limited and for practical purposes a very limited solution to the problem of determining the best way to operate the system.

Table 5.12: Summary of Key Results, Case 30

	case1	case1u	case2	case2u	case3	case3u	case4	case4u	case5	case5u	case6	case6u	case7	case7u	case8	case8u	case9	case9u
E[Operating Costs](k$/day)	180.51	175.74	174.81	168.84	177.56	172.55	171.36	164.14	170.47	164.14	168.89	164.14	168.23	164.14	173.88	168.84	174.93	172.55
E[Gen. Net Revenue] (k$/day)	413.5	456.66	324.22	370.53	356.79	397.99	273.73	321.25	278.02	321.25	272.22	321.25	275.6	321.25	325.33	370.53	352.67	397.99
E[ISO Surplus] (k$/day)	24.38	-4.79	79.24	12.79	31.34	2.1	84.79	18.73	60.56	18.73	95	18.73	71.51	18.73	57.16	12.79	35.66	2.1
E[Payments Loads] (k$/day)	618.39	627.6	578.26	552.15	565.69	572.64	529.87	504.12	509.05	504.12	536.11	504.12	515.34	504.12	556.38	552.15	563.26	572.64
GenCap (MW)	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335	335
E[Wind Energy] (MWh)	0.01	0.01	260.56	249.7	0.01	0.01	260.55	249.44	260.29	249.44	260.22	249.44	260.34	249.44	260.31	249.7	0.01	0.01
E[ESS Energy] (MWh)	0	0	0	0	74.52	86.06	76.01	79.36	70.2	79.36	78.72	79.36	81.44	79.36	0	0	89.39	86.06

CHAPTER 6

CONCLUSIONS AND FUTURE RESEARCH

This work explores the decision making for social planners and individuals in an electricity system with high penetration of renewables. The models proposed in Chapter 2 provide a benchmark for modeling different aspects of the consumer problem as inspired by [60]. Chapter 3 analyzes a multiperiod OPF problem and describes the implementation of a set of functions to run a deterministic UC OPF problem. The analysis done using this model shows the possibility of reducing the hour-to-hour changes in generation, without explicitly including ramping costs. Chapter 4 places this research in the context of the research done at E3RG in Cornell and describes the reason why an stochastic program is necessary to correctly operate the system. This chapter showed the advantages of using endogenous reserves, analyzed the impact that ramping costs have for the management of the system and contrasted the solution obtained from a full stochastic formulation and one in which the uncertainty is valued at the expected level case. Chapter 5 makes use of the multiperiod SuperOPF to study the implications of placement of storage in the system and its interaction with the wind placement. The current research is nowadays being extended to analyze the sensitivity to the modeling of input parameters for the formulation. The main effort comes in the modeling of the scenarios for wind, which will determine the results found in the system.

Other directions for future work include the use of contingencies for each individual time period, refined accuracy in wind modeling and further detail on the kind of storage characteristics and the charging and discharging efficiencies. The selection of a storage technology will be crucially dependent on the proper modeling of the technical characteristics of these devices. This also has policy implications for the kind of investments that system planners and operators should undertake. The support for research in Vehicle-to-grid (V2G) and the use of batteries from transportation, versus utility-scale batteries are clear cases in which scarce resources will limit the degree of adoption. Moreover, the implementation of demand response programs, facilitated by a Smart Grid deployment, will also support the usage of renewables, but capital investments in this area are very expensive.

This is a field of rapid and exciting changes that demands further research and enhanced collaboration among both academics and practitioners.

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APPENDIX A

DETERMINISTIC UNIT COMMITMENT AND OPF PROBLEM

The motivation for this development is to create a tool that can be used for studies that involve the determination of optimal dispatches of a set of conventional generators and inter temporal resources like ESS, taking into account the considerations of startup, shutdown and technical restrictions for thermal generators, in the spirit of a thermal unit commitment. Since the problem is deterministically formulated, to represent the variable nature of certain inputs (e.g. generation from stochastic sources, demand uncertainty, unexpected outages or system contingencies), it would be necessary to do a number of simulations that represent the possible states, replicating them many times. Then, drawing from a probability distribution that represents the nature of the uncertainty taken, each one of the outputs can be weighted by the associated probability of each one of these possible states. Since no constraints are included in this approach to verify the physical capability of the system to transition from one state to another, such an approach does not guarantee feasibility of the solution, nor optimality. Otherwise, a Montecarlo style approach can be built around the set of files provided.

The formulation of this problem is as follows:

$$\min_{\Theta,P,E,u_{i,t},s_{i,t},h_{i,t}\in\{0,1\}} \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{G}^t\cup\mathcal{E}^t} C_{P_i}(p_{it}) + C_{E_i}(e_{it}) + S_i s_{i,t} + H_i h_{i,t} \tag{A.1}$$

subject to

$$g_P^t(\Theta^t, P^t, E^t) = 0, \quad \forall t \in \mathscr{T} \tag{A.2}$$

$$h^t(\Theta^t, P^t, E^t) \leq 0, \quad \forall t \in \mathscr{T} \tag{A.3}$$

$$P_i^{min} u_{i,t} \leq qi, t \quad \forall i \in I, t \in T \tag{A.4}$$

$$qi, t \leq P_i^{max} u_{i,t} \quad \forall i \in I, t \in T \tag{A.5}$$

$$s_{i,t} - h_{i,t} = u_{i,t} - u_{i,t-1} \tag{A.6}$$

$$\textstyle\sum_{y=t-\tau_i^+}^{t} s_{i,y} \leq u_{i,t} \tag{A.7}$$

$$\textstyle\sum_{y=t-\tau_i^-}^{t} h_{i,y} \leq 1 - u_{i,t} \tag{A.8}$$

$$-R_{Pi}^{\text{PHYS}-} \leq p_{it} - p_{i,t-1}^t \leq R_{Pi}^{\text{PHYS}+}, \forall i \in \mathscr{G}, t \in \mathscr{T} \tag{A.9}$$

$$-R_{Ei}^{\text{PHYS}-} \leq e_{it} - e_{i,t-1}^t \leq R_{Ei}^{\text{PHYS}+}, \forall i \in \mathscr{E}, t \in \mathscr{T} \tag{A.10}$$

$$u_{\max,ie} \cdot (sc_{i,0} - 1) \leq \textstyle\sum_{\tau <= t} e_{i\tau} \cdot \alpha \leq u_{\max,ie} \cdot sc_{i0}, \forall i \in \mathscr{E}, t \in \mathscr{T} \tag{A.11}$$

$$\textstyle\sum_{t \in \mathscr{T}} e_{it} \cdot t = 0, \forall i \in \mathscr{E} \tag{A.12}$$

The variables used are defined in table A.1

The minimum up and down times are under current development and are expected to be available soon.

The problem is implemented using IBM ILOG's cplex method *cplexmiqcp*.

Table A.1: Nomenclature for the problem

Variable	Description
$\mathscr{T}$	Set of all time periods, n_t elements.
$\mathscr{B}$	Set of all buses, n_b elements.
$\mathscr{G}$	Set of generating units, n_g elements.
$\mathscr{E}$	Set of ESS units, n_e elements.
Θ	Vector of n_b bus voltage angles
P	Vector of n_g active power injections from generators.
E	Vector of n_e active power injections from ESS units.
$s_{i,t}$	binary variable indicating if unit i was started up in period t
$h_{i,t}$	binary variable indicating if unit i was shut down in period t
$u_{i,t}$	binary variable indicating if unit i was up in period t
$C_{P_i}(\cdot)$	Cost of active injections from generators.
$C_{E_i}(\cdot)$	Cost of active injections for ESS units.
S_i	Cost of startup for generator i
H_i	Cost of shutdown for generator i
$\pm R_{Xi}^{\mathrm{PHYS}\pm}$	Physical limits for active power ($X = P, E$) for generators and ESS respectively.
α	power to energy factor
$u_{\mathrm{max},ie}$	Energy Capacity of the ESS
sc_{i0}	Initial state of charge
τ_i^+	Minimum up-time for generator i
τ_i^-	Minimum down-time for generator i