Quantification of the Impact of Intermittent Renewable Penetration Levels on Power Grid Frequency Performance Using Dynamic Modeling

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QUANTIFICATION OF THE IMPACT OF INTERMITTENT RENEWABLE PENETRATION LEVELS ON POWER GRID FREQUENCY PERFORMANCE USING DYNAMIC MODELING

A Thesis Presented

by

Elizabeth Ann Kirby

to

The Faculty of the Graduate College

of

The University of Vermont

In Partial Fulfillment of the Requirements
For the Degree of Master of Science
Specializing in Electrical Engineering

May, 2015

Defense Date: March 27, 2015

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Abstract

As the technology behind renewable energy sources becomes more advanced and cost-effective, these sources have become an ever-increasing portion of the generation portfolios of power systems across the country. While the shift away from non-renewable resources is generally considered beneficial, the fact remains that intermittent renewable sources present special challenges associated with their unique operating characteristics. Because of the high variability of intermittent renewables, the frequency performance of the system to which they are connected can degrade. Generators assigned to regulate frequency, keeping it close to the desired 60 Hz, are forced to ramp up and down quickly in order to offset the rise and fall of the variable resources (in addition to the rise and fall of load), causing transient frequency deviations, power swings, major interface transfer variations and other significant issues.

This research measures the impact of intermittent renewable resource penetration level on power system frequency performance, and offers methods for managing that performance. Currently, the generally accepted amount of regulation (rapidly-dispatchable reserve, used as a supplement to base generation on a short time scale to avoid performance issues) is 1% of peak load. Because of the high variability associated with intermittent renewables, including wind generation (the focus of this thesis), it is expected that this amount of regulation must increase in order to maintain adequate system frequency performance. Thus, the primary objective of this thesis is to quantify the amount of regulation necessary to maintain adequate frequency performance as a function of the penetration level of wind generation.

Presently, balancing resource requirements are computed, in both industry and in the research literature, using static models, which rely entirely on statistical manipulation of net load, failing to capture the intricacies of dynamic system and generator interactions. Using a dynamic model with high temporal resolution data, instead of these statistical models, this thesis confirms the need for additional regulation as wind generation penetration increases. But beyond that, our research demonstrates an exponentially increasing relationship between necessary regulation and wind generation percentage, indicating that, without further technological breakthroughs, there is a practical limit to the amount of wind generation that a typical system can accommodate. Furthermore, we compare our dynamic model results with those of the statistical models, and show that the majority of current statistical models substantially under-predict the necessary amount of regulation to accommodate significant amounts of wind generation. Finally, we verify that the ramping capability of the regulating generators impacts the amount of necessary regulation, although it is generally ignored in current analysis and related literature.
Dedication

To Rip Kirby; my editor-in-chief, my Yoda, my dad.
Acknowledgements

First, I would like to express my deepest respect and gratitude to Dr. Paul Hines for his role as my graduate advisor. His steadfast guidance and support in this long process have been incomparable. Dr Hines has continually stirred my enthusiasm for engineering as he seems to do with all his students.

Also, I would like to thank Dr. Kurt Oughstun and Dr. Chris Danforth for their willingness to serve as my thesis review committee despite their busy academic schedules. Their enthusiasm and encouragement are greatly appreciated.

I would also like to thank all parties who contributed data and other information to this thesis, including various wind farms, utilities, ISO New England, the Bonneville Power Administration, and IEEE. Data of this detail and quality are often unobtainable, but the cooperation and affability among fellow engineers overcame all.

Additionally, I would like to thank the staff at UVM’s Vermont Advanced Computing Core (VACC) which is supported by NASA (NNX-08AO96G). Having run approximately 50,000 simulations averaging 10 hours per simulation, this research required approximately half a million computer hours. Extensive access to the VACC was indispensable and I am extremely grateful that this resource was made available to me by means of the hard work and dedication of the VACC staff.

I would like to thank Chris Brackett for his love and support during this demanding chapter in my academic life. Despite my occasional self-doubt, he has proven to be thoughtful, perceptive, and understanding.

Finally, I want to thank my family for their unceasing support throughout my education. I could never explain what it has meant to me.
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Chapter 1

Introduction

Renewable energy has experienced a great leap forward around the world in recent years. From Hawaii to Germany to Argentina, renewable penetration levels are growing at unprecedented rates across the globe. Once merely a curiosity, the advent of large-scale intermittent renewable energy production offers certain indisputable benefits.

Intermittent renewables\(^1\) require no fuel (besides sun or wind) in contrast to traditional thermal generators (the fuels for which take millions of years to form), allowing for the possibility of distributed or decentralized generation, and local reliance. Their operation contributes no harmful greenhouse gases (e.g., CO\(_2\), NO\(_x\), SO\(_x\)) during generation, significantly decreasing the atmospheric and environmental impact of electricity use. And, in recent years, their advances, along with various government incentives, have made many of the renewable technologies profitable within the market.

While these benefits have made the adoption of intermittent renewable technologies possible, this adoption has not come without challenges. Intermittent renewable electricity generation, particularly from wind and solar, has quite a different set of operating and control characteristics than traditional thermal generation. Thermal generation is fully controllable; a dispatcher can change the output power of a thermal generator with promptness and precision. Wind and solar power, on the other hand, are much less easily controlled as they are subject to the uncontrollable and largely unpredictable variances in cloud cover and wind velocity.

As seen in Figure 1.1, the thermal generator is controlled in a distinct pattern, ramping up and

\(^1\)We note that there are a number of renewable generation technologies that are dispatchable (i.e., non-intermittent). For instance, both hydro-power and biomass are renewable sources which are controllable; an operator can decide exactly how much wood to throw on the fire to burn, or exactly how much water to let through the turbine instead of over the dam. This paper will not discuss these technologies, and will focus solely on the impact of intermittent renewables. We additionally point out that while this paper will focus solely on wind generation, the concept (though perhaps not the exact quantitative results) apply equally to solar generation because of its intermittent profile.
down for best economic advantage throughout the day (note that the generation output pattern follows approximately a 24 hour cycle), with small “wiggles” as load varies small amounts within those sections. The wind farm, on the other hand, exhibits significant variability, as the wind speed changes continuously in the area.

Figure 1.1: Comparison of thermal generation (top) and wind generation (bottom). The thermal generator in the first graph is controlled in a distinctly-shaped pattern, ramping up and down for best economic advantage throughout the day. The wind generator in the second graph, on the other hand, exhibits significant variability, as the wind speed changes continuously in the area. The thermal generation data were provided by Green Mountain Power, Inc. [26] and the wind data were provided by the Bonneville Power Administration [1].
We note that variability in renewable generation exists on multiple time scales, one day to the next, one hour to the next, one minute to the next, even one second to the next. Different time scales affect the power system in different ways. Day-to-day and hour-to-hour variability are fairly easily predicted; with weather forecasting, we can estimate the expected power output of these sources ahead of time. The shorter time scales, however, prove to be increasingly problematic.

The entirety of the power system rests on the concept of load-generation equilibrium; operators must always be actively correcting toward a balance of generation and load. In other words, for every light that gets switched on or appliance that turns off, the system must incrementally adjust generation toward that ever-changing point. This equilibrium is governed by the swing equation

$$P_g = P_m - D \Delta \omega - M \Delta \dot{\omega}$$  \hspace{1cm} (1.1)

where $P_g$ is the electrical power desired by the system, $P_m$ is the mechanical power output of the turbine, $\Delta \omega$ is the deviation in generator frequency (a.k.a., generator angular speed) from the nominal frequency of 60 Hz, $\Delta \dot{\omega}$ is the first derivative with respect to time of the deviation in generator frequency (a.k.a., generator angular acceleration), and $D$ and $M$ are machine inertia and damping constants, which account for electrical and mechanical “friction” ($D$) and differences in inertia ($M$) among generators. This equation states that the power drawn by the system due to load ($P_g$) must be equal to the mechanical power produced by the generators ($P_m$) minus any deviations in system frequency. In other words, any imbalance between load power and generation power results in frequency deviation. Thus, we aim to balance generation and load in order to maintain the appropriate frequency.

The fundamental challenge of power system operation with intermittent renewables now becomes apparent. Because of the difficulty in both controlling and predicting intermittent renewable generation, they are of little help in correcting toward equilibrium, and in fact may add to the challenge.

Fortunately, the means to solve this problem already exists on the system. The main driver of the system, load (the amount of electric power being drawn from the system by customers), is already quite variable. At any given moment, electronics are being turned on or off, light switches are being flipped, and electrical demand is fluctuating. Thus, the power system already features numerous controls designed to alter generator output in order to correct toward equilibrium. As with wind and solar generation, load is fairly easy to predict on the longer time scales. We know, for instance, on the day-to-day scale that load tends to be lower on the weekends than it does on
weekdays (because fewer people are headed to the office), or that on the hour-to-hour scale, load
will begin to increase around 6 or 7 a.m. as individuals begin waking up and turning on their lights
and coffee pots.

Figure 1.2: Action Time Frames of System Controls

And again, as with wind and solar generation, the shorter time scales of load variance are increas-
ingly difficult to predict. Thus, two types of controls are included to correct toward equilibrium at
these time scales. As seen in Figure 1.2, the first, droop (or primary frequency) control (explained in
more depth in Section 2.2.2), operates on the shortest time scale, adjusting the mechanical output of
the generators, much like cruise control on a car adjusts the output of the engine to maintain speed
as the “load” (required output determined chiefly by the slope of the road) changes. The second,
automatic generation (or secondary) control (AGC) is used to regulate the frequency (and thus is
known as regulation), in order to maintain adequate system performance (as measured via CPS1,
explained in Section 2.2.3).

Given that this solution to load variability already exists, why, then, are intermittent renewables
an issue? The answer is that they significantly increase the amount of variability. Currently, industry
practice is to incorporate enough regulation capacity in the system to absorb up to a 1% unexpected
change in load over the frequency control time scale (droop and AGC). However, this amount
is chosen to capture the expected variability in load alone. As we increase wind, the net load
variability\(^2\) seen by the generators actually increases, as demonstrated in Figure 1.3. Thus, this

\(^2\)Net Load is defined as Load minus Wind. Variability is the change in the value over some time period, and
also can be called step change. Thus, we can discuss Load Variability, Wind Variability, or Net Load Variability.
amount of regulation is likely insufficient to maintain adequate system performance as wind becomes a significant portion of the generation profile. Our task, then, is to determine how much more regulation is necessary in order to maintain adequate system performance as we increase wind generation.

Figure 1.3: Complementary cumulative distribution function (CCDF) of variability in net load with varying levels of wind penetration. We see that for a given step change size, the probability of a step change of this size or greater is much higher for significant wind penetration than for little wind penetration. For instance, a step change of at least 5% in 5 minutes is about 10 times more likely to happen at 20% wind penetration than no wind, and about 100 times more likely to happen at 40% wind penetration (indicated by dashed teal line). Conversely, we see that for a once per week occurrence, total load (no wind) will have a step change of at least 2.5%, net load with 10% wind will have a step change of at least 3%, net load with 20% wind will have a step change of at least 4%, and the net load with 40% wind will have a step change of at least 7% (indicated by dashed purple line); thus, the 40% wind scenario has a step change size of almost 3 times that of 0% wind for the same probability. The 5 minute wind generation data used to produce this figure were provided by Bonneville Power Administration [1] and the 5 minute load data were provided by ISO-NE [19].

In general, the only currently practical way to counteract the variability of these sources is by balancing them with further controllable generation. This is because the main alternative, grid storage\(^3\), has not yet become financially viable, and thus we cannot redirect any of the renewable

For instance, if we discuss the “5 minute step change” or “5 minute variability” of wind, this refers to the difference between the wind power now and the wind power 5 minutes ago.

\(^3\)Grid storage is the conversion of excess electric energy, in this case from solar or wind, to another form using various methods, including batteries, flywheels, or pumped storage. This energy can essentially be saved for later, as with its thermal counterpart. However, due to lack of efficiency and high capital costs, these technologies tend to be cost prohibitive and are currently used only in rare situations or on significantly smaller scales as a backup.
energy. Additionally, the only “control” that individual wind turbines have is to “throw away” the wind (known as “feathering” the blades, in which turbines tilt their blades in order to allow wind to pass by without turning the turbine as strongly). Thus, balancing intermittent renewables with thermal generation is often the only logical and practical option.

This option, however, is expensive. Generators provide regulation by increasing or decreasing their output when the need occurs; this implies that they must operate at a non-optimal point (cost-wise) and must thus be compensated. We cannot, therefore, increase the 1% regulation to a huge number simply to ensure that the necessary amount to account for intermittent renewables is present. It would be financially adverse to apply too much regulation and detrimental to system reliability to apply too little.

A number of studies in recent years have considered similar problems. Some of these examined the impact of increased wind penetration only on primary frequency (droop) control, thereby limiting their time frame to the first 20-30 seconds after a significant wind event [11, 20, 30]. Others considered longer time scales, focusing on how “wind ramps” (large changes in wind generation output over a time scale of minutes to hours) affect longer-term control [5, 32]. Still others considered the impact of increased wind penetration on regulation and/or CPS1 values (an industry standard for measuring system frequency performance, further explained in Section 2.2.3) [2, 7, 8, 38, 40]. This last category, which we might describe as “intermediate term” control, will be the main focus of the remainder of this paper.

Many of the studies which emphasize intermediate term control provide findings consistent with the concepts explained above, including general support for the idea that increased wind penetration increases frequency issues on the power system, prompting a need for additional frequency control. We found, however, a number of shortcomings and areas of insufficient clarity in the existing studies, which need additional research.

The first is that a number of studies, including those corresponding to citations [4, 13, 14, 15, 16, 17, 18, 28, 34, 35, 41], used simple statistical methods to determine the impact of wind on frequency as opposed to using a dynamic simulation model. Two main problems arise from this approach. First, most of these statistical analyses rely upon the underlying assumption that wind variability follows a Gaussian distribution (i.e., a classic “bell curve”), which has been disproven [3, 6, 21, 22, 33]; wind variability tends to exhibit “fat tails” in its distribution, which is to say that the more extreme events happen more often than a Gaussian distribution would indicate. As the extreme events are particularly impactful, it is important to accurately predict their likelihood. Even statistical methods that do not use Gaussian methodology (e.g. percentile distribution) often
have similar if not identical weaknesses, because they too ignore or under-emphasize low-probability, high-impact events.

The second problem with the statistical methods is that the time scale(s) on which wind variability is examined often masks significant shorter-term problems. Most statistical analyses, including the majority of those cited, focus on wind variability on a 5-minute or longer scale, ignoring the variability present at finer resolution. Because regulation operates on a seconds-to-minutes scale, the interaction between wind variability and system corrective response at that level is lost if we look only at longer-term wind variability. In the 5 minutes between one point of longer-term recognition and the next, generator operations due to both primary and secondary frequency control will have taken significant corrective measures to stabilize frequency. These actions will be unrecognized by prior methodologies.

Therefore a key assumption underlying our research is that dynamic modeling (which uses data recognizing the true distribution of wind variability, and can recognize data on much shorter time scales) is generally superior to statistical analysis in determining frequency regulation requirements in cases where intermittent power sources have increased as a percentage of total generation.

In fact, we view this modeling approach as essential, either as the primary analytical tool, or, at a minimum, for calibrating and validating statistical approaches. Using dynamic modeling, we can determine regulation requirements robustly, from which we are able to propose a simple statistical or algebraic function in which we have confidence. However, without the verification provided by the dynamic model, we have no certainty that any given statistical model is correct. In limited circumstances in which dynamic models have actually been used to verify simpler statistical models, the statistical models may be used with confidence.

Nevertheless, it is equally important to continue observing and controlling system frequency during longer time frames as well. As studies performed by Doherty et al., Eto, and Mackin et al. [11, 20, 30] and others have established by means of dynamic modeling, primary frequency response is negatively impacted by increased wind penetration levels, but these particular investigators have left unanswered the question of secondary (i.e., intermediate-term) system frequency behavior. Therefore in this investigation, we look further in time to interpret wind’s effect on secondary frequency response over a longer period, allowing the dynamics to continually respond to the variability of the wind.

Of the prior research papers that recognized and interpreted these relationships in a way most similar to our own [2, 7, 8, 28, 38, 40], we found a number of them in need of further development. Of particular note is that few of these papers provided a direct quantitative relationship between wind
penetration level and necessary regulation. Most demonstrate that increased wind power negatively affects CPS1 or some equivalent measure of frequency adequacy, but without showing precisely how much regulation is necessary to improve the CPS1 to normal levels. While this conceptual relationship is an essential starting point, we wished to determine an explicit functional relationship between wind penetration and the necessary regulation to manage that wind generation variability’s affect on frequency.

Finally, of the few papers that did provide a relationship between wind percentage and necessary regulation (whether through statistical or dynamic analysis) [2, 7, 8, 28, 38, 40], none provided more than a few characteristic points. With only a few points, and with any significant error bound, it is quite difficult to determine whether the resultant function is linear, exponential, or some other shape. Thus, one aim of this thesis is to include enough points to explicitly determine the functional relationship. This objective proved to be worthwhile despite its computational burden.

Our objectives, then, are as follows. This thesis aims to quantify the amount of regulation needed to maintain adequate system performance for varying wind penetration levels, as measured by current industry standards, ensuring we examine a large number of penetration levels with a high bound range. In order to do so, we will employ a dynamic model of the power system using high time resolution data. We will also consider how ramping capability influences system performance, in order to determine its significance in the context of frequency control.
Chapter 2

Model Preparation and Evaluation

2.1 Introduction

In Chapter 1, we explained that intermittent renewables introduce significantly more variability to the load-generation imbalance than is present on a “traditional” system, and, in practice, must be addressed with increased regulation levels. We noted that thus far, no research has completely answered the question of how much additional regulation is needed. We now intend to answer this question by performing various experiments using a precisely-tuned dynamic model.

In this chapter, we will explain the way in which the dynamic model works, the input data and IEEE-provided base system used within the model, and the techniques used to validate the model. While the outcomes of the specific experiments are important, the validation of the model used to generate these results is equally important. All of the results of these experiments are directly dependent on the assumption that the dynamic model is valid. Therefore, we focused much of our effort on the design and validation of that model.

2.2 Dynamic Modeling Methodology

To obtain the desired results, we run a dynamic simulation of the system requiring several steps. Using the input data and the initial system parameters provided by the 39-bus New England model IEEE case (further explained in Section 2.3), the simulation consists of alternating between economic dispatch (E.D.), where we assign each generator its share of the necessary power and regulation output, and numerical integration, where we numerically solve for the state variables of the generators and the power network at each moment in time, such that we can determine the value of any
parameter at any point over our whole run. Every 15 minutes, this iterative process of redispatch and subsequent re-solving is performed, with the simulated time period equal to 24 hours. At the end of the simulation time period, we evaluate our system performance using various standards. If the performance is poor, we may conclude that regulation is inadequate for the given system.

![Diagram of simulation actions](image)

**Figure 2.1**: Pictorial representation of simulation actions. At the beginning of every 15 minute time period, an Economic Dispatch (E.D.) occurs to reset generator set-points, after which numerical integration solves each system parameter at each moment in time for the subsequent 15 minutes until the next dispatch. At the end of the simulation time period, performance metrics are measured using the simulated data.

### 2.2.1 Economic Dispatch

The first step of each interval of the simulation is to perform an economic dispatch for the system. Economic dispatch is used to find the lowest cost combination of generator output power and generator scheduled regulation capacity\(^1\), under a number of constraints. Each generator has a specific set of parameter values influencing characteristics such as how much it can generate, how fast it can change that generation, how expensive its fuel is, and how expensive it is to run regardless of fuel price, among many others, necessitating an optimization algorithm in order to minimize our costs while maintaining the correct amount of power. Specifically, we wish to find all \(P_{Gi}\) and \(R_{Gi}\) to minimize

\[
C_T = \sum_{k=1}^{n_k} \left( C_S S_+(t_k) - C_S S_-(t_k) + \sum_{i=1}^{n_g} C_{P_{Gi}} P_{Gi}(t_k) \right) + \sum_{i=1}^{n_g} C_{R_{Gi}} R_{Gi},
\]

such that

\[
\sum_{i=1}^{n_g} P_{Gi}(t_k) + S_+(t_k) + S_-(t_k) = P_{avg}(t_b : t_e), \forall k, \tag{2.1}
\]

\[
P_{Gi}^{min} + R_{Gi} \leq P_{Gi}(t_k) \leq P_{Gi}^{max} - R_{Gi}, \forall i, k, \tag{2.2}
\]

\(^1\)The amount of generation devoted to regulation detracts from that devoted to serving load. This condition leads to increasing costs as regulation requirements rise.
\[ RR_{Di} \leq P_{Gi}(t_k) - P_{Gi}(t_{k-1}) \pm R_{Gi} \leq RR_{Ui}, \; \forall i, k, \]  

(2.3)

\[ S_+(t_k) > 0, \; \forall k, \]  

(2.4)

\[ S_-(t_k) < 0, \; \forall k, \]  

(2.5)

\[ \sum_{i=1}^{n_g} R_{Gi} = R_T, \]  

(2.6)

\[ 0 \leq R_{Gi} \leq \frac{P_{\text{max}}}{2}, \forall i. \]  

(2.7)

Table 2.1 defines the variables used in Equations 2.1 through 2.7.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Represents</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_T )</td>
<td>Total cost of running generators at their set-points (( P_{Gi} ) &amp; ( R_{Gi} )) over the time horizon</td>
</tr>
<tr>
<td>( C_{Gi} )</td>
<td>Cost in $/MW of running generator ( i )</td>
</tr>
<tr>
<td>( C_S )</td>
<td>Cost associated with the soft constraint</td>
</tr>
<tr>
<td>( P_{Gi}(t_k) )</td>
<td>Amount of power provided by generator ( i ) at time ( t_k )</td>
</tr>
<tr>
<td>( P_{\text{avg}}(t_b : t_e) )</td>
<td>Average load over the interval from time ( t_b ) (beginning of interval) to time ( t_e ) (end of interval)</td>
</tr>
<tr>
<td>( t_k )</td>
<td>Center time point of the interval ( (t_b : t_e) )</td>
</tr>
<tr>
<td>( R_{Gi} )</td>
<td>Amount of regulation capacity provided by generator ( i )</td>
</tr>
<tr>
<td>( R_T )</td>
<td>Total regulation needed over the next hour</td>
</tr>
<tr>
<td>( RR_{Di}, RR_{Ui} )</td>
<td>Maximum ramp rate down (D) and ramp rate up (U) for generator ( i )</td>
</tr>
<tr>
<td>( S_+, S_- )</td>
<td>Slack variables (used to make our constraint “soft”)</td>
</tr>
<tr>
<td>( P_{\text{max}}^{(\text{min})} )</td>
<td>Maximum (minimum) output capacity for generator ( i )</td>
</tr>
<tr>
<td>( n_g )</td>
<td>Number of generators</td>
</tr>
<tr>
<td>( n_k )</td>
<td>Number of time steps</td>
</tr>
<tr>
<td>( \forall )</td>
<td>Mathematical proof symbol meaning “for all”</td>
</tr>
</tbody>
</table>

Our optimization objective is to find the minimum total cost \( (C_T) \), where the total cost is composed of the operating cost of each generator \( (C_{P_{Gi}}) \) for the duration of the time horizon (explained below) plus the slack variable cost \( (C_S) \) for the duration of the time horizon, plus the operating cost of regulation for each generator \( (C_{R_{Gi}}) \).

Constraint (1) is our equilibrium constraint; it states that the average power used by the load over the interval from \( t_b \) to \( t_e \) must be equal to the power provided by the generators at the center of the interval \( (t_k) \), with the slack variables included in case the rest of the constraints prohibit this at
a given point (though with an extremely high cost $C_S$ such that the soft constraint is only employed when no other solution is possible), making the optimization one with “soft” constraints$^2$.

Constraint (2) places an upper and lower limit on the set-point of the generator, using the generator’s maximum (minimum) and shifting down (up) by the amount of regulation capacity the generator must provide; in this way, we ensure each generator will be able to provide the necessary regulation without being told to go outside its physical limits.

Constraint (3) implements a physical generator limit on the speed with which a generator can change its output (known as the ramp rate); this constraint ensures that the amount the generator’s total output set-point is asked to move over the time interval is not more than its maximum ramp rate$^3$.

Constraints (4) and (5) ensure the soft constraints stay respectively above or below 0.

Constraint (6) ensures that the sum of regulation capacity provided by each generator is equal to the total regulation capacity needed on the system over the next hour. As mentioned in Chapter 1, industry practice is to incorporate enough regulation capacity in the system to absorb up to a 1% unexpected change in load over the frequency control time scale (droop on the milliseconds to seconds scale and AGC on the seconds to minutes scale). Thus, $R_T$ is set equal to 1% of average hourly net load (until Section 3.3).

Constraint (7) ensures that the regulation provided by a given generator cannot be more than half its maximum output capacity, as it must be able to go up or down that amount from its current point. Using a linear system problem solver (Matlab’s “linprog” function), the solution indicates the optimal set-points for each generator for each given load level, referred to throughout this writing as “$P_{ref}$,” or the reference power set-point for a generator, and the optimal amount of regulation each generator provides.

As seen in Figure 2.2, we set the $P_{ref}$ input to the numerical analysis (Section 2.2.2) to vary linearly between each optimal set point found in the economic dispatch, creating a piece-wise linear generation schedule. This allows the simulated generators to vary their output smoothly like their

$^2$A soft constraint guarantees that the optimization solves (preventing the whole simulation model from aborting) even if a solution doesn’t strictly exist for the assumed constraints. In this way, if an unattainable ramp is required by the model, we do not simply modify the scenario with an easier ramp (because we would then completely fail to recognize the adverse effects of those low-probability, high-impact events), but instead, we let the system provide a response that comes as close as possible to meeting the ramp demanded, while keeping track of the deficiency in required generation, for recognition in the form of a cost penalty. This prevents simulations from failing due to high wind variability while at the same time avoiding an ill-advised model change that simply ignores the problem. Accordingly, we note that the costs associated with the slack variables $S^+$ and $S^-$ are significantly higher than any other cost within the problem, such that we only use them if there is no other option.

$^3$While it may not be immediately obvious that this is a rate due to the lack of a time divisor, this time divisor is implicit in the calculation as power changes from $t_{k-1}$ to $t_k$ (a defined duration, in our case 15 minutes). For example, if we have 100 MW at time $t_1 = 30$ minutes and 150 MW at time $t_2 = 45$ minutes, taking the difference results in a 50 MW/15min change. Because the duration from $t_{k-1}$ to $t_k$ is always the same, the denominator is implicit.
physical counterparts; had we set $P_{ref}$ to be a flat line over the 15 minute interval, it would cause the generators to make a sharp jump in their output at the beginning of each interval, which would have affected the area control error (ACE) and control performance standards (CPS) calculations (explained in Section 2.3.3). We note that due to the assumed piece-wise linear shape, it is not guaranteed that the energy provided over the 15 minute interval is equal to that used (which is the general goal of constraint 1; if we drew a zero-sloped line using the average load point instead of sloping it into the next interval, we would get equal energy provided and used). However, because the load noise is zero-mean and the total load varies significantly over the 15 minutes, we found that the energy difference was negligible (less than a tenth of a percent difference in energy provided in the interval on average). We also note that, due to re-optimizing each interval, the future values may be slightly different, and thus there usually is a small jump between intervals (though it is comparatively small to the jump if we had a flat $P_{ref}$ profile).

This set of equations is reevaluated every 15 minutes for an eight hour forward time horizon, such that the generators can more closely conform to the load if it has moved significantly in that
15 minutes (and thus is part of load-following control, mentioned in Chapter 1). The optimization is performed for each of the balancing areas separately, to ensure that each area is optimally prepared to provide its own power, thereby keeping its ACE reasonably low for all credible load levels. A time horizon is introduced to ensure that ramping capabilities are included in cost optimization; if we only look at the current moment in time, we may, for example, ask a generator to move toward its maximum when it may be more cost effective to leave it low and keep its ramping capability in reserve for later use.

It is particularly important that this be well implemented for our problem. As explained in Chapter 1, there are various levels of control; if we don’t adequately introduce load-following control, then any results we get which we interpret as related to regulation could actually be a load-following issue. Also of particular note is that the exact value of net load is given to the economic dispatch optimization. This essentially means that our system (unlike the real power grid) has no forecast error. We chose to proceed this way because we want to isolate the impact of wind’s variability on frequency control; including forecast error would confound our results by irrevocably commingling frequency variance with forecast variance. Doing so would result in uncertainty as to how much of the overall impact was due to an imperfect forecast, and how much was due to wind and load variability.

2.2.2 Dynamic Model Formulation

The next step in each simulation interval is to employ numerical integration to predict future system values. Using a dynamic model of our system, we are able to find the values of all pertinent system parameters at any moment in time. Our dynamics are modeled by

\[ P_g = P_m - D\Delta\omega - M\Delta\omega \]  

(2.8)

\[ \delta = \omega_0 \Delta\omega \]  

(2.9)

\[ T_g\dot{P}_m = P_{ref} + \Delta P_c - P_m - \frac{\Delta\omega}{R} \]  

(2.10)

and

\[ \Delta\dot{P}_c = -k \cdot ACE. \]  

(2.11)

Equation 2.8, known as the swing equation, serves as the physical model of the generator, where \( P_g \) is the electrical power desired by the system, \( P_m \) is the mechanical power output of the turbine,
\(\Delta \omega\) is the deviation in generator frequency (a.k.a., generator angular speed) from the nominal frequency of 60 Hz, \(\Delta \dot{\omega}\) is the first derivative with respect to time of the change in generator frequency (a.k.a., generator angular acceleration), and \(M\) and \(D\) are machine inertia and damping constants, which account for differences in inertia (\(M\)) and electrical and mechanical “friction” (\(D\)) among generators. This equation shows that, with the mechanical power held constant, a decrease (increase) in desired generator power \(P_g\) will result in an increase (decrease) in generator frequency. This is analogous to what we experience in a car when we begin going down a hill. If you were to keep pressing on the gas with the same pressure as you begin going down the hill (i.e., hold the mechanical power of your engine constant while decreasing the resistance against the car), the engine would speed up; this is why most of us decrease our gas pedal pressure as we descend.

Equation 2.9 simply states that the generator frequency (angular speed) \(\omega\) is equal to the derivative of the generator angle \(\delta\).

Equation 2.10 governs the primary frequency response of the machine (also known as droop control), where \(\dot{P}_m\) is the change with respect to time of the mechanical power, \(P_{\text{ref}}\) is the set point of the system derived by economic dispatch (Section 2.2.1), \(\Delta P_e\) is the change in the amount of regulation power provided, and \(R\) and \(T_g\) are scaling constants, in which \(R\) sets the gain of the droop feedback response, and \(T_g\) is the time constant of the governor system. Droop, also known as “primary frequency control,” is a control on the time scale of milliseconds to seconds which allows the mechanical output to change in order to help to correct deviation from nominal frequency. Without droop control, the mechanical power output cannot change and instead frequency must provide the entire buffer for when \(P_g\) changes, causing frequency swings and significant grid performance issues. We see that the equation relates \(\dot{P}_m\) to the error between the set point of power and the actual power output \((P_{\text{ref}} + \Delta P_e - P_m)\) and to the error between the current frequency and the nominal frequency \((\frac{\Delta \omega}{R})\). This control, then, alters the mechanical output in response to these errors; if the desired power output is wrong, the simulation is directed to change the output, and if the frequency is too high or low, again, it is directed to change the output (the frequency is directly related to the output via the swing equation). Comparing this with our above downhill car example, this is analogous to decreasing the pressure on the pedal; the difference between the actual power output and the necessary power output is non-zero, and thus we change the mechanical output by moving our foot in order to reestablish zero, instead of allowing the engine to increase speed.

Equation 2.11 governs secondary frequency control, known as automatic generation control (AGC), which operates on the time scale of seconds to minutes, where \(\Delta \dot{P}_e\) is the rate at which regulation power is changing, and, as the North American Electricity Reliability Council explains,
ACE “is used to determine a control area’s control performance with respects to its impact on system frequency,” [37] (explained further in Section 2.2.3, see Equations 2.27 and 2.28). Fundamentally, if an area has a significant frequency deviation and/or generation imbalance (i.e., it is exporting or importing much more than expected), then it must be corrected. This deviation or imbalance results in a non-zero ACE, which is used as the controlling signal for regulation; the bigger the ACE, the faster the regulation power output changes (up to the physical limit of the given generator) to help manage that deviation or imbalance.

In order to obtain our control diagram (as seen in Figure 2.3), we take the Laplace transform of each of the above equations. Starting with Equation 2.11, we have

\[ \triangle \dot{P}_c(t) = -k \cdot ACE(t) \]  

(2.12)

and, taking the Laplace transform,

\[ s \triangle P_c(s) = -k \cdot ACE(s). \]  

(2.13)

Dividing both sides by \( s \), we have

\[ \triangle P_c(s) = \frac{-k}{s} \cdot ACE(s). \]  

(2.14)

Thus, we see in Figure 2.3 below that ACE passes through a gain block of \( \frac{-k}{s} \) to produce \( \triangle P_c \). Additionally, we note that the limits to \( \triangle P_c \) are applied within this block, producing

\[ \triangle P_{c\text{lim}} = \lim (\triangle P_c, [0, R_{g\text{max}}]), \]  

(2.15)

which uses a sigmoidal function to limit the regulation power to stay within the maximum it is ordered to provide. Within Equation 2.10, we define

\[ P_p(t) = P_{\text{ref}}(t) + \triangle P_{c\text{lim}}(t) - \frac{\triangle \omega(t)}{R} \]  

(2.16)

as the power from primary control, and, taking the Laplace transform, we have

\[ P_p(s) = P_{\text{ref}}(s) + \triangle P_{c\text{lim}}(s) - \frac{\triangle \omega(s)}{R} \]  

(2.17)

as shown in the summation on the next step of the block diagram. Limiting this gives us \( P_{p\text{lim}} \).
where

\[ P_{\text{lim}} = \lim (P_p, [P_{g\text{min}}, P_{g\text{max}}]), \]  

(2.18)

which limits the output power to be within the physical limits of the generator. Then, Equation 2.10 can be written as

\[ T_g \dot{P}_m(t) = P_{\text{lim}}(t) - P_m(t). \]  

(2.19)

Taking the Laplace transform, the result is

\[ sT_g P_m(s) = P_{\text{lim}}(s) - P_m(s). \]  

(2.20)

Adding \( P_m \) to the other side, we have

\[ (sT_g + 1) P_m(s) = P_{\text{lim}}(s) \rightarrow P_m = \left( \frac{1}{T_gs + 1} \right) P_{\text{lim}}. \]  

(2.21)

Lastly, we take the Laplace transform of Equation 2.9, resulting in

\[ P_g(s) = P_m(s) - D\Delta \omega(s) - sM\Delta \omega(s) \]  

(2.22)

or

\[ sM\Delta \omega(s) = P_m(s) - P_g(s) - D\Delta \omega(s). \]  

(2.23)

Solving for \( \Delta \omega \), we have

\[ (Ms + D) \Delta \omega(s) = P_m(s) - P_g(s) \rightarrow \Delta \omega(s) = \frac{1}{Ms + D} (P_m(s) - P_g(s)). \]  

(2.24)

As noted above, a number of limits must be applied to the outputs, which is done to more accurately reflect the operation of a physical system. The limit on \( \Delta P_c \) is applied to ensure that the regulation provided by a given generator stays within the defined amount derived by economic dispatch (Section 2.2.1). The limit on \( P_p \) ensures that the generator stays within its absolute maximum and minimum power output. We additionally place a limit on \( \dot{P}_m \) to ensure that the generator ramping does not occur faster than is physically possible; a given generator can only change its output so quickly. Lastly, we apply a limit to \( \Delta \dot{P}_c \) to ensure that the system is not attempting to change \( \Delta \dot{P}_c \) when \( \Delta P_c \) is already at its limit.
In addition to the governing differential equations of the generators, there exists an algebraic equation that must be satisfied in solving. This equation is

\[ P_{\text{inj}} = B \Theta = P_g - P_d \]  

(2.25)

where \( B \) is negative of the system susceptance bus (i.e., \( B = -Y_{\text{bus}} \)), \( \Theta \) is the vector of bus angles, \( P_g \) is the vector of powers generated at each bus, and \( P_d \) is the vector of powers consumed at each bus. The equation represents that the amount of power injected onto the lines of the system at each bus is equal to the power provided to the system by the generators minus the amount of power taken from the system by the loads, which is in turn related to the bus angles via the admittance matrix resulting in a simplified DC power flow. We see that no line losses are included, nor are reactive power components or voltages, because of the use of the DC power flow equation. This Section is represented as the “DCPF” block in Figure 2.3. Using \( P_{\text{inj}} \) from DCPF, we are able to determine the flows on tie lines (i.e., those lines tying the 2 areas together), producing \( \Delta P_{\text{tie}} \).
2.2.3 Control Performance Standards

As proper grid performance is essential to ensuring reliable and economic electric service, there exist many industry standards to measure it. In this thesis, our focus is on the sub-minute time scale performance, and therefore we measure the success of our system’s performance using sub-minute standards. The North American Electric Reliability Council (NERC) is the regulatory body that dictates the standards that all North American utilities must meet. At the time scale on which we are focused, the most important NERC standards to measure are the Control Performance Standards, known as CPS1 and CPS2. Accordingly, at the very end of the simulation, after all time intervals have been simulated, we evaluate the CPS equations.

CPS1 is a measure of a balancing area’s ability to adequately provide (or purchase) its own power and control its own frequency. It is described by the equation

\[ \text{CPS1} = 100\% \cdot [2 - \text{CF}], \]

where

\[ \text{CF} = \frac{\text{CF}_{12 \text{ months}}}{(\epsilon_1)^2}. \]  

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frequency, $F_S$ is the scheduled frequency, and $B$ is the balancing area’s frequency bias in MW/0.1Hz (which has a negative sign). For our purpose, we can assume no scheduled interchange ($P_{\text{schtie}} = 0$) and that the scheduled frequency is always 60 Hz, resulting in

$$ACE(t) = P_{\text{tie}}(t) - 10B(F_A(t) - 60). \quad (2.30)$$

Thus, we see that in Equation 2.25, if frequency deviation and ACE have the same sign, CF increases, and CPS1 decreases, but if they have opposite signs (i.e., the area’s imbalance is helping to correct the system’s frequency deviation), then CF decreases, and CPS1 increases. The minimum acceptable long term score for CPS1 is 100%. However, because NERC has measured the continent-wide average to be 160%, this is the value we used to indicate “adequate system performance” as repeatedly mentioned throughout Chapter 1; if a balancing area has an average CPS1 value of at least 160%, the amount of regulation chosen is considered to be enough (further explained in Section 3.3.1).

CPS2 was originally designed as a supplemental standard to CPS1, and was developed to prevent “gaming the system”. This ruse could be accomplished by periodically introducing large frequency deviations in the opposite direction of existing frequency deviations, which would result in excellent CPS1 scores for that area, but introduces what NERC deems “excessive flows” on inter-area tie lines and might in fact be viewed as exacerbating frequency deviations rather than quelling them. The CPS2 equation is

$$\text{CPS2} = \left[1 - \frac{\text{Violations}_{\text{month}}}{\text{Total Periods}_{\text{month}}}\right] \times 100,$$

where a violation is recorded if the absolute value of the 10 minute average value of ACE is less than the “$L_{10}$” value, specified for a given Balancing Area by NERC. The minimum acceptable CPS2 score is 90%, which translates to less than 1 violation for each ten 10-minute time period [9, 10, 37].

### 2.3 Input Data and System Model

#### 2.3.1 System

For our power system model, we began with the IEEE New England test case\(^4\), which includes 39 buses, 10 generators, and 19 loads, which we adjust in a few ways. We chose to add an additional 4 generators (G11 through G14 in Figure 2.4) which we assigned low maximum outputs but high ramping capabilities; these generators were assigned to provide the bulk of the regulation capacity.

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\(^4\)A greatly simplified and reduced model of the New England generation and transmission system that is made available by IEEE for various academic and research purposes such as this investigation.
These 14 generators do not include the wind plants, which will be added to our model in Section 2.3.3.

Because our analysis is focused around the Area Control Error calculation (explained in more detail in Section 2.2.3), which involves the amount of power exchanged between an area and its immediate neighbors, we chose to include a second area. In order to do so, we duplicated our New England test case, creating two tie lines to connect the two areas (as seen in Figure 2.5). We thus have a 78 bus system model, separated into 2 equally sized areas. We note that due to random variability present in load and wind, each area will still have a different power profile, despite being identical in setup.

Figure 2.4: IEEE 39 Bus New England test case with additional generators (G11-G14) shown at buses 24, 23, 26, and 28
2.3.2 Load

Aggregate load data from 2005 and 2006 for the New England region were provided by ISO-NE at 5 minute intervals [19]. As we are interested in the variability at sub-5 minute time scales, we added noise to the cubic spline\(^5\) of the provided data to mimic realistic load variability. This was done using a mean reverting random walk (MRRW) to ensure a zero-mean variability (as we can subtract the mean out), as well as to provide statistical control over the load; we are able to specify the mean, standard deviation and reversion strength (how strongly the random value tries to get back to its mean) which allows us to produce a specific load profile, from which we subtract the mean and add this noise to the smooth 5 minute load profile provided. Various values for these three parameters were tested to determine the appropriate values to use during simulations to produce the desired load profile (see Section 2.4.2).

The total New England load was uniformly scaled down in magnitude to fit comfortably within our model’s maximum generation capabilities, but apportioned among each of the 39 buses in our 2-area 78 bus system so as to approximate the same load dispersion already found in the IEEE base test case model of New England. The IEEE model’s impedance matrix, which is intended to approximate the New England transmission network, was left unchanged.

2.3.3 Wind

Two-second resolution wind data were provided from a wind farm in the Midwest of the US. Given the two-second resolution, we are able to capture nearly all of the effect of the wind’s variability on the dynamics of the system.

Four buses in each area were arbitrarily chosen as wind generation injection sites, as seen in Figure 2.5. To ensure realistic geographic diversity, we used a different day of wind data for each “farm” in our system. In other words, wind farms that are a significant distance away from each other have little correlation in their power profile. In order to mimic this effect without data from multiple wind farms, we simply chose different days for each farm, because differing days tend to produce little temporal correlation, which is a reasonable surrogate for geographic non-correlation.

As the dynamics of the wind turbines do not matter in the context of our model (because they provide no inertia or feedback control within that model), we are able to simply have our system input be net load, which is the difference for each moment in time between the load and the wind-derived generation. Wind, as a generation source, is thus simply considered negative load within the context\(^5\)A numeric method of interpolation to create a smoothly varying curve.
of our DC model.

Figure 2.5: Full 78 bus system split into 2 areas, with 4 wind generators per area and two tie lines added

2.4 Base Case Simulation Results

Prior to performing any of our wind-based experiments, we wished to ensure that the modeled system performs as closely to the real-life grid as possible. Using a number of standard industry expectations, we calibrated a number of the model’s parameters, until we obtained simulation results that aligned well with typical system performance. Wind generation is not introduced onto the system until the experiments explained in Chapter 3.

2.4.1 Frequency Output and other system parameters

We began validating our system model and associated parameters by applying a number of simple loads and inspecting the subsequent output variables. Each of the examples below shows one hour’s worth of simulated data of various system variables to demonstrate the model reactions. For each, a series of figures is provided. The first figure in each series includes a plot of delta (δ - generator angle in radians, plotted relative to the slack bus) for each generator, a plot of theta (Θ - bus angle in radians) for each bus, a plot of omega (ω - the generator angular frequency in radians per second\(^6\)) for each generator, and \(P_m\) (mechanical power in megawatts [MW]) for each generator. The second figure in each series is a plot of the load power (\(P_d\)) drawn from the system over the hour in MW. The third shows each of the various power components for the system; \(P_d\) is again the load, \(P_m\) is

\(^6\)Note that 60 Hz is equal to \(2\pi \cdot 60\) radians per second, or approximately 376.9911 radians per second
the mechanical power output of all the generator turbines on the system, \(P_g\) is the output power of all the generators on the system, and \(P_{\text{ref}}\) is the scheduled output profile of all the generators provided by economic dispatch. An “accurate system” is one in which the generator/turbine powers (\(P_g\) and \(P_m\)) should stay close to the load (\(P_d\)). The closer the values stay, the better the system performance. The fourth figure in each series plots \(\Delta P_c\) for the system over the hour timeline; this is a measure of the instantaneous amount of power being provided due to regulation.

The next 3 figures provide an alternate view into system performance. The fifth figure in each set plots mean system frequency (i.e., the overall system frequency) over the hour timeline. The sixth plots \(P_{\text{tie}}\), or the net power interchange between the 2 areas (Area 2 will have the opposite sign as Area 1). The seventh plot shows each area’s area control error (ACE) over the hour; we note that an area’s ACE is a combination of its net interchange and the system frequency (as detailed in Section 2.2.3), and thus we are able to identify similar patterns in this figure as the two prior.

### 2.4.1.1 Response to Ramp-shaped Load

The first simple load used is a ramp, as seen in Figure 2.7. In this particular case, we introduced a load which increases approximately 4% over the hour. Because of the smooth and gradual change of this load, we would expect that it should have relatively little impact on frequency; with our perfect forecasting and ramping (i.e., piece-wise linear) economic dispatch, our load following control should change the mechanical power without relying on regulation. We see from the figures below (Figures 2.6 - 2.12) that our model works as expected. The frequency deviation remains approximately zero (though we see a slight tick every time economic dispatch re-optimizes and the system momentarily settles), and the power provided steadily rises over the hour, while \(\Delta P_c\) (the amount of regulation power being provided) remains approximately 0 as well.

Specifically, we see in Figure 2.6, plot 4 that a single generator seems to be providing the overall increase of generation. This is an indication that our economic dispatch has optimized each generator’s \(P_{\text{ref}}\) properly; the cheapest generators are being held at their maximums, the most expensive generators are being held at their minimums, and this generator whose cost is between the two sets performs the entirety of the output change. Had this generator reached its maximum, the next least expensive generator (one of those being held at its minimum) would have begun to increase.
Figure 2.6: Series depicting 4 basic system variables measured during the ramp-shaped load: delta ($\delta$ - individual generator angle in radians for each of the generators), theta ($\theta$ - individual bus phase angle in radians for each of the 78 buses), omega ($\omega$ - individual generator frequency in radians per second for each of generators), and $P_m$ (individual generator mechanical power output in MW for each of the generators).
Figure 2.7: Ramp-shaped load power drawn by the system during the hour.

Figure 2.8: Various system power components recorded during the ramping load: $P_d$ (load power drawn), $P_g$ (the electrical power desired from the generators), $P_m$ (the mechanical power output of the generators), and $P_{ref}$ (the generation set-points as scheduled using Economic Dispatch). We note that the traces overlap so closely that the difference in colors is fully not discernible.

Figure 2.9: System-wide regulation response ($\Delta P_c$) from Secondary Frequency Control during ramp-shaped load hour.

Figure 2.10: System Frequency Deviation from 60 Hz during ramp-shaped load hour.
2.4.1.2 Response to Step-shaped Load

The next load we apply is a nearly-instantaneous step. In the example shown below, we step a single load in Area 1 up by approximately 50 MW, which constitutes about a 0.8% increase in the area load. Because this is a sharp change in load, we expect that economic dispatch cannot foresee the entire change, and thus regulation will need to provide some assistance to the system. We see this outcome in the figures below; in Figure 2.15 we see that $P_{\text{ref}}$ does not follow $P_d$ closely as it did in the example above, and yet the mechanical power of the generators does stay almost exactly with $P_d$, and thus in Figure 2.17 we see the frequency dip less severely than it would have if we depended solely on redispatching. This is because regulation is able to “take up the slack”; we see in Figure 2.16 that at the moment of the increase in load, $\Delta P_c$ jumps up to 25 MW over the span of 1 minute. Because it takes a full minute, we see that frequency does deviate, but, of course, would have deviated more severely without the help of regulation. Additionally, we note that regulation was not required to take up the entire 50 MW change. This is because $P_{\text{ref}}$ addressed part of the 50 MW deficit while $\Delta P_c$ made up the rest.

We also note in this example that the idea of reciprocity, or the mutual responsibility as well as the mutual benefit of multiple areas being connected together, is upheld by our system. We see that at the time the load increases in Area 1, the frequency drops, and Area 1’s $P_{\text{tie}}$ (the net interchange between the areas) shoots negative (i.e., Area 1 is importing power) while Area 2 has an equal and
opposite $P_{\text{tie}}$. This indicates that while all of the generators in Area 1 increased in response to the change in load as fast as they could, the generators in Area 2 did the same, resulting in a net export out of Area 2 (because its increase in generation was not accompanied by an increase in load in its own area); in other words, Area 2 provided relief to Area 1 until Area 1 was able to ramp its generators up completely to manage its own load change. Similarly, had the jump occurred in Area 2, Area 1 would have responded to help Area 2. In this way, interconnectedness on the grid allows for a larger pool of assistance to counteract variability.

As we might expect, the ACE for Area 1 is poorer than that of Area 2, as Area 1 is momentarily unable to control its error. Area 2 does not have an error but is merely helping with the error in Area 1. Mathematically, this stands; in our ACE equation, if $P_{\text{tie}}$ and frequency deviation have the same sign, the magnitude of the ACE increases, while if they have opposite signs (i.e., the area is helping by over-generating and thus exporting when frequency is low or under-generating and thus importing when frequency is high), the magnitude of the ACE decreases.

Additionally, it is important to point out that per the standards, Area 2 is rewarded for assisting Area 1. Referring back to the equation for CPS1, we essentially have

$$CPS1 = 100\% \cdot \left(2 - \frac{\text{ACE} \cdot \Delta F}{c}\right), \quad (2.31)$$

where $c$ is a positive constant (because the sign of $B$ is negative. Thus, if ACE and frequency deviation are both positive or both negative, CPS1 decreases because we would be subtracting a positive value from 2, and if ACE and frequency deviation are of opposite sign, CPS1 increases because we subtract a negative value (i.e., add a positive) to 2, resulting in a CPS1 of greater than 200%. 

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Figure 2.13: Series depicting 4 basic system variables measured during the step-shaped load: delta ($\delta$ - individual generator angle in radians for each of the generators), theta ($\theta$ - individual bus phase angle in radians for each of the buses), omega ($\omega$ - individual generator frequency in radians per second for each of the generators), and $P_m$ (individual generator mechanical power output in MW for each of the generators).
Figure 2.14: Step-shaped load power drawn by the system during the hour.

Figure 2.15: Various system power components recorded during the step-shaped load hour: $P_d$ (load power drawn), $P_g$ (the electrical power desired from the generators), $P_m$ (the mechanical power output of the generators), and $P_{ref}$ (the generation set-points as scheduled using Economic Dispatch).

Figure 2.16: System-wide regulation response ($\Delta P_c$) from Secondary Frequency Control during step-shaped load hour.

Figure 2.17: System Frequency Deviation from 60 Hz during step-shaped load hour.
2.4.1.3 Response to Sine-shaped Load

The third load we apply is a section of a sine wave, which in the hour snap shot completes approximately half of its cycle (i.e., 1 cycle every 2 hours). Here, we must manage variances using both economic dispatch and regulation. Economic dispatch is able to foresee the shape the load will make when performing its optimization, but because the set-point power is piece-wise linear, there is no “perfect” solution to meet load exactly. As can be seen in Figure 2.22, $P_{\text{ref}}$ stays fairly close to the load shape despite its constraints, but there is still a discernible gap between the two. This is where regulation takes up the slack; anything for which load-following control cannot account, regulation will attempt to offset. Thus, we see a much more active $\Delta P_c$, responding in accordance with the moments that $P_{\text{ref}}$ is far from $P_d$.

We observe, as well, a situation in which regulation is pushed to its limits. As mentioned previously in Section 2.2.1, the amount of regulation on our system is equal to 1% of the average future hour net load, and thus is around 125 MW. Because we introduced an unrealistic load (one which changes so significantly and in a shorter amount of time than load following control can respond), we use up all of the capacity we have for regulation. For instance, we see in the approximately 5 minute span before the 30 minute mark that $\Delta P_c$ is rising as $P_{\text{ref}}$ deviates from $P_d$ and it eventually reaches its maximum while $P_{\text{ref}}$ continues to deviate from $P_d$. We see then that droop control must take over, which is indicated by the dramatic rise in frequency. Up until $\Delta P_c$ reached its maximum, frequency had been kept well within a reasonable limit, but was forced to change when secondary
control could no longer assist because it has hit its capacity limit. At the 30 minute mark, economic dispatch resets the generator set-points, returning the frequency to a normal range and allowing $\Delta P_c$ to return toward 0 as the generator set-points ramp in (though the process repeats itself a second time a few moments later due to the quick reversal of the sine wave. We see again, then, the particular importance of maintaining adequate regulation capacity; as long as we have enough capacity, and sufficiently rapid ramping capability, we can prevent or minimize most frequency deviations from occurring.

Lastly, we note that $P_{\text{tie}}$ remained nearly 0 throughout this entire set of results. This is because the sine-shaped load was applied to each load bus in both areas, unlike in the last example where the step was applied to a single bus in a single area. Thus, neither area could assist the other, because each was facing the same problem.

![Series depicting 4 basic system variables measured during the sine-shaped load: delta (\(\delta\) - individual generator angle in radians for each of the generators), theta (\(\theta\) - individual bus phase angle in radians for each of the buses), omega (\(\omega\) - individual generator frequency in radians per second for each of the generators), and $P_m$ (individual generator mechanical power output in MW for each of the generators).](image-url)
Figure 2.21: Slow sine-shaped load power drawn by the system during the hour.

Figure 2.22: Various system power components recorded during the sine-shaped load: $P_d$ (load power drawn), $P_g$ (the electrical power desired from the generators), $P_m$ (the mechanical power output of the generators), and $P_{ref}$ (the generation set-points as scheduled using Economic Dispatch).

Figure 2.23: System-wide regulation response ($\Delta P_c$) from Secondary Frequency Control during sine-shaped load hour.

Figure 2.24: System Frequency Deviation from 60 Hz during sine-shaped load hour.
2.4.1.4 Response to Stochastic Load

The last “artificial” load we introduced to the system before our more realistic empirically-based load profile is a stochastic load. This is created by taking the output of the mean reverting random walk process and using it as is, without applying it to the New England load spline as described in Sections 2.3.2 and 2.4.3. This, too, is a situation that requires all levels of control. We see in Figure 2.29 that the economic dispatch process (producing $P_{\text{ref}}$) is able to capture the average load power fairly well (i.e., the energy delivered over each dispatch period is equal to the energy desired by the load), but, of course, it does not “wiggle” with the load; this is instead the job of regulation.

One important comparison to the previous example is the need for both primary and secondary frequency control. Where before the deviation between $P_{\text{ref}}$ and $P_d$ was smooth, here it is distinctly sharp, requiring significant changes in output power in short increments of time. Because of this and the ramping limit on $\Delta P_c$ (as explained in Section 2.2.2), primary frequency control must assist, resulting in the more significant perturbations of frequency.
Figure 2.27: Series depicting 4 basic system variables measured during the stochastic load: delta ($\delta$ - individual generator angle in radians for each of the generators), theta ($\theta$ - individual bus phase angle in radians for each of the buses), omega ($\omega$ - individual generator frequency in radians per second for each of the generators), and $P_m$ (individual generator mechanical power output in MW for each of the generators).
Figure 2.28: Stochastic load power drawn by the system during the hour.

Figure 2.29: Various system power components recorded during the stochastic load: $P_d$ (load power drawn), $P_g$ (the electrical power desired from the generators), $P_m$ (the mechanical power output of the generators), and $P_{ref}$ (the generation set-points as scheduled using Economic Dispatch).

Figure 2.30: System-wide regulation response ($\Delta P_c$) from Secondary Frequency Control during stochastic load hour.

Figure 2.31: System Frequency Deviation from 60 Hz during stochastic load hour.
Figure 2.32: Area interchanges ($P_{tie}$) during the stochastic load hour. The blue trace indicates the values for Area 1, while the green trace indicates the values for Area 2.

Figure 2.33: Area Control Errors (ACE) for each of the two areas during the stochastic load hour. The blue trace indicates the values for Area 1, while the green trace indicates the values for Area 2.

2.4.2 Empirically-derived Load Noise

To more closely replicate a genuine load profile, we added noise to our five-minute New England load spline using a mean reverting random walk, as mentioned in Section 2.3.2. To create a noise pattern, the mean reverting random walk employs the following relationship

$$x(n + 1) = x(n) + k \cdot (\mu - x(n)) \cdot x(n) \cdot dt + \sigma \cdot d\omega(n) \cdot x(n)$$  \hspace{1cm} (2.32)

where $\mu$ is the desired mean, $\sigma$ is the desired standard deviation, $k$ is the reversion strength (i.e., how strongly the noise reverts back toward the mean) $d\omega(n)$ is a random number from a normal distribution times the time-step $dt$. As we vary the inputs $\mu$, $\sigma$, and $k$, we adjust the profile of the noise, as can be seen in Figure 2.34. (Note that the mean has been subtracted from each signal; over a large number of points, this results in an approximately zero-mean signal. Also be aware that the scale on frame (B) is larger than the rest.).
To produce our desired load profile, we adjusted these values until we found a reasonable combination with two specific characteristics.

First, we wanted the coefficient of variation of the noise portion to be less than 1, as is the case with real load. The coefficient of variation is defined as the ratio of the standard deviation of a signal to its mean; in other words, it is a normalized measure of the spread of a signal (in other words, its total range). We note that as our signal is a MRRW, the input mean and standard deviation are not the same as the output (because of k, the reversion strength); in other words, we cannot simply divide our input standard deviation by our mean to get the coefficient of variation.

Second, we wanted the average CPS1 score produced by our load profile to be approximately 160% (cited by NERC as the average CPS1 score in the industry). Sharp sudden changes in load affect frequency more acutely than smooth gradual changes, and thus the size and speed with which our load changes as determined by the MRRW are the key determinants of CPS1 score.

With these two calibrating objectives in mind, we were able to adjust the MRRW inputs to produce a reasonable load profile. We note that the adjustments done to produce an appropriate
load were done after the proof-of-system described above. We could not, of course, trust that the average CPS1 score was correct until its inputs (net imbalance and area control error) were being correctly solved for, and thus the simple load profiles we used to tune the system were necessary before we could iterate to a truly realistic load profile. In our case, we allowed a coefficient of variation that was slightly above the norm (around 0.8, as opposed to around 0.5 for real load) in order to produce the correct average CPS1; we expect that our simulation performed slightly better than a real scenario because we recognized no adverse issues outside of our scope (e.g., transmission constraints, generator failure, etc) and thus needed to increase the variation of our load to correctly reflect this.

2.4.3 Total Basic Response

We now present in the graphs below an hour’s worth of simulated data of our total “basic” system. This 2-area, 78-bus model has base-load (minimum daily load) of approximately 9500 MW and a maximum daily load of approximately 15000 MW. The system is economically re-dispatched every 15 minutes, and includes an hourly regulation value equal to 1% of the average hourly load (and thus is between approximately 95 MW and 150 MW). For the basic system, no wind generation is included; we wish to record how the system performs before we add additional stress in the form of wind generation (which will be introduced to the system in Chapter 3).
Figure 2.35: Series depicting 4 basic system variables measured during the total basic response run: delta (δ - individual generator angle in radians for each of the generators), theta (θ - individual bus phase angle in radians for each of the buses), omega (ω - individual generator frequency in radians per second for each of the generators), and $P_m$ (individual generator mechanical power output in MW for each of the generators)
Figure 2.36: Empirically-derived load power profile drawn by the system during the hour.

Figure 2.37: Various system power components recorded during the total basic response run: $P_d$ (load power drawn), $P_g$ (the electrical power desired from the generators), $P_m$ (the mechanical power output of the generators), and $P_{ref}$ (the generation set-points as scheduled using Economic Dispatch).

Figure 2.38: System-wide regulation response ($\Delta P_c$) from Secondary Frequency Control during total basic response run hour.

Figure 2.39: System Frequency Deviation from 60 Hz during total basic response run hour.
We now pause to recap where we have been and where we are going next. Chapter 2 described the details of our model. Starting from 5-minute load data, we add specially designed load noise, and apportion these data among the 78 bus, 2 area system. This comprehensive model then iterates back and forth between economic re-dispatch and numerically based dynamic simulations. At the end of the simulation of the 24-hour period, the results are used to calculate the corresponding Control Performance Standard values. We have verified that it behaves quite similarly to a realistic physical system.

Additionally in Chapter 2, (more specifically, in Section 2.3.3) we described how wind generation will be added to our comprehensive model using two-second recorded wind data, resulting in a “net load” model per the equation \( \text{Net Load}(t) = \text{Load}(t) - \text{Wind}(t) \).

We now have everything needed in terms of modeling and methodology to quantify the relationships between wind penetration and necessary regulation (to maintain adequate reliability) as well as the ramping capability of the regulating generators, provided that we add the wind generation data.
Chapter 3

Model Results

3.1 Introduction

Our main focus, as described in Chapter 1, is to consider the influence of wind generation on system performance, and to additionally note other significant influences. We now introduce wind generation onto the “base” system model, and can expect any changes in outcomes compared to this base system to be a direct result of the introduction of the wind generation. In this chapter, we will explain each set of wind-based experiments performed on our system, and their results. We begin by simply increasing the wind generation to various levels, and measuring system performance in the context of the NERC Control Performance Standards for each generation level, while holding all other variables constant.

Next, we vary the regulation amount available to the system for each of those generation levels and again measure the system performance. From these results, we are able to determine the amount of regulation necessary to achieve an average CPS1 value of 160%, our chosen benchmark. We compared this “necessary regulation amount” to amounts determined using various statistical methods, in order to determine if these methods reliably and consistently lead us to our desired CPS1 value. We then look at the effect of the ramping capability of our system on our results.

For each set of experiments, various “percent wind penetration” values will be indicated. This value is calculated based on energy (i.e., average power), as opposed to based on peak power or another instantaneous value. For instance, if we take the mean of the total wind time vector and divide it by the mean of the total load time vector, and we get 0.1, this is 10% wind penetration by energy. We see such an instance in Figure 3.1; dividing the average wind generation of approxi-
mately 1200 MW by the average load of approximately 12000 MW, we get a 10% wind penetration percentage by energy. It is our opinion that the use of energy (i.e., average power) as a measure of wind penetration levels leads to a better representation of system behavior because peak values, by their very nature, are short in duration and of low probability.

![Graph showing system load and wind generation](image)

Figure 3.1: Example of determination of wind percentage by energy. The average of the wind generation over the day is around 1,200 MW (as indicated by the dashed magenta line), and the average of the load over the day is around 12,000 MW (as indicated by the dashed red line), and thus the wind penetration percent by energy is calculated to be \( \frac{1,200}{12,000} \times 100 = 10\% \).

### 3.2 Establishment of Control Performance Standards as a Function of Wind Percentage

#### 3.2.1 Explanation of Experiment

For the first experiment, we wished to demonstrate the influence of the amount of wind generation on our “basic” system (that is, a system with 15 minute dispatch, 1% regulation, etc). In order to do so, we ran simulations of the system for 16 different wind percentage values ranging from 0% to 30% wind generation by energy. For each wind percentage, 50 simulations were performed, simulating 24 hours of system operation, with the Control Performance Standard values (CPS1 and CPS2) being measured for each day’s simulation, and each of the sets of 50 CPS1 and 50 CPS2 values being averaged. Thus, for each wind percentage we have what amounts to a 50 day-based Control
Because these values are generally measured over a year, there is a small chance that a low-probability, high-impact event could have occurred, but for the most part, we found that the data behaved so well that additional simulations were deemed unnecessary.

### 3.2.2 Results

The resulting CPS scores of the 800 simulation runs are shown in Figure 3.2.

The left plot depicts the relationship between the percent of wind penetration and the CPS1 score. As supported by many other studies, including the majority of those cited in Chapter 1, we see that the system performance degrades quite quickly as wind generation is increased as a percentage of total generation. Specifically, we see an exponential decay, which means that as wind power becomes a significant component, the degradation of system performance accelerates. We note that the two solid red lines indicate CPS1 percentages of 165 and 155, and the blue dashed line indicates a CPS1 percentage of 100. As mentioned in Section 2.2.3, NERC has stated that the average CPS1 value tends toward 160%, and thus the red lines denote a generally acceptable range on the plot. At wind penetration percentages as low as 6%, CPS1 begins to fall outside of this range; by 16%, CPS1 is below 100%, the minimum acceptable value as specified by NERC.

We see in the right plot that CPS2 follow a similar pattern, although it stays well above the NERC minimum acceptable value of 90%.

![Figure 3.2: Control Performance Standards versus wind penetration percentage with regulation held at 1%](image)

The red solid lines in the top graph indicate the approximate range of “generally acceptable” CPS1 value (those near 160% percent), while the blue dashed line indicates the minimum acceptable CPS1 value of 100%. Similarly, in the bottom graph, the blue dashed line indicates the minimum acceptable CPS2 value of 90%. The blue dots indicate the values for Area 1, while the green dots indicate the values for Area 2, though they overlap so closely in the bottom graph that the difference in colors is not discernible.
3.2.3 Conclusions Summary for Section 3.2

From the above graphs, we are able to make a number of important conclusions.

First, we can conclude that, as expected, system frequency performance is highly dependent on wind penetration level. Given a fixed regulation amount, we can reasonably expect the system performance to exponentially decrease as wind penetration increases, and the performance degradation is readily predictable.

Second, at 1% regulation, our assumed system could easily incorporate up to 6% wind penetration without any noticeable impact on system performance. However, without introducing any other changes to that system, wind generation penetrations above 6% would noticeably degrade performance, and penetrations above 16% would be highly inadvisable, as they would bring CPS1 below the minimum acceptable value of 100%. At this point, it may reasonably be concluded that we have discovered the general qualitative relationship between wind penetration and frequency performance for a given regulation amount, but not necessarily its specific quantitative relationship for all possible conditions. That is, we would expect the relationship to be generally exponential in nature, as graphed, but not with precisely the same values in all cases.

Last, we conclude that for the objective at hand (which is to characterize system performance vs wind penetration), CPS2 is not a definitive performance standard. The above graph demonstrates that even for high wind penetration scenarios, CPS2 remains well above its minimum acceptable value of 90%. This is unsurprising because, as explained in Section 2.2.3, CPS2 was originally designed as a supplemental standard to CPS1, which intended to prevent “gaming the system”. Such gaming could be accomplished by introducing large frequency deviations that were in the opposite direction of existing frequency deviations, but our simulations do not do this. Thus, going forward, we will focus only on CPS1.

3.3 Establishment of Necessary Regulation as a Function of Wind Percentage

Because of the significant degradation of system performance as wind generation increases, as illustrated in Figure 3.2, some method to improve performance must be introduced. We know that load variability is managed, in part, by regulation control. Logically, then, we expect an increase
in regulation control to similarly address variability due to wind generation. Ultimately, we wish to establish the functional relationship between regulation, wind penetration, and system frequency performance.

### 3.3.1 Explanation of Experiments

In this experiment, we performed simulations for each of the wind percentages specified in Section 3.2, but this time, for each, varied the amount of regulation available to the system. We again measured the corresponding average CPS1 over the runs for each pair of wind percentage and regulation amount. Thus, we were able to plot the relationship between CPS1 and regulation amount (measured as percent of average hourly net load on the graphs below, as explained in Section 2.2.1) for each wind generation percentage.

The number of 24 hour simulations done for each paired combination of wind penetration percentage and regulation amount was increased for higher wind penetration percentages (50 runs for wind percentages ranging from 2% to 8%, 100 runs for wind percentages ranging from 10% to 16%, and 200 runs for wind percentages from 18% up) because the increased variability due to high wind penetration tended to statistically distort results if small sample sizes were used. In other words, if a low-probability, high-impact event occurs once in one area, it may skew results more heavily in a small sample size than in a large one. We found these simulation-group sizes to be a good balance between statistical validity and computational expediency.

Additionally, an exponential line of best fit was applied to the CPS1 scores of each wind percentage in order to quantify a function that maps the regulation amount to CPS1 score. In this way, we were able to find the regulation amount needed to maintain an average CPS1 score of 160%. We consider this value to be the regulation amount necessary to maintain adequate system performance (in other words, the amount of regulation necessary to keep the system performance at the level it is at today, as specified by NERC).

Lastly, we compared our results to multiple statistical models suggested by various prior analyses.

### 3.3.2 Results

#### 3.3.2.1 The Relationship Between CPS1 and Regulation Percentage for Individual Wind Penetration Percentages

In the series of graphs below, we can see the relationship between regulation percentage and average CPS1 score in each area for each wind penetration percentage as well as the best fit line for each
set. As expected, an increase in regulation produces a better CPS1 (i.e., each is a positively sloped function).

Also, the random net load variability due to wind generation intermittency is quite apparent in the dispersion of the points. We see that for 2% wind penetration, the average CPS1 scores tend to coalesce in a well-defined pattern, whereas for 26%, they tend to disperse more broadly. The increased amount of variability at high wind percentage means that in the 200 runs to obtain each pair of points for 26% wind, it is much more likely that the system will have a few low-probability, high-impact events which significantly degrades the CPS1 performance (which, even when averaged with the other nearly 200 runs can bring the average down substantially).

In fact, this is exactly why it is important to not disregard low-probability, high-impact events, as often happens with typical statistical methods. Perhaps only 1 or 2 of these events occur in our 200 days of simulations, but if these events are large enough to so significantly impact our CPS1 when averaged with nearly 200 other points, then, despite their low number, they are the events that are most seriously degrading system performance. As explained previously, this underscores the need for dynamic modeling with a large random sample size, in which no individual samples (simulations) are disregarded.

Figure 3.3: CPS1 score versus percent regulation for each simulated wind penetration level. The blue dots indicate the values for Area 1, while the green dots indicate the values for Area 2. The red line traces the exponential best fit of each function. We note that the x-axis total width is the same (2%) for all graphs except those in the last column, whose widths had to be expanded to fit the data.
3.3.2.2 Regulation Necessary to Maintain Adequate CPS1 (Historic Average)

Using the red fit lines from the results above, we quantified the regulation amount necessary to maintain adequate system performance (i.e., 160% CPS1, as explained in Section 3.3.1) for each wind percentage. These values were then plotted versus the wind percentages, as well as an exponential line of best fit to the data, as shown in Figure 3.4. It is important to specifically note the exponential relationship suggested by the results; the data fit best using an exponential model. This implies that not only does the amount of regulation necessary increase, but as wind generation picks up, it increases exponentially.

![Figure 3.4: Regulation necessary to achieve average CPS1 score of 160% versus wind penetration percentage. These values, plotted as blue dots, were determined by locating the x-axis value (percent regulation) corresponding to the CPS1 value of 160% for each of the fit lines in the series of curves in Figure 3.3. The plotted red line in this figure is an exponential fit to the data.](image-url)
3.3.2.3 Regulation Necessary to Maintain Adequate CPS1 - Comparison with Existing Models

As explained in Chapter 1, nearly all existing models which predict necessary regulation are designed as static models focusing on simple statistical manipulation. Because of this static nature, and a number of implicit assumptions made within these models (e.g., most assume that wind variability is a Gaussian distribution and most assume low-probability, high-impact events can be ignored), it seemed to us that these models would not reflect the results found in Section 3.3.2.2. Thus, we compared the results of our dynamic simulation model with that of a representative selection of existing well-known, purely statistical models which also aimed to predict regulation as a function of wind penetration. These studies included the Southwest Power Pool (SPP) Wind Integration Study performed by Charles River Associates (CRA) in 2010 [4], the wind integration study commissioned by the New York State Energy Research and Development Authority (NYSERDA) and the New York Independent System Operator (NYISO) in 2005 [13], the Wind Generation Study performed by NYISO in 2010 [34], and the Western Wind and Solar Integration Study (WWSIS) performed by the National Renewable Energy Laboratory (NREL) in 2010 [15].

The WWSIS 2010 study concluded that regulation should be equal to the standard deviation of the 10 minute net load variability (step change).

The NYSERDA 2005 study, as with the WWSIS study, used a standard deviation model, but looked at a much smaller time scale than most. NYSERDA’s model set additional regulation amount (that is, the amount on top of the 1% already included for load) equal to 3 standard deviations of 6 second net load variability. While a smaller time-step variability is preferable to time-step sizes exceeding the regulation time scale, we see that the line still does not follow our shape.

The NYISO 2010 study similarly calculates regulation amount based on 3 standard deviations of net load step change, though they instead use a 5 minute step change.

The SPP 2010 study, unlike the other three (and many other statistical models), used a percentile-based model instead of a standard deviation-based model. Their suggested model for “up” regulation (i.e., positive regulation power) is

\[ R_{up} = \left( \sqrt{(0.01 \cdot L_{peak} + L_{10})^2 + a (\Delta W_{95})^2} \right) - L_{10}, \]  

(3.1)

where \( L_{peak} \) is the peak load, \( L_{10} \) is a constant from NERC’s CPS2 standard, \( a \) is “a constant to adjust the relative contributions of wind to regulation requirements” [3, 4], and \( \Delta W_{95} \) is the 95th percentile of ten minute wind variability. (Their model for “down” regulation is the same, except
using the 5th percentile of wind variability.) By using a percentile-based model instead of a standard deviation-based model, they avoid the implicit assumption that wind variability follows a Gaussian distribution.

We see, too, that the SPP model most closely follows the shape demonstrated by our dynamic simulation model. Each of the standard deviation-based statistical models tends to increase almost linearly, completely missing the exponentially increasing shape of our model. The SPP model is a better approximation of our dynamically-based function but still badly underestimates the necessary regulation as wind penetration exceeds 20%. This model, although superior to the other three, still suffers from the implicit assumption that low-probability, high-impact events are of low significance to system performance.

![Figure 3.5: Regulation necessary to achieve average CPS1 of 160% (as plotted in Figure 3.4) compared to “adequate regulation” as determined by several well-known existing statistical models.](image)

3.3.3 Conclusions Summary for Section 3.3

The above results lead us to a number of conclusions, which build upon the conclusions drawn in Section 3.2.

First, we have confirmed that for a given wind penetration percentage, an increase in regulation
does result in a readily predictable increase in frequency performance, as we expected. This is important; had we been incorrect in this assumption, our objective would have rested upon a false premise. Additionally, we note that this increase is not infinite; each graph in the series exhibits an exponentially declining function, leading to an asymptote, indicating there is a limit to how much benefit additional regulation can provide.

Second, we can see that the amount of regulation increase necessary to result in these readily predictable increases in frequency performance themselves increase as wind percentage increases. Specifically, the amount of regulation necessary to maintain our desired level of frequency performance is exponentially increasing as wind percentage is increased. This indicates that there is a maximum amount of wind penetration that a system can incorporate and still maintain its frequency performance, assuming that no changes are made to the system other than an increase in regulation capacity.

Last, we conclude that most existing statistical models poorly predict the relationship between wind penetration level and necessary regulation as the wind percentage becomes significant. In particular, we note the importance of the exponential shape of the relationship demonstrated by the dynamic model as compared with the much more linear statistical models. Using any of these statistically-based functions may be misleading, because they match the dynamically-based function relatively well at low wind percentages, and yet deviate dramatically from it as wind increases. Thus, industry planners may grow to trust these models and eventually be ill-served by them.

3.4 Influence of Ramping Capacity on Outcomes

As demonstrated in Section 3.3, system frequency performance is directly dependent upon regulation capacity. However, there is an additional parameter that proves to be similarly important, as it alters the effectiveness with which regulation can be deployed. The ramping capability of the regulation-providing generators indicates how quickly regulation relief can be delivered to the system; a lower value results in a longer time before full relief is delivered, resulting in a larger frequency deviation as governed by the swing equation\(^1\), and thus we would expect poorer CPS1 performance. Our investigation will now focus on this question.

\(^1\)We note here that the same is true of ramping capability of the generator pool as a whole as it applies to primary frequency (droop) control.
3.4.1 Explanation of Experiments

To examine the effect of ramping capability on frequency performance, we approximately doubled the ramping capability of our simulated regulation-providing generators. In each of the two areas, this changed the ramp rate capability of the regulating generators from just under 200 MW/minute to just over 400 MW/minute. We then repeated the steps of Section 3.3 using this increased ramping, ultimately producing a graph comparable to Figure 3.4.

3.4.2 Results

3.4.2.1 Comparison of 2 Ramping Capacities

Using fit lines to determine the necessary regulation amount to maintain an average CPS1 of 160% for each wind penetration percentage (as done in Section 3.3.2.1 for the originally assumed ramp rate), we determined the relationship between necessary regulation and wind percentage for this increased ramp rate scenario. As expected, we again see an exponential increase in necessary regulation as wind penetration percentage is increased linearly. However, we can see that the increased ramping capability significantly decreases the exact regulation amount that is deemed necessary at higher wind penetration levels, resulting in a much shallower exponential function when compared to that of the function derived using the originally assumed ramp rate in Section 3.3.2.1, as expected.
Figure 3.6: Effect of ramping capability on the regulation amount necessary to maintain an average CPS1 score of 160%. The results obtained using the original ramping capability (as assumed in Sections 3.2 and 3.3) are plotted with blue dots (with a red exponential fit line) and the results obtained using the increased ramping capability are plotted with green squares (with a magenta exponential fit line).

3.4.3 Conclusions

The above results lead us to a number of further conclusions, which build upon the conclusions drawn in the previous sections.

First, ramping capability has a direct effect on how well regulation is deployed, and consequently, a direct effect on the amount of regulation necessary to incorporate a given amount of wind generation. An increased ramping capability means that regulation relief is deployed more quickly, reducing the associated frequency deviations, and improving frequency performance. Thus, as demonstrated in Figure 3.6, increasing ramping capability has a beneficial influence on the outcome of our necessary regulation curves, moderating the increase in need for regulation.

Second, because the ramping capability has such influence on the outcome of necessary regulation versus wind penetration curves, as in Figure 3.6, we conclude that the results presented in previous sections, although conceptually and qualitatively true, do not necessarily reflect the precise quantitative behavior of all systems (i.e., different systems may have different necessary regulation versus wind penetration curves). They provide a guiding shape, but the exact values of necessary
regulation will vary, as was alluded to in Section 3.2.3. Due to computational burdens and time constraints, we were unable to pursue this line of investigation further. Ideally, ramping capability would be more thoroughly tested, leading to the development of a “family of curves” or simply a three-dimensional surface-function relating frequency performance, regulation level, and ramping capability of regulation.

Last, we note that, while already discredited in Section 3.3, the statistical models prove to have an additional flaw. In each of the statistical models we documented, the focus is primarily on variability of net load, with suggested necessary regulation amounts drawn directly from some measure (standard deviation or percentile) of this variability. *These statistical models completely fail to account for the ramping capability of the system, which we have just shown to be essential in determining a precise amount of necessary regulation.*

This underscores the importance of using a dynamic model; statistical models consider only the parameters of the wind generation and the load of a system, while entirely ignoring the unique characteristics and related constraints of the power system connected to that generation and load. In essence, they create a “one-size-fits-all” solution to a “many-sized” problem.
Chapter 4

Summary of All Conclusions

This paper has reached a number of conclusions, which we consider to be of fundamental importance to the power industry as it moves toward increased reliance on energy produced by intermittent renewables, such as wind and solar generation; our research has focused on wind generation but these conclusions apply conceptually to solar generation as well.

In Section 3.2, we confirmed the expectation that system frequency performance is highly dependent on wind penetration level by showing that, with regulation amount held constant, increasing wind penetration resulted in exponentially decreasing frequency performance as measured by CPS1, implying an exponentially increasing need for regulation, which we explored in Section 3.3. We additionally determined that, while a similar shape is exhibited by CPS2, its values stay well above their minimum acceptable level, provided there is no deliberate “gaming” of frequency rules compliance, and thus we concluded that CPS2 is not a definitive performance standard within the theoretical context of our research, which steers clear any such artifice.

In Section 3.3, we demonstrated that, as expected, an increase in regulation results in a readily predictable increase in frequency performance for a given wind penetration level. More importantly, we showed that as wind penetration increases, the amount of regulation necessary to maintain our desired level of frequency performance increases exponentially, indicating that there is a limit to the amount of wind generation a given system can accommodate without additional changes to the system beyond mere regulation additions. Additionally, we have demonstrated that most existing statistical models poorly predict the relationship between wind penetration level and necessary regulation as the wind percentage becomes significant, and that these models severely underestimate the necessary regulation required to maintain adequate frequency performance at these high penetration.
values.

In Section 3.4, we established the importance of system ramping capability on the outcomes of the results in previous sections. We explained that ramping capability has a direct effect on how well regulation is deployed, and thus on frequency performance as measured by CPS1. Because of this influence, we concluded that our specific curves can not be indiscreetly applied to all systems, but do provide a conceptual guide that may then require further analysis for purposes of precise quantification.

And finally, we have noted that our emphasis on dynamic modeling has realized a superior means of performance prediction and remediation than those of the various statistically based models and methods that have come before it.

4.1 Suggestions for Further Research

While we believe this paper has made significant strides in providing the industry with a better understanding of wind integration, there are a number of further explorations that would likely prove to be worthwhile.

As mentioned in Section 3.4.3, computational burdens and time constraints prevented us from thoroughly exploring the exact quantitative impact of ramping capability on necessary regulation as a function of wind percentage. While we were able to demonstrate an obvious qualitative effect, further research and experimentation regarding ramping capability would be required to achieve an exact functional relationship between ramping capability, necessary regulation, and wind penetration.

Additionally, the heretofore unexplored (yet unmistakable) importance of ramping capability suggests the possibility that other system parameters may prove instrumental in determining the exact amount of regulation necessary to accommodate a specific level of wind generation on a given system. Specific generator parameters such as amount of system inertia (rotating momenta), amount of droop provided, or the gain applied to ACE to produce $\Delta P_c$ may similarly alter the outcomes. Furthermore, general system parameters, such as size of Balancing Area or length of time between economic redispatch, may also impact results.

Perhaps there are a fair number of parameters that have at least some affect on the relationship between frequency performance and wind penetration, and, perhaps there is considerable variation in the relative magnitude of their effects. If so, then not only may dynamic modeling be the best means for understanding their interaction, it may be the only practical means to do so. This, however, does not require that we treat every influential system parameter as a variable for dynamic
testing. Given the current state of our understanding, it is suggested that less influential parameters be estimated and then treated as fixed model parameters while those of greater influence be independently tested for alteration and optimization within a dedicated dynamic model. Eventually, further research may lead to a more generalized model, that permits any given system or subsystem to be quickly characterized by all reasonably influential parameters (e.g., regulation level, total ramping capability, total momenta, etc). This model, after being “tuned” for any given system with the various parametric values of importance, could then be used to determine that system’s existing performance, and more importantly identify alternate strategies to accommodate further wind generation (or other intermittent resources).

The advent of intermittent generation sources, particularly those of wind and solar generation, will present the utility industry with new challenges as well as new opportunities. This shifting paradigm will require innovative analytical and planning methods such as those conceived by this research paper. Utilities poised to recognize and manage these changes will find themselves at a distinct advantage over those that continue to rely on outmoded methodologies to cope with this coming revolution.
Bibliography


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