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Unit Commitment Methods to Accommodate High Levels of Wind Generation

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To the Graduate Council:

I am submitting herewith a thesis written by Alexander Charles Melhorn entitled "Unit Commitment Methods to Accommodate High Levels of Wind Generation." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Electrical Engineering.

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Unit Commitment Methods to Accommodate High Levels of Wind Generation

A Thesis Presented for
The Master of Science
Degree
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Alexander Charles Melhorn

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This work is dedicated to my grandfathers, Charles Kulynych and John E. Melhorn. They have been behind me since the day I was born teaching and pushing me to do my best with what is given to me and then aspire for more.

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We cannot solve our problems with the same thinking as we used when we created them.

- Albert Einstein

Abstract

The United State's renewable portfolio standards call for a large increase of renewable energy and improved conservation efforts over today's current system. Wind will play a major role in meeting the renewable portfolio standards. As a result, the amount of wind capacity and generation has been growing exponentially over the past 10 to 15 years. The proposed unit commitment method integrates wind energy into a scheduable resource while keeping the formulation simple using mixed integer programming. A reserve constraint is developed and added to unit commitment giving the forecasted wind energy an effective cost. The reserve constraint can be scaled based on the needs of the system: cost, reliability, or the penetration of wind energy. The results show that approximately 24% of the load can be met in the given test system, while keeping a constant reliability before and after wind is introduced. This amount of wind will alone meet many of the renewable portfolio standards in the United States.

Contents

List of Tables

List of Figures

Nomenclature

COPT	Capacity Outage Probability Table
ED	Economic Dispatch
EENS	Expected Energy Not Served
FOR	Forced Outage Rate
IEEE	Institute of Electrical and Electronics Engineers
LP	Linear Program
LR	Lagrangean Relaxation
MIP	Mixed Integer Program
NS	Number of States
RTS	Reliability Test System
UC	Unit Commitment
WENS	Wind Energy Not Served

Chapter 1

Introduction

As of the 1^{st} quarter of 2011, 30 of the 50 U.S. states have a renewable portfolio standard (RPS) mandating some percentage of generation or sales of energy coming from renewable energy sources [1]. The state RPS call for a large increase of renewable energy and improved conservation efforts over today's current system. Wind will play a major role in meeting the RPSs. As a result, the amount of wind capacity and generation has been growing exponentially over the past 10 to 15 years. This growth will continue as the target dates of the RPS come to term. Figure 1.1 graphs the impressive growth rate of wind generation between 1999 and 2009 [2].

With an increase use of wind energy the effects of its stochastic and volatile nature increase as well. However, a report shows that wind energy over the U.S. eastern shore can be stabilized if the location of the wind farms are planned carefully and are connected sufficiently with the power grid [3]. Moreover, this work shows the cost benefit of building transmission over electrical storage and demonstrates that the correct position of the wind farms can lead to a steady output of electricity. This output rarely reaches full power, or minimum power, and the changes of power occur slowly over the whole system.

Wind is stochastic in nature making it difficult to forecast accurately, especially over long periods of time. The short term forecast error can reach upwards of 15 to

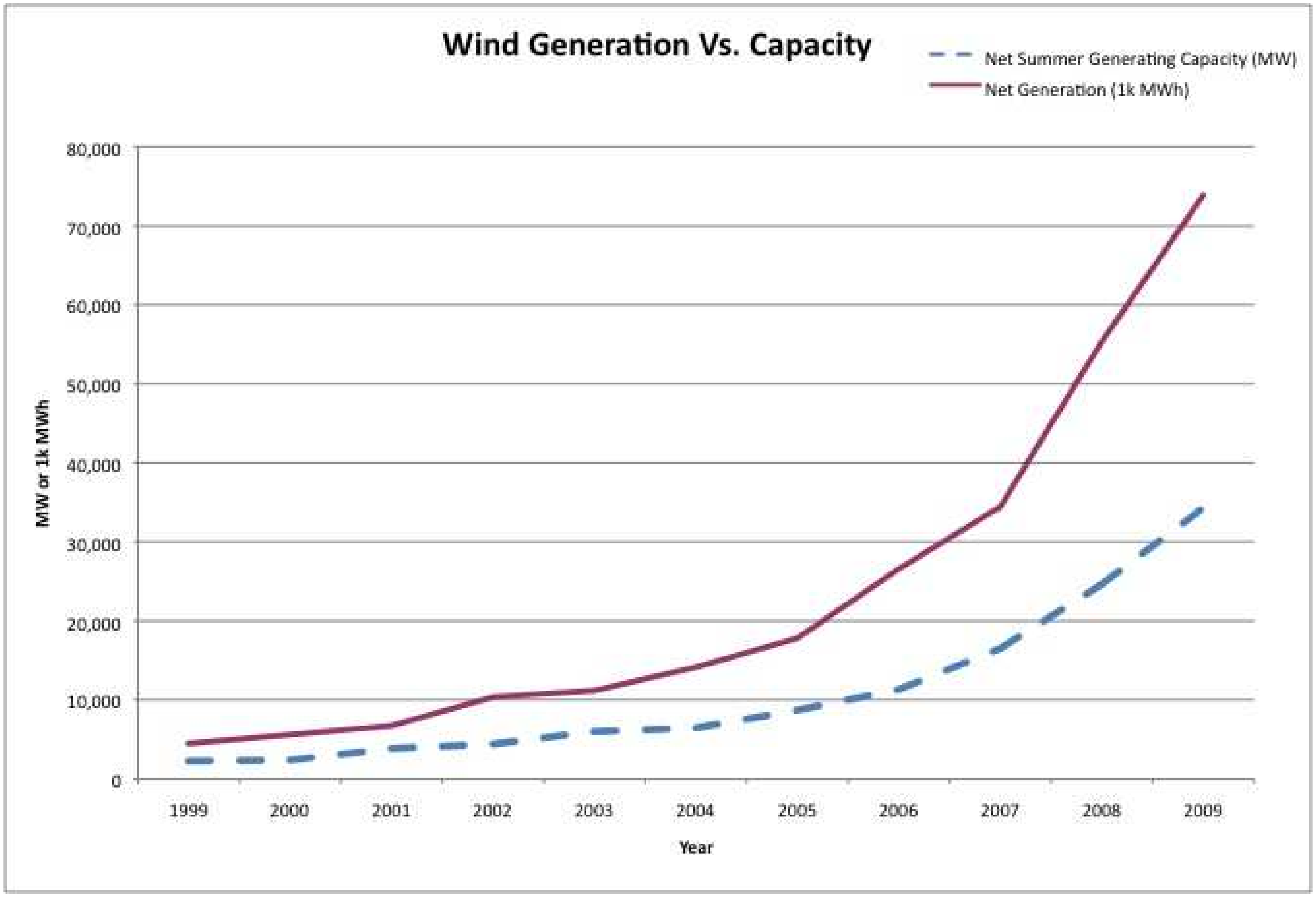

Figure 1.1: Wind Growth Over Ten Years

30 percent [4, 5]. This causes the relative reliability of wind turbines to effectively be between 20 and 50 percent when compared to traditional thermal units, even with a wind turbine's high mechanical availability of 95 percent or more [6], making it impractical to use the standard measures of reliability that are used on traditional thermal units. The effective load carrying capacity (ELCC) [7] is proposed by [6, 8, 9], as an established reliability theory that works well on all unit types, to calculate the capacity factor of wind. The ELCC derives the capacity credit for generator in a specific system. Traditionally, ELCC does not take the transmission constraints into account. The derived capacity credit gives a measurement for wind energy that can be used in a similar fashion to the more common reliability measurement, forced outage rate (FOR), of traditional generators. These methods will be discussed in more detail in Section 2.1.

Unit commitment (UC) is an optimization problem that commits the generation units of the system by optimizing the cost around the forecasted load and other system constraints. Since wind has little to no fuel cost, the direct generation cost cannot be used in committing wind energy. Currently, wind is used as a negative load before UC is run. This means that the forecasted wind generation is subtracted from the forecasted load. Using wind as a negative load can force the base load to operate below its minimum. This causes an excess of energy to be generated which either needs to be spilled or the base load generators need to be shutdown [10, 11]. Both scenarios can be costly. Being able to determine the capacity credit or a similar reliability measurement of wind turbines is very important for integrating wind energy into UC. The reliability measurement allows for a reserve constraint to be added, the main topic in the proposed work. The additional reserve constraint adds a cost to the scheduled wind by adding extra operational cost due to the required reserve that needs to by met from the traditional units.

1.1 Literature Review

Currently, research in integrating wind energy into UC leans towards adding a secondary reserve constraint on top of the traditional N - 1 security criterion, which can be met with spinning reserve [5, 9, 10, 12–18]. The additional reserve constraint addresses the stochastic nature of wind. The amount of reserve and its formulation differs between each method. Some approaches enforce reserve constraints outside of the main UC optimization [15]. If the solution of the UC is found to be infeasible for the set reliability constraints, then the variables are modified and UC is run again. The newer approach integrates the additional reserve constraint directly into the UC formulation [5, 11, 13, 14, 16–19]. While some base the new reserve constraint off of a normal distribution of the wind forecast error [4, 5, 10, 15, 17], others use a two state model model to derive a reliability measurement similar to the FOR of a thermal unit [13].

Traditionally, wind has been used as negative load in UC and some research continues to use this approach [10–12, 17]. It allows for simple use of existing UC approaches to the optimal solution. It is noted that using wind as a negative load mainly effects the commitment of the intermediate and peak load generation units [10]. Minimal load problems can occur when there is a large quantity of wind. These problems increase with the amount of wind energy and it is found that this method only saves on operating costs 50 percent of the time [12]. Using wind as a negative load will not be very effective as the penetration of wind energy in the power system increases.

Optimizing the amount of wind energy scheduled in UC, can help solve minimum load issues with the current load reduction method. One approach represents wind energy as multi-state units and uses the reliability measure of the different states to implement a cost on the wind energy so that an appropriate amount of wind will be scheduled [12]. Another adds a cost constraint to the emissions output of the thermal units. This effectively forces the higher costs of reserve to seem lower than the thermal generation and create a higher use of wind energy [13].

With wind being represented in a different method than the traditional units, new formulations for UC to account for wind unit variations need to be developed. One method uses a genetic algorithm, operated particle swarm optimization, to find an approximation of the optimum and requires a more accurate wind forecast for a more accurate solution [11], while [14, 15, 17, 18] use various forms of mixed integer programing (MIP). MIP gives an absolute solution to UC, based on the respective constraints. The downfall to MIP is that an equilibrium needs to be found between the reserve constraints and the cost [5]. If one is too high or too low, either no wind energy will be used or the system will be overly dependent on wind. The addition of wind to UC has been found to be beneficial by reducing the system risk and increasing its load carrying capacity [9]. This leads to the proposed UC method in this thesis.

1.2 Objectives and Scope

The main objective of this thesis is to demonstrate that an addition reserve constraint will allow the addition of wind into UC. Secondary objectives include keeping the UC simple, using a more traditional yet advanced approach; keeping the over all reliability of the system consistent with the standard test system; lowering the overall cost of generation; and allowing for a high percentage of generation to come from wind energy.

In order to stay focused on the objectives several assumptions are made. The first assumption is that the inter-hour constraints of the units can be ignored and each hour will be evaluated separately. The spinning reserve is assumed to be fast enough to meet the volatile nature of wind and the base load will be consistent enough to assume that the base load units will stay consistently committed. This allows the use a simple MIP method. The second major assumption assumes that no transmission constraints will be considered. Line constraints could become a limiting factor for scheduling wind energy, taking focus away from the proposed reliability constraint. The last assumption involves the distribution of wind and its forecast error. The chosen probability distribution shouldn't effect the proposed method because the multi-state generation levels of the wind energy are broken up by their availability rate, not by the generation level.

1.3 Contributions

The proposed method integrates wind energy into a scheduable resource in a traditional UC format. This method adds a reserve constraint to the wind energy giving the wind an effective cost. The reserve constraint also address the stochastic nature of wind, wind's forecast error, and allows the scheduling of wind energy to be optimized around the required level of reserve. During the research and analysis of the proposed method, several conclusions are made on defining the capacity outage probability table (COPT) for a set of generators. The traditional recursive algorithm used to derive the COPT is found to be missing important details and a lesser known method is reintroduced as a more effective and less complicated probability method.

The contributions of this thesis and the proposed UC are:

- A simple UC formulation that can take advantage of existing approaches
- A multi-state representation of wind energy availability
- An additional reserve constraint to provide wind energy a cost, allowing it to be scheduled within UC
- Results showing the effect of the scaling factor on the reserve constraint compared to the system reliability, generation cost, and amount of scheduled wind
- Demonstrate further steps needed for Billinton's recursive algorithm to derive the COPT
- Bring light to the convolution method for deriving the COPT

Chapter 2

Background Information

2.1 Power System Reliability

Table 2.1 provide the data for four generators that are used in multiple examples in this section. It lists the minimum generation, maximum generation, and the forced outage rate (FOR) of the generators.

2.1.1 Forced Outage Rate

The FOR of a generator is its unavailability rate, (1- availability). This is the standard reliability measure of thermal generator units. Equations (2.1) and (2.2) represent a simple two state model [20]. The two state model will be used to represent all the thermal generators in this thesis. According to [20] the FOR is an adequate estimation for generators with long term cycles but is not adequate for short term.

Table 2.1: Four Generator Example Data

Num. of Gen.	Min. Gen.	Max. Gen.	FOR
1	25	75	0.02
1	15	50	0.05
2	10	20	0.08

Short term cycles include peaking and intermittent operating times, in which case using a multi-state unit is recommended .

$$\text{Availability} = A = \frac{\mu}{\lambda + \mu} = \frac{m}{m + r} = \frac{m}{T} = \frac{f}{\lambda} \tag{2.1}$$

$$\text{Unavailability} = U = FOR = \frac{\lambda}{\lambda + \mu} = \frac{r}{m + r} = \frac{r}{T} = \frac{f}{\mu} \tag{2.2}$$

where:

$\lambda =$ expected failure rate

$\mu =$ expected repair rate

$m =$ mean time to failure $= 1/\lambda$

$r =$ mean time to repair $= 1/\mu$

$m + r =$ mean time between failures $= 1/f$

$T =$ cycle time $= 1/f$

2.1.2 Capacity Outage Probability Tables

A COPT is just array of different states of generation and their respective probabilities. Using the the four generator system in Table 2.1, the COPT 2.2 can be derived. A full COPT using two-state generators will have 2^n states, where n is the number of generators. The example system has four generators, therefor it has 16 states. Table 2.3 illustrates each state and its configuration for the four generator system.

2.1.3 Binomial Distribution Method

The binomial distribution method is a simple way to determine the probabilities for the COPT. It is a straight forward way to calculate the individual probability of every possible state in the system. The first four columns in Table 2.3 represent the availability of one of the four generators. A "1" represents that that unit is available

Table 2.2: Four Generator Capacity Outage Table

MW Out	MW In	Ind. Prob.	Cum. Prob.
0	165	0.7880	1.0000
20	145	0.1370	0.2120
40	125	0.0060	0.0750
50	115	0.0415	0.0690
70	95	0.0072	0.0275
75	90	0.0161	0.0203
90	75	0.0003	0.0042
95	70	0.0028	0.0039
115	50	0.0001	0.0011
125	40	0.0008	0.0010
145	20	0.0001	0.0002
165	0	0.0000	0.0000

and a "0" represents the unit the unit is unavailable. Column five shows the equation to calculate the individual probability. Column six lists the MW of power out of service and columns seven and eight are the individual and cumulative probabilities of each state. The individual probability value is the exact probability that the exact amount of power will be out of service. The cumulative probability is the probability that the listed amount of generation or less will be in service [20].

For example state 6 in Table 2.3 has generator 1 and 3 being out of service and generators 2 and 4 being in service. The equation for the individual probability is then $P(6) = FOR_1(1 - FOR_2)FOR_3(1 - FOR_4)$. The general equation is:

$$\text{Individual Probability} = \prod_{i}^{n} \begin{cases} FOR_i & \text{unit is off} \\ (1 - FOR_i) & \text{unit is on} \end{cases} \tag{2.3}$$

The total individual probability of a given MW outage is the sum of the individual probabilities of all the states with the same MW outage. In the case of 20 MWs out, the probability of states 5 and 9 are summed producing the the result, 0.1370, as listed in Table 2.2.

Table 2.3: Four Generator Binomial Calculation

Unit 1	Unit 2	Unit 3	Unit 4	Probability Calculation				Ind. Prob.	MW Out
1	1	1	1	$(1-0.02)$	$(1-0.05)$	$(1-0.08)$	$(1-0.08)$	0.7880	0
0	1	1	1	(0.02)	$(1-0.05)$	$(1-0.08)$	$(1-0.08)$	0.0161	75
1	0	1	1	$(1-0.02)$	(0.05)	$(1-0.08)$	$(1-0.08)$	0.0415	50
0	0	1	1	(0.02)	(0.05)	$(1-0.08)$	$(1-0.08)$	0.0008	125
1	1	0	1	$(1-0.02)$	$(1-0.05)$	(0.08)	$(1-0.08)$	0.0685	20
0	1	0	1	(0.02)	$(1-0.05)$	(0.08)	$(1-0.08)$	0.0614	95
1	0	0	1	$(1-0.02)$	(0.05)	(0.08)	$(1-0.08)$	0.0036	70
0	0	0	1	(0.02)	(0.05)	(0.08)	$(1-0.08)$	0.0000	145
1	1	1	0	$(1-0.02)$	$(1-0.05)$	$(1-0.08)$	(0.08)	0.0685	20
0	1	1	0	(0.02)	$(1-0.05)$	$(1-0.08)$	(0.08)	0.0014	95
1	0	1	0	$(1-0.02)$	(0.05)	$(1-0.08)$	(0.08)	0.0036	70
0	0	1	0	(0.02)	(0.05)	$(1-0.08)$	(0.08)	0.0000	145
1	1	0	0	$(1-0.02)$	$(1-0.05)$	(0.08)	(0.08)	0.0060	40
0	1	0	0	(0.02)	$(1-0.05)$	(0.08)	(0.08)	0.0001	115
1	0	0	0	$(1-0.02)$	(0.05)	(0.08)	(0.08)	0.0003	90
0	0	0	0	(0.02)	(0.05)	(0.08)	(0.08)	0.0000	165

The cumulative probability is the sum of all of the MW outage probabilities above and including the individual probability of the given outage. Using the 40 MW outage as an example, the cumulative probability is the sum of the individual probabilities of 50, 70, 75, 90, 95, 1115, 125, 145 and 165 MW outage states. The cumulative probability is then 0.0750, as shown in Table 2.2.

The binomial method goes through every possible state of the system, this can make the binomial method very time consuming. The number of states, 2^n, grows exponentially with the number of units, n, in the system. As the number of states to calculate and combine increases so does the time it takes to complete the COPT. The formulation of the COPT has a complexity of $n \cdot 2^n$. Another down fall to using the binomial method occurs with system changes. If any unit in the system changes, even just one unit, the table needs to be recalculated with the new system configuration. The calculation time with this approach becomes impractical with a large number of units.

2.1.4 Recursive Algorithm

Because the entire COPT needs to be recalculated every time there is a change in the system with the binomial distribution method, [20] introduces a recursive algorithm that allows individual units to be added or removed relatively easily. There is also a modified version of the algorithm for multi-state units. Multi-state units are units that have an availability rate calculated in more detail than just the on and off states. Only the two-state, on or off, algorithm will be demonstrated in this thesis. The removal and multi-state algorithms follow in a similar fashion and will not be discussed in detail.

Equation (2.4) is the base equation for the cumulative probability of each state and it is repeated for the addition of each turbine.

$$P(X) = (1 - FOR)P'(X) + (FOR)P'(X - C) \tag{2.4}$$

where:

$$P(X) = \text{cumulative probability of the capacity outage state of } X \text{ after the unit is added}$$

and

$$P'(X) = \text{cumulative probability of the capacity outage state of } X \text{ before the unit is added (the previous } P(X)) \tag{2.5}$$

with:

$X =$ capacity outage state in MW

$C =$ capacity in MW of the unit being added

$FOR =$ forced outage rate of unit being added

The problem is initialized with $P'(X) = 1.0$ for $X \leq 0$ and $P'(X) = 0$ otherwise.

This setup works well for certain block sizes, as in the example listed in [20] where the capacity of each unit is divisible by 25 MW, but in practice several more steps need to be added to the formulation. Equation (2.5) then becomes

$$P'(X^{k+1}) = \begin{cases} 1.0 & X^{k+1} \leq 0 \\ P(X^k) & X^{k+1} = X^k \\ 0 & X^{k+1} > X^k_{max} \\ P(X^k_{min}) & X^{k+1} < X^k_{min} \end{cases} \tag{2.6}$$

Example 2.1 demonstrates the use of the recursive algorithm, using the four generator example system with the additional formulation, Equation (2.6).

Example 2.1 (Recursive Algorithm)**.** *Step 1 add the 75 MW unit*

$$P(0) = (1 - 0.02)P'(0) + (0.02)P'(0 - 75)$$
$$P(0) = (1 - 0.02)(1.0) + (0.02)(1.0) = 1.0$$
$$P(75) = (1 - 0.02)P'(75) + (0.02)P'(75 - 75)$$
$$P(75) = (1 - 0.02)(0) + (0.02)(1.0) = 0.02$$

Step 2 add the 50 MW unit

$$P(0) = (1 - 0.05)(1.0) + (0.05)(1.0) = 1.0$$
$$P(50) = (1 - 0.05)P'(50) + (0.05)P'(50 - 50)$$
$$P(50) = (1 - 0.05)(0.02) + (0.05)(1.0) = 0.0690$$
$$P(75) = (1 - 0.05)(0.02) + (0.05)(0.02) = 0.0200$$
$$P(125) = (1 - 0.05)P'(125) + (0.05)P'(125 - 50)$$
$$P(125) = (1 - 0.05)(0) + (0.05)(0.02) = 0.0010$$

Step 3 and step 4, adding the two 20 MW units, follow in the same way until you get table 2.2.

Both the binomial distribution method and [20]'s recursive algorithm are used in the development of this thesis. In addition to making the addition and removal of units more efficient the recursive algorithm can also calculate the COPT more efficiently. The algorithm is more efficient as it allows the MW outage states with less than a given probability to be ignored. Once these states have been determined and ignored they are no longer used by the algorithm for any further calculations, therefore leaving fewer states for the algorithm to calculate. As the number of units grow so do the number of states which can be ignored. The binomial distribution method can also ignore these states but it does not improve the calculation speed as the probability needs to be calculated before it can be determined to be below the probability threshold. The recursive algorithm is slower in generating COPTs for a small system. It takes a larger system for the efficiency of the algorithm to offset the additional overhead.

2.1.5 Convolution Algorithm

The process of calculating all of the probabilities in Table 2.1 using the binomial distribution method is known as convolution. The convolution between two functions can be defined as

$$f_3(x) = f_1(x) * f_2(x) \tag{2.7}$$

$$\begin{aligned} f_3(x) &= \int_{-\infty}^{\infty} f_1(y) f_2(x-y) dy \\ &= \int_{-\infty}^{\infty} f_1(x-y) f_2(y) dy \end{aligned} \tag{2.8}$$

An easier solution for the convolution of two functions is to use a fourier transform. The fourier transform, transforms the two functions from the time domain into the frequency domain. In the frequency domain, convolution becomes point-by-point multiplication. Then by using the inverse fourier transform on the solution, it is transformed back into the time domain. [21]

The probability of a generator's availability can be represented as a discrete function. By making the time interval, an interval of power in MW, say 1 MW apart, the probability function of a two-state unit with the capacity of P MW becomes

$$f(x) = FOR\delta(x) + (1 - FOR)\delta(x - P) \tag{2.9}$$

Notice that the function is composed of impulses. The fourier transform of an impulse is a constant. The function can then just be represented as a polynomial.

$$f(x) = FORx_0 + (1 - FOR)x_P \tag{2.10}$$

Then equation (2.8) becomes

$$\begin{aligned} f_3(x) =& FOR_1 FOR_2 x_0 + (1 - FOR_1) FOR_2 x_{P_1} + \\ & FOR_1(1 - FOR_2)x_{P_2} + (1 - FOR_1)(1 - FOR2)x_{P_1+P_2} \end{aligned} \tag{2.11}$$

This significantly speeds up the derivation of the COPT. Since the algorithm depends on the number of generators, n, not the number of states, 2^n. Example 2.2 demonstrates the use of the convolution algorithm using the four generator system.

Example 2.2 (Convolution Algorithm)**.**

$$f_1(x) = 0.02x_0 + 0.98x_{75}$$
$$f_2(x) = 0.05x_0 + 0.95x_{50}$$
$$f_3(x) = 0.08x_0 + 0.92x_{20}$$
$$f_4(x) = 0.08x_0 + 0.92x_{20}$$

$$f_{COPT}(x) = f_1(x) * f_2(x) * f_3(x) * f_4(x)$$

$$\begin{aligned} f_{COPT}(x) =& (0.02x_0 + 0.98x_{75}) \times (0.05x_0 + 0.95x_{50}) \times \\ & (0.08x_0 + 0.92x_{20}) \times (0.08x_0 + 0.92x_{20}) \end{aligned}$$

$$\begin{aligned} f_{COPT}(x) =& 0.0001x_{20} + 0.0008x_{40} + 0.0001x_{50} + 0.0028x_{70} + \\ & 0.0003x_{75} + 0.0616x_{90} + 0.0072x_{95} + 0.0415x_{115} + \\ & 0.0060x_{125} + 0.1370x_{145} + 0.7880x_{165} \end{aligned}$$

2.1.6 Loss of Load Indices

The next step in determining the reliability of the system is calculating the loss of load indices. The two most commonly used forms are the loss of load probability (LOLP) and the loss of load expectation (LOLE). NERC [22] defines the LOLP as:

> *the building block of probabilistic analyses. LOLP is typically defined as the probability of firm load demand not being met in any given time period. In some areas, the determination is whether firm load demand plus operating reserves, or a portion thereof, can be met in a given time period. When the probabilities of events are summed over time, the result is an expectation.*

and the LOLE as:

> *the sum of LOLP values over time. For example, if a system was always short of capacity, in every hour in a year, with no chance of having enough capacity, the LOLE would be 8760 Loss of Load Hours per year or 365 Loss of Load Days per year, or 260 Loss of Load Weekdays per year.*

The NERC standard BAL-502-RFC-02 [23] requires the LOLE for a US power system to be equal to 0.1 days/year, which is known as the one day in 10 years criterion.

A mathematical definition of the LOLE is given by [20]

$$\text{LOLE} = \sum_{i}^{n} P_i(C_i - L_i) \text{ days/period} \tag{2.12}$$

where:

C_i = available capacity on day i

L_i = forecasted peak load on day i

$P_i(C_i - L_i)$ = probability of loss of load on day i. This value is obtained directly from the COPT

The LOLE can also be calculated using the individual probabilities from the COPT [20].

$$\text{LOLE} = \sum_{k}^{n} p_k t_k \tag{2.13}$$

where:

$$\begin{aligned} p_k &= \text{individual probabilities associated} \\ &\quad \text{with the capacity outage state} \\ t_k &= \text{the time units where the load is} \\ &\quad \text{greater than the capacity outage state} \end{aligned}$$

The LOLE is easy to calculate for any load level. All that is needed is the COPT with either the cumulative probabilities or individual probabilities and a peak load curve (PLC) for the system.

Example 2.3 (Loss of Load Expectation - LOLE)**.** *Using the four generators listed in Table 2.1 the LOLE can be determined from Table 2.2 and a given PLC. The peak load curve will be represented in a linear form for ease of calculation and demonstration. The equation for the peak load curve is:*

$$PLC = PL - 0.65 \cdot PL \cdot x$$

with:

$$\begin{aligned} x &= [0, 100] \\ PL &= 120\ MW\ (peak\ load) \end{aligned}$$

and a graph of the PLC can be seen in Figure 2.1. Using equation (2.13) the LOLE is:

$$
\begin{aligned}
LOLE &= P(115) \times (0.0641) + P(95) \times (0.3205) + P(90) \times (0.3846) \\
&\quad + P(75) \times (0.5769) + P(70) \times (0.6410) + P(50) \times (0.8974) \\
&= 0.0308
\end{aligned}
$$

This is in a given time period per year.

2.1.7 Effective Load Carrying Capacity

Several approaches in the reviewed literature use effective load carrying capacity (ELCC) to evaluate the capacity credit of wind and its effect on the over all reliability of its respective system. ELCC is also explored as a possible method in representing the amount of energy the forecasted wind can apply to the system.

ELCC is a graphical method used to approximate the effective capacity of a unit to the system to which it is added. ELCC is defined as “the distance in load megawatts between the annual risk functions before and after a unit addition” [7] and as, “the increase in system load-carrying capability at a given risk level due to the unit addition” [20].

This method remains applicable with wind generators and their stochastic and volatile nature. The main issue in determining the ELCC, is the heavy dependence on the system configuration. As the system changes, so does the ELCC for each unit. A study shows how drastically the ELCC can change for a wind generator in slightly different power system configurations [24].

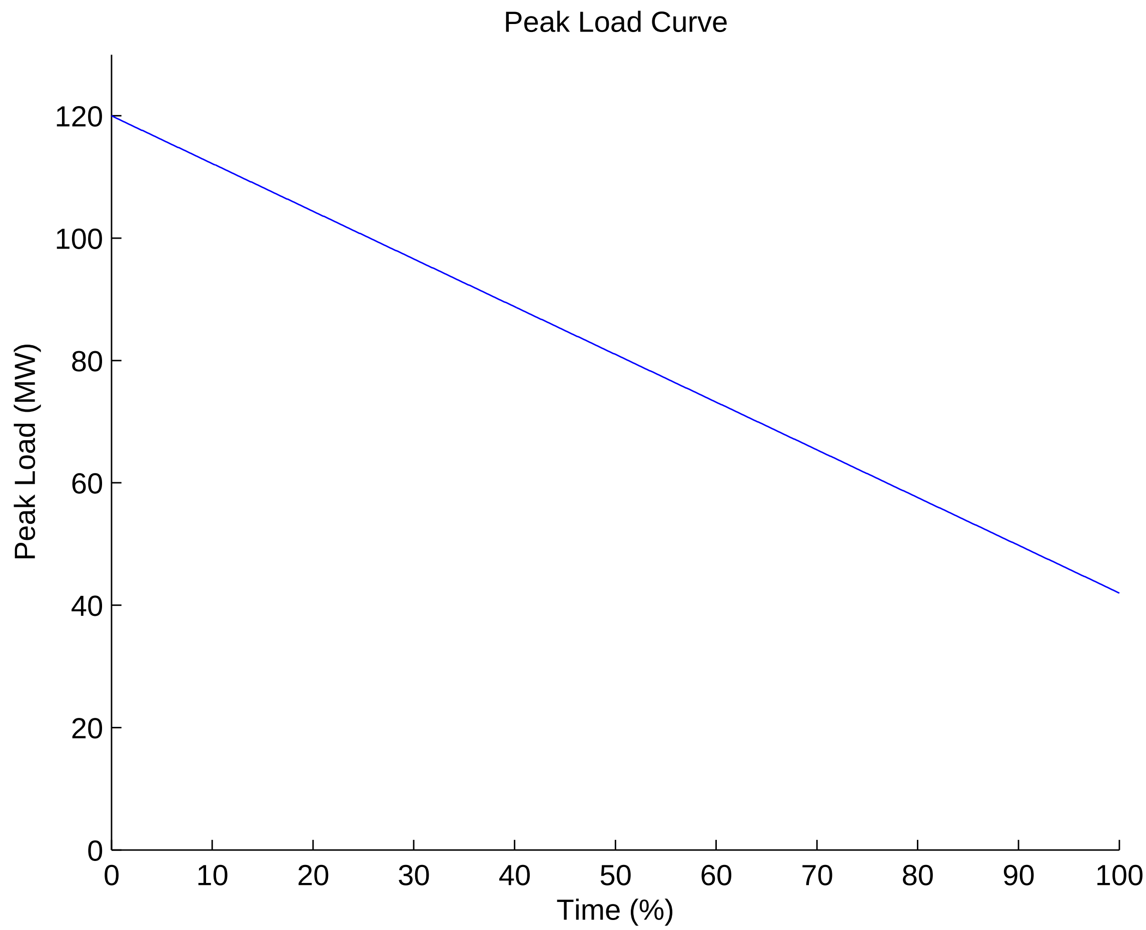

Figure 2.1: Example 2.3 - Peak Load Curve

2.2 Power System Operations

2.2.1 Economic Dispatch

Economic dispatch (ED) is a small part of UC, the focus of this thesis. The objective of ED is to minimize the cost of generation for a given set of generators, load, and any other system constraint. ED can be solved using a linear program (LP). The objective of a LP is the cost function and the constraints consist of the load, generator constraints and system constraints. The following equations show a basic setup for ED.

Objective:

$$\text{minimize} \sum_{i}^{n} A_i + B_i P_i \tag{2.14}$$

where:

$$\sum_{i}^{n} P_i = Load \tag{2.15}$$

$$P_i \geq Min_i \qquad \forall i \tag{2.16}$$

$$P_i \leq Max_i \qquad \forall i \tag{2.17}$$

2.2.2 Unit Commitment

ED assumes that all of the generator units are connected to the system and will be used at least at their minimum to fulfill the load requirement. UC, however; assumes that all of the units are available, but not connected to the system and all the possible generator combinations need to be considered. UC minimizes the operating cost by determining which subset of the units will minimize the cost, while still meeting the demand of the load forecast and all of the other constraints. ED is used in UC as each of the generator subsets require an ED solution [25].

Full UC requires determining the on/off schedules of thermal units over a given load forecast, maintaining the required spinning reserve and minimizing the cost. The solution of a number of both discrete and continuous variables are needed for UC. This makes UC one of the most complex optimization problems for power system economics and operations. Without a large number of assumptions and approximations UC becomes non-linear, with its variables reaching a high dimensionality [25] [11].

UC is traditionally calculated 24 hours ahead of time, in one hour divisions. The optimum running configuration is determined for each hour. In addition to the load and system constraints, different running constraints can be added to the system. Most of the extra constraints are related to length of time involved with running the generators and the amount of time needed to startup, shut down, run and stay down time of the generators between cycles. Most of these constrains will not be discussed in further detail in this thesis as they are out of the defined scope. During the 24 hour period, units will be turned on and off, this is called committing and decommitting respectively. The most difficult part of UC is in choosing what units to commit or decommit. Sometimes the previous hour is the main influence on the cost causing a different subset to be chosen than what would normally, for the next hour. Take the five subsets: A, B, C, D and E for example. If subset A is the optimal choice for a given hour independent of the previous hour, then B may be the optimal subset for that same hour if D was the optimal subset for the previous hour with a dependence on the previous hour. The same change can happen when looking an hour ahead. If the given hour's subset was originally A it could change to C when the next hour is taken into account and its optimal subset is E.

There are many different methods for solving UC [25]. These methods include: the priority list method, dynamic programming, and lagrangean relaxation (LR). Today, mixed integer programming (MIP) has become the state-of-the-art approach and will be used as the solution method here. All of these methods use a set of optimization techniques with their own advantages and disadvantages.

2.3 Optimization

A solid foundation of optimization techniques are needed to fully understand traditional UC methods and the MIP method being introduced in this thesis. The two main methods that are discussed here are LP and MIP.

2.3.1 Linear Programming

In order to use linear programming (LP) to optimize a function, the objective and constraints must be linear. A linear function is a function that contains terms, each of which are composed of only a single continuous variable raised to (and only to) the power of 1. No functions such as $cos(x)$, $log(x)$, or $exp(x)$ may be involved [26]. A LP consists of an objective function, to either minimize or maximize, and a set of constraints that the solution must fit within. The objective is defined as a mathematical function which represents a desire to either maximize profit or minimize cost. A constraint is defined as a mathematical equality or inequality that represents some sort of restriction on the system [26]. Since the problem setup is straight forward for UC, the setup of a LP will not be discussed. The main focus will be in the solution of a LP and some of its variations. A similar method is used to solve quadratic programs, but it will not be discussed in detail.

In order for a solution to be optimal it first must be feasible. A feasible solution is any solution that "satisfies all of the constraints of the LP" [26]. Every solution must fall in the feasible region. A non-negativity constraint is assumed for most variables in a LP because it is impossible to have a negative amount of something real. An infeasible solution is then any solution that does not satisfy one, more than one or all of the LP's constraints. The optimal solution is a feasible solution that maximizes or minimizes the objective function. The feasible area and optimal solution can be found fairly easily for two variable and some three variable linear programs. The following example can be solved graphically as seen in Figure 2.2.

Example 2.4 (Linear Programming)**.** *Objective:*

$$max:\ f = 20x_1 + 40x_2$$

where:

$$x_1 + x_2 \leq 100$$
$$8x_1 + 5x_2 \geq 370$$
$$x_1 \geq 10$$

with:

$$x_1 \text{ and } x_2 \geq 0$$

The feasible region is labeled and marked in grey. In the example there are four extreme points. An extreme point is a point that is in the feasible region and at the intersection of two or more constraints. The optimum solution is always on an extreme point. The only exception to this is when the objective is normal (perpendicular) to one of the boundaries. Then the optimal solution may lie on any intermediate point of that boundary. In Example 2.4 the optimal solution is point (10,90). The solution can also be checked mathematically using the simplex method. Since the simplex method is an iterative method, it can be very time consuming and complex to compute by hand. Matlab's linprog function will therefor be used to solve the LP's in this thesis. The linprog function uses a modified version of the simplex method. More information on the simplex method can be found in [26].

2.3.2 Mixed Integer Programming

There are times when some or all of the variables need to be restricted to integer values. In manufacturing partial products cannot be produced. It wouldn't make any sense to manufacture 0.27th of a chair or 0.64th of a car. These products need to be produced in integer values. Restricting some variables to integer variables in a LP

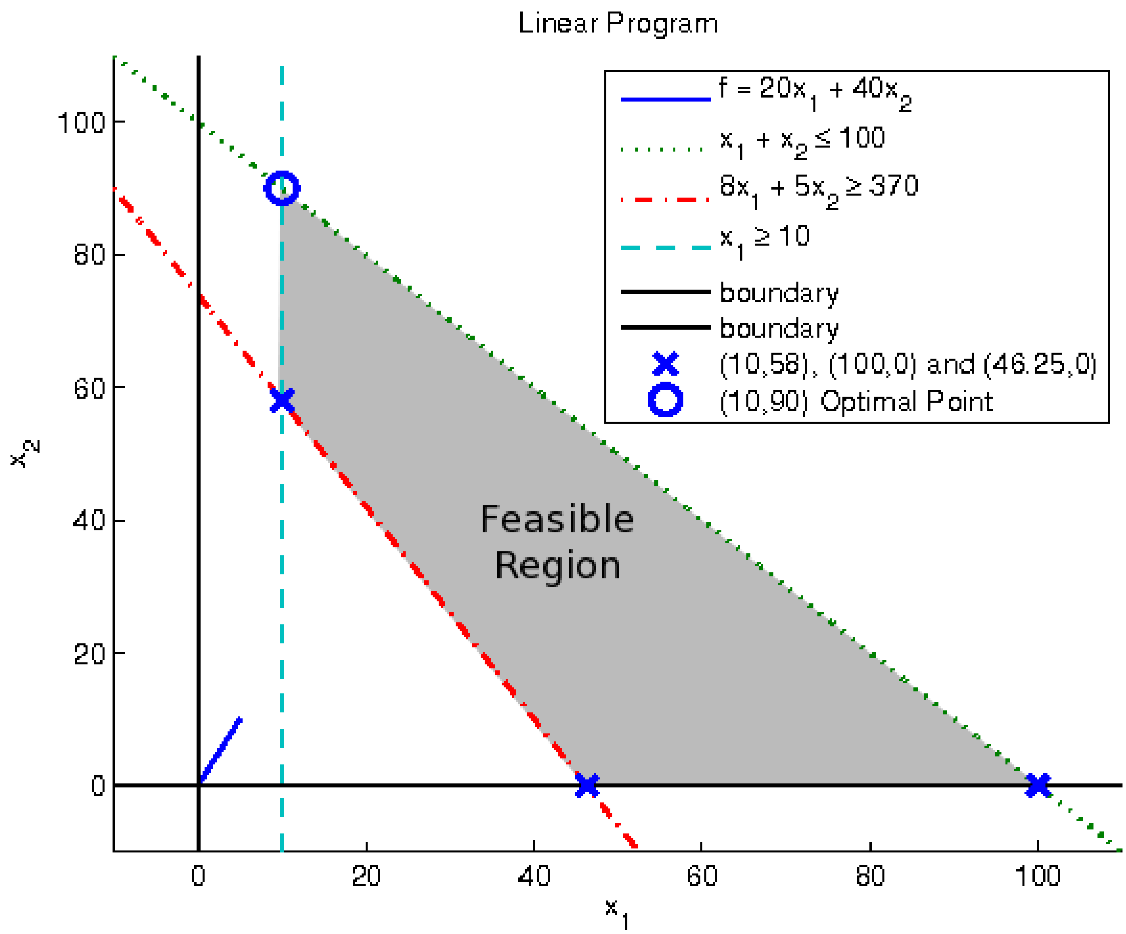

Figure 2.2: Example 2.4 - Graphical Solution of Linear Program

is called mixed integer programming (MIP). A MIP is solved using LP iteratively as the algorithm searches through the feasible points. The branch and bound method is used here to solve all MIPs. The branch and bound method searches through the feasible points starting with the optimal continuous solution. The branch and bound method consists of three steps: branching, bounding and fathoming. Branching consists of adding new constraints to MIP to create a new sub-problems and bounding is then calculating the optimal solution for the new sub-problems. The fathoming step determines if the solution is optimal, non-optimal, or infeasible. The method continuously solves LP's for new versions of the MIP as it narrows down the integer solution. Example 2.5 is an example MIP problem shown graphically in Figure 2.3 and Figure 2.4 shows a graphical representation of the branch and bound method.

Example 2.5 (Mixed Integer Programming)**.** *Objective:*

$$\textit{max: } f = -2x_1 - 5x_2$$

where:

$$20x_1 + 35x_2 \leq 107$$
$$x_2 \leq 1.52$$

with:

$$x_1 \textit{ and } x_2 \geq 0 \textit{ and integers}$$

The first step in solving the MIP is finding the continuous optimal solution. The optimal point, (x_1^*, x_2^*)*, is (2.69, 1.52) with an optimum,* f^**, of -12.98. Since neither* x_1 *or* x_2 *are integers, the integer constraint has not been met for this problem. The integer solution will be less than the continuous solution because the continuous solution is already best optimal solution. The first step is to branch. The algorithm branches first on* x_1*. The continuous optimum for* x_1 *is 1.87. This is not an integer* *so two new constraints are formed:* $x_1 \leq 2$ *and* $x_1 \geq 3$*. Adding the constraint* $x_1 \leq 2$ *to the original MIP creates the first sub-problem and branch 1 in Figure 2.4.*

Objective:

$$\text{max: } f = -x_1 - 3x_2$$

where:

$$20x_1 + 35x_2 \leq 107$$
$$x_2 \leq 1.52$$
$$x_1 \leq 2$$

with:

$$x_1 \text{ and } x_2 \geq 0 \text{ and integers}$$

The new problem is bounded and the optimal point is (2, 1.52) with an optimum of -11.6. The integer constraint is still not met since $x_2 = 1.52$*. Now that a integer solution for* x_1 *was found* x_2 *will be addressed. Branch 2 is created by adding the constraint* $x_2 \leq 1$ *to the current sub-MIP. The MIP is solved and the optimal point is (2, 1) and an optimum of -9. This is the only optimal solution that meets all the constraints so far and is marked as the current optimal solution. This may not be the optimal solution for the MIP since there are still several branches that have yet to be bounded and fathomed. To make sure the global optimal solution is found the branch and bound method must be continued. Branch 3 is an extension from branch 1. The constraint* $x_2 \geq 2$ *is added to the sub-MIP from branch 1. This creates an infeasible solution. Now that all possible optimal solutions have been searched from branch 1, branch 4 is created by adding the constraint* $x_1 \geq 3$ *that was formed with the first branch. The constraint is added to the original MIP to form branch 4. The optimal point is (3, 1.34) with an optimum of -12.71. Even though the solution does not meet the integer constraint the optimum is still smaller than the current optimal integer variable solution. This indicates that a better integer variable solution may still exist.*

The method is continued through branch 6, 7, 8, 9 and 10. In branch 6 the optimal point is (3, 1) with an optimum solution of -11. This solution is less than branch 2 and becomes the new integer variable optimum solution. Branch 8 has an optimal point of (5.35, 0) with an optimum of solution of -10.7. This point does not meet the integer constraint. No branch comes off of branch 8 because the optimum is greater than the current optimal integer variable solution. Branch 9 and 10 are infeasible solutions. This makes the optimal MIP solution branch 6. The optimal point is (3, 1) with an optimum of -11.

A special form of MIP is binary programming. Binary programming is the same as MIP except the specified variables are bounded to 0 and 1.

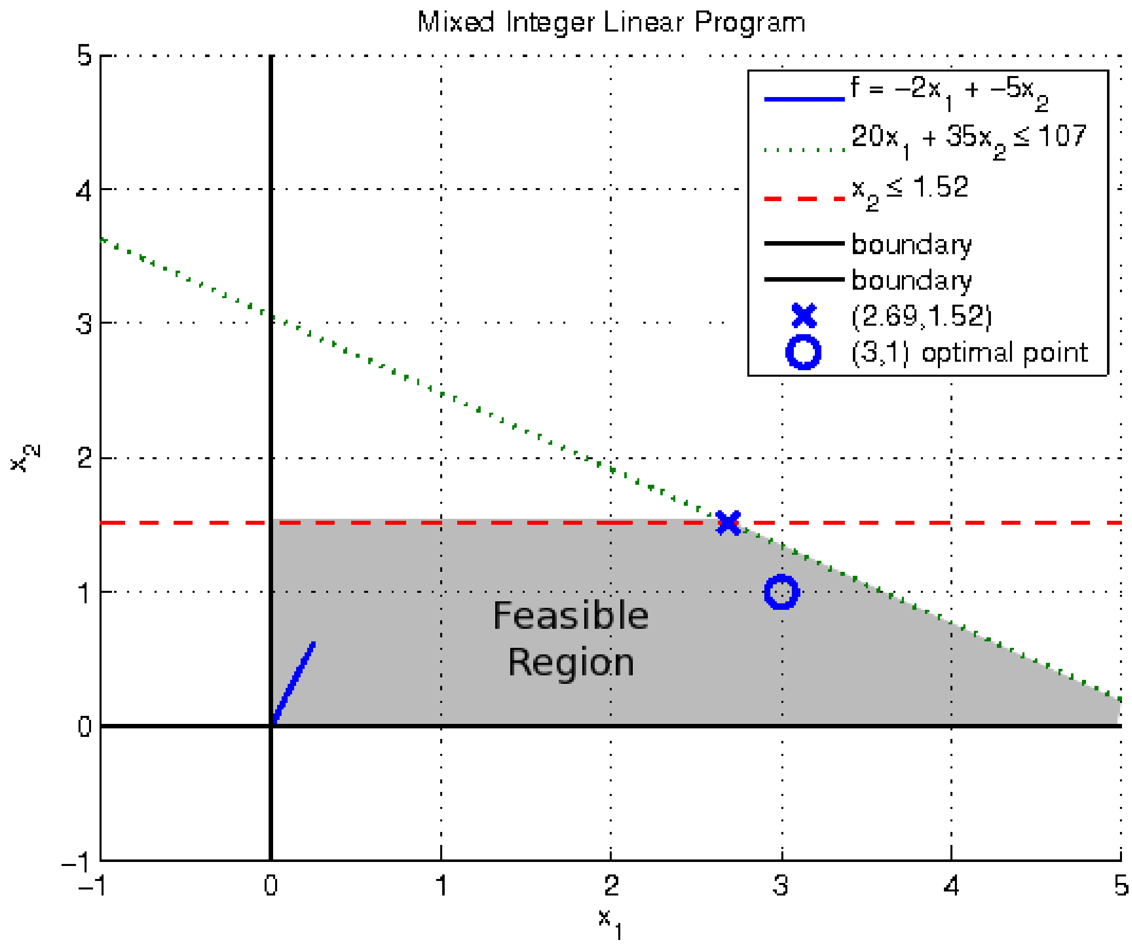

Figure 2.3: Example 2.5 - Graphical Solution of Mixed Integer Program

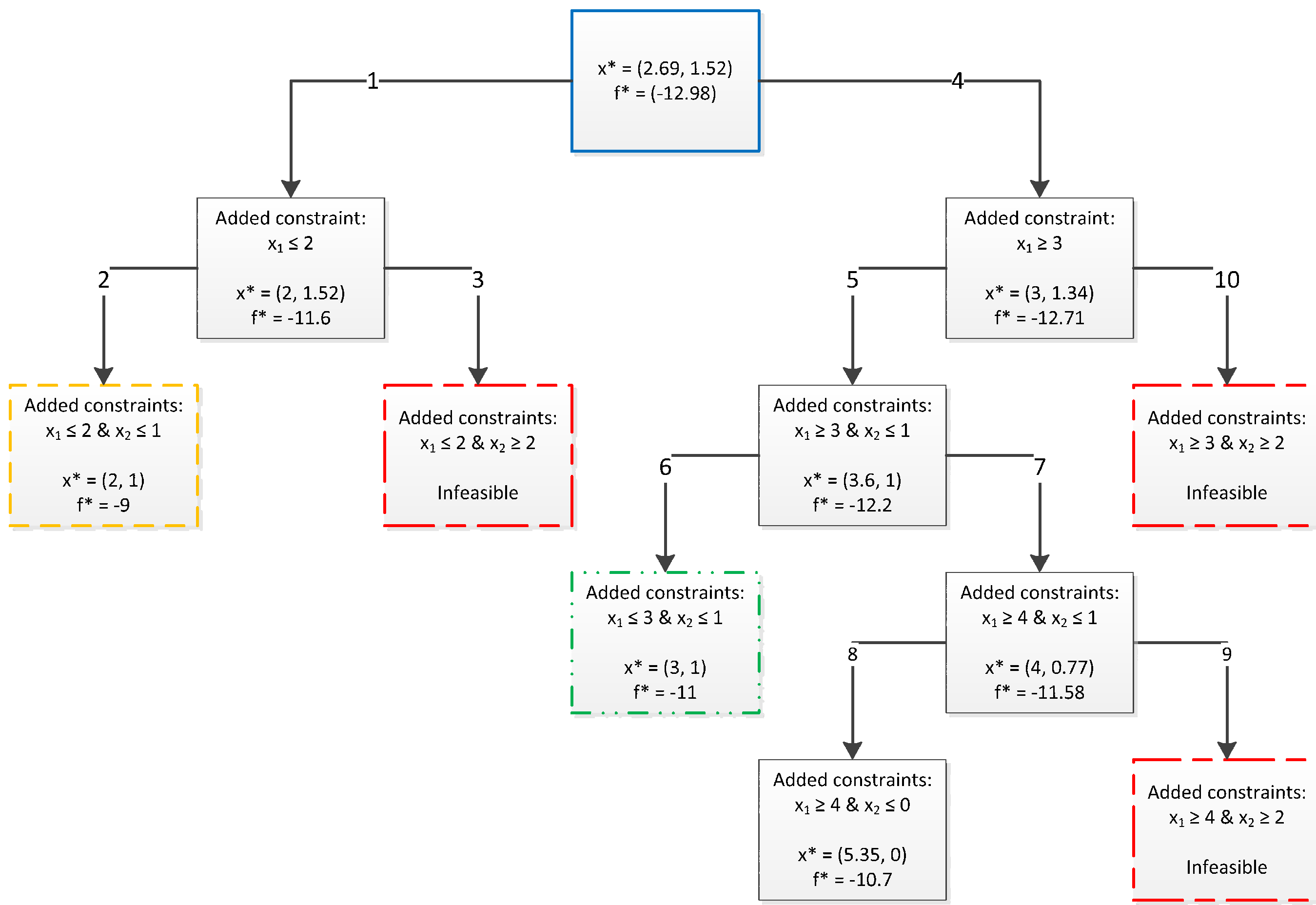

Figure 2.4: Example 2.5 - Branch and Bound Method Diagram

Chapter 3

Concept and Approach

Research for this thesis starts by looking at the capacity credit of wind turbines. The mechanical model for wind turbines is well known and defined but the power output model is not. Wind is stochastic in nature and it's the fuel for wind turbines. The capacity of wind depends on the connected system. The topology of the power system has a drastic effect on the wind generator's measured capacity [24]. Current research uses ELCC to approximate the capacity that the wind turbines provide for the system [6] [8] [27]. The issue with this method is that the derived capacity depends on the wind forecast and the current status of the power system. Wind is stochastic and the units supplying the load in a system change with UC, therefore the wind's capacity credit becomes stochastic.

In UC, the generator model is important. As stated before the models of thermal units and the mechanical models of wind turbines are well known, but not their power output. Instead of trying to define the capacity of the wind turbines separately, it is better to incorporate the modeling into the UC. This allows the optimal capacity to be found while determining the operating points of all the generators.

Traditional UC is optimized around the generation cost and it also uses part of the N - 1 security criterion for a reserve constraint. The N - 1 criterion is used in respect to the units committed. There must be enough reserve in the system to handle an outage of the single largest unit. Wind units cannot be modeled the same. Wind is very volatile in nature and has a very low to zero running cost. Wind would be scheduled to its fullest extent if a traditional version of UC is applied. This can cause the system to become very unreliable. Wind forecast error can be very high and the turbines rarely perform at their maximum output. In order to keep the system's reliability at a comparable level a new objective or set of constraints need to be added to UC. Here a set of additional constraints are added to keep the new UC method simple.

One approach to incorporating wind into UC is to add a system reliability constraint much like the NERC system constraint, that the LOLE must be less than or equal to 0.1%, one day every ten years. This requires the COPT to be derived for very possible state that is examined and then calculate its LOLE from the forecasted load. In order to derive the COPT of the system, a FOR is derived for the wind turbines. This leads back to the original problem of defining the capacity credit of the wind turbines. At first, the FOR are estimated to validate the new constraints. The genetic algorithm (GA) is originally chosen as the optimization tool for its simplicity in adding and removing constraints, as long as there is an appropriate cost associated with them. Figure 3.1 is a block diagram of UC using a GA.

There are several issues with using a GA. First off, a GA is generally not very reliable. It does not result in the same solution with every run of the algorithm. By controlling the initial population of the GA, the consistency of the result rises to a more acceptable rate. Another issue with this method is the solution time, the time it takes to derive a solution. Even though several if-loops are used to cut out computation time from infeasible states, it still takes an extraordinary amount of time to solve the UC for a single hour. As the load increases so does the amount of generation needed to meet the load, the number of generators needed increases and therefore the number of possible states to increases exponentially. This exponential growth is directly proportional to the GA derivation time. The slow down is related to calculating the COPT. Every time the genetic algorithm produces a new population,

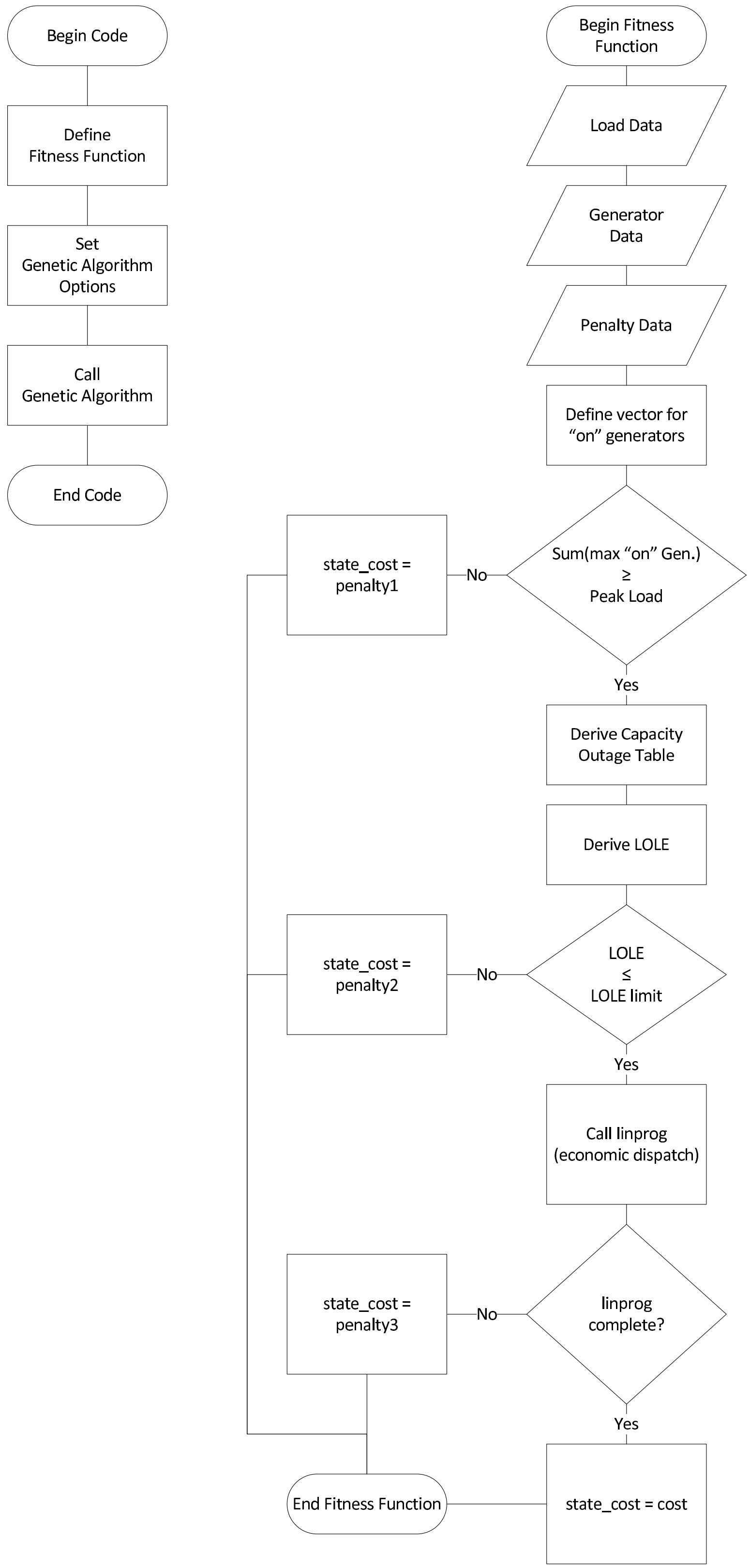

Figure 3.1: Original Code - Flow Chart

the COPT needs to be recalculated. This requires 2^n states for every possible feasible solution that is produced. As the number of generators increases so does the calculation time.

A majority of the states can be ignored due to a low probability of occurring and have little to no effect on the out come of the COPT and the resulting LOLE. Still, it is difficult to just ignore these states. If the state is ignored based on its probability, the probability still needs to be calculated. This does not speed up the derivation. One approach is to ignore any state with x number of generators "off". x can be controlled so that the number of generators that need to be "off" decreases as the number of generators present increases. This allows the accuracy of the the reliability calculations to remain uniform without regard to the number of generators being optimized.

The third major problem using the LOLE constraint is its use of a set generation amount per block of wind energy. Each set amount of generation represents a given MW level of wind energy. The FOR is designed to be based off of the wind forecast. This does not allow for the amount of wind and its reliability to be be committed optimally. The idea of modeling wind as a multi-state unit is demonstrated by [14]. The forecasted wind energy is broken into several states based off of the availability rate determined by the wind forecast. This allows the amount of wind to be committed on both the forecasted generation and its reliability on meeting the given forecast. Figure 3.2 shows the updated flowchart for the UC.

This is an improvement over the original formulation, but not a significant one. It still uses a GA as its optimization tool and creating the COPT in each iteration remains time consuming. The recursive algorithm defined by [20] shows to be more efficient in calculating the COPT than the binomial distribution method. The algorithm given is missing a few key steps. Even with the corrections made in Section 2.1.4 and neglecting all states with a probability less than a set amount, in most cases this probability limit is set to 10^{-8}, the recursive algorithm is still very slow

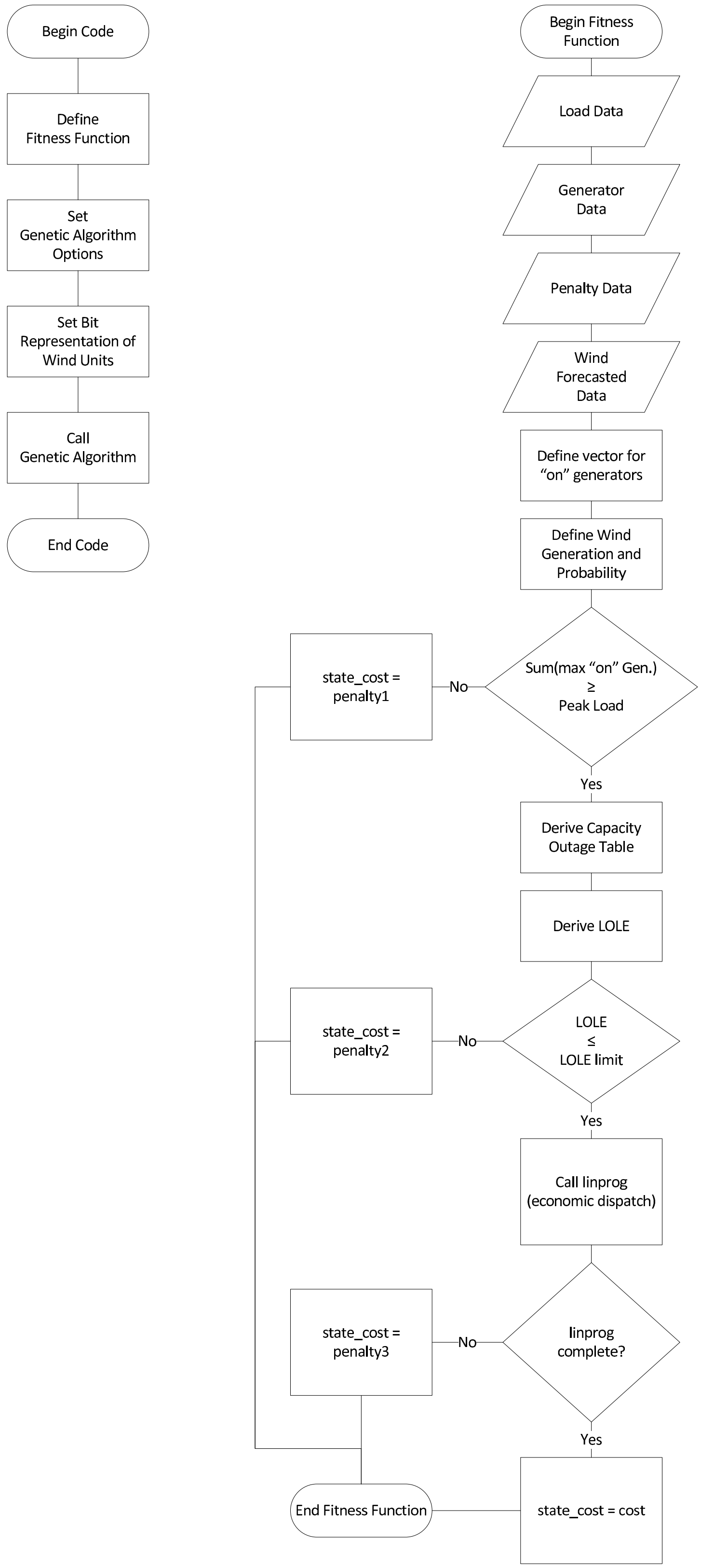

Figure 3.2: Updated Code - Flow Chart

and cumbersome as the number of generators grow because the number of possible states continuous to grow exponentially with the number of generators.

Even with all of the improvements made, the reliability constraint UC approach is not efficient enough for operations use. This leads into using a simpler optimization tool, MIP. Other simplifications were made to increase the efficiency as well. A major change comes in the derivation of the COPT. The convolution method is found to be accurate and very time efficient in calculating the COPT for a given system, greatly speeding up the reliability calculation.

Chapter 4

Implementation

Traditional UC deals primarily with thermal generation units. Here, wind turbines will be added to the generation system. The Institute of Electrical and Electronics Engineers (IEEE) Reliability Test System (RTS) [28] [29] will be used for the base power system. First, the problem will be setup using the base system and UC performed without any wind turbines. The cost, reliability and wind energy penetration will be saved for comparison. Next, the wind turbines will be broken into large blocks of generation and added to the system. When the wind turbines are added to the system, the objective and several constraints need to be modified due to wind's stochastic nature and real-world reserve constraints.

In UC, the cost function is the operational cost, of the thermal units and the wind turbines as they are added, at scheduled generation amounts. The constraints represent the physical limitations of the system and other requirements that may be needed to solve UC. An example constraint is the system's load must be equal to the system's generation. Another constraint is a reliability constraint. The power system as a whole, not just the units committed, is required to meet the NERC standard BAL-502-RFC-02 that the LOLE must be equal to or less than 1 day in 10 years, 10% for an entire year [23]. Several different methods were derived to meet this new constraint in the development of this new method of UC.

One approach is to add a LOLE constraint to UC. In this approach the COPT is derived for every possible state of the power system and then the LOLE is calculated, if the state meets all of the constraints. A GA is used to solve for this optimal state. The GA is chosen because it is very easy to add and remove constraints, unlike LR. The limitation of this method is the time and memory needed to derive the COPT.

When determining the security of a system using probability methods, an unit availability rate (UAR) or FOR needs to derived for the wind turbines as they are added to the system. Instead of determining a UAR for each individual wind turbine, it is easier to place the forecasted wind energy into blocks and give availability rates to the different amounts of forecasted generation. This method takes the correlation between the wind turbines and the wind forecast into account when determining the availability rates. One method demonstrates a way of breaking the blocks of wind energy into different generation levels broken up by their availability rate [14]. Each block of generation is represented as a multi-state unit, compared to the typical on-off states of thermal units. These blocks are broken into several set availability rates with the generation amounts changing dependent on the wind forecast.

With the availability rates of the multi-state blocks of wind energy determined, the next step becomes finding a way to represent or determine a reserve equal to the thermal units' loss of largest unit reserve constraint, N-1 constraint. A reserve requirement can be formulated based on the chosen wind energy state and its respective availability rate [14]. This reserve requirement is called expected energy not served (EENS). The EENS of the system is the sum of the EENS for all of the wind turbines. EENS will be reserved for a later calculation in the thesis, Section 4.8, so the reserve method derived here will be renamed wind energy not served (WENS), Section 4.5. The total WENS for the system is the sum of the WENS of each wind turbine, while the N-1 inspired reserve constraint for the thermal units is determined from the single largest unit committed.

With the wind forecast represented in a similar fashion to thermal units, the optimization technique is revisited. Since the wind power is represented as multi-state units it is difficult to generate a LR solution. However, starting with the base LP a MIP is derived with modifications to force the objective and all of the constraints linear. The MIP can then be used with relative ease as the optimization technique for UC.

4.1 Cost Minimization Problem

In the cost minimum formulation of UC the main constraints consist of the load, the generator constraints, and the reserve constraint. The load constraint (4.2) guarantees that the total generation will meet the peak load level. The generator constraints (4.3) (4.4) ensure that when the generator is turned on, $U_i = 1$, it will be at least generating its minimum and not above its maximum. A unit's committed generation and reserve cannot exceed the maximum rated generation. The reserve constrains (4.5) (4.6) enforce the N-1 reserve constraint, again this translates to the reserve needing to be equal to or greater than the single largest unit.

Objective:

$$\text{minimize: Cost } = \sum_{i}^{n}(A_i + B_i P_i + \frac{1}{2} C_i P_i^2 + D_i R_i + \frac{1}{2} E_i R_i^2) U_i \tag{4.1}$$

where:

$$Load = \sum_{i}^{n} P_i \tag{4.2}$$

$$P_i \geq P_i^{min} \qquad \forall i \tag{4.3}$$

$$P_i + R_i \leq P_i^{max} \qquad \forall i \tag{4.4}$$

$$Reserve = \text{Max}(P_i^{max}) \tag{4.5}$$

$$Reserve = \sum_{i}^{n} R_i \tag{4.6}$$

with:

$n =$ number of generators

$U_i =$ binary on and off representation

$P_i =$ committed generation

$R_i =$ committed reserve

$A_i =$ constant cost

$B_i =$ generator linear cost

$C_i =$ generator quadratic cost

$D_i =$ reserve linear cost

$E_i =$ reserve quadratic cost

4.2 Mixed Integer Programming Formulaation

Traditionally, UC is solved using LR. Recent years MIP has become the state-of-the-art formulation for UC. LR is complicated, it is difficult to add new constraints and more importantly it cannot guarantee an optimum solution. The method proposed here solves the optimization problem directly with a MIP. The objective and constraints are modified into a linear form so they can be solved with a LP. The minimization cost problem (4.1) then becomes the following:

Objective:

$$\text{min: Cost } = \sum_{i}^{n} A_i U_i + B_i P_i + D_i R_i \tag{4.7}$$

and the constraints follow suit:

where:

$$Load = \sum_{i}^{n} P_i \tag{4.8}$$

$$P_i \geq P_i^{min} U_i \qquad \forall i \tag{4.9}$$

$$P_i + R_i \leq P_i^{max} U_i \qquad \forall i \tag{4.10}$$

$$Reserve = \text{Max}(P_i^{max} U_i) \tag{4.11}$$

$$Reserve = \sum_{i}^{n} R_i \tag{4.12}$$

4.3 Thermal Units

The IEEE RTS [28] and [29] is the base system for the testing of the proposed unit commitment method. Table 4.1 gives the generators' size, the number of them in the system, their type and their FOR. Table 4.2 gives the fuel cost per MBtu for each type of unit. The fuel costs are off of a 1979 base, but it is used here because the ratio between the fuel costs is the same in present day. The heat constant cost, linear cost and quadratic costs for operating the generators are listed in Table 4.3 and are derived from equation (4.13).

$$HR \cdot P = CC + LC \cdot P + QC \cdot P^2 \tag{4.13}$$

with:

$$\begin{aligned}
HR &= \text{ heat rate } (\frac{MBtu}{MW}) \\
P &= \text{ generation amount } (MW) \\
CC &= \text{ constant heat cost } (MBtu) \\
LC &= \text{ linear heat cost } (\frac{MBtu}{MW}) \\
QC &= \text{ quadratic heat cost } (\frac{MBtu}{MW^2})
\end{aligned}$$

The cost per MW is the fuel cost times the heat cost and the reserve costs for the units are a percentage of the linear cost. Since a balance between the amount of reserve required for the wind energy and its cost is needed, the reserve costs need to be adjusted until an equilibrium is found.

Table 4.1: Thermal Generator Data

Unit Size (MW)	# of Generators	Unit Type	Forced Outage Rate
12	5	# 6 Oil	0.02
20	4	#2 Oil	0.10
50	6	Hydro	0.01
76	4	Coal	0.02
100	3	#6 Oil	0.04
155	4	Coal	0.04
197	3	# 6 Oil	0.05
350	1	Coal	0.06
400	2	Nuclear	0.12

Table 4.2: Fuel Cost (1979 base)

Fuel Type	Cost
# 6 Oil	$ 2.30/MBtu
# 2 Oil	$ 3.00/MBtu
coal	$ 1.20/MBtu
nuclear	$ 0.60/MBtu

Table 4.3: Thermal Generator Cost

Size (MW)	Constant (MBtu)	Linear (MBtu/MW)	Quadratic (MBtu/MW^2)
12	10.80	11.10	0.00
20	0.00	17.00	0.25
50	NA	NA	NA
76	68.40	11.10	0.00
100	122.22	7.89	0.0178
155	170.26	7.77	0.0107
197	189.35	7.66	0.0099
350	320.67	7.46	0.0004
400	350.00	9.03	0.0005

4.4 Wind Energy

The wind data is actual recorded power output in 10 minute intervals, in MW over the course of six years, from January 1, 2004 to December 31, 2009 [30]. Each year is used to represent an individual wind farm or block of energy. With six years of recorded power output, there are six wind farms represented by the data. The ten minute data is then averaged into hourly amounts. This hourly average then represents the wind power forecast for each hour throughout one year. The maximum output of wind energy is approximately 2000 MW or 70% of the peak load, but it is very unlikely that all of the wind units will ever be at their maximum output at the same time and that all of the energy be scheduled for use by UC.

One of the most difficult issues in adding wind turbines to UC is determining the amount of wind that can be relied on at each time step. With the addition of wind turbines the objective function of the cost minimization problem (4.14) becomes:

$$\text{minimize: Cost } = \sum_{i}^{n}(A_iU_i + B_iP_i + D_iR_i) + \sum_{k}^{wg}\left(\sum_{j}^{ns}(F_kU_{jk}) + G_kW_k\right) \quad (4.14)$$

The load constraint (4.2) becomes:

$$Load = \sum_{i}^{n} P_i + \sum_{k}^{wg} W_k \quad (4.15)$$

The following wind energy constraints are added to help determine their scheduled states.

$$W_k = \sum_{j}^{ns} GA_{jk}U_{jk} \qquad \forall k \quad (4.16)$$

$$\sum_{j}^{ns} U_{jk} \leq 1 \qquad \forall k \quad (4.17)$$

with:

$n =$ number of thermal generators

$wg =$ number of wind turbines

$U_i =$ are binary for on/off representation of thermal units

$U_{jk} =$ are binary for on/off representation of wind turbines multiple states

$P_i =$ generation amount of thermal unit

$W_k =$ generation amount of wind turbines

$A_i =$ constant cost of thermal units

$B_i =$ linear cost of thermal units

$D_i =$ reserve linear cost of thermal units

$F_k =$ constant cost of wind turbines

$G_k =$ linear cost of wind turbines

$GA_{jk} =$ generation amount for each respective turbine state

Equation (4.15) ensures that the sum of the generation of the thermal units and the wind turbines meets the load requirement of the system. Equation (4.16) sets the amount of wind energy for each block of wind. While (4.17) provides that only one of the possible states of forecasted wind energy is chosen, so there is not an over scheduling of wind.

4.5 Wind Energy Not Served

Traditional UC uses a N-1 reserve constraint. This makes sure that if the largest unit in the system goes down then no load will be lost. Wind turbines are stochastic and their output is forecasted with a probabilistic error. With the addition of the wind turbines an additional security constraint is needed. The new approach uses the same basic structure of traditional UC. Here, the reserve constraint includes an estimation of the expected WENS [14] for the forecasted generation of the wind units along with the traditional reserve constraint for the thermal units. The wind generation forecasted is separated into five different levels of output, each with their own percent availability. The five availability levels used are: 100%, 80%, 60%, 40% and 20%. These levels represent the percent guaranteed that the wind energy will be its respective forecast of higher. Table 4.4 shows an example generation forecast for three wind turbines.

Equation (4.18) is the constraint added to the unit commitment problem to find the addition reserve needed when adding the wind turbines into the system.

$$WENS = \sum_{k}^{wg} \sum_{j}^{ns} [(1 - UA_{jk}) \cdot GA_{jk}] U_{jk} \tag{4.18}$$

Equation (4.11) then becomes (4.19)

$$Reserve = \text{Max}(P_i^{max} U_i) + \beta \cdot WENS \tag{4.19}$$

Table 4.4: Three Wind Turbine Generation Forecast

Wind Turbine	100% Availability	80% Availability	60% Availability	40% Availability	20% Availability
Turbine 1	0 MW	17 MW	34 MW	52 MW	86 MW
Turbine 2	0 MW	59 MW	117 MW	176 MW	294 MW
Turbine 3	0 MW	35 MW	70 MW	106 MW	176 MW

with:

$wg =$ number of wind turbines

$ns =$ number of unit availability states

$UA_{jk} =$ unit availability for each specific level of generation

$\beta =$ scaling factor for final system reliability

$GA_{jk} =$ forecasted power in respect to state k

$U_{jk} =$ binary representation of the chosen state for the wind turbine k

β plays an important role as the scaling factor in (4.19). It allows the scheduled amount of wind to be tuned for either a lower system operating cost or a lower generation system reliability. β can be set anywhere between zero and one. $\beta = 0$ represents the case where no extra reserve is added to the system for the scheduled wind and $\beta = 1$ represents the case where the complete WENS is added to the required amount of reserve. In this configuration β is dependent on the system constraints and defined operating costs. Section 4.8 discusses how the different factors of β are tested and Section 4.9 goes into more detail on the effects of β and the penetration of wind energy on the system and its effects on the operating cost and generating reliability.

4.6 Load Information

The load data is obtained from [29]. Using the the IEEE RTS makes it easier to compare the results and show the impact of the proposed UC. The annual peak load is set at 2850 MW. Tables 4.6 and 4.5 list the load as a percentage of the annual and weekly peak load respectively.

Table 4.5: Daily Peak Load (% of Weekly Peak)

Day	Peak Load
Monday	93
Tuesday	100
Wednesday	98
Thursday	96
Friday	94
Saturday	77
Sunday	75

Table 4.6: Weekly Peak Load (% of Annual Peak)

Week	Peak Load	Week	Peak Load
1	86.2	27	75.7
2	90.0	28	81.6
3	87.8	29	80.1
4	83.4	30	88.0
5	88.0	31	72.2
6	84.1	32	77.6
7	83.2	33	80.0
8	80.6	34	72.9
9	74.0	35	72.6
10	73.7	36	70.5
11	71.5	37	78.0
12	72.7	38	69.5
13	70.4	39	72.4
14	75.0	40	72.4
15	72.1	41	74.3
16	80.0	42	74.4
17	75.4	43	80.0
18	83.7	44	88.1
19	87.0	45	88.5
20	88.0	46	90.9
21	85.6	47	94.0
22	81.1	48	89.0
23	90.0	49	94.2
24	88.7	50	97.0
25	89.6	51	100.0
26	86.1	52	95.2

4.7 Final MIP UC Setup

The final UC setup is:

Objective:

$$\text{min: Cost } = \sum_{i}^{n}(A_iU_i + B_iP_i + D_iR_i) + \sum_{k}^{wg}\left(\sum_{j}^{ns}(F_kU_{jk}) + G_kW_k\right) \tag{4.20}$$

where:

$$Load = \sum_{i}^{n} P_i + \sum_{k}^{wg} W_k \tag{4.21}$$

$$P_i \geq P_i^{min}U_i \qquad \forall i \tag{4.22}$$

$$P_i + R_i \leq P_i^{max}U_i \qquad \forall i \tag{4.23}$$

$$WENS = \sum_{k}^{nw}\sum_{j}^{ns}[(1 - UA_{jk}) \cdot WG_{jk}]U_{jk} \tag{4.24}$$

$$Reserve = \text{Max}(P_i^{max}U_i) + \beta \cdot WENS \tag{4.25}$$

$$Reserve = \sum_{i}^{n} R_i \tag{4.26}$$

with:

$n =$ number of thermal generators

$wg =$ number of wind turbines

$ns =$ number of unit availability states

$U_i =$ are binary for on/off representation of thermal units

$U_{jk} =$ are binary for on/off representation of wind turbines multiple states

$P_i =$ generation amount of thermal unit

$W_k =$ generation amount of wind turbines

$A_i =$ constant cost of thermal units

$B_i =$ linear cost of thermal units

$D_i =$ reserve linear cost of thermal units

$F_k =$ constant cost of wind turbines

$G_k =$ linear cost of wind turbines

$UA_{jk} =$ unit availability for each specific level of generation

$\beta =$ scaling factor to dial in final system reliability

$WG_{jk} =$ forecasted power in respect to state k

4.8 Evaluation

To test the proposed method, two different systems are setup. The first system is just the basic IEEE RTS [28] and [29] with the base 32 thermal units. The second system uses the IEEE RTS as its base and adds 6 blocks of wind energy. Each block is one of the 6 years of recorded wind output discussed in section 4.4. This gives the system a total of 38 units to commit/schedule.

The first test system is run over a year long projected forecast, with each 24-hour period averaged into a single period. UC is run once for each day in a 52 week period using the peak load data from the IEEE RTS. Again, this test system is run without any wind and will be used as the base case.

The second test system is run over the same projected time period with the same load data, but the forecasted wind energy is included. The forecasted wind output is averaged from its 10 minute intervals into a single output for every time period, 24 hours. The actual wind data used as the forecasted data corresponds to the same day as the forecasted load. UC is then run 11 times, each time increasing β by 10%, starting with $\beta = 0\%$ till $\beta = 100\%$.

For both sets of test systems the average operating cost; required reserve; scheduled wind; percentage of load met by wind; and system reliability, EENS, are recorded and listed in Table 4.7.

The EENS is found in two steps. The units' probabilities are first convolved, Section 2.1.5, to form a COPT. The wind is expressed slightly different than the thermal units in this formulation. The wind is represented as a multi-state unit and therefore has more than just the two polynomials as in (2.10). Equation (4.27) gives an example of the probability function for turbine 1 in Table 4.4.

$$f_1(x) = 0.10x_{17} + 0.20x_{34} + 0.30x_{52} + 0.40x_{86} \tag{4.27}$$

After the COPT is derived the EENS can be calculated. The EENS is defined as

$$EENS = CumProb \cdot PeakLoad \tag{4.28}$$

where

$$\begin{aligned} CumProb &= \text{The cumulative probability of the first MW} \\ &\quad \text{outage to be below the } PeakLoad \\ PeakLoad &= \text{The average peak load for the given day} \\ &\quad \text{provided by the IEEE RTS (MW)} \end{aligned}$$

4.9 Results

Table 4.7 shows that the EENS of the base system is 218.58 MW, with a reserve of 400 MW. This corresponds to adding 67.64 MW of reserve when introducing 508.8 MW of wind energy on average to the system with $\beta = 0.2$. This level of β gives approximately the same level of reliability of the base system but with 24% of the load met by wind on average. This gives wind a capacity of 25% of its total maximum output.

Notice as β increases the reliability of the system increases exponentially along with the cost as the amount of wind scheduled decreases exponentially. Figures 4.1, 4.2, and 4.3 show the exponential growth of all three measurements with respect to β.

Table 4.7: Results

Beta	Test System	Cost ($/MW)	Req. Reserve	EENS	Avg. Load	Scheduled Wind	Wind Penetration
NA	Base Case	15.25	400 MW	218.58	2110 MW	NA	NA
0.0	Wind Energy	10.82	400.0 MW	682.45	2110 MW	749.39 MW	24%
0.1	Wind Energy	12.28	458.29 MW	541.27	2110 MW	734.2 MW	34.8%
0.2	Wind Energy	13.52	467.64 MW	225.27	2110 MW	508.8 MW	24.1%
0.3	Wind Energy	14.03	440.35 MW	69.69	2110 MW	311.8 MW	14.8%
0.4	Wind Energy	14.29	435.85 MW	48.86	2110 MW	248.7 MW	11.8%
0.5	Wind Energy	14.46	428.77 MW	35.82	2110 MW	195.7 MW	9.3%
0.6	Wind Energy	14.57	423.41 MW	27.67	2110 MW	164.6 MW	7.8%
0.7	Wind Energy	14.64	422.38 MW	24.49	2110 MW	152.7 MW	7.2%
0.8	Wind Energy	14.71	424.16 MW	22.97	2110 MW	149.0 MW	24%
0.9	Wind Energy	14.78	426.38 MW	22.24	2110 MW	146.1 MW	24%
1.0	Wind Energy	14.85	428.34 MW	21.51	2110 MW	141.6 MW	24%

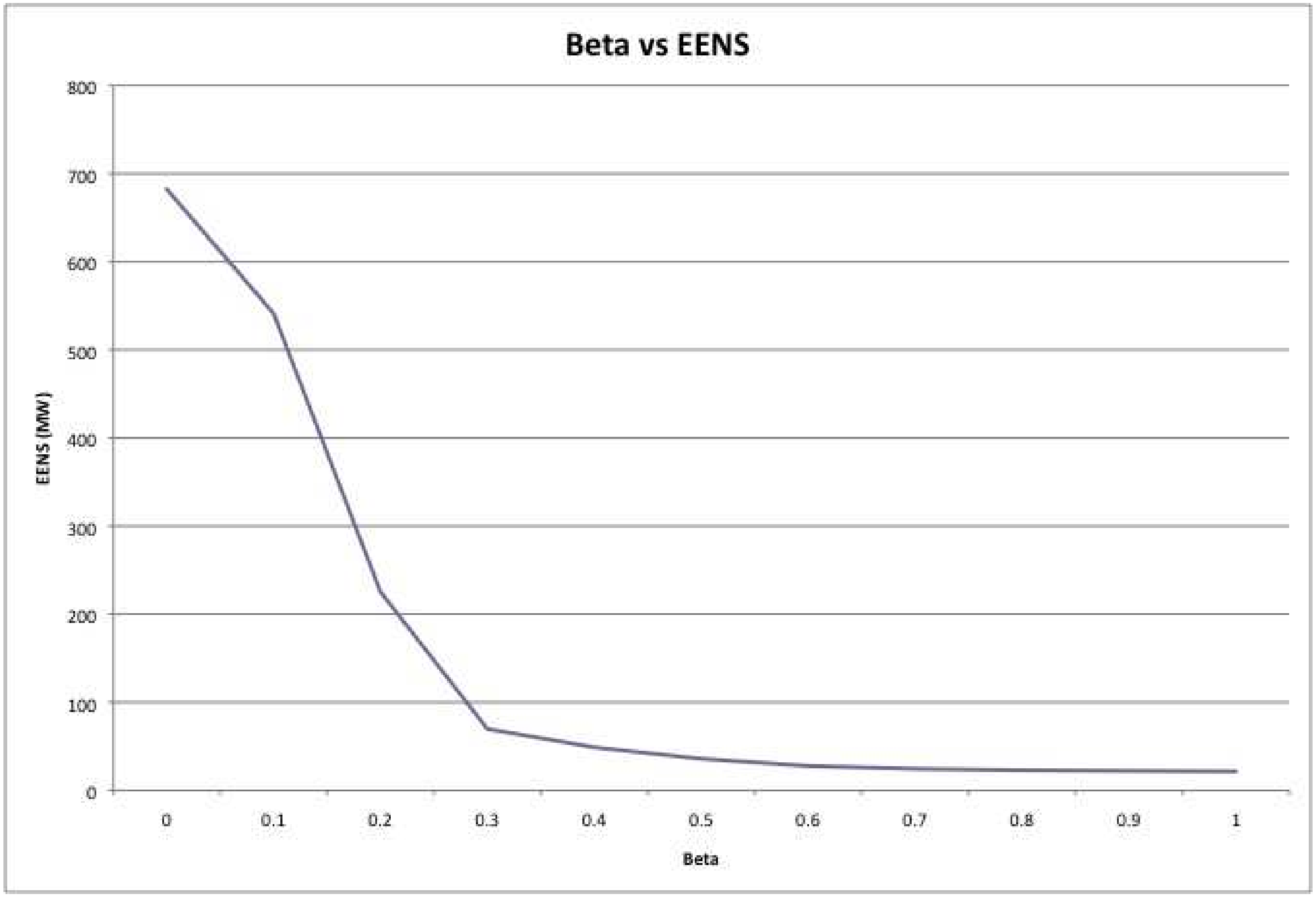

Figure 4.1: Beta Versus System Reliability

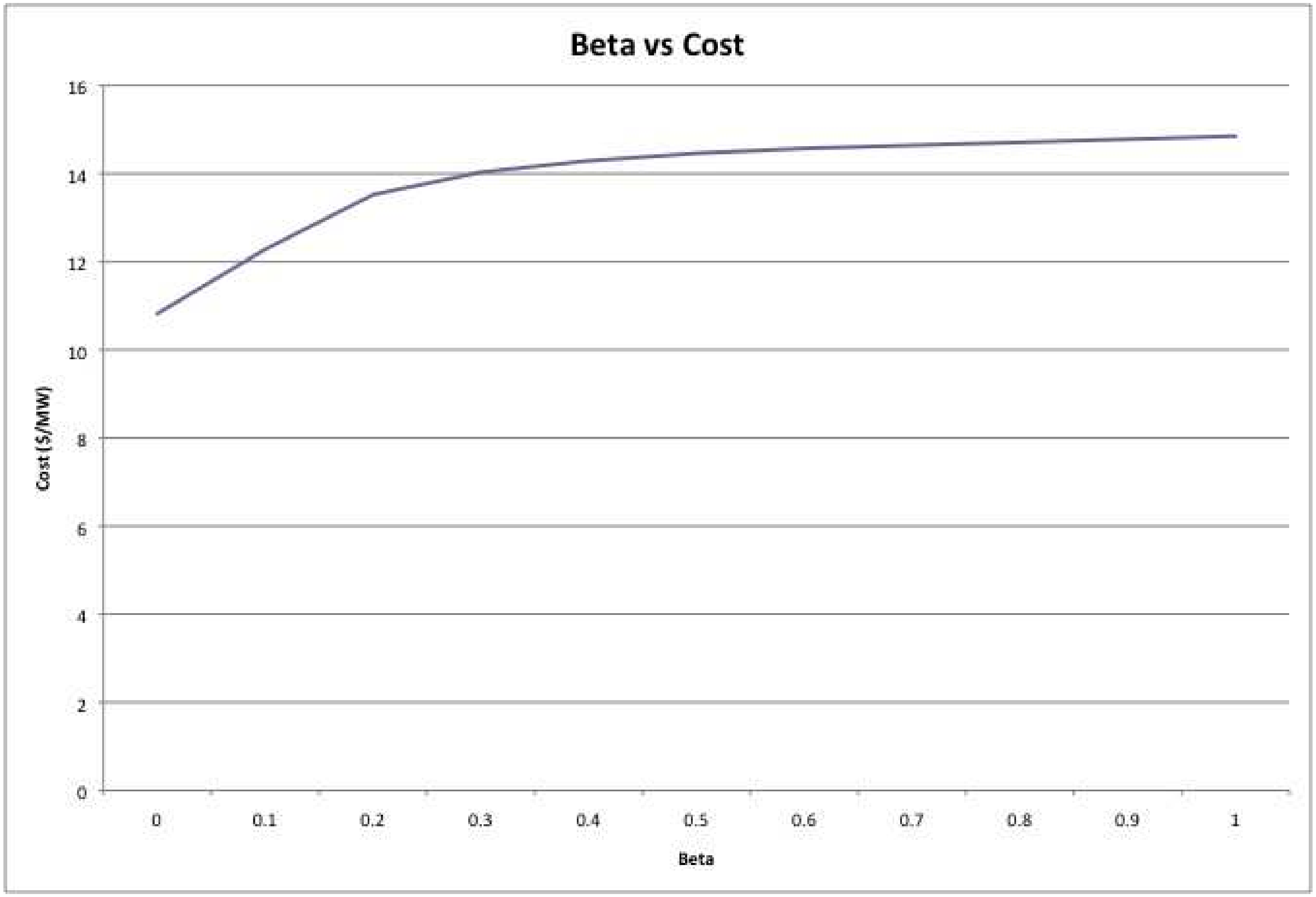

Figure 4.2: Beta Versus Operational Cost

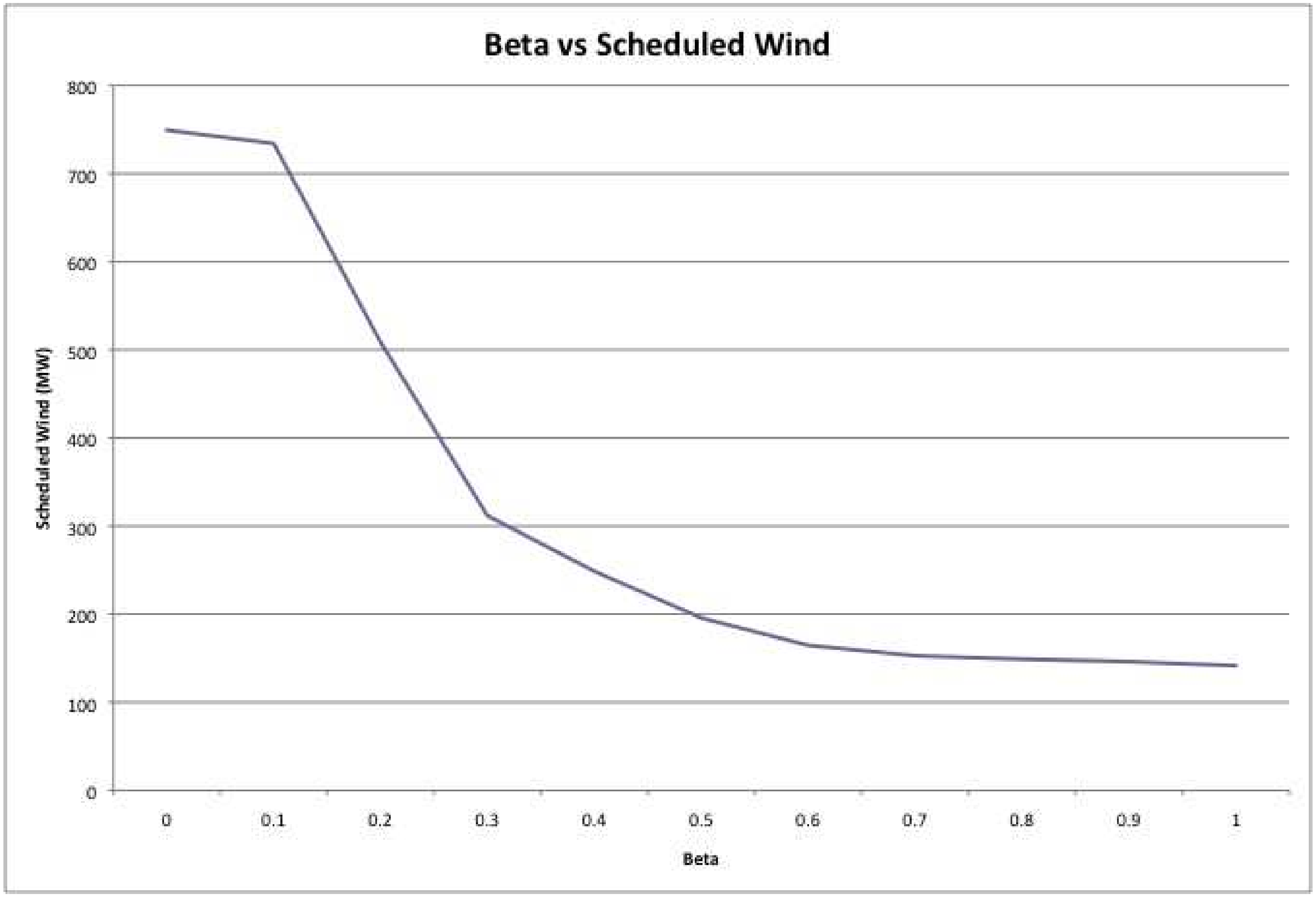

Figure 4.3: Beta Versus the amount of Scheduled Wind

Chapter 5

Conclusions

A majority of the proposed method's limitations come from the defined scope. One of the main limitations is the lack of inter-hour constraints. It is assumed that the amount of wind energy scheduled will not effect the base load, therefore there will be no effect on the base load generators, and that the spinning reserve will react fast enough to the volatile nature of wind. The second major limitation in this method is the modeling of the forecasted wind data. The forecast is currently taken directly from actual historical data. It is then given a pessimistic linear based distribution. The maximum amount of schedulable wind is the forecasted amount. This never allows the UC to assume that the actual wind output can be greater than the forecasted amount. The last major limitation is from the lack of transmission constraints, mainly line constraints. This could allow an unlimited amount of power to flow down restricted lines. Line constraints are left out because it is difficult to run a power flow inside of UC, especially when UC is solved in a linear fashion, as with the proposed MIP method.

Even with a majority of the scope remaining the same, several improvements can be made in future work on this method. One step would be to integrate β, the reserve scaling factor, in UC. β could be optimized around a given amount of wind penetration, system reliability or generation cost; depending on the needs of the operator. This would allow a single call of UC instead of several to dial in the reserve scaling factor.

Another major step would be to use the actual wind forecast and then compare the results to the measured wind output. Analyzing the several sets of the data will give a more accurate distribution of wind's forecast error. This can also help rid the pessimistic view of the wind forecast. It may become necessary to include inter-hour constraints as the distribution becomes more accurate, if the volatile nature of wind is found to have a faster effect on the power system than the current reserve can meet.

The addition of inter-hour or line constraints can make the system very hard to model linearly. It will be useful to model the system in a quadratic form. It may be possible to form a MIP from a quadratic program (QP). A QP is similar to LP but allows the objective and constraints to contain quadratic terms in addition to linear ones.

Throughout the development and design of the approach of the proposed method several insights were made in determining the COPT for the committed generation system. The COPT is mainly used for power system reliability analysis and its derivation time is of low importance, but it becomes more important as system reliability calculations will be needed in power systems operations which require calculations to complete in small windows.

In conclusion, the proposed UC method is simple and it allows the scheduled amount of wind energy to be adjusted for operation, cost, or reliability. The results show that approximately 24% of the load can be met in the given test system, while keeping a constant reliability before and after wind is introduced. This amount of wind will alone meet many of the RPS in the U.S.

Bibliography

Bibliography

[1] [Online]. Available: http://www.awea.org/learnabout/publications/factsheets/factsheets_state.cfm 1

[2] "Wind generation vs. capacity." [Online]. Available: http://www.eia.gov/cneaf/solar.renewables/page/wind/wind.html 1

[3] W. Kempton, F. M. Pimenta, D. E. Veron, and B. A. Colle, "Electric power from offshore wind via synoptic-scale interconnection," *Proceedings of the National Academy of Sciences*, vol. 107, no. 16, pp. 7240–7245, 2010. [Online]. Available: http://www.pnas.org/content/107/16/7240.abstract 1

[4] P. Yang, L. Zhao, and Z. Li, "A practical method of unit commitment considering wind power," in *World Non-Grid-Connected Wind Power and Energy Conference (WNWEC), 2010*, nov. 2010, pp. 1 –7. 3, 4

[5] Z. Li and X. Han, "Risk constrained unit commitment considering uncertainty of wind power and load," in *Sustainable Power Generation and Supply, 2009. SUPERGEN '09. International Conference on*, april 2009, pp. 1 –5. 3, 4, 5

[6] M. Milligan and K. Porter, "The capacity value of wind in the united states: Methods and implementation," *The Electricity Journal*, vol. 19, no. 2, pp. 91 – 99, 2006. [Online]. Available: http://www.sciencedirect.com/science/article/B6VSS-4J7300H-1/2/010030001446f5fc24b6044 3, 31

[7] L. Garver, "Effective load carrying capability of generating units," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-85, no. 8, pp. 910 – 919, aug. 1966. 3, 19

[8] E. P. Kahn, "Effective load carrying capability of wind generation: Initial results with public data," *The Electricity Journal*, vol. 17, no. 10, pp. 85 – 95, 2004. [Online]. Available: http://www.sciencedirect.com/science/article/B6VSS-4DXTHW4-1/2/479518be0cc29eb6b40f 3, 31

[9] R. Billinton, B. Karki, R. Karki, and G. Ramakrishna, "Unit commitment risk analysis of wind integrated power systems," *IEEE Transactions on Power Systems*, vol. 24, no. 2, pp. 930 –939, may 2009. 3, 4, 5

[10] K. Methaprayoon, C. Yingvivatanapong, W.-J. Lee, and J. Liao, "An integration of ann wind power estimation into unit commitment considering the forecasting uncertainty," *IEEE Transactions on Industry Applications*, vol. 43, no. 6, pp. 1441 –1448, nov.-dec. 2007. 3, 4

[11] T. Senjyu, S. Chakraborty, A. Saber, H. Toyama, A. Yona, and T. Funabashi, "Thermal unit commitment strategy with solar and wind energy systems using genetic algorithm operated particle swarm optimization," in *Power and Energy Conference, 2008. PECon 2008. IEEE 2nd International*, dec. 2008, pp. 866 –871. 3, 4, 5, 22

[12] B. Ummels, M. Gibescu, E. Pelgrum, W. Kling, and A. Brand, "Impacts of wind power on thermal generation unit commitment and dispatch," *IEEE Transactions on Energy Conversion*, vol. 22, no. 1, pp. 44 –51, mar. 2007. 4

[13] S. Hosseini and E. Abbasi, "Probabilistic unit commitment with wind farms considerations," in *Power Engineering, 2007 Large Engineering Systems Conference on*, oct. 2007, pp. 73 –77. 4, 5

[14] B. Venkatesh, P. Yu, H. Gooi, and D. Choling, "Fuzzy milp unit commitment incorporating wind generators," *IEEE Transactions on Power Systems*, vol. 23, no. 4, pp. 1738 –1746, nov. 2008. 4, 5, 34, 38, 46

[15] J. Wang, M. Shahidehpour, and Z. Li, "Security-constrained unit commitment with volatile wind power generation," *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 1319 –1327, aug. 2008. 4, 5

[16] A. Tuohy, P. Meibom, E. Denny, and M. O'Malley, "Unit commitment for systems with significant wind penetration," *IEEE Transactions on Power Systems*, vol. 24, no. 2, pp. 592 –601, may 2009. 4

[17] J. Restrepo and F. Galiana, "Assessing the yearly impact of wind power through a new hybrid deterministic/stochastic unit commitment," *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 401 –410, feb. 2011. 4, 5

[18] X. Sun and C. Fang, "Interval mixed-integer programming for daily unit commitment and dispatch incorporating wind power," in *Power System Technology (POWERCON), 2010 International Conference on*, oct. 2010, pp. 1 –6. 4, 5

[19] R. Ye, H. Chen, and P. Chen, "Security constrained unit commitment with multiple wind farms integrated," in *IPEC, 2010 Conference Proceedings*, oct. 2010, pp. 116 –121. 4

[20] R. Billinton and R. N. Allan, *Reliability Evaluation of Power Systems*, 2nd ed. 233 Spring Street, New York, NY 10013: Plenum Press, 1996. 8, 10, 12, 13, 14, 17, 18, 19, 34

[21] R. Allan, A. L. da Silva, A. Abu-Nasser, and R. Burchett, "Discrete convolution in power system reliability," *IEEE Transactions on Reliability*, vol. R-30, no. 5, pp. 452 –456, dec. 1981. 15

[22] Reliability assesment guidebook, v2.1. [Online]. Available: www.nerc.com/files/Reliability%20Assessment%20Guidebook%20v2.1.pdf 17

[23] Reliability standards for the bulk electric systems of north america. [Online]. Available: http://www.nerc.com/files/Reliability_Standards_Complete_Set.pdf 17, 37

[24] S. Patil and R. Ramakumar, "A study of the parameters influencing the capacity credit of wecs- a simplified approach," in *Power and Energy Society General Meeting, 2010 IEEE*, july 2010, pp. 1 –7. 19, 31

[25] A. J. Wood and B. F. Wollenberg, *Power Generation Operation and Control*, 2nd ed. 605 Third Avenue, New York, NY 10158: John Wiley and Sons, Inc., 1996. 21, 22

[26] J. P. Ignizio and T. M. Cavalier, *Linear Programming*. Upper Saddle River, New Jersey 07458: Prentice Hall, 1994. 23, 24

[27] C. D'Annunzio and S. Santoso, "Noniterative method to approximate the effective load carrying capability of a wind plant," *IEEE Transactions on Energy Conversion*, vol. 23, no. 2, pp. 544 –550, jun. 2008. 31

[28] P. Subcommittee, "Ieee reliability test system," *IEEE Transactions on Power Apparatus and Systems*, vol. PAS-98, no. 6, pp. 2047 –2054, nov. 1979. 37, 42, 53

[29] C. Grigg, P. Wong, P. Albrecht, R. Allan, M. Bhavaraju, R. Billinton, Q. Chen, C. Fong, S. Haddad, S. Kuruganty, W. Li, R. Mukerji, D. Patton, N. Rau, D. Reppen, A. Schneider, M. Shahidehpour, and C. Singh, "The ieee reliability test system-1996. a report prepared by the reliability test system task force of the application of probability methods subcommittee," *IEEE Transactions on Power Systems*, vol. 14, no. 3, pp. 1010 –1020, aug 1999. 37, 42, 49, 53

[30] Data requested by uoc. [Online]. Available: http://www.aeso.ca/downloads/data_requested_by_uoc(1).csv 44

Vita

Alexander Melhorn was born in York, PA, to the parents of Christopher and Susan Melhorn. He attended Tate's School of Discovery, transfered to Sacred Heart Cathedral School and continued to complete high school with Seton Home Study School also receiving his Eagle Scout Award with the Boy Scouts of America. After his graduation, Alex completed two years at Pellissippi State Community College completing many of his core college courses and receiving a drafting certificate. While at PSTCC he won the state math competition two years in a row and placed third in nationals his second year. He continued his education in electrical engineering at the University of Tennessee, Knoxville, where he received the Min Kao scholarship, after working in the university's National Science Foundation's Research Experience for Undergraduates Internship. Alex is a member of Phi Delta Theta Fraternity where he served several positions and is currently on the Young Alumni Board and Tennessee Gamma's Chapter Advisory Board. He obtained his Bachelors of Science degree from the University of Tennessee in May 2009 in Electrical Engineering. He accepted the prestigious Bodenheimer Fellowship along with a graduate research and teaching assistantship at the University of Tennessee, in the Electrical Engineering Power Lab. Alex is currently pursuing a Masters of Science in Electrical Engineering and is on track to graduate in August 2011. He is continuing his education with a Ph.D. in Electrical Engineering at the Georgia Institute of Technology in Atlanta, GA.