ABSTRACT

WANG, SHU. Reliability Assessment of Power Systems with Wind Power Generation.
(Under the direction of Dr. Mesut E Baran.)

Wind power generation, the most promising renewable energy, is increasingly attractive to power industry and the whole society and becomes more significant in the portfolio of generation systems. However, because of the unfavorable features of wind power, it affects all aspects of traditional processes of power system planning and operation. Power systems primarily planned for providing reliable and economic electric power to their customers. Therefore, it is critical to assess and understand the impacts of wind power on power system reliability.

This thesis focuses on reliability assessment of power systems with wind power generation. Based on the investigation of reliability evaluation methodology and power system operations, a Monte Carlo based production cost simulation model is proposed and has been developed in the thesis. The model closely simulates actual system operation processes and takes system random behaviors into account. A simplified unit commitment method is created to fit the simulation for reliability evaluation purpose. The effects of wind forecast error is addressed in the model by applying forecasted value for day-ahead unit commitment and actual value for real-time operation. A process of Auto-Regressive Moving Average is designed to automatically perform day-ahead hourly wind generation forecasting through the whole simulation period. Methods for evaluating capacity value of wind power generation are also investigated. A realistic case study shows the proposed Monte Carlo based production cost simulation model can be used to assess reliability of power systems with wind power generation.

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Reliability Assessment of Power Systems with Wind Power Generation

by
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DEDICATION

To Dong

For my wonderful wife

For our everlasting love

BIOGRAPHY

Shu Wang was born in Tianjin, China in 1978. He earned his Bachelor degree and Master degree both in Electrical Engineering and Automation from Tianjin University in Tianjin, China, in 2001 and 2004, respectively. In July 2004, he left his home town the place he spent 25 years since childhood and came to the United State to embark on his splendid venture overseas.

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Chapter 1 Introduction

1.1. Development of Wind Power in United States

Wind power, the most promising renewable energy, is one of the fastest growing electric generation technologies in United States as well as the whole world. Based on American Wind Energy Association (AWEA) 2008 first quarter market report [1], total installed capacity of wind power throughout United States is 18302 MW and there are 5736 MW wind power projects under construction. Distribution of existing wind power in United States is illustrated in Figure 1-1. Throughout the entire territory of United States, wind energy resource is fairly abundant but not evenly distributed in terms of wind resource atlas in Figure 1-2. The major wind resource concentrated regions include western region, middle region, northwest region, the Great Lakes, the Pacific coast, the Texas Gulf coast and the Atlantic coast. Accordingly, wind generations are mainly allocated in west, middle-west and south of United States.

Driven by cost competitiveness, increasing concerns of high fuel price and environmental issues, Renewable Portfolio Standards (RPS) filed by states or regions require certain percentage of electric generation to come from renewable sources. California's RPS originally established in 2002 is one of the most ambitious renewable energy standards in United States. The RPS program requires electric corporations to increase procurement from eligible renewable energy resources by at least 1% of their retail sales annually, until they reach 20% by 2010. RPS of New York State calls for an increase in renewable energy used in the state from the current requirement level of about 19% to 25% by the year 2013.

1.2. Wind Power Generation Pros and Cons

Wind generation brings a number of pretty attractive features to power industry and the whole society. Wind, the so-called “renewable” energy, is the primary fuel of wind generation. Production cost of wind generation is fairly cheap in comparison with that of conventional generation. A conventional generator can be understood as a controllable generator, such as thermal units. From system economic viewpoint, wind generation is the “must-taken” energy whenever it produces. Therefore, this portion of load demand that used to be served by thermal generation is now provided by wind generation. In result,

- ◆ Overall system production cost will reduce from the reduction of high cost thermal generation, while assuming proper operation procedure is taken place.
- ◆ The amount of emission, such as CO₂, SO₂, NO_x, released from coal and gas power plants before wind power integration will diminish. This will be greatly beneficial for already deteriorative environment.
- ◆ The consumption of major fuels by thermal generation, such as coal, natural gas and oil, will decrease.

In addition, development of a wind power project can be implemented much easier and faster than building a thermal or hydro plant. It is also a potential and economic solution for

providing energy around remote areas that can not be reached by major transmission networks.

Meanwhile, wind generation brings a series of difficulties to the traditional power systems due to the unfavorable build-in natures.

- ◆ Uncontrollability: With regard to a generating unit, controllability means that the generation can be fully governed at any level from minimum capacity to maximum capacity by a system operator. Wind generation mostly depends on wind availability. Only if wind blows, wind turbine produces electric power.
- ◆ Intermittence: Wind generation shows irregularly fluctuating and intermittent behavior. Fast ramp up and down of wind generation created by intensive fluctuation of wind will potentially lead to operational difficulties and endanger system reliability. For security consideration, when wind speed exceeds the “cut out” speed, like a gust, wind turbine will totally stop generating instead of keeping at maximum capacity. Consequently, all of a sudden, system may lose a group of generating resource and sufficient emergency actions must be taken in respond to such contingency.
- ◆ Poor predictability: Due to the random and irregular behavior of wind, it is very hard to accurately forecast wind generation. Long-term from seasons to years, mid-term from hours to days and short-term from seconds to minutes of wind forecast are typically used for wind project planning, daily resource scheduling and real-time operation, respectively. In a power system with high wind power penetration, mid-term wind forecast that predicts the hourly wind generation for a time horizon of 1–48 hours has great value for daily system operations. Unfortunately, state-of-the-art wind forecasting methods only show a Mean Absolute Error (MAE) of 10–15% of installed capacity of a wind project [2].
- ◆ Unfavorable seasonal and daily pattern: Around some wind farm locations, seasonal and daily wind patterns are out of phase with the patterns of local load, which means heavy wind generation happens during low load period and poor wind generation

happens during peak load period. The worst scenario is that a wind project is sited where wind is rich at night during winter season, meanwhile, system load peak takes place in daytime during summer season. Figure 1-3 shows an area load profile and an aggregated wind generation of several wind farms for 24 hours in a day in the western region. It is obvious that the trends of load shape and wind generation deviate from each other.

Figure 1-3 Unfavorable daily wind generation pattern

1.3. Impact of Wind Power on Power System Planning and Operation

In power system operations, the main goal is to ensure the reliability of an electric power supply system which continuously faces anticipated and unanticipated changing conditions. Comprehensive processes of long-term planning and short-term operation are carried out to resolve the issues in the time frame from multiple years to milliseconds. In a traditional power system, operator dominates all available controllable resources to reliably serve the

primary independent uncontrollable variable, system load. Wind generation, as an undispachable generating resource, almost entirely relies on wind availability. Integration of wind generation into existing power systems will definitely impact system planning and operation process in all time frames.

Figure 1-4 illustrates the time frames from long term to short term for planning and operation [3]. Investigation of wind generation integration must be carefully performed to accommodate to system's needs for different time frames.

- ◆ In the long-term planning time frame, expansion decision of system infrastructure including resource and transmission are made with looking several years ahead to meet demand growth and satisfy reliability requirement. Wind generation, depending on geographical location and climatic condition, varies a lot from season to season and from year to year. Development of wind generation needs collaborate with generation and transmission planning, especially for the conventional generating units, to satisfy resource adequacy.
- ◆ During day-to-day scheduling, available generating resources are scheduled beforehand based on the predicted upcoming load demand and wind generation, as well as other system conditions, such as transmission constraints and maintenances. Not like system load that conforms to diurnal cycle, availability of wind is largely unpredictable. To some extent, forecast error of wind generation is much greater than that of load, particularly for mid-term and long-term forecast. Logic of unit commitment considering operation reserve requirement needs be adjusted under high wind penetration condition.
- ◆ During an operation day, also known as real-time operation, economic dispatch determines the minute-to-minute generation from the generating units that are committed based on unit commitment decision in the past, typically previous day. Unit commitment is potentially refined to accommodate the deviation between the forecast and actual value of load and wind generation and any other types of contingencies.

- ◆ In the fastest time frame, minute to second level, generating facilities are handled by automatic generation control and governor action without much operator intervention in response to system variations to meet system frequency and scheduled interchange among control areas. Large and high frequency variations of wind generation barely happen in such short period. Therefore, impact in this time frame is relatively small and could be negligible.

Figure 1-4 Time frames for power systems planning and operation

1.4. Wind Generation Integration Issues

Intermittence, uncontrollability, poor predictability and unfavorable seasonal and daily pattern in nature of wind generation raise a series of issues to power systems whether load demand can be continuously reliably served in terms of the influence of wind generation in all stages of planning and operation.

- ◆ How does the system reliability change when individual wind project is integrated in a system to reach different penetration level? Is the existing power system able to maintain the reliability requirement when high wind power penetration happens?
- ◆ What is the optimal development order of a wind project queue, which can improve system reliability?
- ◆ How does the performance of wind generation forecast affect scheduling and operation as well as the overall system reliability?
- ◆ How does the traditional resource planning cooperate with wind generation to create a desirable generation mix to meet future load demand?
- ◆ Besides the anticipatory contingencies in an existing system, is current operation reserve able to cover uncertainty of wind generation? How to determine the operational reserve requirement under certain level of wind penetration?
- ◆ Is wind generation qualified for capacity value? If so, how to quantify the appropriate amount for individual wind project?
- ◆ Should traditional system operating practices including unit commitment and economic dispatch be changed in respond to intermittent wind generation?
- ◆ Should power market rules be adjusted to accommodate the nondispatchable nature of wind generation, and maintain a fair and competitive market?
- ◆ How does the utilization of different types of conventional generating unit change?
- ◆ How do overall system production cost, generation revenue and load payment change? Is there any additional integration cost for wind generation due to the unfavorable behaviors?

About a decade ago, installed capacity of wind generation was just a very small portion among the entire generating resources in bulk power systems and the effects on system reliability could be negligible. Along with large-scale wind power penetration into bulk power systems, the amount of wind power generation is comparable to the amount of existing conventional generating resources. Power systems primarily emphasize on providing a reliable and economic supply of electrical energy to customers. New methods for system planning and operation need to be introduced due to the significant impacts of wind intermittence on operating conventional generation resource. Especially, in the impartially competitive electric markets, Independent System Operator (ISO) and Regional Transmission Organization (RTO) have to deeply understand and investigate technical and economic impacts of wind power on deregulated power systems so that reasonable market regulations specifically for wind power can be established.

1.5. Thesis Overview

In order to address some of the issues regarding integration of wind power, a Monte Carlo based production cost simulation model has been investigated. The model simulates realistic processes of system planning and operation and takes wind generation into account. The main objective of the proposed model is to evaluate reliability of a power system integrated with wind generation. It also can be used for estimating the effects of wind generation forecasting, system reserve requirement, capacity value of a wind project, and so on.

Chapter 2 presents the concepts of power system reliability and its evaluation methods. There are basically two main branches for reliability evaluation, analytical based method and Monte Carlo simulation method. Typical power system operation process including day-ahead scheduling and real-time operation is also described in this chapter.

Chapter 3 mainly focuses on wind generation related topics. Firstly, the fundamentals of wind generation are introduced. In addition, the applications and state-of-the-art methodologies of wind power forecasting are simply reviewed. At the end, the basic concept of capacity value of wind power is discussed.

Chapter 4 proposed a Monte Carlo based production cost simulation model that mainly will be applied for reliability evaluation of power systems with wind power integration. In the model, there are three major iteration loops including, Monte Carlo replication loop, daily loop and hourly loop. Actual system operation processes considering wind generation, such as day-ahead unit commitment and real-time refinement are mimicked. A simplified unit commitment method is adopted to fit the simulation for reliability evaluation purpose. An automatic process for day-ahead hourly wind generation forecasting is proposed as well using Auto-Regressive Moving Average (ARMA) model. The forecasted and actual values of wind generation are applied for day-ahead and real-time scheduling, respectively. At the end, the IEEE Reliability Test System (RTS) is simulated using the proposed model to verify its feasibility and validity. Results show that the reliability indices reported from the proposed model is reasonably close to the one calculated by analytical method.

Chapter 5 is a case study using the proposed Monte Carlo simulation model. A power system as a base case with a desired generation mix is created based on the data from real power systems. The annual hourly generation profiles of four wind projects are prepared. The study shows that power system reliability as well as system economics and generation utilization are indeed highly impacted by wind generation integration. The importance of wind forecast performance is also proven by simulation results. Capacity value of a wind project is assessed using different methods.

Chapter 6 concludes the thesis and suggests the future works to further improve the Monte Carlo simulation model.

1.6. Abbreviations

- ◆ NERC: North American Electric Reliability Corporation
- ◆ LOLE: Loss of Load Expectation
- ◆ EENS: Expected Energy Not Served
- ◆ WTGS: Wind Turbine Generator System
- ◆ ISO: Independent System Operator

- ◆ RTO: Regional Transmission Organization
- ◆ ARMA: Auto-Regressive Moving Average
- ◆ RMSE: Root Mean Square Error
- ◆ FOR: Forced Outage Rate
- ◆ MTTR: Mean Time To Repair
- ◆ MTTF: Mean Time To Failure
- ◆ ELCC: Effective Load Carrying Capability

Chapter 2 Power System Reliability

2.1. *Concept of Power System Reliability*

Reliability is the probability of a device performing its purpose adequately for the period of time intended under the operating conditions encountered [4]. Bulk power system reliability has two aspects, each requiring its own set of criteria and system testing procedures. NERC defines reliability as follows [5].

- ◆ Adequacy - The ability of the bulk power system to supply the aggregate electrical demand and energy requirements of the customers at all times, taking into account scheduled and reasonably expected unscheduled outages of system elements.
- ◆ Security - The ability of the bulk power system to withstand sudden disturbances such as electric short circuits or unanticipated loss of system elements from credible contingencies. With a set of operating and design criteria to ensure system secure operations and system stress level before any credible contingency under various operating conditions and active and reactive power reserves on the system plays a major role in deciding the generation dispatches.

Adequacy and security are considered the basic inputs to the generation side of system reliability. In despite of distinct concepts, they are closely correlated. A system with adequate capacity can maintain enough security to reduce periods of involuntary load shedding [6].

Regarding adequacy, system operators can and should take controlled actions or procedures to maintain a continual balance between supply and demand within a balancing area. A system is adequate if the probability of having sufficient transmission and generation

to meet expected demand is equal to or less than the system's standard. Two main components affect adequacy are generation system and transmission system.

The methods for assessing generating resource adequacy can be categorized as deterministic methods and probabilistic methods. Capacity margin, a typical deterministic metric, is the amount by which capacity exceeds system peak demand expressed as percent of capacity resources. Probabilistic method is associated with an evaluation that explicitly accounts for the likelihood and consequences of possible contingencies sequences in an integrated fashion and provide the expected reliability indices. Power systems frequently experience random disturbances such as outage of generator or loss of transmission line, so-called contingencies. Therefore, it is logical to assess such system using probabilistic techniques. The essence of probabilistic based adequacy can be accounted by load curtailment measures (e.g., LOLE) that estimates the minimum amount of load that needs to be curtailed to avoid unacceptable system problems following contingencies and utilizing all available system adjustments. The commonly accepted quantitative indices of reliability assessment are Loss of Load Expectation (LOLE), Loss of Load Probability (LOLP) and Expect Energy Not Served (EENS).

2.2. Reliability Evaluation Methodology

Power system reliability can be estimated using a variety of methods. There are basically two main approaches for power system reliability evaluation that are widely accepted in the industry, analytical based method and Monte Carlo simulation based method [7]. Either of them is able to compute reliability indices. In the thesis, reliability methods mainly focus on assessing generation adequacy.

2.2.1. Analytical Method

Analytical techniques assess system reliability using direct numerical solutions. The expected risk of loss of load is calculated using applicable system capacity outage probability table combined with the system load characteristic.

The basic generating unit model used in reliability evaluation is a two-state model that represents the probability of finding the unit on forced outage at some distant time in the future. The probability is defined as the unit unavailability, and historically in power system applications it is known as unit Forced Outage Rate (FOR). The concepts of the availability and unavailability are illustrated in Equation (1) and Equation (2).

$$Unavailability(FOR) = U = \frac{r}{m+r} = \frac{\sum DownTime}{\sum DownTime + \sum UpTime} \quad (1)$$

$$Availability = A = \frac{m}{m+r} = \frac{\sum UpTime}{\sum DownTime + \sum UpTime} \quad (2)$$

where, m is Mean Time To Failure (MTTF), r is Mean Time To Repair (MTTR) and m+r is Mean Time Between Failures (MTBF).

FOR in equation is associated with the two-state outage model, in Figure 2-1, that can be directly applicable to a generating unit which is either operating or forced out of service. In Figure 2-1, λ is the expected failure rate, as in Equation (3), and μ is expected repair rate, as in Equation (4).

Figure 2-1 Two-state model of a unit availability

$$\lambda = 1/MTTF \quad (3)$$

$$\mu = 1/MTTR \quad (4)$$

Capacity outage probability table tabulates total available generating capacity amounts and their associated probabilities. It is created based on installed capacity and unavailability probability of each individual generating unit in the system. The basic probability concept can be applied to calculate the probabilities of different availability status combinations of all generators.

In an example system, there are two 3 MW units and one 5 MW unit. All their FOR are 0.02. The capacity outage table is listed in Table 2-1. For instance, there are two situations will lead to total out of service capacity of 3 MW. One is the first 3 MW units and the 5 MW unit are in service and the second 3 MW is out of service. Another one is the second 3 MW units and the 5 MW unit are in service and the first 3 MW is out of service. Its probability can be found in Equation (5), assuming the service status of each unit is an independent event.

Table 2-1 Capacity outage probability table

Capacity out of service (MW)	Individual probability	Cumulative probability
0	0.941129	1.000000
3	0.038416	0.058808
5	0.019208	0.020392
6	0.000392	0.001184
8	0.000784	0.000792
11	0.000008	0.000008

$$Probability = 0.02 * (1 - 0.02) * (1 - 0.02) + 0.02 * (1 - 0.02) * (1 - 0.02) \quad (5)$$

In realistic systems, the number of units is huge. Exhaustively enumerating the service status combinations of all units is not feasible in terms of the large computation efforts. Techniques have been developed to create capacity outage table for real systems. More details can be found in [7].

Reliability indices can be mathematically calculated with combining system load profile and capacity outage probability table. LOLE can be measured by different period, such as hours/year, days/year or hours/month. Equation (6) shows LOLE calculation. If an annual

system load is provided on hourly basis, in the equation, N is the total number of hours in a year. LOLE is the accumulated value of loss of load probability at each hour. Probability of loss of load at individual hour can be directly obtained from the capacity outage probability table.

$$LOLE = \sum_{i=1}^N P_i(C_i - L_i) \quad (6)$$

where, C_i is total capacity in system at hour i , L_i is system load at hour i , and $P_i(C_i - L_i)$ is the probability of loss of load at hour i .

Analytical method generally provides expectation reliability indices in a relatively short computing time. It relies on capacity outage table that tells the exact probability of each level of outage capacity. However, building capacity outage table for the real power systems is much more complicated due to the huge amount of outage combinations among generators in the system.

2.2.2. Monte Carlo Simulation Based Method

Monte Carlo methods are a class of computational algorithms that rely on repeated random sampling to compute the statistics. More broadly, Monte Carlo methods are useful for modeling phenomena with significant uncertainty in the systems. It is used for obtaining numerical solutions to problems which are too complicated to solve analytically. In an analytical method, unfortunately, assumptions are frequently required in order to simplify the problems. The resulting analysis possibly fails to catch its significance. Particularly, when complex systems and complex operating procedures have to be considered, analytical method is not even capable to achieve the correct solution. Therefore, the simulation techniques are very important in the reliability evaluation in such situation. In the past, the majority techniques for reliability evaluation are analytical based methods. Nowadays, especially after the booming of power markets, Monte Carlo simulation is increasingly considered by system

planner due to the capability of modeling system behavior more comprehensively and informatively. Sequential Monte Carlo method is typically applied for solving the uncertainty of a system in chronological order. If the operating life of the system is sufficiently simulated using Monte Carlo method, it is possible to conclude the behavior of the system and obtain a clear picture of the type of deficiencies that the system may suffer.

Monte Carlo simulation methods estimate power system reliability indices by simulating the actual operations and random events in the system. The method treats the problem as a series of real experiments. The techniques can take into account virtually all aspects and contingencies inherent in the operation of a power system. The goal of Monte Carlo simulation is to achieve the statistics of the realistic system by making a large amount of trials for the happening in the system. This recorded information permits the expected values of reliability indices together with their frequency distributions to be evaluated. First of all, it is worthwhile to introduce the basic concepts of power system operations.

2.2.2.1. Power System Operations

A power system is an extremely large and complicated system that contains thousand of individual components. The most important goal in power system operation and planning is to continually provide reliable electric energy to customers. Meanwhile, the system must optimize the available resources to minimize the total system production cost subject to all kinds of constraints.

In Unites States, besides the traditional vertically-integrated utilities, power markets are established all over the places. ISO and RTO are not-for-profit corporations that ensure the reliability of electric power supply systems, operate and administer wholesale electricity markets and manage the regional electric resource and transmission planning for its control area. The existing power markets in Unite States include:

- ◆ Pennsylvania New Jersey Maryland Interconnection (PJM RTO)
- ◆ New York ISO (NYISO)
- ◆ ISO New England (ISO-NE)

- ◆ California ISO (CAISO)
- ◆ Midwest ISO (MISO)
- ◆ Southwest Power Pool (SPP)
- ◆ Electric Reliability Council of Texas (ERCOT)

A control area overseen by ISO consists of generating units, load and transmission facilities that are owned by market participants. An ISO optimizes the available resources to minimize the total system production cost subject to all kinds of constraints. Typically, in a power market, the operating activities are broken down into two settlement systems and performed on continuously basis. The simple description of the two settlement systems, day-ahead market and real-time market, can be found as follows.

In day-ahead market, the basic information needs to be collected from market participants for the following day scheduling are load forecasting, renewable generation forecast, generator bid cost and load purchase offer. System operators will perform least cost Security Constraint Unit Commitment (SCUC) to determine the next day hourly schedule of generators considering all system constraints.

In real-time market, system operators make any necessary refinement for generating resources to closely serve actual system load during the day of operation by performing least cost Security Constraint Economic Dispatch (SCED) for every five minutes. The real-time system conditions could deviate from the forecasted value and incur unexpected contingencies. Random events, such as generator forced outage, may happen any time during operation.

The operation activities in the form of a time line that is referred from scheduling operation manual of PJM market is shown in Figure 2-2 [8]. The reference point of the timeline is the operating day. Specific detailed operation rules can be found in different power markets.

2.2.2.2. Unit Commitment

Among the operation procedures, unit commitment is very critical. Firstly, it decides the available capacity to be dispatched for load serving during real time. Secondly, it affects overall system economic efficiency. Meanwhile, it has to take system uncertainties into account so that sufficient capacity is available for maintaining system reliability. Unit commitment problem can be defined as the production scheduling of electric power generating units over certain time horizon. Meanwhile, the problem solution must respect both generator physical constraints and system operational constraints. The key outcomes determine each generating unit's hourly status that is to either be committed online, namely, synchronized with system or stay offline. Unit commitment is essentially an optimization problem that can be mathematically represented by Equation (7) to Equation (14) in which each generator is marked by unit index i and hour number t .

$$\text{Minimize} \quad \sum_{i,t} \text{FixedCost}_{it} + \sum_{i,t} \text{GenerationCost}_{it} + \sum_{i,t} \text{StartupCost}_{it} \quad (7)$$

subject to,

$$\sum_i \text{TotalGeneration}_{it} = \text{Load}_t \quad (8)$$

$$\sum_i \text{SpinningReserve}_{it} = \text{SpinningReserveRequirement}_t \quad (9)$$

$$\text{MinimumCapacity}_i \leq \text{Generation}_{it} \leq \text{MaximumCapacity}_i \quad (10)$$

$$\text{MinimumUpTime Constraint} \quad (11)$$

$$\text{MinimumDownTime Constraint} \quad (12)$$

$$\text{Ramping Constraint} \quad (13)$$

$$\text{Transmission System Constraint} \quad (14)$$

The objective function of the optimization is to minimize the total system production cost that contains:

- ◆ Fixed cost is a constant cost whenever the generator is committed and not associated with generation dispatch.
- ◆ Generation cost associated with dispatch amount of a generator typically includes fuel cost and Operation and Maintenance (O&M) cost.
- ◆ Startup cost is the cost for turning on a generator from offline status. Because the temperature and pressure of a thermal unit must be moved slowly, a certain amount of energy must be expended to bring the unit on-line. This energy does not result in any generation from the unit and it brought into the unit commitment problem as startup cost.

There are different kinds of constraints that make the optimization really complicated.

- ◆ Energy balance constraint makes sure total generation from committed generators meets system load for each hour.
- ◆ Operational spinning reserve as a part of ancillary services is to help maintain the security and the quality of electricity supply. Spinning reserve can be generally defined as the unused capacity which can be activated on decision of the system operator and which is provided by generating units which are synchronized to the network and able to affect the active power. Spinning reserve is a critical resource to respond to unforeseen events, such as unit forced outage, wind generation forecast error. Its requirement can be given by a fixed value based on the most serious contingency. Spinning reserve amount from qualified generators needs to satisfy system reserve requirement.
- ◆ Total output from each generator is limited by maximum and minimum capacity.
- ◆ Output from each generator for spinning reserve purpose is limited by maximum and minimum spinning reserve capacity.
- ◆ Minimum up time, also known as minimum run time, is the minimum number of hours of operation at or above the minimum generation. In another word, once the

unit is committed to generate power, it must stay online and can not be turned off for specific hours.

- ◆ Minimum down time is the minimum number of hours between the time the generator is shut down and the time the generator is re-committed to generate power.
- ◆ Ramping constraints restrict the deviation of individual generation dispatch between present hour and next hour in terms of ramp up rate and ramp down rate.
- ◆ Transmission constraints honor the limitation of the transfer capability of transmission systems, such as thermal rating of individual transmission line, contingency constraint, flow gate constraint, etc.

Unit commitment could be a large-scale and very complicated optimization problem according to the size of system, required constraints and the level of model details. Unit commitment can be solved by various optimization methods, such as priority-list schemes, Dynamic Programming (DP), Mixed Integer Programming (MIP) and so on. MIP is able to very well represent unit commitment. Term “Integer” in MIP appropriately represents the binary variable for the hourly commitment status of a generator. One MIP may determine the hourly generator scheduling for certain period in terms of the planning needs, for example, one day or one week. Therefore, the number of the integer variables for hourly commitment status of individual generator is the total number of hour in the optimization period. Nevertheless, due to the solving difficulty, MIP is still under investigation and improvement. The latest research of unit commitment is detailed in [9].

2.2.2.3. Reliability Assessment

Reliability evaluation using Monte Carlo simulation requires significant amount of calculation effort. The expect value of the statistics based on the simulation results is achieved by largely replicating realistic system planning and operation processes during specific period. Chronological load profile needs to be prepared. A typical procedure is consisted of the following steps.

1. Simulation starts typically at the beginning of a year.

2. Perform day-ahead unit commitment.
3. Perform real-time operation by economic dispatch based on generator availability and load profile. Meanwhile, system random behaviors, such as generator forced outage, are modeled.
4. Repeat step 2 and step 3 until the end of the year.
5. Count the annual number of hours at which the total available generating capacity is not enough to serve the corresponding load. Sum up the amount of unserved load for all hours, if any, to get total unserved load in MW for the whole year.
6. Repeat step 1 to 5 until the stop criterion, such as the maximum number of replication, is reached.

After plentiful replications of system operation for the same period, statistic expectation of any system performance is computed. Calculation of reliability indices LOLE and EENS can be found in Equation (15) and Equation (16), where N is the total number of trials and y is the trial number.

$$LOLE = \frac{\sum_{y=1}^N \text{Total Hours of Loss of Load}_y}{N} \quad (\text{Hours / Year}) \quad (15)$$

$$EENS = \frac{\sum_{y=1}^N \text{Total Amount of Loss of Load}_y}{N} \quad (\text{MWh / Year}) \quad (16)$$

Chapter 3 Wind Power Generation Fundamentals

3.1. Wind Power Production

The kinetic energy per unit time, or power, from wind is given by Equation (1) [10]. Wind power is proportional to the cube of the wind velocity.

$$\text{Power of Wind} = \frac{1}{2} * \rho * A * V^3 \quad (1)$$

where, P is power in watts, ρ is air density in kg/m³, A is area exposed to the wind (m²), and V is wind speed in m/s.

The actual power production potential of a wind turbine must take into account the fluid mechanics of the flow passing through a power producing rotor, the aerodynamics and efficiency of the combination of rotor and generator. In practice, a maximum of about 45% of the available wind energy is harvested by the best modern wind turbines. Power output from wind turbine can be seen in Equation (2).

$$\text{Wind Turbine Power Output} = \frac{1}{2} * \rho * A * C_p * V^3 * N_g * N_b \quad (2)$$

where, P is power in watts, ρ is air density in kg/m³, A is area exposed to the wind (m²), V is wind speed in m/s, C_p is performance coefficient (Maximum 0.59), N_g is generator efficiency (80% on average for grid-connected induction generators), and N_b is gearbox and bearings efficiency (Maximum 95%).

The power produced by a wind turbine can be shown by a power curve. The power curve of a wind turbine is a function that indicates how large the electrical power output will approximately be for the turbine at different wind speeds. The power curve illustrates three important characteristic velocities:

- ◆ Rated wind speed: the wind speed at which the rated power of a wind turbine, generally the maximum power output of a generator at highest efficiency, is produced.
- ◆ Cut-in wind speed: the minimum wind speed at which a generator starts delivering power.
- ◆ Cut-out wind speed: the maximum wind speed at which the turbine is allowed to produce power, usually limited by engineering design and safety constraints. No power will be produced by a wind turbine beyond the cut-out speed.

Figure 3-1 shows the power curve of GE 3.6 MW offshore series wind turbine, where rated speed is 14 m/s, cut-in speed is 3.5 m/s and cut-out speed is 27 m/s.

Figure 3-1 Power curve of GE 3.6 MW offshore wind turbine

A group of wind turbines at the same location are interconnected with a medium voltage power collection system and communication networks, which forms a wind farm. Figure 3-2 shows a typical configuration of a wind farm. The power generated from individual turbine

are aggregated and delivered to major power systems from the substation at wind farm through transmission systems. A wind farm may be located offshore to take advantage of strong and steady winds blowing over the surface of an ocean or lake.

Figure 3-2 Wind farm configuration

3.2. Impacts on Power Systems

In chapter one, the favorable and unfavorable features of wind generation are described. Even though wind generation brings various benefits to power system, it introduces challenges to electric grids due to its unpredictability, intermittence and high fluctuation. Wind generation, as an uncontrollable generating resource, will impact power system long-term planning and short-term operation process.

During operation scheduling stage, system operators assume to employ the best forecasted wind generation for making commitment decision of conventional generators. Certain amount of capacity including energy and reserve requirement will be committed online at designated time to server upcoming, typically next day, load demand. While it is very

difficult to accurately forecast wind generation and no perfect wind forecasts are guaranteed. Consequentially, difference between forecasted and actual amount of wind generation will raise issues for system reliability and extra operating cost during operating hours. There are two scenarios can be expected.

3.2.1. Under forecast of wind generation

The day-ahead forecasted value is less than the real-time actual value, which possibly leads to over-commitment. If capacity is over-committed, some units might need to reduce dispatch at real time. If capacity is too much over-committed, consequently, the total minimum capacity of all the committed generators is greater than the actual net load that is difference between actual load and actual wind generation. In order to maintain operation feasibility, some generators have to be shut down or wind generation is curtailed. The reason of this is that the forecast of wind generation is much low than the actual wind generation. Unnecessary startup or shutting down will incur additional operating cost. However, under forecast of wind generation will normally not jeopardize system reliability.

3.2.2. Over Forecast of Wind Generation

The day-ahead forecasted value is greater than the real-time actual value. In this scenario, committed capacity, as well as the import power from outside of the system, which are scheduled during day-ahead unit commitment, may not be able to entirely meet the real-time net load. Typically, operation reserve will pick up a small amount of generation deficiency. If operation reserve is not enough to deal with such emergency, in result, during real-time dispatch, more expensive units including quick start units must be immediately fired up to recover the capacity shortage, which will also cause energy price rising. If available units are not quick enough to respond, load shedding will happen.

Wind characterizes volatility and unpredictability, so does wind generation. Moreover, the fast ramping up and down is hard to be captured by day-ahead hourly forecast and large forecast error between day-ahead forecast and the actual value at present hour is expected.

Figure 3-3 shows the historical hourly generation of wind farm Prince in Canada on September 7th, 2007. It is obviously to see the fast ramping up and down in the plot. Wind generation suddenly drops 92 MW from 2pm to 3pm and bumps up 108 MW from 4pm to 5pm. These features of wind generation will make difficulties for system operation and forecast, particularly, when high wind penetration happens in bulk power systems.

Figure 3-3 Fast ramp up and down of wind generation

From the analysis of the impacts by wind generation, on the one hand, the system may incur additional operating cost due to the adjustment of operation scheduling. On the other hand, more seriously, system reliability is potentially endangered due to the unfavorable features of wind generation that may create operation difficulties. Actions, such as adjustment of spinning reserve requirement, preparation of more quick start units, must be taken when high penetration of wind generation occurs in power systems.

3.3. Wind Energy Forecasting

One of the most important prerequisites for effective wind power planning and operation in bulk power systems is the precise wind power and speed forecasting. Highly random

fluctuation of wind affected by conditions of atmosphere, weather and terrain results in the difficulties of forecasting and it happens on all time scales from short-term to long-term. In comparison with load daily, weekly and seasonal patterns, there are much less patterns of wind can be obeyed. Therefore, wind generation is considered as one of the most difficult predictable variables [11]. Wind power forecasting were investigated over the decades, some researches can be seen in [12], [13], [14], [15], [16], [17] and [18].

Basic economic operating functions such as unit commitment, interchange evaluation and security assessment require a reliable and accurate wind power forecasting. The applications of wind power forecasts over a varying period of time include following items:

- ◆ Very short-term wind forecast from seconds to minutes is applied for wind turbine control systems that include yaw orientation and blades rotation.
- ◆ For the optimization of conventional power plants scheduling, such as economic dispatch, prediction horizons can vary from minutes to several hours depending on the size of the system and the types of conventional units.
- ◆ In day-ahead market, predictions looking ahead from 1 hour to 48 hours are required by different types of end-users for different functions such as unit commitment, dynamic security assessment for operators, bidding strategies for market participants in the power market.
- ◆ Longer time scales would be interested by maintenance planning of large power plants, wind turbines or transmission systems. However, the accuracy of weather predictions decreases strongly looking at 5-7 days in advance.
- ◆ Long-term wind forecasts is used for development planning of wind power generation, as well as power system planning with integration of wind generation.

3.3.1. Importance of Wind Forecasting

Accurate wind power forecasts are beneficial for wind plant operators, utility operators, and utility customers. An accurate forecast allows grid operators to schedule generation economically and efficiently to meet demand of electrical customers. In particular, under

deregulated power market environment, reliable long-term wind power forecast is beneficial for system resource and transmission planning to ensure the generation adequacy. Furthermore, as the must-taken energy, wind generation plays a very important role by straightly impacting SCUC and SCED, reserve requirement and market clearing price in day-ahead and real-time market. System operators will be benefit from accurate short-term wind forecasting by economically scheduling generation to reliably serve the load.

3.3.2. Wind Forecasting Methodology

Persistence forecasting model, also called naive method, is the most frequently used model. It is the simplest forecasting models. In this model, forecast for all times ahead is set to be the value as present value, in another word, wind speed at time $t + x$ is the same as it was at time t . For short-term forecast, persistence model performs very well for up to 3 hours ahead forecast. The accuracy of this forecasting method quick reduces when increasing x . Therefore, by definition, error for zero time steps ahead is zero. For short prediction horizons (seconds, minutes to hours level), this model is the benchmark all other prediction models have to beat.

The common used criteria to evaluate the performance of wind power forecasting are listed below. They are computed by comparing wind power forecasts with historical data or persistent model forecast results.

- ◆ Root Mean Square Error (RMSE)
- ◆ Mean Absolute Error (MAE)
- ◆ Median Error (ME)
- ◆ Frequency distribution of error

Short-term wind power forecasting is used for wind turbine controls, real-time dispatch or generation scheduling depending on the time scale of specific purpose. In general, forecasting methods can be broken down into two main categories or their combination.

- ◆ Physical model considers Numerical Weather Prediction (NWP), detailed conditions of wind farms and their surrounding terrain. It reaches the best possible estimation of the local wind speed and reduces the remaining error.

- ◆ Statistical time-series related methods include Auto-Regressive Moving Average (ARMA) [12], [13], Artificial Neural Networks (ANN) [14], [15], Fuzzy Logic [16], Kalman Filter, and so on. Statistical models catch the relationships between variables including NWP results and online measured data and usually employ recursive techniques. Prediction capabilities and accuracy of the models or their combination are quite different in terms of forecasting interval. The overview of short-term wind power forecasting methodologies and their corresponding performance can be found in [17]. Typical input and output data of commercial wind power forecasting tool can be found in Figure 3-4.

Figure 3-4 Structure of commercial wind power forecasting tool

Long-term wind forecasting typically scaled from several months to multiple years is applied to estimate overall wind resource condition, optimize wind turbines layout in a wind farm and determine the wind farm sites. A number of possible approaches including statistical method, computer modeling, wind atlas, ecological methods have been developed.

3.3.3. Time Series Models

One of the widely used time series models is Auto-Regressive Moving Average (ARMA). ARMA procedure analyzes and forecasts equally spaced univariate time series data, transfer function data, and intervention data. An ARMA model predicts a value in a response time series as a linear combination of its own past values, past errors and current and past values of other time series. The model is usually referred to as ARMA (p, q) model where p is the order of auto-regressive part and q is the order of the moving average part. Mathematical representation of ARMA (p, q) can be seen in Equation (3).

$$x_t = \varepsilon_t + \sum_{i=1}^p \varphi_i x_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} \quad (3)$$

where, $\varphi_i (i=1,2,\dots,p)$ are the parameters for Auto-Regressive (AR), $\theta_j (j=1,2,\dots,q)$ are the parameters for Moving Average (MA), and ε_t is a normal white noise process with zero mean and a variance of σ_a^2 , namely, $\alpha_t \in N(0, \sigma_a^2)$.

An ARMA analysis is typically divided into three stages, corresponding to the stages described by Box and Jenkins [19].

1. **Identification:** In the identification stage, the response series will be specified. The pre-processing of the input time series includes basic statistics analysis, computation of autocorrelations, inverse autocorrelations, partial autocorrelations, and cross-correlations. Stationarity tests can be performed to determine if differencing is necessary. The orders of AR and MA will be tentatively determined.
2. **Estimation:** In the estimation and diagnostic checking stage, the parameters of ARMA model to fit to the variable specified in the previous stage will be estimated. Diagnostic statistics can be produced to judge the adequacy of the model. Significance tests for parameter estimation indicate whether some terms in the model might be unnecessary. White noise tests for residuals indicate whether the residual

series contains additional information that might be used by a more complex model. If the diagnostic tests indicate problems with the model, another model will be estimated and then repeat the estimation and diagnostic checking stage.

3. **Forecasting:** In the forecasting stage, future values of the time series will be forecasted based on the selected ARMA model from previous stage and confidence intervals for these forecasts from the ARMA model will be generated as well.

3.4. Capacity Value of Wind Power

Wind generation brings a great amount of benefit to power systems, such as cheap energy, emission reduction, power provision for remote areas, etc. However, whether a WTGS can be assigned any capacity credit is controversial among power markets and utilities. If so, how much appropriate capacity credit can be assigned?

Capacity value of a wind generating system must be carefully decided. In order to ensure electric supply reliability, ISO and RTO as well as utilities measure resource adequacy. When capacity value of wind generation is considered as part of generation planning process, system operators and planners are able to estimate conventional generation expansion in which the sites, timing and amount of new generation additions are determined. Accurately evaluating wind capacity value may stint the investments of new generation additions for the purpose of maintaining capacity reserve. When wind capacity value is underestimated, system may overpay for reliability by investing too much reserve capacity.

Capacity value of a WTGS can be paid in capacity markets. In a deregulated power market environment, wind generation is treated as the must-taken energy and is paid based on market clearing price and the amount of generation. According to different markets settlement rules, a WTGS will be charged for penalty cost if scheduled energy can not be delivered on time. The economic benefit of a WTGS can not be guaranteed all the time. In addition, subsidizing program and tax reduction are founded for the economic incentives for wind power development. A WTGS may receive revenue from capacity markets based on its capacity value. Generally speaking, in a locational capacity market, suppliers are paid based

on their demonstrated ability to supply energy or reserves in shortage hours in which there is a shortage of operating reserves. Thus, only supply that contributes to reliability is rewarded [20]. Revenue from capacity market is the supplement of WTGS's revenue received from the energy and reserves markets.

3.4.1. Methodologies for Capacity Value Estimation of A WTGS

Capacity value of a WTGS is determined mainly by its impact on power system reliability and resource scheduling. In general, capacity value of a generating unit is not the nameplate capacity and primarily depends on the actual availability of generating capability during critical periods with high risks, such as system peak load period, which can be determined based on the installed capacity, force outage rate, maintenance requirement, fuel availability, and so on.

Because wind generators only generate electricity when wind blows, effective forced outage rate, namely, the probability of unavailability, for wind generators may be much higher than one of conventional generators when recognizing the intermittent, fluctuant availability of wind. In addition, capacity value of a WTGS to a specific electric system may also vary quite a bit. Generation from certain wind farms may highly positively correlate with system load and thereby can be seen as supplying capacity when it is most needed. In this situation, a wind generating plant should have a relatively high capacity credit. On the other hand, output from other wind generating plants could be out of phase with system load, and therefore a lower capacity value to the electric system should be assigned [21].

A metric evaluating capacity value needs recognize the probability of generating failure during critical period and reward a generating unit that experiences less outage more capacity credit than the one with more unavailability. The capacity value must therefore be a probabilistic-based metric that can take wind generation and system load profile into account. The way to assign capacity credit for a WTGS currently varies among power markets and utilities [22]. Basically, there are three methods to estimate the capacity value of a WTGS.

3.4.1.1. Effective Load Carrying Capability (ELCC)

ELCC is deemed the prevalent metric of the capacity value of any generating unit. The very original concept of ELCC was developed in 1966 and can be found in [23]. Conceptually, ELCC is the additional load peak value that can be served with satisfying the same reliability standard of existing system after the integration of any new generating unit. It also can be applied to evaluate the capacity value for a wind generating system, such as a wind farm, that produces the energy aggregated from individual wind turbine. ELCC can be carried out by a power system reliability model. If yearly LOLE is measured for reliability index, Equation (4) shows the calculation of ELCC.

$$LOLE(\sum_{i=1}^N C_i, L) = LOLE(\sum_{i=1}^N C_i + \sum_{j=1}^M W_j, L + ELCC) \quad (4)$$

where, N is the number of existing generating units, C_i is the capacity of unit i , L is annual peak load, M is the number of additional wind farms, W_j is the capacity of wind farm j .

The left hand side stands for the reliability value of existing system with N generating units. After integrating M wind farms into system, ELCC value can be found using the new system peak load when the reliability value in the right hand side is equal to the one in left hand side. Figure 3-5 more vividly explains the concept of ELCC. The blue line is assumed the reliability criterion R_c , for example, 1 day in ten years. ELCC is the difference part on the blue curve between existing system and the new system with new wind generation.

Figure 3-5 ELCC illustration

3.4.1.2. Equivalent Conventional Generating Unit

The characteristics of the conventional generating units, such as thermal units and hydro units are well known. The method is to compare a WTGS with a conventional generating unit to server the same system load at same reliability level and take the capacity of the conventional generating unit as the capacity value of a WTGS.

Firstly, the existing power system is modeled without a WTGS. By using a reliability evaluation model, system load is adjusted to achieve a certain level of reliability requirement, for example, LOLE of one day in ten years. Once the desired LOLE target is achieved, the WTGS is integrated into the system and the system reliability is re-estimated. The new, lower LOLE (higher reliability) is noted, and the WTGS is removed from the system. Then the benchmark unit is added to the system by taking small incremental capacities until the LOLE with the benchmark unit matches the LOLE that was achieved with the WTGS. The capacity of the benchmark unit is then noted, and becomes the ELCC of the renewable generator. It is important to note that the ELCC documents the capacity that achieves the same risk level as would be achieved without the renewable generator.

3.4.1.3. Customized Capacity Factor Method

The capacity factor method is a much simplified method than the previous two in terms of the data collection and computation effort. The only required data are hourly load profile and hourly wind generation for at least one year. This approach is appealing in its simplicity, but it does not capture the potential system risks that are part of the other methods discussed above. Capacity factor of a generating unit during certain period is defined as the ratio of the average generation and its installed capacity. Capacity value of a WTGS can be straightforward calculated by the wind capacity factor over specified time period, for example, peak load months. Typically, the calculations are carried out for the top 1% to 30% of highest loads, using an increment of 1%. Although an ideal match can not be achieved, the result of capacity factor method should be within a few percentage of deviation from the ELCC using reliability model.

Chapter 4 Reliability Assessment of Power Systems with Wind Power Generation

4.1. Introduction

In order to address the wind power integration issues, particularly, the impact on power system reliability, a Monte Carlo based production cost simulation model is proposed and developed in the thesis. The major objective is to evaluate reliability of a power system integrated with wind power by simulating realistic system planning and operation process.

Monte Carlo simulation method estimates reliability indices by repeatedly simulating actual day-to-day scheduling and hour-to-hour operation of a power system and random behaviors in the system. Hence, the enhancement of Monte Carlo simulation for a system including wind generation is investigated. In order to mimic operational procedures, especially under present power market environment, unit commitment is performed one day in advance to the actual operating day in the model and pre-determines the generating utilization of conventional units at each hour of next day based on forecasted load and forecasted wind generation, as well as reserve requirement. Unit commitment also addresses system economics to ensure cost efficiency. During real-time operating hours, available capacity based on day-ahead unit commitment decision is ready to serve net load that is the value subtract actual wind generation from actual load. Meanwhile, system is facing random generator forced outages and deviation between forecasted and actual value of load and wind generation. Emergency actions, such as applying spinning reserve and committing quick start units are taken, if available capacity is insufficient. Hourly wind generation applied for day-ahead unit commitment is forecasted based on historical values. Therefore, an automatic

forecasting process of day-ahead hourly wind generation has been developed as well using ARMA model.

4.2. Monte Carlo Based Production Cost Simulation Model

Monte Carlo simulation especially for reliability evaluation is typically performed on yearly basis and it requires large amount of trials to replicate hour-to-hour system operations through a year. During each yearly simulation, random events, such as generator outages, will happen on hourly basis.

The main structure of Monte Carlo simulation is illustrated in Figure 4-1. There are three major iteration loops including, Monte Carlo replication loop, daily loop and hourly loop. Simulation starts from the first hour of the simulation year at first trial. Within the Monte Carlo replication loop, simulation advances from the beginning of the year to the end of the year. Unit commitment is performed in the daily loop to determine commitment status of each generator in the next day. At each real-time hour, generation scheduling and emergency actions will be executed to simulate actual system conditions. After completing the whole year simulation, program will reset all the variables and replicate the yearly simulation again until the maximum number of trials is reached. At the end of all the simulations, reliability indices and other statistics such as generation utilization and system economics are calculated. The main reliability indices used in the research are LOLE and EENS. LOLE (Hours/Year) measures how many hours on average loss of load occurs in the system and EENS (MWh/Year) shows the average total energy of load shedding in a year.

Figure 4-1 Main structure of the simulation model

4.2.1. Model Input and Output

Reliability study period is typically one year. Therefore, temporal data input must be provided for the whole simulation year. The data flow can be seen in Figure 4-2.

Figure 4-2 Model input and output

The main inputs of simulation engine include:

- ◆ Hourly system load profile for the simulation year
- ◆ Hourly wind generation of individual wind farm for the simulation year
- ◆ Conventional generating units data
 - Maximum capacity and minimum capacity
 - Forced outage rate (FOR) and Mean Time To Repair (MTTR)
 - Minimum up time and minimum down time
 - Combined cost considering fuel cost, startup cost and O&M cost
 - Quick start capability

After Monte Carlo simulation, the major output results include:

- ◆ Reliability indices
 - Loss of Load Expectation (LOLE) and Expected Energy Not Served (EENS)
 - Histogram and variation curve of loss of load
- ◆ Statistics for conventional generating units

- Generation utilization
- Commitment of quick start units, etc.

4.2.2. Daily Loop for Day-ahead Unit Commitment

Unit commitment can be a very complicated optimization problem depending on different modeling purposes. When it is formulated by a mixed integer problem, however, the unit commitment problem will be definitely a very large and complex mathematical programming problem. For instance, in a small power system that contains 17 generators to be scheduled over a seven-day (168-hour) period, MIP requires more than 25755 variables including 2856 integer variables and 48939 constraints [9]. Solving MIP takes a great amount of computation efforts. Monte Carlo simulation requires a large amount of replications of operations thought a year and can not afford such a time-consuming optimization model.

Therefore, in the research, the optimization of unit commitment is reasonably simplified to adapt for the Monte Carlo simulation without compromising the critical constraints. The solution of simplified unit commitment is capable to capture the major operational schedules and reflect the system economics to ensure cost efficiency. No similar to the complex MIP that combines schedules of multiple hours into one objective function, the unit commitment of reliability evaluation is solved for individual hour. The flow chart of day-ahead unit commitment procedure is shown in Figure 4-3. Every day-ahead unit commitment is broken down into 24 sub-optimization problems for each hour in a day. Operational constraints are imposed for each sub-optimization. The decomposition is mainly based on the approximation on the cost associated with generating units.

Figure 4-3 Flow chart of day-ahead unit commitment

4.2.2.1. Variable Cost of Generating Units

Cost of producing power for individual generator is a critical factor to decide its commitment status. The approximated variable cost is determined as follows. With the approximation of cost, unit commitment can be simplified and completed on hourly basis.

Startup cost is the cost for turning on a generator from offline status. Startup cost in dollar may vary from a maximum cold-start value to a much smaller value if the unit was only turned off recently and is still relatively close to operation temperature. The difficulty to consider startup cost in unit commitment logic is that the startup cost is given by a dollar amount while variable cost requires dollar per MWh in the model. An empirical formula in Equation (1) can be used to convert startup cost in dollar for the need for unit commitment. Total generation per cycle in denominator is an estimated energy production from one commitment to the immediate de-commitment based on the feature of a unit. The calculated value reflects the startup cost in dollar is allocated to each unit of generation. For example, on average, a base load coal unit generates power normally for one week (168 hours) for each start. An expensive gas turbine normally dispatch during peak load period only for several hours.

$$\frac{\text{Startup Cost}}{\text{Total Generation in One Cycle}} \Rightarrow \$ / MWh \quad (1)$$

O&M cost represents the non-fuel cost component that is proportional to generator output. O&M cost is normally provided in \$/MWh and can be varied monthly and annually.

For a thermal unit, fuel cost is a major part of the total cost for generation. Fuel cost of different types of thermal generator may vary quite a bit depending on generation efficiency and usage of certain fuel type. The function between generation and fuel consumption can be represented by heat rate. A net heat rate characteristic of a steam turbine generator is shown in Figure 4-4.

Figure 4-4 Net heat rate of a steam turbine generator

In power industry, full load average fuel cost is commonly used for unit commitment purpose and can be interpreted as the total fuel cost when the generator dispatches at the maximum capacity. The cost of fuel is expressed in \$/MMBtu and can be varied thought time. Then the fuel cost per MW of a generator can be calculated by Equation (2).

$$FuelCost(\$ / MWh) = \frac{FuelConsumption @ MaxCap(MMBtu)}{MaxCapacity(MWh)} * FuelPrice(\$ / MMBtu) \quad (2)$$

4.2.2.2. Generator Availability

For any time of a year, it is not necessary that all the generators in the system are flexible to be scheduled due to operational limitations. At the beginning of each unit commitment, unit availability is verified based on forced outage status, minimum up and down time, as well as maintenance status.

- ◆ **Maintenance:** Every year, a generator is required to be maintained for specific period to make sure the normal operation. During maintenance period, the generator will not

be available to dispatch. Generator maintenance is well planned in advance by staffs who manage the generation plant.

- ◆ **Forced Outage Status:** A generator can be randomly forced offline any time during the course of a year and will not be able to generate power for certain period that depends on how fast the outage problem is fixed. In the simulation, forced outage duration is decided by MTTR. For example, a typical MTTR value of a small gas turbine whose maximum capacity is less than 100 MW is 64 hours, according to Generating Unit Statistical Brochure (2000-2004) [5]. Due to remaining in forced outage, the unit will not be available to be committed to generate power. If a large amount of forced outages happen at the same time, the system will face capacity shortage and possibly shed load.
- ◆ **Minimum Up Time (MUT):** In the simulation, program starts counting the minimum up time of a generator whenever the generator is committed from off-line at any hour. In the unit commitment routine, the generators that are restricted by minimum up time will not be involved in the optimization of unit commitment. Instead, they will be forced online and total value of their maximum capacity will be considered for the hourly committed capacity requirement.
- ◆ **Minimum Down Time (MDT):** In the simulation, program starts counting the minimum down time of a generator whenever the generator is de-committed from dispatch. At any hour, the generators that are restricted by minimum down time will not be involved in the optimization of unit commitment. Instead, they will be forced offline. No capacity will be considered for serving load at present hour.

Typically, for thermal generators, large units require higher value of minimum up/down time than small units. For example, according to the unit parameter summary from PJM [8], minimum down time of a small combustion turbine with up to 29 MW capacity is 2 hours or less, comparatively, minimum down time of a large coal unit with hundreds of MW capacity requires 84 hours.

4.2.2.3. Commitment Decision

The requirement of committed capacity for each hour of next day must be decided before unit commitment routine. During the day-ahead unit commitment, the actual load demand and actual wind generation for next day are unknown. The day-ahead hourly forecasted values will be used for how to schedule the conventional generation in advance. In the simulation, spinning reserve is calculated based on the specific percentage of hourly load value and varies though time. The percentage value of spinning reserve must be carefully decided because it will directly affect the unit commitment and impact overall reliability. When the percentage is too low or zero, there may not be enough committed capacity to cover the uncertainty to keep system reliable. On the other hand, high reserve requirement that strengthens system reliability may show economically unreasonable, because redundant capacity will be synchronized online. A tradeoff between system reliability and economics must be made for spinning reserve requirement. In all, the committed capacity requirement at certain hour that determines the amount of committed units is calculated in Equation (3).

$$\text{CommittedCapacityRequirement} = \text{NetLoad} + \text{ReserveRequirement} \quad (3)$$

where,

$$\text{NetLoad} = \text{ForecastedLoad} - \text{ForecastedWindGeneration} \quad (4)$$

$$\text{ReserveRequirement} = \text{ForecastedLoad} * \text{ReservePercentage} \quad (5)$$

Once the available generators for individual hour unit commitment are found, this group of generators will be determined who will be committed to dispatch power based on the composite variable cost, which is so-called merit order method. The low cost generator will be committed first and more expensive generator will be continuously committed whereafter until the total committed capacity can meet the net load demand plus reserve requirement, see Equation (6), where net load is forecasted load demand subtract forecasted wind generation.

$$\sum_i MaxCapacity_i \geq NetLoad + ReserveRequirement \quad (6)$$

An example in Table 4-1 shows the status of each generator from the simulation of a test case after unit commitment at specific hour. One may see that there are diversified reasons for determining the commitment status of a unit.

Table 4-1 Commitment status of units

Unit ID	Status	Reason
u1	Must online	Minimum Up Time
u2	Committed	Economic
u3	Committed	Economic
u4	Committed	Economic
u5	Committed	Economic
u6	Committed	Economic
u7	Committed	Economic
u8	Offline	Uneconomic
u9	Offline	Uneconomic
u10	Offline	Minimum Down Time
u11	Offline	Uneconomic
u12	Offline	Forced Outage
u13	Offline	Uneconomic
u14	Offline	Uneconomic
u15	Offline	Forced Outage
u16	Offline	Minimum Down Time
u17	Committed	Economic
u18	Committed	Economic
u19	Offline	Uneconomic
u20	Committed	Economic
u21	Committed	Economic
u22	Committed	Economic
u23	Committed	Economic
u24	Committed	Economic
u25	Committed	Economic
u26	Committed	Economic
u27	Committed	Economic
u28	Committed	Economic

After unit commitment, the following information needs to be updated for usage of the next hour unit commitment.

- ◆ Unit run time hour is reset to be one if the unit is newly committed from offline status at previous hour.
- ◆ Unit run time hour increases one if the unit is continuously committed from committed status at previous hour.
- ◆ Unit down time hour is reset to be one if the unit is newly de-committed from committed status at previous hour.
- ◆ Unit down time hour increases one if the unit is continuously de-committed from offline status at previous hour.

Unit commitment is more art than math. Due to the complexity of the model, no one guaranty the global optimized solution can be achieved, especially for bulk power systems. In the research, Monte Carlo simulation requires large amount of calculation efforts. The tradeoff between how much details are comprehensively modeled and the acceptable calculation efforts has to be made. From the economic point of view, the solution of simplified unit commitment will be definitely not the exactly same as the one from complicated unit commitment. However, the major trends of the usage of different types of units can be still captured, such as that the nuclear units serve based load and gas turbines are committed during peak hours. Simplified unit commitment is expected not to dramatically affect the reliability evaluation if Monte Carlo simulation for long-term period with large number of trials is performed. Moreover, unit commitment is a relatively independent routine in the whole model. Any other unit commitment algorithms can be easily plugged in the model and Monte Carlo simulation can still be performed.

4.2.3. Hourly Loop for Real-time Operation

Hourly loop simulates the events during actual real-time operation. Figure 4-5 shows the main steps in this loop. Randomly forced outage for committed generators is simulated first. Actual generating resource adequacy is evaluated based on the real load demand and wind

generation as well as the available committed capacity. Commitment of quick start units is performed if system faces capacity shortage. Finally, loss of load value is calculated based on actual load demand, actual wind generation and total available committed generating capacity.

Figure 4-5 Logic of real-time operation

In general, uncertainties in the system can be categorized by generation, demand and network.

- ◆ **Generation.** Generator may be forced out of service at any time during the course of a year due to startup failure, equipments faults, human mistake, and so on. Different kinds of generating units behave different uncertainties. Thermal generation can be affected by fuel supply and fluctuation of its price. Hydro generation depends on the stochastic water inflow. The amount of wind generation is fully based on availability of highly volatile wind.
- ◆ **Demand.** Electric demand, an uncontrollable factor in power system, is much relevant to human behavior. Load demand mostly conforms to daily and seasonal patterns and is relatively easy to accurately predict. In addition, the techniques of load forecasting had been researched for decades and are pretty mature. Even though load forecast error cannot be ignored, it will not seriously affect power system reliability.
- ◆ **Network.** Transmission lines as well as distribution feeders may randomly be tripped off because of severe weather, substation failure, etc. Outages of critical transmission lines are considered as serious contingencies and possibly lead to change of power flow pattern, overload of surrounding transmission systems, reduction of transfer capability and even system load shedding. However, since this research focuses on evaluating generation adequacy, transmission random outage is not modeled.

4.2.3.1. Generator Forced Outage

In the program, during real hourly operation, dispatch failure of a generator may happen. In another word, any committed generators can be randomly forced out of service. A forced outage generator does not provide any capacity value to serve system load and it will be back in service after certain time. In the simulation, MTTR determines forced outage duration of a generator.

To determine the forced outage status of a generator, the following steps are processed.

- ◆ A uniform random number U in range 0 to 1 needs to be generated.
- ◆ Compare U and the generator's outage probability in Equation (7).

$$V = \frac{1}{MTTR + MTTF} \quad \text{in times / hour} \quad (7)$$

- ♦ if $U \geq V$, the generator stays online.
- ♦ if $U < V$, the generator is forced outage.

4.2.3.2. Real-time Generating Resource Adequacy

If a generator trips during operation, then system operators must identify generating resource adequacy and if there are any other available resources that they can use to make up for potential power loss. The actual available committed capacity of conventional generators is calculated after processing forced outage of committed generators. At the real-time, load value and wind generation are not necessary exactly same as the forecasted ones. Forecast errors and generator forced outage can possibly lead to the capacity shortage to serve the load. During real-time dispatch, the adequacy of committed capacity needs to be checked according to Equation (8). Available committed capacity comes from subtracting randomly forced outage capacity from total committed capacity of conventional units.

$$\text{Generating Resource Adequacy} = \text{Net Load} - \text{Available Committed Capacity} \quad (8)$$

where,

$$\text{Net Load} = \text{Actual Load} - \text{Actual Wind Generation} \quad (9)$$

If no capacity shortage is found, operations of current hourly loop are completed and no load shedding will happen. However, if the calculated adequacy is greater than zero, emergency commitment of quick start units must be executed.

4.2.3.3. Commitment of Quick Start Units

Adequate fast response operating reserves is critical to maintain secure and reliably power grid operations in anticipation of possible forced outages of generating units. There are

basically two ways to provide the required fast response operating reserves: spinning reserve from on-line generating units and quick start resources from off line units. Spinning reserve refers to the un-utilized capacity of on-line generation that is able to respond immediately to serve load. Quick start resources are not synchronized to the system, but can be started up and loaded to the rated capacity within very short period.

Day-ahead unit commitment commits conventional generating units based on forecasting values of load demand and wind generation. It also takes spinning reserve requirement into consideration to prevent the systems outage from any types of contingencies. Normally, spinning reserve is able to keep system reliability for most of the time. However, when system is facing severe circumstances, such as, multiple outages of large capacity units at the same time or large wind generation forecast errors, quick start units have to be committed to compensate capacity deficiency that can not be provided by spinning reserve.

To avoid loss of load due to either contingency or over forecast of wind generation, quick start units must be prepared in the system. In the simulation model, commitment of quick start units, listed in Figure 4-6, is scheduled during real-time when capacity shortage happens at any hour. Quick start units will be committed economically in terms of composite variable cost. Similar to day-head unit commitment, program also checks the availability of the quick start units in advance based on status of forced outage and commitment status. Commitment of quick start units will be continued until the committed capacity of quick start units fully compensates the capacity shortage. Random forced outage will be applied for the committed quick start units as well. However, the total capacity of available quick start units may not be enough to solve the problem of capacity deficiency. If so, loss of load will occur in the system.

Figure 4-6 Logic of commitment of quick start units

4.2.3.4. Loss of Load Calculation

After committing quick start units, total generating resource is composed of the capacity of available committed conventional unit, the capacity of committed quick start units and actual wind generation. Capacity adequacy at current hour is calculated in Equation (10). If the value is greater than zero, loss of load happens and will be recorded for the overall reliability evaluation.

$$LossOfLoad = ActualLoad - (AvailableCommittedCapacity + ActualWindGeneration) \quad (10)$$

where,

$$AvailableCommittedCapacity = \sum ConventionalUnitCap + \sum QuickStartUnitCap \quad (11)$$

4.3. Day-ahead Hourly Wind Generation Forecasting

If wind generation participates in day-ahead operation schedule, by the end of each day, hourly wind generation of next day needs to be forecasted based on the available historical wind generation. The forecasted 24-hour wind generation will be considered by day-ahead unit commitment to determine the schedules of conventional generating units in the next day. Similar to what happen in the real systems, in the thesis, a process using ARMA model is created and developed to automatically forecast day-ahead 24 hours wind generation for each day in the simulation period, typically one year. And the forecasted wind generation is applied for day-ahead unit commitment routine in the Monte Carlo simulation.

The automatic forecasting process for the whole simulation period can be broken down into individual day-ahead wind generation forecast. For individual forecast process, historical data during certain period is fit into an ARMA model and 24-hour data will be forecasted using a trained ARMA model. Then the training period shift forward by one day, namely, 24 hours and the next forecast process can be performed. One may imagine the automatic

forecast process as a fixed length historical data window that moves from the beginning of the simulation period to the end of the simulation period by the step of one day at a time.

For instance, if the length of historical data window is assumed to be four weeks that contains 672 hourly data, Table 4-2 lists the detailed historical data range and date of forecast for year 2007. For each ARMA process, 672 data will be available to evaluate the parameters for AR and MA and 24 data will be forecasted.

Table 4-2 Data range of each forecasting process

Hourly Historical Data Range	Date of Hourly Forecasts
1/1/2007 - 1/28/2007	1/29/2007
1/2/2007 - 1/29/2008	1/30/2007
1/3/2007 - 1/30/2009	1/31/2007
.....	
.....	
12/2/2007 - 12/29/2007	12/30/2007
12/3/2007 - 12/30/2007	12/31/2007

To further interpret the idea, Figure 4-7 illustrates forecast process for two days in a roll in the middle of year 2007. At the end of 06/28/2007, historical data from 06/01/2007 to 06/28/2007 is prepared for day-ahead hourly forecast for date 06/29/2007. Similarly, at the end of 06/29/2007, historical data from 06/02/2007 to 06/29/2007 will be prepared for day-ahead hourly forecast for date 06/30/2007 and actual hourly data on 06/29/2007 is known by then.

Figure 4-7 Day-ahead forecasts for two consecutive days

SAS/ETS (Econometrics & Time Series) software is applied for analysis of ARMA model in the research. SAS (Statistical Analysis Software) is the most sophisticated statistical analysis tool in the world. The software package, SAS/ETS, offers a broad array of time series, forecasting and econometric techniques that enable modeling, forecasting and simulation of business processes for improved strategic and tactical planning. ETS provides detailed ARMA analysis from identification, estimation to forecast and enables the implementation of automatic process of wind generation forecast.

4.3.1. Automatic Forecasting Process Details

The automatic forecasting process using ARMA will be elaborated in this section. Meanwhile, the process is demonstrated for forecasting the hourly wind generation of Melancthon wind farm in year 2007. Melancthon wind farm has 67.5 MW installed generating capacity and is located around Township of Melancthon in Ontario, Canada. Historical hourly wind generation in year 2007 of the project is shown in Figure 4-8.

Figure 4-8 Hourly wind generation of Melancthon wind farm

Data sanity checking must be done before carrying out the forecasting process. In the original wind generation series of Melancthon I wind farm, abnormal data that appears all zero MW generation was found from 12/01/2006 to 12/10/2006, which is most likely caused by either maintenance of equipments or faults of monitoring systems. To avoid incorrectly ARMA modeling due to any data errors, especially for the forecasts of the hours around the beginning of year 2007, all the abnormal data was replaced by the data during 12/01/2007 and 12/10/2007 by assuming that wind generation patterns are similar during the same period of each year.

When the automatic forecasting is performed for whole year 2007, there are 365 individual forecast processes using ARMA. An ARMA analysis is typically divided into three stages: identification, estimation and forecasting. During identification stage, basic statistics is analyzed for historical data series and the orders of AR and MA are identified by human judgement. Estimation and forecasting can be automatically completed if the orders of AR and MA are given. Length of historical data series also plays an important role that affects overall performance of the automatic forecasting process. An appropriate amount of

historical data for ARMA needs to be found. Once the orders of ARMA and length of historical data series are decided, they will be applied through the whole automatic forecasting process.

In the research, Root Mean Square Error (RMSE), defined in Equation (12), is calculated based on historical value and forecast result of wind generation to evaluate the performance of specific ARMA model.

$$RMSE = \sqrt{\frac{\sum_{hr=1}^N (Hist_{hr} - Fore_{hr})^2}{N}} \quad (12)$$

where, $Hist_{hr}$ is historical value at hour hr , $Fore_{hr}$ is forecasted value at hour hr and N is the total number of hour in the forecast period.

4.3.2. Individual Day-ahead Forecast Using ARMA

Whole year hourly forecast is broken down to individual ARMA forecast. An ARMA process based on the historical hourly wind generation in the third week in February from 02/16/2007 to 02/22/2007 will be illustrated. The data series is plotted in Figure 4-9 and the basic statistics of the series is listed in Table 4-3. ARMA analysis of the given data series is interpreted for three stages: identification, estimation and forecasting.

Figure 4-9 Hourly historical wind generation

Table 4-3 Statistics of the one week hourly historical wind generation

Statistics	Value
Number of Observations	168
Maximum	64
Minimum	0
Mean of Working Series	30.69
Standard Deviation	20.77

4.3.2.1. Identification

During the identification stage, analysis of autocorrelations, partial autocorrelations and inverse autocorrelations are displayed in Figure 4-10. Plots of these autocorrelation functions show the degree of correlation with past values of the series as a function of the number of hours in the past at which the correlation is computed. In this case, a visual inspection of the autocorrelation function plot indicates that the historical series is non-stationary, since the autocorrelations function decays very slowly.

Figure 4-10 Analysis of autocorrelations, partial autocorrelations and inverse autocorrelations

The white noise test bar chart on the right-hand-side of Figure 4-11 shows significance probabilities of the Ljung-Box chi square statistic and their numerical results are listed in Table 4-4. Each bar shows the probability computed on autocorrelations up to the given lag. Longer bars favor rejection of the null hypothesis that the prediction errors represent white noise. In this example, they are all significant beyond the 0.001 probability level, so that the high level of significance at all lags makes it clear that the linear trend model is inadequate for this series. The significance probabilities of the augmented Dickey-Fuller test for unit root are shown in the left-hand-side of figure. For example, the bar at lag zero indicates a probability of 0.4038, so that the null hypothesis that the series is non-stationary is rejected. According to the statistic analysis of the original series in identification stage, different order combinations of AR and MA as well as simple differencing for the original series need to be tested and compared to find the best model.

Figure 4-11 White noise tests and unit root tests

Table 4-4 Autocorrelation check for white noise

To Lag	Chi- Square	DF	Pr > ChiSq	-----Autocorrelations-----					
6	585.35	6	<.0001	0.945	0.876	0.788	0.698	0.596	0.511
12	667.11	12	<.0001	0.424	0.355	0.281	0.214	0.142	0.086
18	683.47	18	<.0001	0.032	-0.019	-0.071	-0.119	-0.164	-0.198
24	733.82	24	<.0001	-0.221	-0.226	-0.223	-0.209	-0.189	-0.172

4.3.2.2. Estimation

ARMA ((3), (2)) model that only includes the third order item of AR and the second order item of MA showed the best performance for this example. After the estimation stage using SAS, the estimated ARMA ((3), (2)) model is listed in Table 4-5. The graphical check of prediction error autocorrelations, partial autocorrelations and inverse autocorrelations are

plotted in Figure 4-12. The residual correlation plots show that one can not reject the hypothesis that the residuals are uncorrelated. Moreover, numeric result of prediction error autocorrelations is generated in Table 4-6. The chi square test statistics for the residuals series further indicate that the residuals are uncorrelated. In another word, the predict error is very close to while noise with zero mean. The histogram of the residual of this example is plotted in Figure 4-13 as well. The statistic results conclude that the ARMA ((3), (2)) is adequate to represent this particular wind generation series.

Table 4-5 ARMA model estimation

```

Model for variable s47
Estimated Mean      33.91667

Autoregressive Factors
Factor 1:  1 - 0.71753 B**(3)

Moving Average Factors
Factor 1:  1 + 0.567 B**(2)

```

Figure 4-12 Autocorrelations, partial autocorrelations and inverse autocorrelations of residuals

Table 4-6 Autocorrelation check of residuals

To Lag	Chi-Square	DF	Pr > ChiSq	-----Autocorrelations-----					
6	85.78	4	<.0001	0.623	0.175	0.063	0.236	0.116	-0.086
12	93.44	10	<.0001	-0.110	0.087	0.110	-0.006	-0.105	-0.003
18	102.25	16	<.0001	0.085	0.047	-0.064	-0.082	-0.088	-0.137
24	122.18	22	<.0001	-0.214	-0.189	-0.127	-0.045	0.011	0.059
30	125.01	28	<.0001	0.079	0.060	0.045	0.006	-0.017	-0.044

Figure 4-13 Histogram of residuals

4.3.2.3. Forecasting

In Figure 4-14, blue curve was created based on the estimated ARMA ((3), (2)) model, the black star points are the original historical data. Figure 4-14 shows ARMA ((3), (2)) model is able to closely reflect the historical series. On the right-hand side of the vertical dashed line, 24 hours forecasted value and their confidence interval are drawn. Based on the forecasting, wind generation will decline in the next day. The comparison between actual and forecasted hourly wind generation are plotted in Figure 4-15. Even though the forecasted values do not exactly match actual data, their trend is closely followed.

Figure 4-14 Simulated original data series and forecasted data using estimated ARMA model

Figure 4-15 Comparison between actual and forecasted hourly wind generation

4.3.3. Day-ahead Forecasting through Simulation Period

Once the recommended orders of AR and MA of individual forecast process are determined, hourly day-ahead wind generation forecast will be performed for the whole year by the automatic forecasting process. Ideally, the orders of AR and MA are expected to be adjusted based on specific data series for each of the forecast process. However, because of the unavailability of automatic identification of ARMA orders, this may take large amount of efforts since there are 365 forecast actions that need to be completed for a series of wind generation in a year. In the research, the overall yearly reliability will be evaluated using Monte Carlo simulation with a large number of replications. The somewhat compromised forecast accuracy is not expected to affect the reliability calculation too much. Therefore, specific ARMA order will be identically applied for each forecast process throughout the whole year.

A variety of ARMA models based on one week historical data input had been fitted using SAS and their performances in RMSE of whole year forecast are listed in Table 4-7. In the table, the values of p , q and d stand for the order of AR, MA and differencing, respectively. On the one hand, the order selections were based on the comprehensive testing results of individual ARMA analysis, for example, using data from different seasons. On the other hand, some valuable references as follows are considered.

- ◆ Box and Jenkins provided empirical guidelines for determination of AR and MA orders and showed that any stationary stochastic system can be approximated as closely as required by an ARMA model of order $(n, n-1)$ [19] [24].
- ◆ Wind speed may characterize strong daily pattern that depends on the location and the season. Typically, high wind speed happens in the night and low wind speed happens during daytime.
- ◆ A nonstationary series can be transformed to be a stationary series by differencing.

Different ARMA models and their forecasting performances in RMSE are listed in Table 4-7. The ARMA models considering daily pattern and differencing do not help to improve

the forecast accuracy. The ARMA model with $p=(3)$ and $q=(2)$ shows the best forecast accuracy.

Table 4-7 Forecasting performance comparison of ARMA models

ARMA Order	RMSE
$p=(1, 2)$	17.48
$p=(1, 2, 3) \ q=(1, 2)$	18.25
$p=(2)$	17.37
$p=(3) \ q=(2)$	16.96
$p=(4) \ q=(3)$	17.29
$p=(1) \ q=(24)$	17.79
$p=(1) \ q=(23)$	17.74
$p=(2) \ d=(1)$	20.69
$p=(3) \ d=(1) \ q=(2)$	20.61
$p=(1) \ d=(1) \ q=(24)$	21.09
$p=(1)(24) \ d=(1) \ q=(1)(24)$	20.93

In addition, length of historical data series plays an important role that affects the overall performance of the automatic forecasting process. The tradeoff between the information provided to ARMA and the constraints that are imposed by the parameters of ARMA must be made [12]. For an extreme case, a single ARMA model that is fit over a period of one year, 8760 historical data, will potentially have the capability to use a great amount of information that is embedded in the wind signal. Because different physical mechanisms can affect the level of wind resource at different times of the year, the variability of the wind can also have different statistical properties during these periods. This implies that either a very large number of model parameters may be needed to fully describe the process, or the parameters themselves could be a function of time. Partitioning the year into a number of distinct time periods allows the model parameters to be re-fit to account for different climatological properties during different times of the year. However, choosing a too short period for ARMA training could leave out some important information that would determine forecasting accuracy. The ideal training period would pick up the important drivers and

patterns for different period of the year. Parameters based on one set of climatic drivers should not be imposed on other time periods if it is known that another set of climatic drivers affects the wind resource.

In order to achieve the best performance of automatic forecasting process, different periods from one week (168 data) to eight weeks (1344 data) for historical data series had been selected to fit ARMA model for 24 hours ahead forecast. Two kinds of ARMA models were chosen and their forecast performances measured by RMSE are plotted in Figure 4-16. As expectation from previous discussion, forecast accuracy increases when the length of historical data period increases from one week to six weeks. However, when the period is too long, the forecast performance starts decreasing. From the plot, the ARMA models are able to fully capture the most recent wind generation behavior when the six weeks' historical hourly wind generation is provided. Intuitively, six weeks (one and half months) length is a reasonable period to represent the latest seasonal characteristics that is a key factor of wind speed.

Figure 4-16 Forecasting performance comparison of different historical data period

After the comparisons of ARMA models and length of historical period, the overall forecasted hourly wind generation in 2007 with six weeks historical training period is plotted

along with the actual data in Figure 4-17. RMSE of 16.59 MW of this forecast performs the best among others and is also better than RMSE of 23.81 MW of persistent forecast method. The histogram of the error residuals in Figure 4-18 shows an approximate normal distribution with mean of -0.49, which indicates the ARMA model is reasonably adequate for the forecast.

Figure 4-17 Actual and forecasted wind generation

Figure 4-18 Histogram of forecast residuals

One important claim must be made that the accuracy of the day-ahead forecast of hourly wind generation in this research can not be comparable to that of commercial wind power forecasting software. The commercial wind power forecasting tools are much more sophisticated and provide highly accurate forecast results employing time series methods, numeric weather information, geographical information, and so on [17]. The research mainly focuses on the development of the methodology how to evaluate impact of wind penetration on power system reliability. Even though six hours ahead forecast is approximately the limitation of purely statistical forecasting methods, ARMA is used for the 24 hours day-ahead wind forecasting in the research for the purpose to assist and support the proposed methodology. In result, the absolute values of any reliability indices evaluation involving wind power forecasting may not 100% represent what happen in real life.

4.4. Verification of the Monte Carlo Simulation Model

To verify the proposed methodology, a small case system was created based on IEEE Reliability Test System (RTS) and its reliability was assessed by the developed program. RTS was developed by the Application of Probability Method Subcommittee [25], [26], and [27]. RTS had been used to compare and test a wide range of generating capacity and composite system evaluation techniques. IEEE-RTS was original created in year 1979 and had been modified and extended regularly to meet more comprehensive testing purpose [28]. The basic RTS will be tentatively tested by the Monte Carlo simulation program.

4.4.1. Load Model of RTS

The annual peak load for the system is 185 MW. The load profile is given by the pattern of weekly peak loads in percent of the annual peak load, daily peak load in percent of the weekly peak, and hourly peak load in percent of the daily peak. The load pattern data can be seen in Tables 1, 2 and 3 in [27]. The chronological load profile for 8736 hours based on given weekly, daily and hourly pattern is shown in Figure 4-19.

Figure 4-19 Load profile of RTS

4.4.2. Generating System of RTS

According to RTS, the generating system is transferred in the format that will be used for the Monte Carlo simulation model. There are totally 12 units including 7 hydro units, 4 thermal units and 1 gas turbine quick start unit. System installed capacity is 250 MW that leads to 35.14% capacity margin. The minimum up and down times of all units are all one hour due to small size of the generators. Only variable cost that contains fuel cost and operation cost is used for unit commitment logic and fixed cost and capital cost are not considered. Detailed data of the generating system is listed in Table 4-8.

Table 4-8 Generating system information of RTS

Name	ID	Maximum Capacity	Minimum Capacity	Forced Outage Rate	Mean Time To Repair	Minimum Up Time	Minimum Down Time	Aggregated Cost
<i>HY_5_1</i>	1	5	0	0.01	45	1	1	0.5
<i>HY_5_2</i>	2	5	0	0.01	45	1	1	0.5
<i>HY_20_1</i>	3	20	0	0.015	55	1	1	0.5
<i>HY_20_2</i>	4	20	0	0.015	55	1	1	0.5
<i>HY_20_3</i>	5	20	0	0.015	55	1	1	0.5
<i>HY_20_4</i>	6	20	0	0.015	55	1	1	0.5
<i>HY_40_1</i>	7	40	0	0.02	60	1	1	0.5
<i>TH_10_1</i>	8	10	0	0.02	45	1	1	12.5
<i>TH_20_1</i>	9	20	0	0.025	45	1	1	12.25
<i>TH_40_1</i>	10	40	0	0.03	45	1	1	12
<i>TH_40_2</i>	11	40	0	0.03	45	1	1	12
<i>GT_10_1</i>	12	10	0	0.12	75	1	1	56.5

4.4.3. Reliability Evaluation of RTS

RTS was simulated for 2000 trials using Monte Carlo simulation program. The comparison of reliability evaluation between Monte Carlo simulation and the analytical method in [27] is listed in Table 4-9. LOLE and EENS value are reasonable close between the two methods, which proves the usability and feasibility of the developed model. Exactly same results are not expected due to difference of the underlying approaches.

Table 4-9 Reliability indices comparison

Reliability Indices	Analitical	Monte Carlo
<i>LOLE (hours/year)</i>	1.09	1.34
<i>EENS (MWh/year)</i>	9.83	7.61

The variation of LOLE and EENS against the number of trial is plotted in Figure 4-20. The values of Y coordinate represent the rolling average of the reliability indices for the corresponding number of trials. The averages of the reliability indices fluctuate considerably for small trial numbers at the beginning part, but eventually settle to the values around LOLE of 1.34 hours/year and EENS of 7.61 MWh/year. In general, the smaller the case in terms of

the number of generators, the faster the reliability indices converge. The results of RTS case are relatively stable after 500 trials.

Figure 4-20 Reliability indices variation

Histogram of loss of load value is plotted in Figure 4-21. Histogram, commonly used for statistics, is a graphical display of tabulated frequencies. It shows what proportion of the trials fall into each of several loss of load range. In the plot, the very left-hand-side bar is remarkably taller than rest of the bars, which indicates that there is almost no loss of load for around 700 trials out of 1000 trials. All the shorter bars show yearly loss of load occasionally happen for some trials. For an extreme case in the very right side, about total 450 MW load was shed in a trial year.

Figure 4-21 Histogram of loss of load

4.4.4. Reliability Evaluation of RTS with Wind Power Generation

Based on the basic RTS, a wind farm is integrated to primarily test the reliability evaluation of the case with wind generation. In the simulation, the persistent method was applied for day-ahead wind generation forecasting. Actual and forecasted hourly wind generation through the simulation year is plotted in Figure 4-22.

Figure 4-22 Historical and forecasted wind generation

Two cases with 10% and 30% wind penetration level, the ratio of installed capacity of all wind projects and system annual peak load, were prepared. The wind profiles were proportionally adjusted for 10% and 30% cases based on the original wind generation profile. Simulations were performed for 2000 trials and the results are listed in Table 4-10.

Table 4-10 Reliability indices of 10% penetration case and 30% penetration case

Reliability Indices	10% Penetration	30% Penetration
<i>LOLE (hours/year)</i>	1.33	7.54
<i>EENS (MWh/year)</i>	284.62	2285.23

In the result, system reliability of 30% penetration cases is much worse than the basic RTS case. The main reason is that the persistent forecast model does not provide accurate forecasted value, which causes the frequent shortage of available committed capacity during real-time dispatch, especially when wind penetration level is remarkably high. On the contrary, another observation is that the reliability is improved after 10% wind penetration in

comparison with basic RTS. It can be explain that the quick start unit is able to fix most of the forecast error when wind penetration level is low. The histogram and variation of reliability indices of the 30% penetration case are plotted in Figure 4-23 and Figure 4-24.

Figure 4-23 Histogram of loss of load for 30% penetration case

Figure 4-24 Reliability indices variation for 30% penetration case

Chapter 5 Case Study

5.1. General Description of the Study System

In this research, a power system that contains hourly load profile, conventional generation data and wind generation was created. All data in the study system is based on real power system data that is publicly available and reasonably adjusted to adapt to the research purposes.

Even though IEEE Reliability Test System (RTS) can be used for the purpose of model testing, it is not capable to reflect practical generation mix. For instance, RTS only include small units whose minimum up/down time and mean time to repair are very short. From the operational point of view, they will act similar to peakers or quick start units that can be quickly committed to dispatch. However, large capacity generators, for example, large coal plant or nuclear plant definitely exist in the real system. The large units require much longer minimum up/down time for operation and repair time after outage. When a nuclear unit is forced out of service, the system possibly faces to a severe condition of capacity shortage for more than 100 hours, especially in summer peak load period. By contraries, in RTS, losing any individual generator will not make big trouble for system reliability, because it will resume available for dispatch very soon.

Because Monte Carlo simulation requests a large amount of computation, the study system must be carefully created to be solved in an acceptable time range. Run-time of the simulation strongly depends on the total number of generating units. On the one hand, if the number of generators is too small, the system may not be able to well represent real life. On the other hand, the number can not be too large so that Matlab program can not handle. Eventually, the total generating capacity is fixed at 6180 MW from 50 individual generators.

The major purpose of study system simulation is system reliability evaluations. Firstly, A base case system that only contains conventional generating resource is created. Then, diverse wind generation scenarios are simulated to estimate the reliability impacts. For a very robust system, the reliability index, such as LOLE, is normally a very small real number, such as 0.1 hour/year. However, such a small value is really hard to be justified if there is any tiny change when the generating system is incrementally changed, for example, adding 20 MW thermal unit to total 6180 MW capacity system. Therefore, the generation adequacy is intentionally set to be low to create greater LOLE value. In the study system, the capacity margin is 10% that derived from 6180 MW generating capacity and 5618 MW annual peak load.

5.1.1. System Load Profile

The load profile of the base case is based on the load profile of NYISO control area in year 2006 [30]. To coordinate with the generation system, the hourly load profile is proportionally scaled down to reach annual peak in summer as 5618 MW and total annual energy as 26851 GWh. Figure 5-1 shows the 8760 hours load value.

Figure 5-1 Load profile of the study system

5.1.2. Conventional Generating System

Because Monte Carlo simulation integrated production cost model mimics hour-to-hour generation operations of a power system, a comprehensive generation mix including thermal generation, hydro generation and renewable resource is necessary to represent real systems. In reality, the categories of generation resource are commonly known as base load units, shoulder load units and peak load units. Furthermore, operation behaviors and cost efficiency among different types of generation resource are quite different. The desired generation mix enables system operators to effectively schedule generation dispatch for serving different level of load and minimize the system production cost.

The references of conventional generation data are New York ISO 2007 Load & Capacity Data (a.k.a Gold Book) that specifies the existing resource capacity in New York Control Area (NYCA) [30], [31]. In the New York ISO system, there are about 38,900 MW installed capacity that is mainly composed of nuclear, coal, gas, oil, hydro and wind in terms of fuel types. Reasonable generation mix of different types of generating units plays a great deal of system reliability and economics, because the system possesses the generators from expensive to economic, from robust to unreliable, from start quick to slow warm-up , to meet different reliability and operation goals. To imitate the generation mix in NYCA, the installed capacity of each type was equally scaled down to suitable to a smaller power system. In the case system, there are totally 50 generation units and the composition of 6180 MW installed capacity by fuel type can be seen in Table 5-1 and Figure 5-2. Table 5-2 lists the detailed information of all generators.

Table 5-1 Summary of generation resource in study system

Type	Amount (MW)	Percentage	Number of Units
Hydro	559	9%	12
Nuclear	900	15%	2
Coal	1376	22%	9
Gas	3093	50%	20
Oil	252	4%	7
Total	6180	100%	50

Figure 5-2 Pie chart of the generation resource in study system

Table 5-2 Detailed data of generation system

Generator ID	Generator Name	Maximum Capacity	Minimum Capacity	Forced Outage Rate	Meam Time To Failure	Minimum Down Time	Minimum Up Time	Variable Cost
1	HYDRO_1	10	0	0.0455	86	1	1	1
2	HYDRO_2	15	0	0.0455	86	1	1	1.1
3	HYDRO_3	16	0	0.0455	86	2	2	1.1
4	HYDRO_4	19	0	0.0455	86	2	2	1.1
5	HYDRO_5	23	0	0.0455	86	1	1	0.4
6	HYDRO_6	29	0	0.0455	86	1	1	1.1
7	HYDRO_7	31	0	0.029	84	1	1	1.1
8	HYDRO_8	40	0	0.029	84	1	1	0.9
9	HYDRO_9	47	0	0.029	84	1	1	0.3
10	HYDRO_10	51	0	0.029	84	1	1	0.4
11	HYDRO_11	91	0	0.029	84	1	1	0
12	HYDRO_12	187	0	0.029	84	1	1	0.3
13	NUCLEAR_1	400	200	0.0659	167	168	168	8.4
14	NUCLEAR_2	500	250	0.0659	167	168	168	9.5
15	COAL_1	38	0	0.0605	41	2	2	30.3
16	COAL_2	55	0	0.0605	41	4	4	28
17	COAL_3	81	37	0.0605	41	4	4	24.4
18	COAL_4	92	46	0.0605	41	8	8	24.3
19	COAL_5	125	52	0.059	44	8	8	23.4
20	COAL_6	161	40	0.059	44	4	4	21.6
21	COAL_7	188	47	0.059	44	4	4	23.8
22	COAL_8	236	32	0.0565	40	4	4	23.9
23	COAL_9	400	176	0.0708	39	12	12	19.5
24	NG_1	11	0	0.0637	64	1	1	78.7
25	NG_2	29	0	0.0637	64	1	1	67.9
26	NG_3	35	12	0.0637	64	4	4	66.9
27	NG_4	40	0	0.0637	64	4	4	66.8
28	NG_5	45	5	0.0637	64	2	3	125.4
29	NG_6	49	0	0.0637	64	1	1	63.1
30	NG_7	57	0	0.0637	64	1	1	69.6
31	NG_8	70	18	0.0637	64	4	4	71.8
32	NG_9	79	0	0.0637	64	4	4	114.4
33	NG_10	80	0	0.0637	64	4	4	62.6
34	NG_11	85	40	0.0637	64	8	8	69.5
35	NG_12	91	0	0.0637	64	4	4	66.3
36	NG_13	117	19	0.0632	64	8	8	101.5
37	NG_14	159	31	0.0632	64	8	8	77.4
38	NG_15	199	38	0.0632	64	8	8	66.1
39	NG_16	287	94	0.0528	52	8	8	95.1
40	NG_17	300	93	0.0559	34	8	8	65.8
41	NG_18	410	151	0.0595	47	8	8	105.3
42	NG_19	450	137	0.0595	47	8	8	74.8
43	NG_20	500	138	0.0595	47	12	12	62.8
44	OIL_1	10	0	0.1101	77	1	1	203.5
45	OIL_2	15	10	0.1101	77	2	2	167.4
46	OIL_3	16	0	0.1101	77	1	1	158.5
47	OIL_4	38	14	0.1101	77	1	1	171.5
48	OIL_5	48	0	0.1101	77	1	1	174
49	OIL_6	57	0	0.1101	77	1	1	171.2
50	OIL_7	68	14	0.1101	77	1	1	135.7

In the Monte Carlo simulation, one of the key factors to correctly simulate the system uncertainty is the random outages of the conventional generators. Therefore, Forced Outage Rate (FOR) and outage duration of all types of generators are pivotal parameters to decide the generator outage. In the case system, unavailability related data comes from Generating Availability Data System (GADS) that is maintained by NERC [5]. GADS provides the generating unit statistics categorized by primary fuel type and capacity. The sample data of GADS statistics comes from the performance of generating units and their related equipments throughout North America over 25 years. According to the statistics of GADS, generators outage behavior varies quite a bit from one fuel type to another. In view of the importance, nuclear unit performs more stable and has lower outage rate, however, once it is forced out, it will take long period of time to recover to normal operation. One can also see the outage rate of small gas turbine may be two or three times higher than the outage probability of large nuclear unit. As an example, the statistics of coal-fired generating unit is listed in Table 5-3 where FOR and MTTR are given by the category of each 100 MW from small size to large size. In the study system, the values of equivalent FOR and MTTR are assigned to each generator according to its fuel type and unit size.

Table 5-3 Availability statistics of coal-fired generating units in GADS

Nameplate Capacity (MW)	# of Units	Unit Years	EFORd	MTTR (Hours)
All Sizes	895	4011	6.25	41
1-99	156	666	6.05	41
100-199	244	1104	5.90	44
200-299	117	545	5.65	40
300-399	83	360	6.57	38
400-599	163	730	7.08	39
600-799	95	427	6.80	38
800-999	25	120	4.29	33
1000 Plus	12	60	9.74	68

Cost efficiency, namely, variable cost will primarily affect unit commitment solution. Generator fuel cost, O&M cost and startup cost need to be considered in unit commitment.

Cost information mainly refers to Seams Steering Group – Western Interconnection (SSG-WI) 2005 Transmission Planning Program. Fuel cost is decided by heat rate that is commonly represented by piece wise linear incremental heat rate and fuel price that varies month by month. To simplify the scale of unit commitment optimization, full load average fuel cost of individual generator is calculated based on incremental heat rate. Units in descending order of variable cost are hydro unit, nuclear unit, coal unit, gas unit and oil unit. The equivalent system input-output stack chart based on the aggregated cost and capacity of all units is plotted in Figure 5-3. The curve can be understood that when system produces certain amount of generation (5000 MW), how much production cost will be paid for generating next MW (78 \$).

Figure 5-3 System equivalent production cost curve

From previous discussion, quick start units are necessary for maintaining system reliability from severe contingencies. In the study system, the conventional gas-fired and oil generating units with one hour minimum up/down time are designated as quick start units due to the quick action capability. The quick starts and their parameters are listed in Table 5-4. The

totally capacity of quick start units is 383 MW that is 6.2% of total system capacity. Because the variable costs of all quick starts are relatively more expensive than the cost of hydro and base load units, they will normally not be committed for energy during normal conditions and will stand by for contingencies.

Table 5-4 Data for quick start units in the study system

Generator Name	Maximum Capacity	Forced Outage Rate	Meam Time To Failure	Variable Cost
NG_6	49	0.0637	64	63.1
NG_2	29	0.0637	64	67.9
NG_7	57	0.0637	64	69.6
NG_1	11	0.0637	64	78.7
OIL_7	68	0.1101	77	135.7
OIL_3	16	0.1101	77	158.5
OIL_6	57	0.1101	77	171.2
OIL_4	38	0.1101	77	171.5
OIL_5	48	0.1101	77	174
OIL_1	10	0.1101	77	203.5

5.1.3. Wind Power Generation System

Four existing wind projects in commercial operation in Canada, listed in Table 5-5, are utilized for the analysis of the case study. The historical hourly wind generation from year 2006 to 2007 of all four projects is obtained from the Independent Electricity System Operator (IESO) [32].

Table 5-5 Installed capacity of wind projects

Name	Capacity (MW)
Melancthon I	67.5
Kingsbridge I	39.6
Erie Shores	99
Prince I & II	189

Figure 5-4 shows the monthly average wind generation of four projects. It is clear to see the patterns of high wind in winter and low wind in summer. This is not a favor for the system load with summer peak, as well as the system reliability.

Figure 5-4 Monthly average generation of the wind projects

Automatic process, described in Chapter 4, for day-ahead hourly wind generation forecasting for the whole year for all wind projects were carried out. For individual forecasting, ARMA ((3), (2)) model was applied and the length of historical data series was six weeks. The actual and forecasted hourly wind generations of year 2007 for all wind projects are plotted in Figure 5-5, Figure 5-6, Figure 5-7 and Figure 5-8. According to the Monte Carlo simulation model, forecasted wind generation is applied for day-ahead unit commitment and actual wind generation is applied for real-time operation.

Figure 5-5 Hourly wind generation of Melancthon I wind project

Figure 5-6 Hourly wind generation of Kingsbridge I wind project

Figure 5-7 Hourly wind generation of Erie Shores wind project

Figure 5-8 Hourly wind generation of Prince I & II wind project

In the simulation, the hourly generation of all wind projects will be accumulated as the total wind generation for system scheduling. Besides the wind generation profile, the generation change, also known as hourly ramp rate, between each hour and its previous hour was investigated. During the whole year, maximum ramp up rate and maximum ramp down rate of the aggregation of four wind projects are 133 MW/hour and 104 MW/hour, respectively. Histogram of the hourly ramp rate is plotted in Figure 5-9 that illustrates most of the generation changes are centralized around 0 MW and distributed from -50 and 50. No

significant difficulty of operation caused by ramping of wind generation is expected according to the existing system configuration. However, when the installed capacities of the wind projects are proportionally increased, the ramp up/down rate will increase accordingly.

Figure 5-9 Histogram of hourly ramping rate of the aggregated wind generation

5.2. Base case Reliability

In the study, base case only includes conventional generating units and no wind generation. The reserve requirement is 6% of hourly load. Based on the Monte Carlo simulation for 4000 trials, reliability indices of base case are listed in Table 5-6. Histogram of loss of load and the variation of reliability indices are plotted in Figure 5-10 and Figure 5-11. The variation plot shows that the average reliability indices are very stable after about 3000 trials. LOLE and EENS of the base case system will be the benchmark to evaluate the impact of wind generation on system reliability.

Table 5-6 Reliability indices of base case

Reliability	Value
EENS (MWh/Year)	900.54
LOLE (Hours/Year)	4.47

Figure 5-10 Reliability indices variation for base case

Figure 5-11 Histogram of loss of load for base case

5.3. *Wind Generation Integration*

The main purpose of the research is to evaluate the impact of wind generation on power system reliability. Typically, wind generation is gradually integrated into existing power systems. As the must-taken energy, wind generation acts as purely load-shaving. Due to the highly unpredictability and volatility, however, it also introduces difficulties of operation and scheduling. Different level of wind generation penetration will be expected to display different impacts on system reliability. Moreover, reliability may be improved or jeopardized from it if no other action is taken.

In the case study, wind generation will be gradually integrated into the base case from 1.2% up to about 28% penetration. Wind penetration level is defined in Equation (1). Four wind projects in Canada with a total 395 MW installed capacity were applied. However, 395 MW wind capacity is only 7% of system peak load of 5618 MW. Due to the limited data availability, the four wind projects are assumed to be expanded locally and duplicated to meet higher level of penetration.

$$\text{Wind Penetration Level} = \frac{\text{Total Wind Installed Capacity}}{\text{System Peak Load}} \quad (1)$$

All cases with different levels of penetration are listed in Table 5-7. To simplify the expression, the first character is extracted from the full name of the wind project. ‘M’ stands for Melancthon I project, ‘K’ stands for Kingsbridge I project, ‘E’ stands for Erie Shores project and ‘P’ stands for Prince I & II project. At the beginning, each wind project will be added on top of the existing wind project from M to P. Wind installed capacity is more aggressively penetrated into the system in the last three scenarios.

Table 5-7 Installed capacity for wind penetration scenarios

Case Name	Total Wind Installed Capacity	Penetration Level
M	67.5	1.20%
M+K	107.1	1.91%
M+K+E	206.1	3.67%
M+K+E+P	395.1	7.03%
Double (M+K+E+P)	790.2	14.07%
Triple (M+K+E+P)	1185.3	21.10%
Quadruple (M+K+E+P)	1580.4	28.13%

When wind projects are installed, the base case conditions including load profile and conventional generators stay the same. The reserve requirement is still 6% of hourly load. ARMA model is applied for the day-ahead forecast of hourly wind generation for unit commitment.

Reliability results of each case are listed in Table 5-8. In the results, reliabilities of the top four cases are indeed more or less improved in comparison with the reliability of base case. Especially, the un-served energy amount monotonically decreases from 900.54 MWh/Year in base case to 716.64 MWh/Year in M+K+E+P case whose penetration level is 7.03%. However, reliability is becoming worse from the case doubled the four wind projects. Particularly, the Quadruple (M+K+E+P) case reaches an unacceptable reliability level of LOLE of 73.09 Hours/Year and EENS of 5230.06 MWh/Year. Histogram of Quadruple (M+K+E+P) case is shown in Figure 5-12.

Table 5-8 Reliability indices for different wind penetration cases

Case Name	LOLE (Hours/Year)	EENS (MWh/Year)
M	4.39	869.23
M+K	4.14	777.38
M+K+E	4.29	768.11
M+K+E+P	4.43	716.64
Double (M+K+E+P)	6.29	784.86
Triple (M+K+E+P)	11.07	1229.82
Quadruple (M+K+E+P)	73.09	5230.06

Figure 5-12 Histogram of loss of load for Quadruple (M+K+E+P) case

The result reveals that it is not absolutely true for wind generation to bring the benefit to system reliability if no associated action is taken. In the base case, the generating system is designed to be competent to withstand the unexpected contingencies and keep system reliable. Spinning reserve and quick start units are all able to protect system reliability from generator randomly forced outage. When wind generation is introduced, extra uncertainty, such as wind forecast error, must be taken into account. The power system with certain reliability abundance may be getting more reliable, when wind penetration level is low. Because the wind forecast error combined from all wind projects can be countervailed by the capacity adequacy of conventional generators and operational reserve. Nevertheless, if plentiful wind power is integrated, for example 30% penetration level, the existing system most likely will not be capable to keep the same reliability standard. In consequence, system must take necessary actions to benefit from wind generation and reliably serve the load demand.

5.3.1. Economic Analysis

The proposed Monte Carlo simulation not only evaluates the reliability, but also takes economic aspect into account. Another interesting analysis focuses on overall system economics. A power system basically faces two types of cost: the production cost for serving load and the penalty cost for shedding load. In the simulation engine, unit commitment is performed for each hour to decide the utilization of generators based on the variable cost. However, economic dispatch is not built in the engine, because it requires more calculation and is not very useful for purpose of capacity adequacy evaluation. Therefore, the ballpark of production cost for serving load can be calculated in Equation (2), where G the total number of generators.

$$Production \text{ Cost} = \sum_i^G VariableCost_i * MaxCapacity_i * NumCommittedHour_i \quad (2)$$

The major part of the production cost is contributed by fuel cost. The ascending order of the cost of different fuels is wind, hydro, uranium, coal, gas and oil. Table 5-9 lists the annual total system production cost for all cases and the production cost saving for each wind scenario case in comparison with the cost of base case without wind generation. Because wind generation is treated as free energy due to the free fuel, wind, in result, conventional generators provide less energy then they do in base case. In general, the more wind power is integrated, the less overall system production cost.

Table 5-9 Production cost analysis for different wind penetration cases

Case	Production Cost (M\$)	Production Cost Saving (M\$)
Basecase	763.31	N/A
M	752.91	10.39
M+K	746.44	16.86
M+K+E	732.46	30.84
M+K+E+P	706.96	56.34
Double (M+K+E+P)	660.82	102.48
Triple (M+K+E+P)	626.92	136.38
Quadruple (M+K+E+P)	608.64	154.67

Meanwhile, system may also pay the penalty cost for the un-served energy. It is very hard to decide how much penalty cost will be incurred for each MWh among the diversified load categories. Based on 1990 Pacific Gas & Electric (PG&E) survey, 24000 \$/MWh is assigned as the penalty cost of un-served energy. Table 5-10 lists the annual system total penalty cost for all cases and the penalty cost saving of the wind scenario case in comparison with the cost of base case without wind generation. For the low wind penetration cases, system does pay less penalty cost due to the improvement of reliability. The penalty cost is paid much more in the Quadruple case.

Table 5-10 Penalty cost of load shedding for different wind penetration cases

Case	EENS (MWh/Year)	Penalty Cost (M\$)	Penalty Cost Saving (M\$)
Basecase	900.54	21.61	N/A
M	808.21	19.40	2.22
M+K	777.38	18.66	2.96
M+K+E	768.11	18.43	3.18
M+K+E+P	716.64	17.20	4.41
Double (M+K+E+P)	784.86	18.84	2.78
Triple (M+K+E+P)	1229.82	29.52	-7.90
Quadruple (M+K+E+P)	5230.06	125.52	-103.91

The total economic benefit of wind generation integration combines the production cost saving and penalty cost saving. The economic benefit of each wind penetration scenario is plotted in Figure 5-13. System keeps getting economic benefit until the Triple case. Interestingly, the economic benefit drops quite a bit for the Quadruple case with about 30%

wind penetration level. It can be interpreted that penalty cost of unserved load compromises the benefit of production cost saving when high wind penetration badly damages system reliability.

Figure 5-13 Economic benefit analysis for different wind penetration cases

5.3.2. Generator Utilization

Utilization of generator is mainly determined by economic efficiency, as well as other characteristics, minimum up/down time, forced outage rate, and so on. According to different fuel types, Table 5-11 lists the total commitment hours averaged over the simulation for all the cases. The statistics illustrate that the overall utilizations of base load units including hydro units, nuclear units and coal units do not change too much from base case. Between base case and quadruple case, nuclear and coal units are committed 16.24% and 14.27% less, respectively. In the high wind quadruple case, expensive units using natural gas and oil dispatch much less generation than they do in base case. A simple conclusion can be made

that wind generation brings a great amount of economic benefit in terms of the energy saving from existing expensive generators.

Table 5-11 Generator utilization for different wind penetration cases

Case	Hydro	Nuclear	Coal	Gas	Oil
Basecase	101348	16452	62549	37668	164
M	101345	16444	62043	36786	157
M+K	101325	16434	61674	36238	151
M+K+E	101344	16443	60982	34991	145
M+K+E+P	101351	16440	59565	32797	131
Double (M+K+E+P)	101343	16230	56559	29144	103
Triple (M+K+E+P)	101227	15498	54429	27044	87
Quadruple (M+K+E+P)	100814	13780	53623	26492	67

Quick start unit is prepared for standing against contingencies and maintaining system reliability. Figure 5-14 shows yearly average utilization of quick start units in all the cases, specifically for emergency purposes. The numbers of committed hours for emergency in case M, M+K, M+K+E and M+K+E+P are very similar with or even less than the one in the base case due to certain reliability improvement by wind integration. However, with higher wind penetration, the utilization of quick start units tremendously increases. In the quadruple case, on average, each quick unit is committed for emergency purposes for 672 hours in a year.

Figure 5-14 Utilization of quick start units for different wind penetration cases

Based on the previous analysis from reliability and economics points of view, the existing power system is not yet ready to accept high level penetration of wind generation. System must take necessary actions to benefit from wind generation without comprising reliability requirement. The basic actions may include:

- ◆ Adjustment of reserve requirement.
- ◆ Conventional generation expansion, especially for quick start unit.
- ◆ Improve wind power forecasting performance.

5.4. Reserve Requirement Adjustment

When forecast error of wind generation becomes higher when increase of wind penetration, one of the options for maintaining system reliability is to increase the spinning reserve requirement, because more capacity will be requested to be committed at each hour. In the case study, the basic target of the adjustment of reserve requirement is to re-satisfy the reliability standard if wind integration leads to unsatisfied reliability. The Double (M+K+E+P) case was chosen in this task due to its worse reliability. Also, the reliability

standard is assumed to be 4.47 hours/year in the base case. In the Double (M+K+E+P) case, the spinning reserve requirement had been incrementally increased from 6% in the base case to 9.5% by each step of 0.5% and each scenario was performed by Monte Carlo simulation.

Figure 5-15 plots the LOLE value against the reserve requirement. System reliability is improved with the increase of spinning reserve. In the figure, the red line represents the LOLE value of base case. The anticipated adjustment of reserve can be seen at the intersection between the blue curve and the red line. The reserve requirement has to stay in somewhere between 8% and 8.5% to meet the reliability standard for 4.47 hours/year for 14.07% wind penetration.

Figure 5-15 Reserve requirement adjustment

5.5. *Impact of Quality of Wind Generation Forecasting on Reliability*

Wind forecast error is one of the key factors to create the operational difficulties, even loss of load, since the total committed capacity affected by forecasted wind generation may not be

sufficient to serve the actual load demand. Accurate wind forecast will definitely ameliorate system reliability. To conceptually prove the idea, three different wind generation forecast methods were applied on the hourly wind profiles.

- ◆ Perfect forecast. The forecasted value is exactly the same as the actual value.
- ◆ ARMA model. ARMA will be applied for day-ahead hourly forecast.
- ◆ Persistent model. The day-ahead hourly forecasted value will be the same as the ones in present day.

For instance, for hourly wind profile of project Melancthon I, the annual average forecast error in RMSE of perfect forecast, ARMA model and persistent model are 0 MW, 16.16 MW and 23.81 MW, respectively. Again, the Double (M+K+E+P) case is simulated using three different forecast methods with original 6% reserve requirement.

Table 5-12 lists the reliability indices of the three cases. Case of perfect forecast shows the best performance of reliability. If wind forecast is 100% accurate, the wind generation is the purely load-shaver so that the net load profile as well as the peak load are reduced. Intuitively, the reliability is certainly improved. Reliability in persistent forecast case is the worst among the three. Even though the RMSE of persistent model is only higher 7.65 MW then the one of ARMA model case, the LOLE and EENS illustrate about 8 times difference between these two cases. Therefore, one may expect that more accurate wind forecast model will certainly reduce the probability of loss of load and even improve the reliability of the existing power systems.

Table 5-12 Reliability indices using different wind forecasting methods

Case Name	LOLE (Hours/Year)	EENS (MWh/Year)
Perfect	2.99	574.96
ARMA	6.29	784.86
Persistent	51.52	3298.81

5.6. Capacity Value Evaluation

Besides the cheap and clean energy generated by wind generation, a WTGS may also brings capacity value to improve system reliability. According to the methodologies described in chapter 3, capacity value of a wind project is evaluated here using the Monte Carlo simulation model. In order to clarify the analysis of capacity value of individual wind project, no more than one wind project is mingled together in the system. In the case study of capacity value evaluation, only Erie Shores wind project with installed capacity of 99 MW was chosen and integrated in the base case system and no other wind project was involved. Three methods including ELCC, Equivalent Conventional Generating Unit and Customized Capacity Factor Method, were applied in the evaluation. Again, 4.47 hours/year for LOLE of base case without any wind project is set as the reliability standard.

Wind generation profile of Erie Shores project is shown in Figure 5-16. Furthermore, the monthly average values of system load profile and Erie Shores generation profile are plotted in Figure 5-17. The curve shows the monthly patterns over the year. Obviously, monthly patterns of system load and the wind generation are quite different and even negatively correlated, because load reaches peak value during summer period and wind generation are rich during winter period. Therefore, Erie Shores project is not expected to be assigned high capacity value, possibly, much lower than the installed capacity of 99 MW.

Figure 5-16 Historical hourly wind generation of Erie Shores wind project

Figure 5-17 Monthly average value of wind generation and system load

5.6.1. Effective Load Carrying Capability (ELCC)

ELCC is deemed the prevalent metric of the capacity value of any generating unit. ELCC is the additional load peak value that can be served with satisfying the same reliability standard of existing system after the integration of any new generating unit. In the study, firstly, Erie Shores wind project was integrated in the base case system. The forecasted wind generation using ARMA model was applied for day-ahead unit commitment. Then, cases with different system peak load scenarios were performed. Accordingly, the value of each system hourly load was proportionally scaled up by the incremental increase of peak load value by each step of 20 MW.

Figure 5-18 shows the simulation result, where each point of the blue curve represents the LOLE value at different peak loads and the red curve stands for the reliability standard that needs to be reached. After the integration of Erie Shore wind project, the new system peak load with maintaining LOLE at 4.47 hours/year is approximately 5625 MW with the assumption of the linear trend of LOLE versus peak load. Based on the definition, ELCC value is 7 MW that is the difference between the peak load of base case 5618 and the peak load of wind case 5625 MW.

Figure 5-18 ELCC analysis for Erie Shore wind project using ARMA forecasting

The capacity value 7 MW is surprisingly low for a wind project with 99 MW installed capacity. One major reason is that the wind generation of Erie Shore indeed can not provide much capacity value during system load peak period and not help system maintain reliability. Another possible reason is the forecast error between ARMA forecasted value and actual wind generation. When forecasted value is higher than the actual value, committed capacity may not be enough to serve the net load so that load shedding will happen subsequently.

The perfect forecast of wind generation is applied for the ELCC estimation and the results are shown in Figure 5-19. ELCC for perfect forecast case is about 10 MW that is a little bit greater than the previous one using ARMA model. Quality of wind generation forecast partially influences the reliability contribution of a WTGS.

Figure 5-19 ELCC analysis for Erie Shore wind project using perfect forecasting

5.6.2. Equivalent Conventional Generating Unit

The capacity value of a WTGS can be measured by the installed capacity of a conventional generating unit. The procedure of the method is listed below.

- ◆ The case combined base case and Erie Shore wind project was simulated using Monte Carlo simulation model and the reliability index LOLE is recorded.
- ◆ Erie Shore wind project was removed from the base case and an equivalent conventional generator was built in the base case. In the study, a thermal unit using natural gas as primary fuel was applied and its parameters is listed in Table 5-13. Simulations were performed for cases with incremental installed capacity of the equivalent thermal unit.

Table 5-13 Data of equivalent thermal unit

FOR	MTTR	Min Down Time	Min Up Time	Variable Cost
0.0637	64	1	1	67.9

Figure 5-20 shows the result of previous simulations. Blue curve shows the LOLE value of the equivalent thermal case and the system reliability is improved with increase of the unit's capacity from 0 to 60 MW. The red curve represents standard LOLE value of 4.351 hours/year. The capacity value of Erie Shore project should be the capacity of the thermal unit when the reliability reaches same level if they are built in the base case separately. Therefore, the capacity value of Erie Shore project is approximately 6 MW.

Figure 5-20 Analysis of equivalent thermal unit method

5.6.3. Customized Capacity Factor Method

Capacity factor method is applied for capacity value estimation in the case study as well. Capacity factor of a generating unit is defined as the ratio of hourly average generation and its installed capacity. Since wind generation is provided by hourly value, capacity factor can be calculated for each hour. It would be worthwhile to mention in advance that the annual average capacity factor of Erie Shore project is 28.05%.

First estimation adopted the method from PJM [8]. The capacity credit for wind project in PJM is based on the wind generator's capacity factor during the hours from 3 p.m. to 7 p.m., in the months from June 1 through August 31. Wind hourly generation of Erie Shore project was retrieved for the specified time period. The average capacity factor of the hourly value is 15.84%, which implies the capacity value is 15.68 MW. Even though the high load is implicitly recognized during the specified period, the highest reliability risk is not fully highlighted. Instead, it is averaged out for the long period.

Another customized capacity factor method applied the average capacity factor for the hours occurring peak load values. Firstly, the hour of the year, for example 1 to 8760 in a leap year, is sorted based on the descending order of annual load profile. In another word, the peak load hours are listed on the top. Wind generation at the corresponding hours needs to be found. Average capacity factor of the wind generation based on this specified order was calculated. The annual load profile in the base case and the Erie Shore wind project are used here. In Figure 5-21, the curve represents the average capacity factor against the percentage of total top load hours. The result illustrates there is very few capacity value and almost no capacity contribution during the peak load period, namely, the highest risk period for reliability. For example, the average capacity factor is 11.87% for the top 2% highest load. The result here is consistent with the results from Monte Carlo simulation.

Figure 5-21 Average capacity factor against highest load percentage

Chapter 6 Conclusions and Future Work

6.1. *Conclusions*

Over the decades, power systems primarily emphasize on providing reliable and economic electric power supply to their customers. Infrastructure of power systems is continuously reinforced to ensure the adequacy of generation and transmission. In recent years, wind generation, a promising renewable energy, was booming throughout United States and the whole world. The development of wind power will persist in the coming future. It is very timely and critical to appreciate and understand the impact of high penetration level of wind generation on power system planning and operation.

The thesis mainly focused on evaluation of the impact of wind generation on power system reliability. A Monte Carlo based production cost simulation model was proposed and implemented to evaluate reliability of power systems with wind power generation. The model closely mimics actual system operation processes. A simplified unit commitment method was created to fit the simulation for reliability evaluation purpose. The effects of wind forecast error was addressed in the model by applying forecasted value for day-ahead unit commitment and applying actual value for real-time operation. A process of ARMA was designed to automatically perform day-ahead hourly wind generation forecast through the whole simulation period.

A study system was created based on data from real power systems. By using the proposed simulation model, diversified analysis about the impacts of wind power generation on power systems were carried out. The study showed that wind generation within certain level of penetration indeed improved system reliability. However, the existing study system was not ready to accept very high penetration of wind power due to the issues of jeopardized

reliability, as well as the worse system economics. Accordingly, measures such as adjustment of reserve requirement, adding more quick start units, must be adopted to maintain reliability criterion. The study also illustrated the importance of wind power forecasting performance by seeing the better quality of wind power forecasting, the more reliability benefit for the system. Using methods of ELCC and equivalent conventional generating unit, capacity value of a wind project in the study system was estimated by the model. Results of both methods concluded very less capacity value for the wind project, mainly because the wind generation is largely out-of-phase with the system load profile.

According to the analysis of case study, the model is able to estimate the reliability sensitivity of small incremental changes in the system. The model can be applied for evaluation of capacity value of a wind project. It also correctly reflects generation utilization. All in all, the proposed Monte Carlo based production cost simulation model is proven to be competent to evaluate the reliability of power system with wind power generation.

6.2. *Suggestions for Future Work*

The proposed Monte Carlo simulation model is still under improvement and modification. The whole model is highly modularized during the stages of design and implementation. Individual component can be easily embedded into the model.

Generation availability is one of the key factors to determine capacity adequacy. Two-state mode representation for generator outage may not accurately reflect the actual capacity outage sometimes. Four-state outage model can be introduced to the simulation to take into account the partial outage and capacity de-rating.

In the thesis, a simplified unit commitment was presented. However, more sophisticated unit commitment logic should be investigated to achieve better system economics and more reasonable generation utilization. Again, accuracy of unit commitment decision and computation effort of the whole simulation must be balanced.

Based on the analysis in Chapter 5, as well as the investigations from the reference, quality of wind generation forecasting largely impacts integration cost, capacity value and system

reliability contribution of a wind project. In addition to ARMA model, other forecasting methods, such as Artificial Neural Networks, Numerical Weather Prediction, etc. can be considered to fit into the simulation.

Further system studies are also needed. A study of a system that is comparable to the real power system in scope and complexity is a good way to promote the proposed model to a practical application. Ideally, the reliability evaluation using the proposed model is benchmarked against the one from any existing tool. Then, diversified simulation can be conducted to fully understand the impacts of new wind projects on the existing system reliability.

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