# Evaluating Wind Power Generating Capacity Adequacy Using MCMC Time Series Model

by

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# AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

# Abstract

In recent decades, there has been a dramatic increase in utilizing renewable energy resources by many power utilities around the world. The tendency toward using renewable energy resources is mainly due to the environmental concerns and fuel cost escalation associated with conventional generation. Among renewable resources, wind energy is a proven source for power generation that positively contributes to global, social, and economic environments. Nowadays, wind energy is a mature, abundant, and emission-free power generation technology, and a significant percentage of electrical power demand is supplied by wind. However, the intermittent nature of wind generation introduces various challenges for both the operation and planning of power systems. One of the problems of increasing the use of wind generation can be seen from the reliability assessment point of view. Indeed, there is a recognized need to study the contribution of wind generation to overall system reliability and to ensure the adequacy of generation capacity.

Wind power generation is different than conventional generation (i.e., fossil-based) in that wind power is variable and non-controllable, which can affect power system reliability. Therefore, modeling wind generation in a reliability assessment calls for reliable stochastic simulation techniques that can properly handle the uncertainty and precisely reflect the variable characteristics of the wind at a particular site. The research presented in this thesis focuses on developing a reliable and appropriate model for the reliability assessment of power system generation, including wind energy sources. This thesis uses the Monte Carlo Markov Chain (MCMC) technique due to its ability to produce synthetic wind power time series data that sufficiently consider the randomness of the wind along with keeping the statistical and temporal characteristics of the measured data. Thereafter, the synthetic wind power time series based on MCMC is coupled with a probabilistic sequential methodology for conventional generation in order to assess the overall adequacy of generating systems.

The study presented in this thesis is applied to two test systems, designated the Roy Billinton Test System (RBTS) and the IEEE Reliability Test System (IEEE-RTS). A wide range of reliability indices are then calculated, including loss of load expectation (LOLE), loss of energy expectation (LOEE), loss of load frequency (LOLF), energy not supplied per interruption (ENSPI), demand not supplied per interruption (DNSPI), and expected duration per interruption (EDPI). To show the effectiveness of the proposed methodology, a further study is conducted to compare the obtained reliability indices using the MCMC model and the ARMA model, which is often used in reliability studies. The methodologies and the results illustrated in this thesis aim to provide useful information to planners or developers who endeavor to assess the reliability of power generation systems that contain wind generation.

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# Dedication

To my parents

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# Chapter 1
# Introduction

## 1.1 Motivation

In recent decades, there has been a dramatic increase in utilizing renewable energy resources by many power utilities around the world. The tendency toward using renewable energy resources is mainly due to the environmental concerns and fuel cost escalation associated with conventional resources. Among renewable resources, wind energy is a proven source for power generation that positively contributes to global, social, and economic environments. In recent years, wind energy has received considerable attention for modern electrical power systems, and this considerable attention facilitates the rapid improvement in wind generation technologies and encourages increasing the penetration of wind energy. Wind energy is now a mature and emission-free technology, and a significant portion of electrical power can be generated from wind energy.

In many electric utilities all over the world, wind energy has become a significant resource over the past two decades. Figure 1-1 shows global cumulative installed wind capacity from 1996 to 2012 [1]. A total of 282 GW of capacity had been installed worldwide by the end of 2012. Twenty-four countries have installed capacity of more than 1 GW: sixteen in Europe, four in Asia (China, India, Japan, Australia), three in North America (Canada, Mexico, US), and one in Latin America (Brazil) [1].

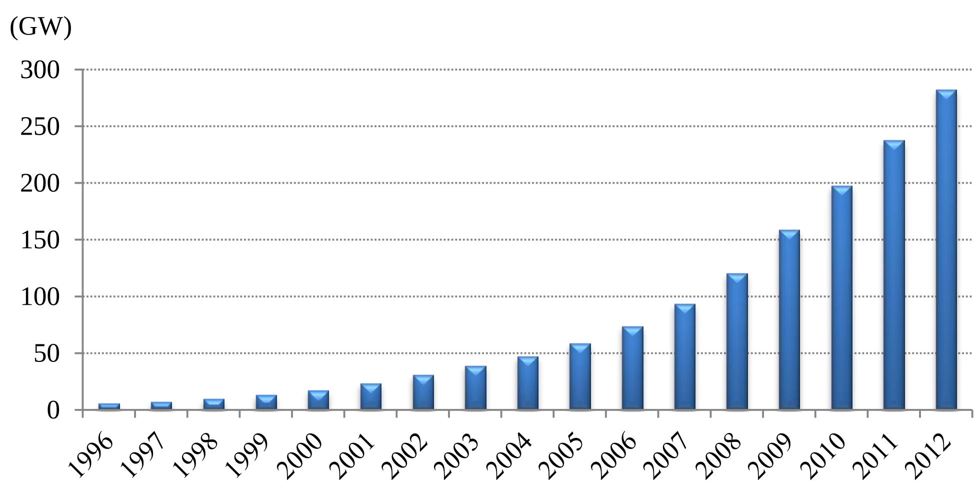



Figure 1-1 Global Cumulative Installed Wind Capacity 1996-2012 [1]

By 2013, Canada had become one of the top ten countries in terms of wind-energy installation. Canada’s current total installed wind capacity is about 7803 MW, which is enough to meet 3% of the country’s electricity needs [2]. According to the Canadian Wind Energy Association (CanWEA), Canada’s wind energy industry is intended to reach 12,000MW of total capacity by 2016 in order to attain CanWEA’s national wind vision target of supplying 20% of Canada’s electricity demand by 2025. Each province has its own independent programs and incentives for renewable energy development. Table 1-1 illustrates the distribution of the current installed capacity of wind energy generation across Canada [2]. Among all provinces, Ontario is at the forefront of wind energy capacity, with 2,470.5MW currently connected to the power grid.

Table 1-1 Current Capacity of Wind Energy in Canada [2]

| Province | Installed Capacity (MW) |
|---|---|
| Alberta | 1120.3 |
| British Columbia | 488.7 |
| Manitoba | 258.4 |
| New Brunswick | 294 |
| Newfoundland and Labrador | 54.7 |
| Northwest Territories | 9.2 |
| Nova Scotia | 335.8 |
| Ontario | 2470.5 |
| Prince Edward Island | 173.6 |
| Québec | 2398.3 |
| Saskatchewan | 198.4 |
| Yukon | 0.81 |

Since wind energy has become a significant portion of power generation resources, it introduces various challenges for both the operation and planning of power systems. This is mainly due to that fact that wind power generation behaves unlike conventional generation (fossil-based power), as wind power is variable and non-controllable. Indeed, the uncertain nature of wind generation makes its operation and planning a complex problem that makes the integration of wind energy into the power system a prime concern to system planners and operators. One of the great challenges of integrating wind energy in power systems can be seen from the reliability assessment perspective. Particularly, the method of involving wind generation capacity into the overall generation capacity assessment is a major challenge that often raises research questions.

Probabilistic methods of reliability evaluation for conventional generation are well established and used by many power utilities worldwide [3]. With respect to the evaluation of the reliability of power systems that incorporate wind energy, a variety of criteria and techniques has been showcased in numerous publications over the last two decades [4, 5]. However, there is still an ongoing need to develop appropriate models for the reliability assessment of power generation systems that include wind energy sources. Such models should consider the main issues that arise when implementing wind generation into the adequacy assessment of generating systems. These issues are summarized as follows:

1. Variability and uncertainty of the wind speed at a particular site
2. Wind Turbine Generator (WTG) operational parameters and specifications that determine the relationship between power output and site resources
3. The dependent capacity distribution of all WTGs in a wind farm on the same site resource
4. Unavailability of the WTG expressed as forced outage rate (*FOR*)

In reality, there is a recognized need to address these challenges and ensure generation adequacy, and to study the reliability assessment of power generation systems that incorporate wind energy. The overall goal of the study presented in this thesis is to develop a reliable and appropriate model that can help planners assess wind generation adequacy with regard to overall generating capacity.

## 1.2 Research Objectives

The main objective of the study presented in this thesis focuses on developing reliable and appropriate adequacy evaluation model for generating systems including wind energy. The specific objectives of this research are summarized as follows:

I. Build probabilistic techniques to evaluate the adequacy of conventional generation capacity based on analytical and Monte Carlo Simulation (MCS) techniques.
II. Develop a synthetic wind power time series model based on Monte Carlo Markov Chain (MCMC) technique.

III. Assess the adequacy of overall generating capacity by combining the conventional generation capacity obtained by using the sequential MCS technique with the wind generation capacity obtained by using the MCMC model.

Achieving the ultimate objectives of this research will be accomplished by focusing on the following aspects:

A. Development of an adequacy evaluation model for conventional generating systems (Chapter 3):

1- Build aggregated representation models for the adequacy assessment of conventional generation based on the three probabilistic techniques (analytical, sequential MCS, and non-sequential MCS), considering the suitable load model (i.e., load duration curve or chronological load model).

2- Apply the built models in Step 1 to two test systems, designated the Roy Billiton test system (RBTS) and the IEEE reliability test system (IEEE-RTS).

3- Validate and verify the results obtained using the three probabilistic techniques with the ones available in the literature.

4- Conduct sensitivity analyses on these models in order to examine the effects of a number of factors that have influence on the adequacy assessment results, and also to verify the validation of these techniques and test their performance and applicability.

B. Inclusion of wind farm modeling into the conventional generation adequacy evaluation (Chapter 4):

1- Choose the method, based on the comparison analysis in Part A, that best provides the most comprehensive representation for assessing the adequacy of conventional generation and that facilitates the integration of wind generation.

2- Develop a synthetic wind power time series model based on MCMC technique.

3- Verify the developed synthetic wind power time series model by considering three statistical aspects: i.e., probability distribution functions, autocorrelation functions, and monthly variations.

4- Combine the chronological conventional generation data from the MCS model (Step 1) with the synthetically simulated wind power data from the time-series-based

MCMC model (Step 2) over the chosen sampling years to assess the adequacy of overall generating capacity.

5- Compare the obtained reliability indices using the MCMC model with the ARMA model in order to show the validation and efficiency of the proposed methodology.

## 1.3 Thesis Outline

The rest of this thesis is organized as follows: Chapter 2 presents background information pertaining to power system reliability and its relevant aspects. This chapter also reviews the related concepts and the available techniques of generating system adequacy assessment, and surveys the previously developed models with regard to wind energy in particular.

In Chapter 3, the required models and calculations to evaluate the adequacy for conventional generation are presented using the most common probabilistic techniques (analytical, sequential MCS, and non-sequential MCS). This chapter also introduces the relevant information with regard to the systems under study, and they are two extensively used test systems in the reliability analysis designated the RBTS and the IEEE-RTS. The obtained results using these techniques are compared to each other and are also verified with the available results in the literature

Chapter 4 proposes an assessment framework for the adequacy of overall generating capacity by combining the conventional generation capacity obtained by using the sequential MCS technique with the wind generation capacity obtained by using the MCMC model. The developed synthetic wind power time series model based on MCMC is verified by considering some statistical aspects, such as hourly auto-correlation, monthly characteristics, and diurnal distribution of wind power data. In this chapter, a case study is further conducted to show the validation and efficiency of the proposed methodology so that the obtained reliability indices using the MCMC model are compared with the results of the ARMA model, which is often used in reliability studies. Chapter 5 presents the thesis summary, conclusions, and recommendations for future research. Figure 1-2 shows the overall layout of the thesis.

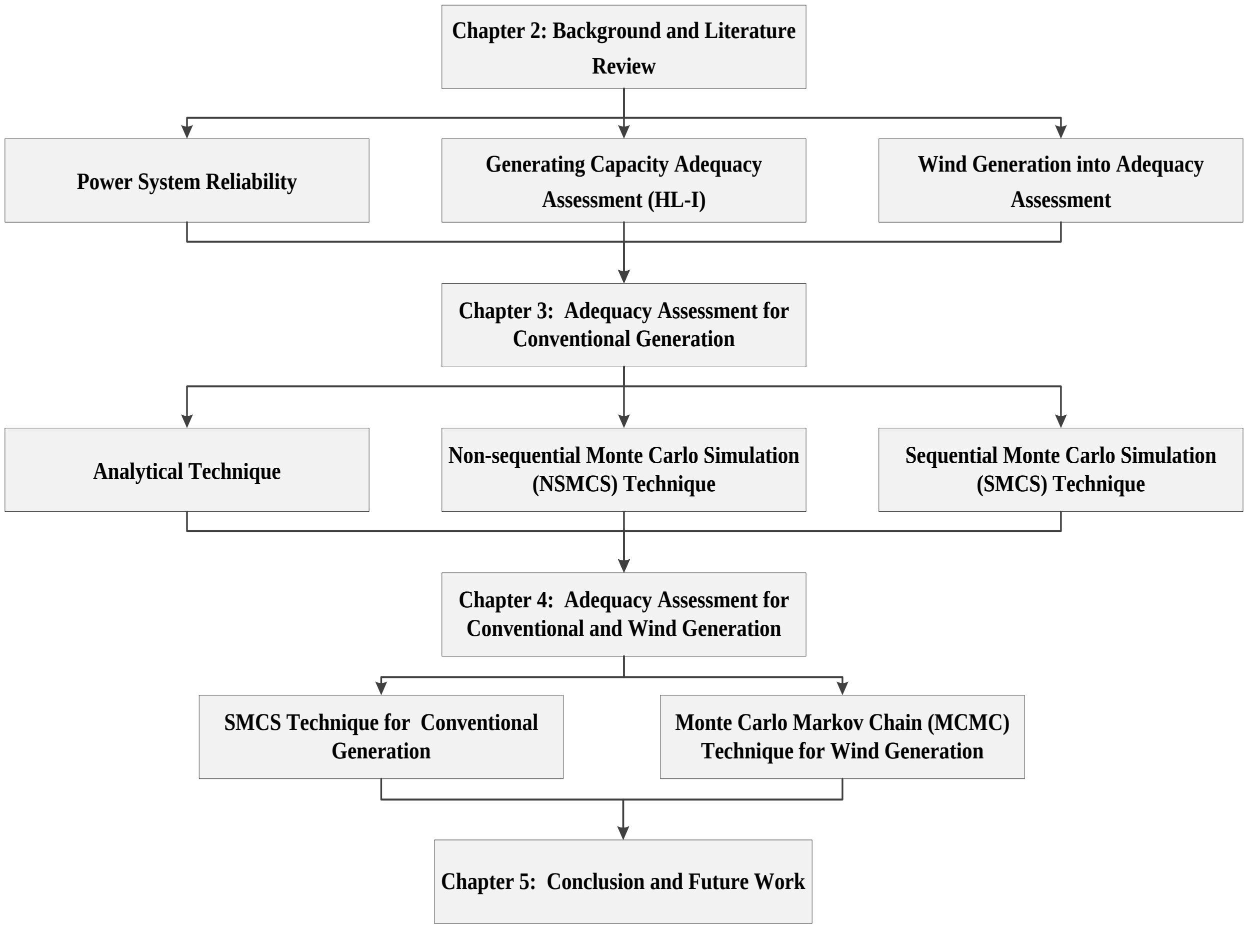



Figure 1-2 Overall Layout of the Thesis

# Chapter 2
# Background and Literature Review

## 2.1 Introduction

In Chapter 1, the motivations and research objectives of the work presented in this thesis have been discussed and presented, whereas this chapter is dedicated to reviewing the literature pertaining to power system reliability in general and generating system adequacy assessment, with regard to wind energy in particular. This chapter is divided into three main parts. The first part reviews the general aspects associated with power system reliability, covering its scientific definitions as well as main types and categories. The second part reviews the basic concepts and related aspects of generating system adequacy assessment, and includes the adequacy problem statement, detailed description of the involved elements, and the existing commonly-used techniques. The last part of this chapter discusses the generation adequacy problem when wind generation is integrated. It also reviews what some of the reported works have proposed to involve wind generation into adequacy assessment.

The literature and background information review presented in this chapter is a modest attempt and cannot cover all existing works. However, the references are carefully selected to be a comprehensive and adequate representative for their specific areas.

## 2.2 Power System Reliability Evolution

One of the main objectives of modern electrical power system utilities is to provide their customers with reliable electrical energy at an acceptable cost. Achieving this goal is a significant concern for all parties associated with modern power systems: generation companies, transmission companies, distribution companies, individual operators, and end users. Resolving the conflict between the economic and the reliability constraints inherent in power systems has always given rise to relevant concerns and has resulted in many decades of development of planning and operating strategies [3].

### 2.2.1 Definition and Categories

The term "reliability" can be defined as the probability that a component or system will perform its required function for a given period of time under a steady state condition [6]. With regard to a power system, reliability is the measure of the overall ability of the power system supply to meet the electrical energy needs of the customers [7]. According to the North American Electric Reliability Corporation (NERC), power system reliability can be defined as "*the ability to meet the electricity needs of end-use customers, even when unexpected equipment failures or other conditions reduce the amount of available power supply*." Power system reliability is typically viewed as having two aspects: system adequacy and system security [8, 9], as depicted in Figure 2-1.

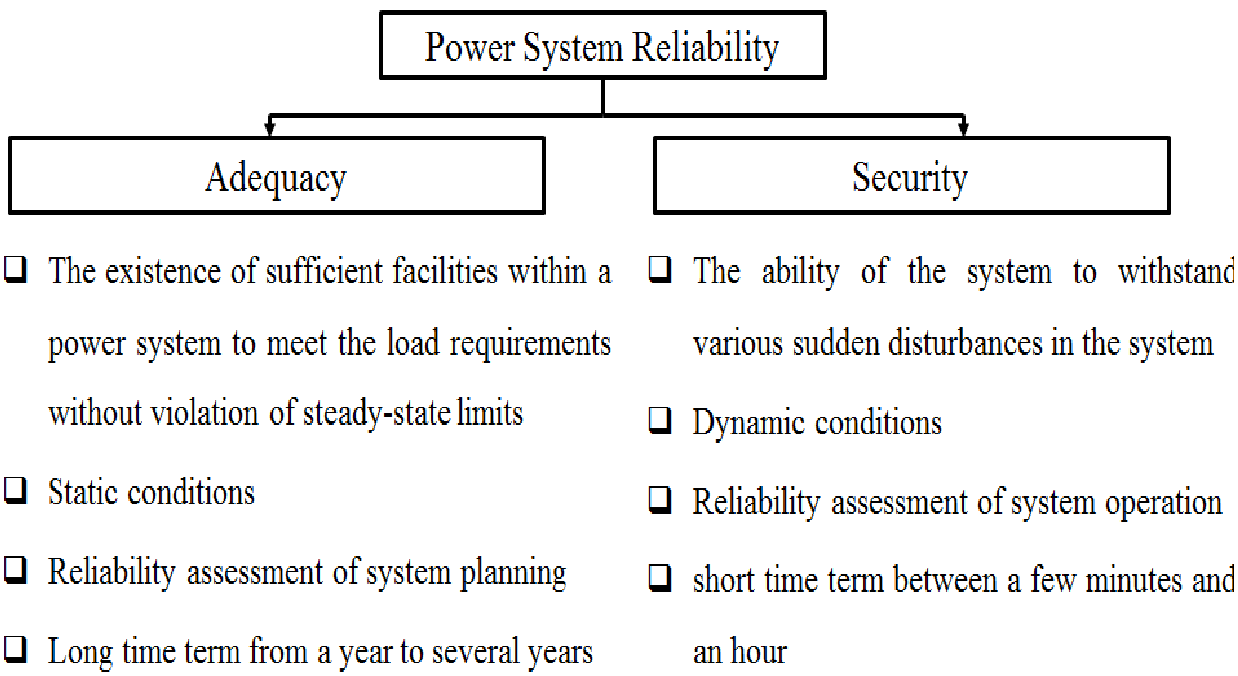



Figure 2-1 Subdivisions of System Reliability

System adequacy can be defined as the existence of sufficient facilities within a power system to meet the load requirements without violation of steady-state limits. System adequacy refers to static conditions rather than system dynamic and transient disturbances, and is normally associated with the reliability assessment of system planning in a long-time term from a year to several years. System security, however, signifies the ability of the system to withstand various sudden disturbances in the system, such as voltage instability situations or unanticipated sudden loss of system elements. System security is therefore associated with dynamic or operational measures in a short-time term of between a few minutes and an hour.

The research work presented in this thesis is devoted to the aspect of adequacy assessment of power generating systems incorporating wind energy.

### 2.2.2 Hierarchical Levels

Modern power systems are very large, highly integrated, complex networks. In this respect, it is difficult, if not impossible, to evaluate the reliability of an entire power system [3]. Within the field of power system reliability evolution, a power system is traditionally divided into three functional zones (generation, transmission, and distribution) to provide a succinct means of identifying the part of the power system being analyzed. The three functional zones can be organized into three hierarchical levels, as shown in Figure 2-2 [8].

At hierarchical level I (HL-I), reliability evaluation is usually defined as the generating capacity adequacy, with the only concern being an examination of the ability of the system to meet the aggregated system load. At this level, the transmission and distribution facilities are disregarded. Adequacy evaluation at hierarchical level II (HL-II) includes both the generation and transmission facilities and is usually referred to the evaluation of the reliability of the composite system or bulk power system. At this level, adequacy evaluation becomes an assessment of the integrated ability of the generation and transmission systems to deliver energy to the load points. The last level indicates an overall assessment that includes consideration of all three functional segments and is identified as hierarchical level III (HL-III). Adequacy evaluation at HL-III, which includes all three functional zones simultaneously, is quite difficult to conduct in a practical system due to the computational complexity and large-scale modeling involved. Thus, reliability analysis at this level (HL-III) is usually performed separately, only in the distribution functional zone, using the results of HL-II as an input.

The research work presented in this thesis deals only with the HL-I adequacy analysis.

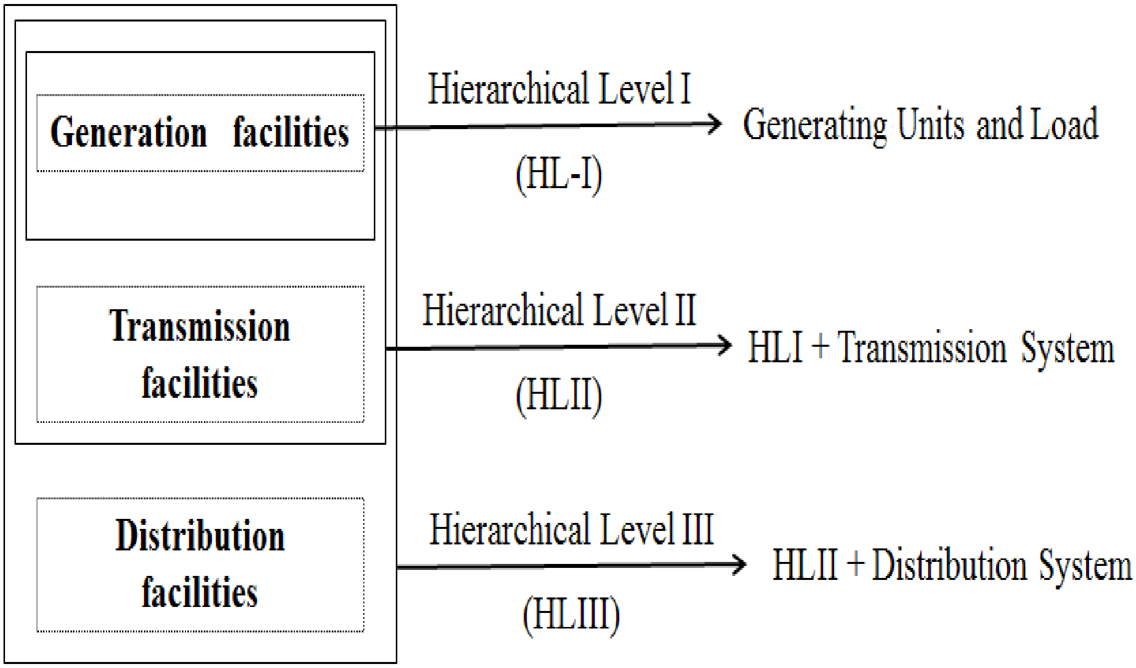



Figure 2-2 Reliability Assessment Hierarchical Levels [8]

### 2.3 Basic Concepts for Hierarchical Level One Assessment

The main concern with regard to HL-I adequacy assessment is measurement of the ability of the installed generating capacity to meet the requirements of a single lumped load. The generation model and the load model represent the two main components of an electric power generating system that must be examined in order to evaluate the adequacy of generating capacity. The basic representation for a system being analyzed in HL-I is that it can be considered as a single bus where both the generation and load models are connected to it, as shown in Figure 2-3. For HL-I adequacy assessment, the transmission system and its ability to deliver the generated energy to the customer load point is assumed to be perfectly reliable.

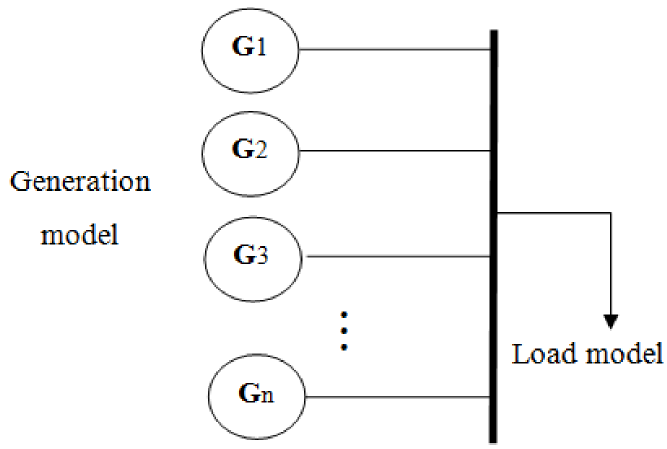



Figure 2-3 System Representation of Adequacy Assessment Problem

With respect to the evaluation of power system reliability, a variety of criteria and techniques have been developed and utilized by numerous utilities over a number of decades [3, 7, 8]. Of these, deterministic and probabilistic techniques are the ones widely used for the evaluation of generating capacity adequacy. Figure 2-4 shows a comparison between deterministic and probabilistic techniques. Deterministic techniques were used early on practical applications, and some power system utilities are still dependent on these techniques. Deterministic techniques are based on past experience to estimate capacity reserve above the peak demand, attempting to insure that generation is adequate to meet the load. The most common deterministic techniques [3, 10] are as follows:

1. Percent Margin: A required reserve margin should be equal to a fixed percentage value of either the total installed capacity or the predicted demand. So, the appropriate percentage value is determined based primarily on past experience.
2. Loss of the Largest Unit: A required reserve margin should be equal to the capacity of the largest generator unit connected to the system.
3. Loss of the Largest Unit and Percent Margin: A required reserve margin should be equal to the capacity of the largest generator unit plus a fixed percentage value of either the total installed capacity or the predicted demand.

The major disadvantage of deterministic techniques is that they fail to take into account the stochastic nature of the system behavior that results from component failures or demand increase [8]. Thus, relying on deterministic methods can provide either under- or overestimation of reliability. Although overestimation of reliability is required, it requires a very high investment cost. In the past, a number of factors, such as lack of reliability data and computational resources, created a preference for the use of deterministic techniques. However, with the availability of applicable reliability data and advancements in computational technologies, these factors no longer apply, and logic now dictates the use of probabilistic techniques, which can include consideration of the stochastic nature of the behavior of  power systems, which has a critical influence on power system reliability [3, 7].

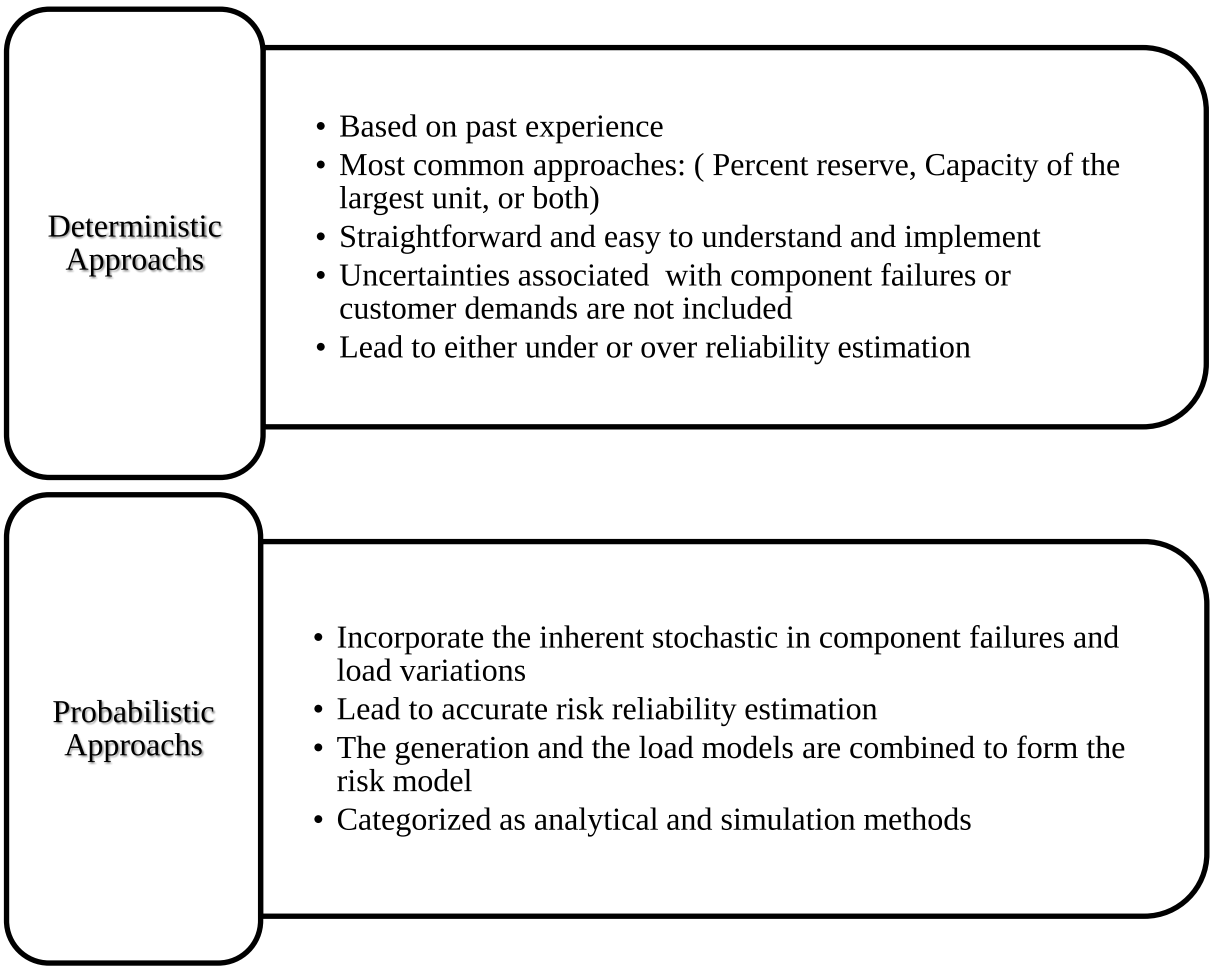



Figure 2-4 A Comparison between Deterministic and Probabilistic Techniques

### 2.3.1 Probabilistic Techniques

As discussed in the previous section, deterministic techniques rely on past experience and personal judgment to estimate the reserve required to maintain an acceptable level of system reliability. Accordingly, they do not recognize the stochastic nature of the behavior of power systems in component failure or demand variation. Probabilistic methods, on the other hand, are able to respond to the inherent stochastic in component failures and load variations and lead to accurate risk reliability estimation. From the 1930s until now there has been a huge set of publications (books, papers, articles, etc.) dealing with development and application of probabilistic techniques in evaluating the reliability of power systems [3, 7-9, 11-15].

Most probabilistic techniques developed for the evaluation of generating capacity can be categorized into two general types: analytical and Monte Carlo simulation (MCS) [11, 15]. An analytical technique relies on basic mathematical models as representations of system elements and then produces system reliability indices using direct numerical solutions. MCS methods, on the other hand, estimate reliability indices using simulations of the actual process and random behavior of the system. The MCS techniques are further classified into two types: non-sequential and sequential [13, 14, 16]. In non-sequential techniques, the system states for all components are sampled and each time point is considered independently without the chronological time being taken into account. In contrast, in order to create the complete system operating cycle, sequential techniques include consideration of the chronology so that the operating cycles of all the components are simulated and then combined.

Each method has advantages and disadvantages, so the appropriate method is determined based primarily on the type of evaluation desired as well as the nature of the problem. A comparison of these techniques from different perspectives is extracted from the available literature [3, 7-9, 12-17] , summarized in Table 2-1, and explained in detail as follows. An analytical method is fairly simple to understand and apply using computational programs. The analytical approach can provide system planners with the basic expected adequacy assessment indices (i.e., LOLP, LOLE, LOEE) in a simple manner and with very short computational time compared to MCS techniques. It is very efficient in the case of an adequacy assessment of conventional generation and for cases when the system is relatively small. However, if the system model is relatively complicated or large and includes variable energy sources such as wind and solar generation, the analytical method is not appropriate due to the complexity of the system. For evaluating such systems, MCS methods (sequential or non-sequential) are more suitable, and they have received growing interest in recent years. The main disadvantage of MCS methods is that they require extensive computation time. However, rapid advancements recently in computer technologies have to a large extent eliminated this drawback and made the use of simulation methods practical and viable.

Table 2-1 Comparison of Probabilistic Techniques from Different Perspectives

| Analytical (numeration) Technique | Non-sequential MCS Technique | Sequential MCS Technique |
|---|---|---|
| ✓ Short computational time<br>✓ Very efficient for small systems and for 2-state units<br>✓ Very good method for expected indices (LOLE, LOEE)<br>✘ Relatively complicated for large systems and for multi-state units<br>✘ The chronological nature of generation and load models is not considered<br>✘ Time-based indices cannot be easily and accurately calculated | ✓ Practical for a large system that contains a large number of elements<br>✓ Easily incorporates multi-state components without increase in complexity or computing time<br>✓ Requires less computing time and effort than does the Sequential Monte Carlo method<br>✘ The chronological nature of generation and load models are not considered<br>✘ Time-based indices cannot be easily and accurately calculated | ✓ The chronology of the generation model and load model are considered<br>✓ Very efficient for a system that contains variable energy resources, such as wind and solar<br>✓ Provides a wider range of indices (i.e., expected indices, time-based indices, and index probability distributions)<br>✘ Requires greater computing time and effort, as well as more complex procedures |

A non-sequential MCS method is practical for systems that are complicated or that contain a large number of elements, and it can easily incorporate multi-state components without further increase in complexity or computing time. As mentioned, in non-sequential MCS methods, the simulation process does not move chronologically, and each time interval is considered to be independent. The major advantage of a sequential MCS method is that it incorporates recognition of the chronology of events and the stochastic behavior of the system elements, essential features for evaluating a power system that includes non-conventional generation, such as wind and solar, which are time-dependent and correlated. Among these techniques, sequential MCS can comprehensively evaluate the reliability of power systems and provide a wider range of indices and the indices' probability distributions than do analytical and non-sequential MCS techniques such as time-based indices (loss of load frequency and duration).

In the next chapter, the detailed methodologies and procedures for each probabilistic method will be presented and compared to each other when applied to two well-known test systems.

### 2.3.2 System Modeling in Probabilistic Techniques

As mentioned earlier, the generation model and the load model represent the two main models of an electric power generating system that must be examined in order to evaluate the adequacy of the generating capacity. In probabilistic methods, the generation and load models are then combined to form the risk model, as shown in Figure 2-5 [8]. Detailed description of each model will be presented in the flowing subsections.

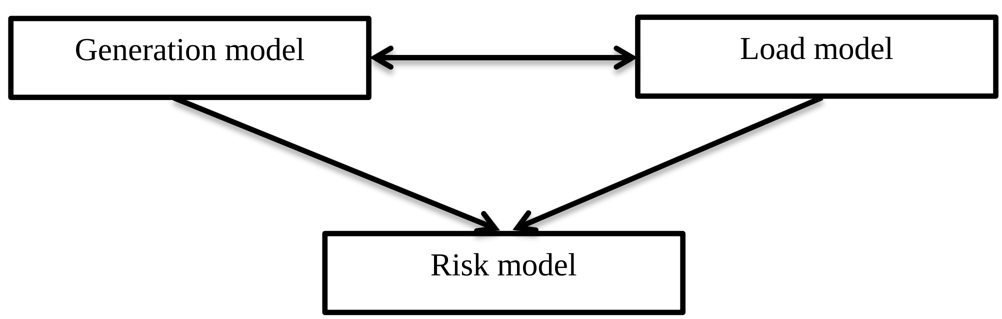



Figure 2-5 Basic Representation of Conceptual Tasks in Generating Capacity Adequacy [8]

#### 2.3.2.1 Generation Model

In the generation model, a generating unit is represented by either a two-state model (fully rated state or failed state), or a multi-state Markov model [3], as shown in Figures 2-6 and 2-7 respectively. The failure rate λ is equal to the reciprocal of the mean time to failure (*MTTF*), while the repair rate μ is equal to the reciprocal of the mean time to repair (*MTTR*). The forced outage rate (*FOR*) of the generating unit is defined as the probability of finding a unit in a forced outage state and is also indicated according to its unavailability (*U*). The *FOR* is usually calculated based on the historical operating data for the unit, as shown in equation (2.1). In addition, if the failure rate $\lambda$ and the repair rate $\mu$ of the unit are known, equation (2.2) can be used to obtain the *FOR*. For the opposite case, equation (2.3) denotes the probability of finding a unit in its rated state and is also indicated according to its availability (*A*). All of these equations are applicable for the case of a two-state model.

However, in addition to being in a fully functional or failed state, a generating unit can also be represented by multiple de-rated states, during which it operates at a reduced capacity [3]. The two-state models were considered to represent conventional units in the study presented in this thesis.

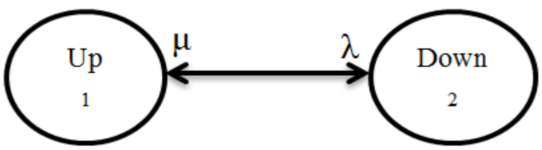



Figure 2-6 Two-state Model

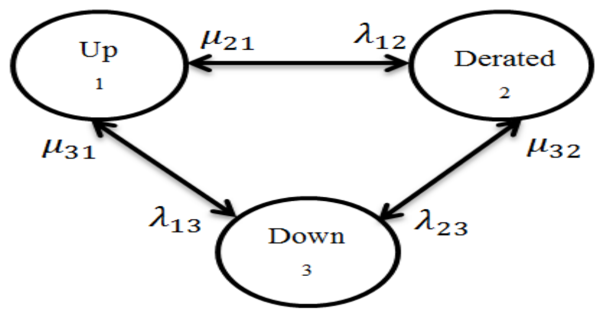



Figure 2-7 Multi-state Model

$$FOR = \frac{\sum T_{down}}{\sum T_{up} + \sum T_{down}} \tag{2.1}$$

$$FOR = U = \frac{\lambda}{\lambda+\mu} = \frac{MTTR}{MTTF+MTTR} \tag{2.2}$$

$$A = 1 - U = \frac{\mu}{\lambda+\mu} = \frac{MTTF}{MTTF+MTTR} \tag{2.3}$$

### 2.3.2.2 Load Models

The load model represents system energy demand over a specific period of time. A variety of load models have been utilized to investigate the evaluation of adequacy of the generating capacity. These models can be categorized into two types: load duration curve (LDC) and chronological load models. Figure 2-8 shows LDC concurrently with the chronological load model. The load duration curve (LDC), known also as the hourly peak load variation curve, is frequently used and is created by arranging the individual hourly peak loads in descending order. Similarly, the daily peak load variation curve (DPLVC) can also be used if only the individual daily peak load data is available.

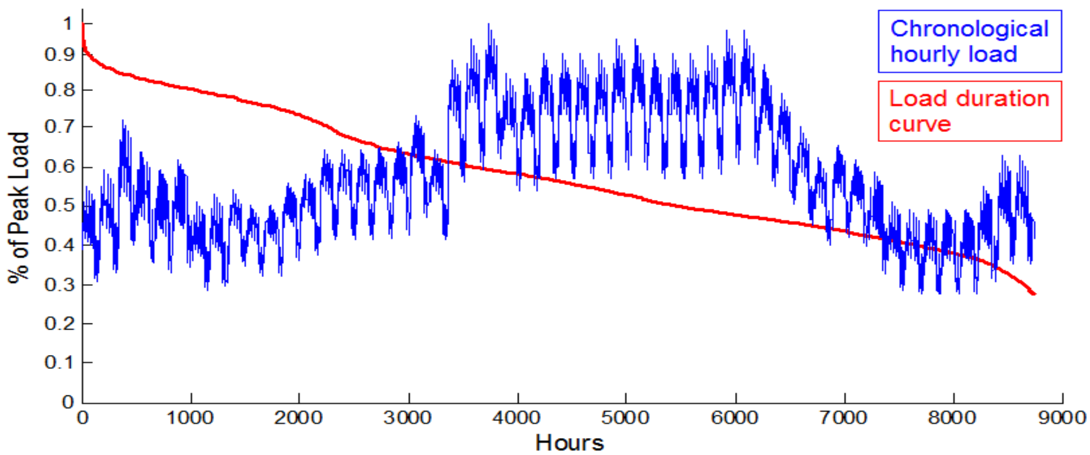



Figure 2-8 Chronological Hourly Load and LDC over One Year

For simplification and time-saving purposes, the LDC and DPLVC are usually divided into finite load steps. However, annual LDC on an hourly basis (8760 hours) is considered to be the accurate and comprehensive representation. Thus, the number of load levels or steps must be precisely well-defined, because reducing the number of steps can lead to inaccurate results. The LDC and DPLVC are used in the analytical technique [3, 15] and the non-sequential MCS technique [13, 14, 16]. The chronological load model, recognized also as the time series load model, is often used in sequential MCS techniques [12-16]. It is a straightforward model which can be formed based on the available hourly load data for a given period of time, which is typically one year.

#### 2.3.2.3 Risk Model

Power system reliability is usually reflected by indices that measure the reliability and adequacy of the system. The indices most widely accepted and used for the assessment of generating capacity adequacy are as follows [3, 17]:

1. **Loss of load probability (LOLP) (dimensionless):** This is defined as the expected annual probability during which the load will exceed the available generation.
2. **Loss of load expectation (LOLE) (hours/year):** This denotes the expected annual average number of hours/days during which the existing generating capacity fails to meet the demand.
3. **Loss of energy expectation (LOEE) (MWh/year):** This represents the expected annual amount of energy not supplied due to a shortage of generation capacity.

There is also a set of indices that have additional physical meaning and can provide the system planners with sensitive and useful information. Although these indices are well established and documented in the literature, they are not widely used due to the additional data and complexity that they need [7, 8]. Some of these indices are as follows [7, 8, 12]:

1. **Loss of load frequency (LOLF) (occurrences/year):** This signifies the expected annual frequency of encountering a generation deficiency in supplying the required load.
2. **Expected duration per interruption (EDPI) (hours/interruption):** This indicates the average duration of each occurrence when the load exceeds the available generation.
3. **Energy not supplied per interruption (ENSPI) (MWh/ interruption):** This denotes the average amount of energy not supplied for each occurrence in which the available generation cannot supply the demand.
4. **Demand not supplied per interruption (DNSPI) (MW/interruption):** This indicates the expected demand capacity not supplied for each occurrence in which the load is not supplied.

### 2.4 A Review on Adequacy Assessment for wind power generation

Three decades ago, the generated power from wind farms had no significant impact on the generation adequacy of power systems, and this is mainly due to the fact that the installed wind capacity was relatively small. In recent years, however, there has been a dramatic increase in utilizing wind-based generation in many power system utilities around the world. As wind energy has become a significant electrical supply resource, it is important to develop comprehensive reliability evaluation models to include the wind capacity in conventional adequacy assessment.

As previously discussed, probabilistic methods of reliability evaluation for conventional units (fossil-based) have been well documented and used by many power system utilities worldwide. Unlike conventional generating units, where the rate of energy output is controllable and they are capable to generate rated power during normal operation, wind integration raises some new concerns in the analysis of power system reliability. The power output of wind generation is variable, uncertain, and non-controllable, and wind power output is extremely dependent on the variable characteristics of the wind speed at a particular site.

With respect to the evaluation of the reliability of power systems incorporating wind energy, a variety of criteria and techniques have been developed over the years [4, 5]. However, there is still an ongoing need to develop appropriate models for the reliability assessment of power system generation systems which include wind energy sources. Such models should consider the main issues arising when implementing wind generation into the adequacy assessment of generating systems.

The most weighty issues in most reported works are summarized in the following points and depicted in Figure 2-9 [18, 19]. First, the output power of WTGs is mainly based on the availability of wind, which is random and intermittent in nature. Hence, developing an appropriate and accurate wind speed model is an essential step prior to reliability analysis in order to cope with the variability and uncertainty of the wind speed at a particular site. Second, each WTG in a wind farm is dependent on the same energy source, i.e., wind, and therefore they cannot have independent capacity distribution. Third, the nonlinear relationship between the power output of a WTG and the wind speed at a site is represented by the characteristics of the WTG when influenced by the cut-in, rated, and cut-out speed. Fourth, the unavailability of the WTG, as expressed by *FOR*, is sometime taken into account, although some studies in the literature [20, 21] have stated that ignoring the WTG's *FOR* will not have a considerable effect on the calculated reliability indices.

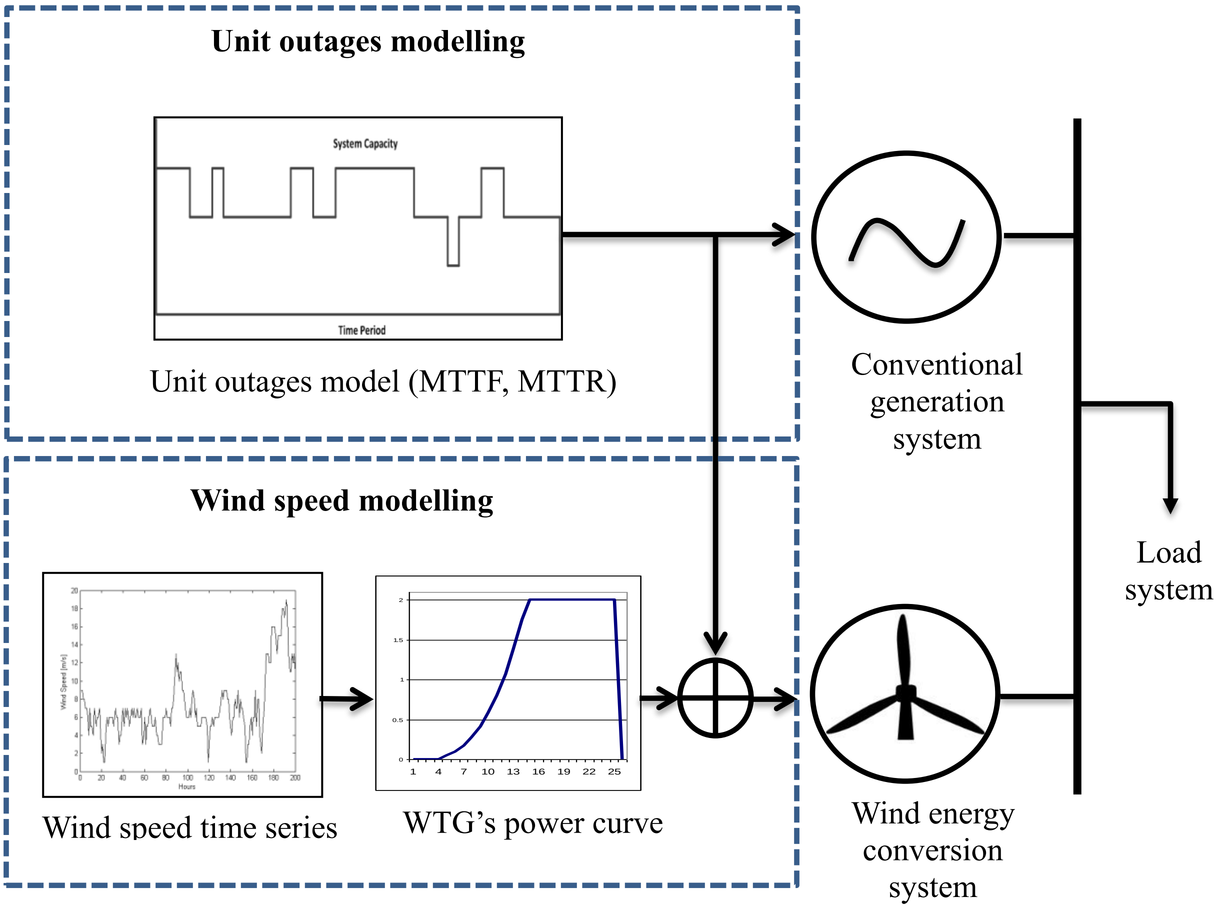



Figure 2-9 Conceptual Tasks in Generating Capacity Adequacy Assessment for Systems Containing Wind Energy

### 2.4.1 Stochastic Wind Speed/Power Simulation Model

It is worth emphasizing the wind speed modeling over the other issues, as it plays a fundamental role in representing the characteristics of wind speed. Modeling the wind generation in the reliability assessment requires large historical wind speed/power measurements to accurately capture the stochastic nature and random behavior of the wind at a particular site. However, the unavailability of sufficient data calls for reliable stochastic wind simulation techniques. Such synthetic wind power/speed models should preserve the main characteristics of the historical measurement data (e.g., the diurnal distribution and chronological correlation of the wind power/speed data). In the literature, different models are available that aim to model distributional and/or temporal variations of the wind speed/power.

Many models for implementing wind generation into different power system problems use a Weibull distribution to represent the wind speed variations. These models rely on the conclusions of some studies that have reported on statistical tests for wind speeds at several wind sites, and these studies revealed that the wind speed variations approximately followed a Weibull distribution [5]. However, from the perspective of reliability evaluation of wind generation, the methods using Weibull distributions suffer from some drawbacks. First, recent investigations into wind speed data have confirmed that wind speeds at several wind sites may follow different types of distributions based on the random behavior of the wind speed at each specific site [22]. Therefore, it may not be realistic to generalize the use of Weibull distribution for all wind farms, as it may lead to inaccurate reliability indices. Second, the most evident deficiency of these models is that they can only consider the stochastic nature of the wind speeds at a geographic location without considering the chronological characteristics of the wind speed [23]. Third, collected historical hourly wind speed data for a wind farm site over a considerable period of time should be available in order to accurately estimate the distribution parameters (scale, and shape parameters).

In recent years, there has been considerable research towards time series wind speed/power simulation models, owing to their ability to preserve the chronological variability and stochastic nature of the wind. The stochastic wind simulation models proposed in the reported work are typically classified into two categories: stochastic wind speed models and stochastic wind power models [24]. The former models are based on wind speed measurements, while the latter is based on wind power measurements, as shown in Figure 2-10. Considerable work has been founded on the basis of wind speed models, such as autoregressive moving average (ARMA) models [23, 25] and Monte Carlo Markov Chain (MCMC) models [26, 27]. An error in wind speed modeling is increased by a cubic factor in wind power when the speed is between the cut-in and rated values [24]. This drawback can be alleviated by transforming the measured wind speed data to wind power data as a prior step.

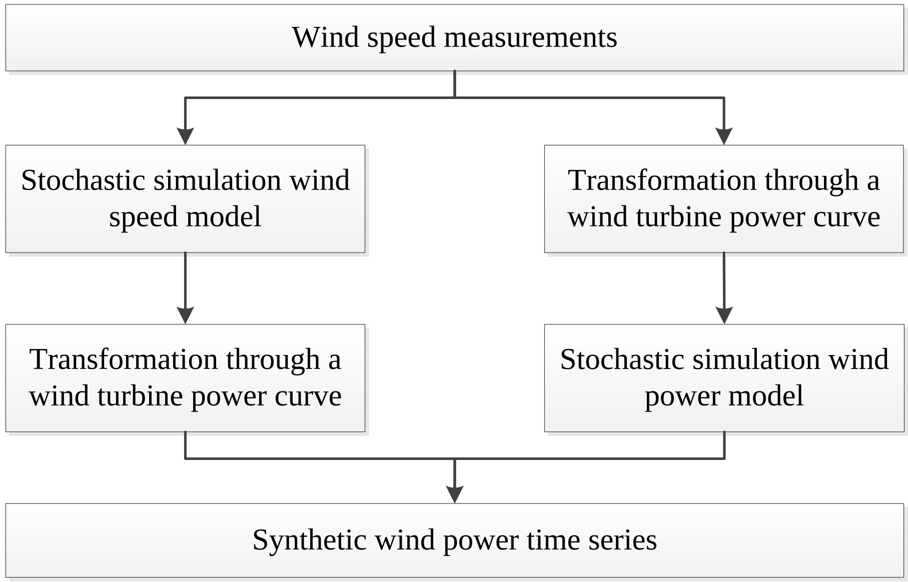



Figure 2-10 Classification of Stochastic Wind Simulation Models

Studies are widely available in the literature that have used the ARMA model to simulate time series wind speeds [23, 25]. The ARMA time series model is a basic linear model of time series that has been developed on the basis of combining the properties of the auto-regressive and moving average models. The ARMA model is dependent on past wind speed observations, prediction errors, and a random term [28]. Moreover, The ARMA model is typically associated with certain orders, referred to as ARMA (p, q), where p is the order of the AR model and q is the order of the MA model which indicate the appropriate lagged time that should be considered to provide the best fit of the simulated wind speed time series with the wind measurement data. The basic advantage of ARMA models is that they require fewer parameters compared to MCMC, and they also provide a desired autocorrelation of the simulated time series. However, ARMA models cannot guarantee a best fit for the probability distribution function (PDF) of the simulated time series, as discussed in [29]. In [24], it also is revealed that the direct application of ARMA models to build the stochastic wind power model is not feasible, since the nature of wind power generation is a non-stationary, non-Gaussian, random process.

Considerable work in the literature has widely studied the application of MCMC in developing a stochastic time series for either wind speed or wind power [26, 27, 29, 30]. For the Markov Chain process, the probability of a given state in a given instant can be deduced from information about the preceding state [27]. A Markov chain represents a system of elements moving from one state to another over time. Transition matrices of a Markov chain are used to mimic the pattern of the hourly changes of historical wind data so that the simulated wind data tracks that pattern.

At the earlier stage of developing such models based on MCMC, the models suffer from some practical shortcomings, such as the imperfect preservation of autocorrelation characteristics and inaccuracy and complexity associated with the discretization process. However, there are various studies published aimed at eliminating these drawbacks and improving the efficiency of MCMC models. The study presented in [27] uses the first-order and second-order schemes of a Markov Chain model to simulate synthetic wind speed data, and it concluded that a higher-order scheme of a Markov Chain model can slightly improve the results. The effect of different choices of state Markov Chain discretization is examined in [26]. The conclusions reveal that an increase in the dimension size of the Markov model provides a more accurate result. In [29], a comparison of the synthetic wind speed and wind power time series using MCMC model is presented. The results show that the development of a synthetic wind power model from data measured directly in the power domain is more accurate and provides an excellent fit for both the probability distribution and chronological correlation. For further improvements on MCMC, the authors in [30] suggested using a transition Markov Chain matrix for each particular month, aiming to include the monthly variation, so that the probability distribution and chronological correlation are improved.

### 2.4.2 Integrating Models for Wind Power in Adequacy Assessment Analysis

Over a period of almost thirty years, a series of publications in the literature have been concerned with developing evaluation models to include the potential contribution of wind farms to the adequacy of generation capacity. Most of these have acknowledged and modeled wind generation in the reliability assessment analysis by means of probabilistic techniques (analytical and simulation). Of these, generic analytical probabilistic techniques are the ones widely used for the evaluation of the adequacy of generating capacity that includes wind energy [18-21]. Simulation approaches have also been intensively used owing to their remarkable features, and they mainly refer to the non-sequential MCS approach [21, 22, 31] and the sequential MCS approach [32-36].

Most developed models for involving wind generation capacity in adequacy assessment analysis refer usually to one of two representation models: 1) the multi-state model; and 2) the load adjustment model [19, 37]. The following subsections discuss detailed descriptions of these representations, including some previous works developed on their basis, and their potential limitations.

#### 2.4.2.1 Multi-State Model

A multi-state wind model is commonly used to integrate wind generation into many power system studies. From the adequacy analysis perspective, a wind farm is treated as a conventional unit with multi-states (fully rated state or failed state, potential de-rated states). Each state represents a certain level of wind farm capacity with individual probability, and is therefore involved in the adequacy calculations in a manner similar to conventional units. The critical task in using this model is to determine the appropriate number of states that accurately represent potential wind speed scenarios [4]. The number of states should be determined primarily upon a trade-off between the desired accuracy of the results and the desired degree of sophistication of the analysis. In this section, some of the available previous work that used multi-state representation will be reviewed, and the used discretization techniques will be described.

The fundamental concept of dealing with a wind plant as a multi-state unit in adequacy assessment analysis is proposed in [18]. The basic idea is to create an aggregated wind farm multi-state model that takes into account the wind power output and the *FOR* of WTGs. The main procedures of this model can be summarized as follows:

1- Input the hourly wind speed data.
2- Transform the hourly wind speed data to wind power data using the Wind Turbine Power Output Curve.
3- Divide the output power of the WTG into a finite number of states. The equivalent state method is used to define the states; each state represent approximate 10% of rated power.
4- Assign the hourly wind output power (Step 2) to its corresponding state.
5- Find the probability of each state by dividing the total number of occurrences for each state by the total data.

6- Create a multi-state model for the wind farm, called a capacity outage probability table (COPT). This is done by multiplying the output power of each state (Step 3) by the number of WTGs, and then taking the same probability in that state.
7- Create another multi-state model for the wind farm that only considers the *FOR* of the WTGs. This is can be performed in the same way as for the conventional units. If the WTGs are identical, binominal distribution is used; however, the recursive algorithm in [3] can be convenient if the WTGs are not identical (discussed in Section 3.2.1, Chapter 3).
8- Combine the multi-state models (Step 6 & Step 7) to create the final form of a multistate wind farm model that includes the wind power output and the *FOR* of the WTGs.
9- Merge the COPT of the wind farm (Step 8) into the reliability model of conventional units using the analytical techniques in order to obtain the adequacy indices.

The essential conclusion in [18] is that each WTG cannot be individually convolved with the reliability model since all the WTGs are based on the same resource. So, the statistical dependence of the WTGs must be considered by aggregating all WTGs to present a single equivalent unit with some potential de-rated states. The same aforementioned procedures are followed by [21] with some different considerations. The authors' attention in [21] was mainly towards developing and examining appropriate multi-state wind farm models to evaluate generating system adequacy. The ARMA model is used to simulate hourly wind speeds, and also used the apportioning method to create multi-state models for a wind farm containing a number of WTGs. The apportioning method attempts to reduce the number of de-rated states by distributing the probabilities of the actual de-rated states between the up or down states and pre-assigned states based on the higher contribution the actual states make to the closer pre-assigned states. The studies in [21] used two quite diverse wind sites, and the analyses are applied to test systems (RBTS, and IEEE-RTS) using the analytical method and the non-sequential MSC technique. Two significant observations are presented in [21] : 1) a five-state wind farm model is reasonably sufficient to incorporate wind farms into power system adequacy studies; 2) ignoring the WTGs' *FOR* can significantly simplify the modeling procedures without considerably affecting the calculated reliability indices.

It is important to develop proper methods for wind power assessment to overcome the challenges and complexity involved in the process of obtaining the suitable wind speed model and appropriate number of states. With regard to this, the authors in [20] developed a simplified generic wind speed model that can be used to represent a wind farm generation model in the reliability evaluation at any geographic site. The essential advantage of the proposed approach is shown in the few parameters it needs to develop such a model, where only the annual mean wind speed value $\mu$ and the standard deviation $\sigma$ are required for a particular site. It is very efficient for a site which has a lack of historical wind data. The annual mean and standard deviation of wind speed for each site are used to obtain the close wind speed distribution, and then the common wind speed model is derived by combining the probability distribution for all selected sites. The authors derived a generic 6-step common wind speed model ($SW_i$), as seen in equation (2.4), which can be applied to integrate a wind farm generation model in the reliability evaluation using an analytical technique. The obtained results from the developed 6-step common wind speed model provide reasonable accuracy compared with the results obtained using a wind speed model derived from the ARMA.

$$SW_i = \mu + (i-3) * \left(\frac{5\sigma}{3}\right) \quad for \quad (i = 1, \dots \dots \dots .. 6) \qquad 2.4$$

In order to integrate the wind farm's multi-state with other conventional units, most of the reported work usually use an analytical technique [18-21] or a non-sequential MCS technique [21, 22, 31] . However, the multi-state representation model, along with the analytical or non-sequential MCS techniques, suffers from two main drawbacks. First, the chronological characteristics of the wind speed cannot be considered, and thus some time-based indices (frequency and duration indices) cannot be accurately evaluated. Second, the inaccuracy and complexity associated with the discretization process make it very difficult to develop an accurate model of a wind farm. Alternatively, there is a growing consensus and an increasing tendency in utilizing the load adjustment model (also called a time series model), which will be discussed in the next subsection.

#### 2.4.2.2 Load Adjustment Model

With regard to incorporating wind generation into generating capacity adequacy assessment, considerable work has been done using time series models. These models are acknowledged as being useful for wind generation because of their essential feature of preserving the chronological variability of the wind, which facilitates the integration of wind generation into the sequential MCS process for conventional generation. Indeed, they support the major advantages of a sequential MCS method that can comprehensively evaluate the reliability of power system and provide a wider range of indices than do analytical and non-sequential MCS methods. As mentioned earlier, most of the available time series wind models are based ARMA and MCMC models. The descriptions, advantages, and drawbacks for each model are described in section (2.4.1); this subsection is dedicated only to the integration of wind generation time series models into adequacy assessment analyses.

A reliability research group at the University of Saskatchewan developed a time series model for wind power reliability evaluation based on the ARMA model [23]. They considered different orders of the ARMA model to investigate the best fit between the simulated wind speed time series with the measured wind data. Their conclusion was that the simulated wind speed data using the developed ARMA time series model satisfied basic statistical tests, such as for hourly auto-correlation, seasonal characteristics, and diurnal distribution of wind speed, and thus can be used as a suitable time series model for wind integration into the reliability evaluation of generating systems. This model is extensively used for incorporating wind generation into the adequacy assessment of generating systems [32-36].

The authors in [35] proposed the methodology of wind generation modeling based on the ARMA model in conjunction with a sequential MCS method for conventional generation. The basic simulation procedures are briefly summarized as follows:

1. Create a capacity model for conventional generation by simulating the operating cycles of all conventional units using the sequential MCS method.
2. Construct a capacity model for wind generation by simulating the time series wind power data based on the ARMA model.
3. Create a capacity model for all WTGs, incorporating their failure and repair rates, the same as was done for conventional units in Step 1.

4. Combine the capacity models obtained in Steps 2 and 3 to form the total available wind generation capacity model.
5. Obtain the total available capacity of the generation system by combining the capacity models obtained in Steps 1 and 4.
6. Superimpose the total available capacity of the generation system on the hourly chronological IEEE-RTS load model (8760 hrs.).
7. Obtain the reliability indices by observing the system capacity reserve model over a large number of sampling years.

In [36], the generating capacity adequacy indices are compared using five wind speed models: mean observed, ARMA, MA, normal distribution, and Markov Chain. The results show that the ARMA model can provide a comprehensive representation of the actual wind regime better than the other wind speed models, and that it is the most suitable model for use in a sequential simulation process. Procedures similar to those mentioned above were followed in [33] and the study presented in that paper was devoted to observing the effect of WTG parameters (cut-in, cut-out, and rated) on adequacy capacity indices in order to help select the most suitable WTG for a specific site. The results reveal that considering different cut-in and rated values of wind speeds is significant, affecting the system indices, while the cut-out value is insignificant.

In [34], the impact of the contribution of wind generation on the adequacy capacity of a generating system are quantified considering many factors, such as wind conditions, wind penetration level, and the number of independent wind farms. The main observations of the results obtained using the RBTS and RTS are as follows: 1) the contribution of a wind farm to system reliability is extremely dependent on the wind conditions at a particular site, and an optimistic contribution can be achieved at a site with a high mean wind speed; 2) at a certain level, any increase in the wind penetration level may not further enhance system reliability; and 3) multiple independent wind farms in a system contributes positively to system reliability.

Remote areas are often supplied by renewable resources, and thus their reliability is a critical concern due to the intermittent, uncertain nature of those resources. With respect to this, it was acknowledged in [32] that facilitation can be offered by the ARMA time series model with the sequential MCS method to integrate battery storage systems in the evaluation of the generating capacity adequacy of small stand-alone wind energy conversion systems (SSWECS).

The results presented in [32] confirm that the integration of energy storage systems and increasing their capability in SSWECS can significantly improve system reliability.

To the best of our knowledge, there are few or no studies offering a critical evaluation of the application of MCMC models for wind power time series in generating capacity adequacy assessment. This thesis is aimed at assessing the contribution of wind energy to the adequacy of overall generating capacity using a sequential MCS method coupled with an MCMC model. In this thesis, MCMC is used to generate the synthetic wind power time series considering the recommendations in the literature, such as developing a synthetic wind model in the power domain [29], selecting appropriate states of Markov Chain discretization [26], and creating transition Markov Chain matrices on a monthly basis [30].

## 2.5 Summary

This chapter first presented a general background of the reliability assessment of power systems, including the standard definitions and different hierarchical levels. As a focus of the thesis, the related models, well-known indices, and commonly used techniques for generation adequacy assessment HLI are presented, and the main observations are as follows. Deterministic and probabilistic techniques are the ones widely used for the evaluation of generating capacity adequacy. In the past, the use of deterministic techniques was preferred due to lack of reliability data and computational resources, although they did not consider the stochastic nature of the system behavior.

Later, the availability of the applicable reliability data and advancements in computational technologies dictated the use of probabilistic techniques because of their essential feature of considering the inherent stochastic power systems. These techniques are typically classified into two categories: analytical techniques and Monte Carlo Simulation (MCS) techniques (sequential or non-sequential). As has been clarified in this chapter, each method has its own advantages and disadvantages, so the choice of method should be based on the type of evaluation desired and the nature of the problem. Evaluating the adequacy of generating capacity using a probabilistic technique is achieved by examining two main components: the generation model and the load model. The two models are then combined to form a risk model represented by a set of indices.

This chapter also tackled the issues imposed when implementing wind generation into the adequacy assessment of generating systems, the most significant of which is the availability of wind, which is random and intermittent in nature. In order to cope with wind variability, an essential task in the reliability analysis of wind generation is to develop an appropriate and accurate wind speed model. According to the literature, most available models that aim to capture distributional and temporal variations of the wind speed can be classified into two categories: ARMA and MCMC models. Their description, advantages, and disadvantages have been briefly discussed in this chapter.

Finally, this chapter described and discussed two representation models, the multi-state model and the load adjustment model, which are mostly used in the reported work to integrate wind generation capacity into the adequacy assessment. The load adjustment model is more desirable, since in addition to the inaccuracy and complexity associated with the discretization process, the multi-state model cannot consider the chronological characteristics of the wind speed.

The next chapter of this thesis provides methodologies and analyses of the applications of the three probabilistic techniques to conventional generation systems as they apply to two well-known test systems.

# Chapter 3
# Generation Adequacy Assessment for Conventional Generation Systems

## 3.1 Introduction

Chapter 2 provided an overview of power system reliability in general, and emphasized the essential concepts of generating system adequacy assessment for HL-I. In addition, it reviewed and highlighted the existing work with regard to the reliability assessment of power generation systems that include wind energy sources.

In this chapter, the required modeling and calculations to evaluate the adequacy capacity for conventional generation are developed using the most common probabilistic techniques (analytical, sequential MCS, and non-sequential MCS). This chapter is divided into three main sections. The first section discusses in depth the main procedures of generating capacity adequacy assessment based on each probabilistic technique. The second section introduces the relevant information about the systems under study, and they are two test systems designated the the Roy Billiton test system (RBTS) and the IEEE reliability test system (IEEE-RTS). Then, the last section of this chapter presents and compares the analyses and results using the three mentioned probabilistic techniques.

## 3.2 Probabilistic Techniques

As discussed in the previous chapter, generating capacity adequacy assessment can be performed using either a deterministic method or a probabilistic approach. Deterministic methods cannot recognize the stochastic nature of the behavior of power systems under component failure or demand variation, leading to inaccurate risk reliability estimation. Instead, there is considerable attention on probabilistic methods due to their ability to respond to the stochastic inherent in component failures and load variations, and thus they can reflect the actual risk associated with a given system.

The probabilistic techniques that have been developed for the evaluation of generating capacity adequacy can be categorized into two general types: analytical and Monte Carlo simulation (MCS) [4]. The following subsections are dedicated to discussing the main procedures of developing a generating capacity adequacy assessment model using three of the most common probabilistic techniques, which are analytical, sequential MCS, and non-sequential MCS techniques.

### 3.2.1 Analytical Technique

In an analytical technique, the basic generation model can be represented by a model usually called a capacity outage probability table (COPT). A recursive algorithm, in [3], can be used to create the COPT as an array of capacity levels with their associated probabilities of existence. In this algorithm, considering all the generating units, generating unit states are inserted in the COPT one at a time in sequential process until the COPT is totally formed. Each probability associated with a certain capacity level in the COPT represents the cumulative probability $P(X \geq C)$ of having a capacity outage X MW greater than or equal to C MW.

In COPT calculations, a generating unit can be represented by either a two-state model or a multi-state Markov model. For a two-state model, equation (3.1) represents the cumulative probability for a certain capacity level after adding a two-state unit with unavailability (*U*):

$$P^A(X) = (1 - FOR) * P^B(X) + (FOR) * P^B(X - C) \qquad 3.1$$

where, $P^A(X)$ and $P^B(X)$ are the cumulative probabilities of the system capacity outage level (X MW) after and before the addition of a two-state unit. In equation (3.1), $P^B(X)$ is assumed initially to be equal to1.0 for $X \leq 0$ and equal to 0 for X > 0.

The following example, from [3], illustrates the procedures of constructing a COPT using the recursive algorithm for a simple power system. The simple system consists of two 25 MW units and one 50 MW unit, all of which have forced outage rates (*FOR*) or unavailability (*U*) of 0.02. The COPT is created by adding generating units in a sequential process one at a time as follows:

Step I: After adding the first unit with a full capacity of 25 MW, the system will have two capacity outage levels:

$P^A(0) = (1 - 0.02) * P^B(0) + (0.02) * P^B(0 - 25) = (0.98) * (1) + (0.02) * (1)$=1

$P^A(25) = (1 - 0.02) * P^B(25) + (0.02) * P^B(25 - 25) = (0.98) * (0) + (0.02) * (1)$=0.02

Step II: After adding the second unit with a full capacity of 25 MW, the system will have three capacity outage levels:

$P^A(0) = (1 - 0.02) * P^B(0) + (0.02) * P^B(0 - 25) = (0.98) * (1) + (0.02) * (1) = 1$

$P^A(25) = (1 - 0.02) * P^B(25) + (0.02) * P^B(25 - 25) = (0.98) * (0.02) + (0.02) * (1) = 0.0396$

$P^A(50) = (1 - 0.02) * P^B(50) + (0.02) * P^B(50 - 25) = (0.98) * (0) + (0.02) * (0.02) = 0.0004$

Step III: After adding the third unit with a full capacity of 50 MW, the system will have five capacity outage levels:

$P^A(0) = (1 - 0.02) * P^B(0) + (0.02) * P^B(0 - 50) = (0.98) * (1) + (0.02) * (1) = 1$

$P^A(25) = (1 - 0.02) * P^B(25) + (0.02) * P^B(25 - 50) = (0.98) * (0.0396) + (0.02) * (1)$

$= 0.058808$

$P^A(50) = (1 - 0.02) * P^B(50) + (0.02) * P^B(50 - 50) = (0.98) * (0.0004) + (0.02) * (1)$

$= 0.020392$

$P^A(75) = (1 - 0.02) * P^B(75) + (0.02) * P^B(75 - 50) = (0.98) * (0) + (0.02) * (0.0396)$

$= 0.000792$

$P^A(100) = (1 - 0.02) * P^B(100) + (0.02) * P^B(100 - 50) = (0.98) * (0) + (0.02) * (0.0004)$

$= 0.000008$

Table 3-1 Capacity Outage Probability Table (COPT)

| Capacity Outage (MW) | Probability |
|---|---|
| 0 | 1 |
| 25 | 0.058808 |
| 50 | 0.020392 |
| 75 | 0.000729 |
| 100 | 0.000008 |

After adding the last unit, the obtained system capacity outage levels and their associated cumulative probabilities are the final form of COPT that represents the generation model in the analytical technique, as shown in Table 3-1. Similarly, multi-state generating units, which can exist in *n* partial capacity outage states ($C_i$) of individual probability ($p_i$), can be included in the

COPT calculations by modifying equation (3.1), as shown in equation (3.2). The details of the recursive algorithms are available in [3].

$$P^A(X) = \sum_{i=1}^{n} p_i * P^B(X - C_i) \tag{3.2}$$

The COPT is then combined with a suitable LDC or DPLVC load model in order to evaluate the reliability indices. Figure 3-1 shows the method of combining the different system capacity states in a generation model with the LDC. From Figure 3-1, it is seen that any capacity outage level $X$ MW calculated in COPT which failed to meet the demand over the designated period $(t_k)$ will contribute to the system LOLE. As indicated in equation (3.3), the system LOLE can be calculated by the summation of the multiplication of the probability of existence of failed capacity level with its designated period $(t_k)$. As mentioned earlier, the LOLE index is represented by either hours or days per year, depending on the load model used: the LOLE index is hours per year using the LDC, and days per year using the DPLVC.

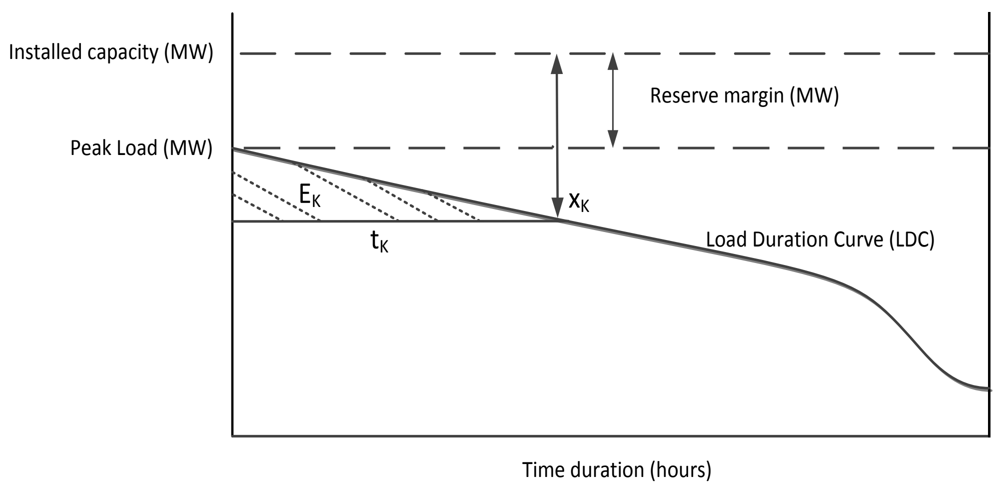



Figure 3-1 Relationship between Capacity, Load, and Reserve [3]

It is worth mentioning that the system loss of load probability (LOLP) can be obtained using the same method as for LOLE but excluding the associated period of time for each failed capacity level. As shown in equation (3.4), the system LOLP can be calculated by the summation of the associated probability of existence of the failed capacity level. The system LOEE is usually obtained by combining the COPT with the LDC load model using equation (3.5), which expresses the expected total amount of shortage energy when the available generation capacity fails to meet the demand over the designated period. As seen from Figure 3-1, any capacity outage level $X$ MW which failed to meet the demand over the designated period $(t_k)$ will contribute to the system LOEE by the amount of energy not supplied during the designated period $(t_k)$. The system LOEE can be calculated by the summation of the multiplication of the associated probability of existence of failed capacity level with the amount of energy not supplied and its designated period $(t_k)$.

$$LOLE = \sum_{k}^{n} t_k * P_k\big(X > Ins_{cap} - L\big) \tag{3.3}$$

$$LOLP = \sum_{k}^{n} P_k\big(X > Ins_{cap} - L\big) \tag{3.4}$$

$$LOEE = \sum_{k}^{n} t_k * \big(X - (Ins_{cap} - L)\big) * P_k\big(X > Ins_{cap} - L\big) \tag{3.5}$$

where:

$n$ = the number of the encountering capacity outage

$P_k$ = the probability of the existence of the capacity outage

$t_k$ = the time during which the loss of load will occur due to the capacity outage.

$X$ = capacity outage states in COPT

$Ins_{cap}$= the system installed capacity

$L$ = the value of load level

### 3.2.2 Non-Sequential Monte Carlo Simulation Technique

In a non-sequential, or state-sampling, MCS method [14], the status of all system components is sampled based on a uniform distributed random number (*RN*) between 0 and 1 in each simulation interval. Each simulation interval of sampled system states is randomly selected and independent from both the preceding and succeeding samples. In the case of a two-state model, the value of a random number is compared with the *FOR* of a unit, as shown in equation (3.6), where the generation unit is presented as being in either a fully rated state (*Up*) or a failed state (*Down*). The system state can then be obtained by combining the states of each individual generation unit, as seen in equation (3.7).

$$S_i = \begin{Bmatrix} Up & if & RN_i > FOR_i \\ Dwon & if & RN_i \leq FOR_i \end{Bmatrix} \quad 3.6$$

$$S_{sys} = \sum_{i=1}^{n} S_i \quad 3.7$$

where:

$S_i$ = the state of the $i^{th}$ generating unit

$RN_i$ = the random number for the $i^{th}$ generating unit

$FOR_i$ = the forced outage rate for the $i^{th}$ generating unit

$S_{sys}$ = the state of the system generation

$n$ = the number of generating units

To determine the system load level represented by the LDC or DPLVC, another uniform random number is generated. When the random number lies between the probabilities of load level $P_{i-1}$ and the probabilities of load level $P_i$, the load level $L_i$ is chosen. Then, the state of the system generation is compared with the selected load level in each iteration.

The range of expected reliability indices for evaluating the adequacy generating capacity in N samples can be obtained using a non-sequential MCS, as follows:

1- The LOLP can be calculated using equation (3.8)

$$LOLP = \frac{\sum_{i=1}^{N} D_i}{N} \quad where, \quad D_i = \begin{Bmatrix} 1 & if & S_{sys,i} < L_i \\ 0 & if & S_{sys,i} > L_i \end{Bmatrix} \quad 3.8$$

2- The LOLE (hrs/year) can be calculated using equation (3.9)

$$LOLE = \frac{\sum_{i=1}^{N} D_i}{N} * 8760 \qquad 3.9$$

3- The LOEE (MWh/year) can be calculated using equation (3.10)

$$LOEE = \frac{\sum_{i=1}^{N} ENS_i}{N} * 8760 \; where, ENS_i = \begin{Bmatrix} L_i - S_{sys,i} & if \;\; S_{sys,i} < L_i \\ 0 & if \;\; S_{sys,i} > L_i \end{Bmatrix} \qquad 3.10$$

where:

$N$ = the number of iterations

$D_i$ = the state of the system generation in the $i^{th}$ iteration

$L_i$ = the load level in the $i^{th}$ iteration

$S_{sys.i}$ = the state of the system generation in the $i^{th}$ iteration

$ENS_i$ = the amount of energy not supplied in the $i^{th}$ iteration

### 3.2.3 Sequential Monte Carlo Simulation Technique

The sequential MCS approach simulates the basic intervals in sequential order so that the correlation between the time intervals preceding and succeeding the system state is considered [12, 14, 16]. In conjunction with the *MTTF* and *MTTR* parameters of the operating history of the generating unit, uniform random numbers are utilized to simulate a state history that consists of a series for each generating unit in the system. The state history of a generating unit that contains random up and down times is also known as the state residence. The state residence time is sampled from its probability distribution and is usually assumed to be exponentially distrusted [12].

In general, the basic methodology of sequential MCS for the evaluation of the adequacy of the generating capacity can be briefly summarized in the following steps [14, 16]:

Step 1: All units are initially assumed to be in a success or “up” state.

Step 2: The operating history of each unit, in the form of chronological up-down-up operating cycles, is generated based on a random selection from the residence time distribution, as shown in Figure 3-2 (a). The duration of each state is calculated using equations (3.11) and (3.12), where TTF denotes the time to failure and TTR denotes the time to repair:

$$TTF_i = -MTTF * Ln\ RN_i \tag{3.11}$$

$$TTR_i = -MTTR * Ln\ RN_i \tag{3.12}$$

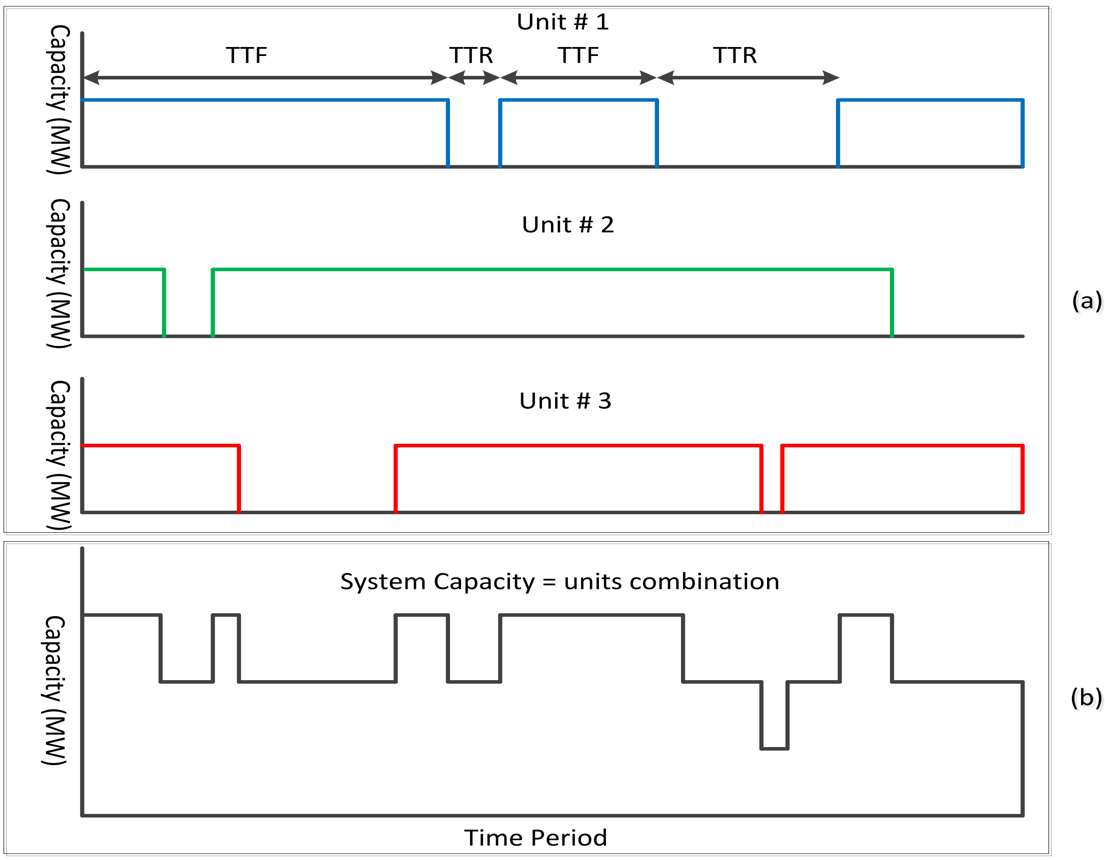



Figure 3-2 Sequential Operating Cycle Capacity for Each Unit (a) and for the Whole System (b)

Step 3: The operating cycles of all the generating units in the system are combined chronologically in order to provide the available capacity of the system, as shown in Figure 3-2 (b).

Step 4: The available capacity of the system obtained is then combined with the hourly chronological load model as shown in Figure 3-3.

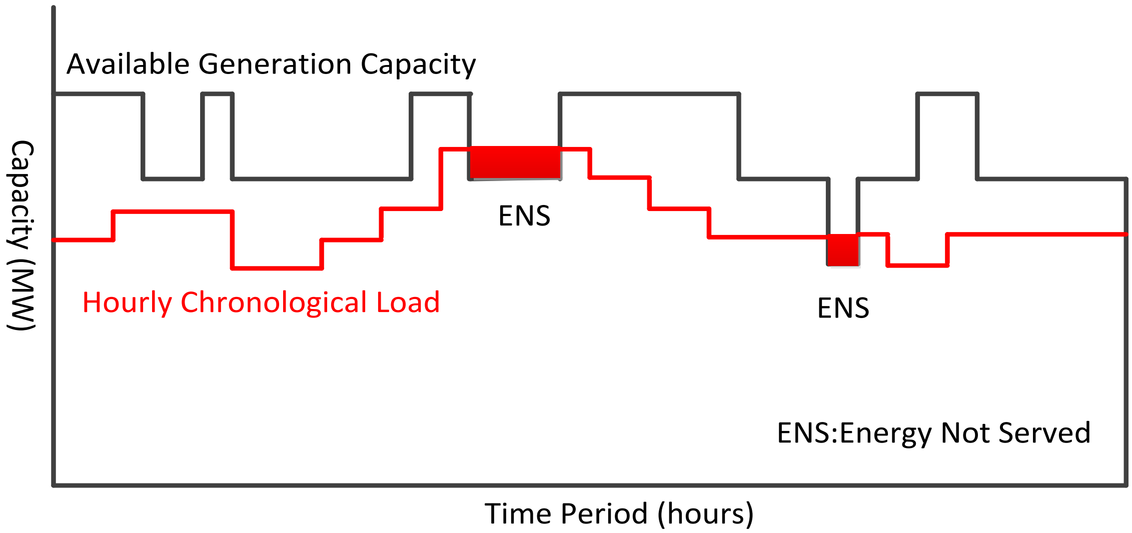



Figure 3-3 The Available Generation Capacity Superimposed on the Hourly Chronological Load

Step 5: The wide range of reliability indices can be calculated after large number of sampling years (N). Theses indices are viewed as two categories: annual system indices and interruption indices, as seen in the following equations [12]:

**Annual system indices:**

1- The LOLE (hrs/year) can be calculated using equation (3.13)

$$LOLE = \frac{\sum_{i=1}^{N} h_i}{N} \qquad 3.13$$

2- The LOEE (MWh/year) can be calculated using equation (3.14)

$$LOEE = \frac{\sum_{i=1}^{N} ENS_i}{N} \qquad 3.14$$

3- The LOLF (occurrence /year) can be calculated using equation (3.15)

$$LOLF = \frac{\sum_{i=1}^{N} f_i}{N} \qquad 3.15$$

**Interruption Indices:**

4- ENSPI (MWh/int.) can be calculated using equation (3.16)

$$ENSPI = \frac{\sum_{i=1}^{N} ENS_i}{n} = \frac{LOEE}{LOLF} \tag{3.16}$$

5- DNSPI (MW/int.) can be calculated using equation (3.17)

$$DNSPI = \frac{\sum_{k=1}^{n} D_k}{n} = \frac{LOEE}{LOLE} \tag{3.17}$$

6- EDPI (hrs/int.) can be calculated using equation (3.18)

$$EDPI = \frac{\sum_{i=1}^{N} h_i}{n} = \frac{LOLE}{LOLF} \tag{3.18}$$

where:

$N$ = the number of sampling years

$h_i$ = the number of hours in which loss of load is encountered in the $i^{th}$ sample year

$ENS_i$ = the amount of energy not supplied in the $i^{th}$ sample year

$f_i$ = the number of occurrences of loss of load in the $i^{th}$ sample year

$n$ = the total number of occurrences of loss of load in the $N$ sampling years

$D_k$ = the demand not supplied in MW in interruption $k$.

### 3.2.4 Stopping Criterion for Monte Carlo Simulation Techniques

Both MCS methods estimate reliability indices using simulations of the actual process, so reliance on a few numbers of samples is desired but cannot guarantee an accurate estimate. Conversely, increasing the number of samples definitely increases the accuracy, but also increases the time computation. Thus, MCS methods are generally associated with convergence criteria that identify the appropriate number of simulations ensuring a high level of confidence of the accuracy. In power system reliability assessment, the coefficient of variation of an index is often used as a convergence criterion or a stopping rule for MCS methods [16], as seen in equation 3.19:

$$\alpha = \frac{\sigma[E(x)]}{E(x)} \tag{3.19}$$

where x is the estimated value of the index ( i.e., LOLE, LOEE, etc.), E(x) is the expectation of system index, and $\sigma$ is the standard deviation of the estimated expectation of system index. The simulation break in proceedings further samples if the coefficient of variation reaches the pre-specified tolerance value $\varepsilon$. Sensitivity analyses in earlier studies [14] have revealed that stopping the simulation process relying on coefficient of variation of LOEE index can guarantee reasonable accuracy for other indices, since it has the lowest rate of convergence.

## 3.3 Systems under Study

In the study presented in this chapter, the three discussed probabilistic methods are used to evaluate the adequacy of conventional generating capacity. These methods are applied to two well-known test systems often used in reliability studies, which are the Roy Billinton Test System (RBTS) [38] and the IEEE Reliability Test System (IEEE-RTS) [39]. Figures 3-4 and 3-5 show the single line diagrams of the RBTS and the IEEE-RTS, respectively.

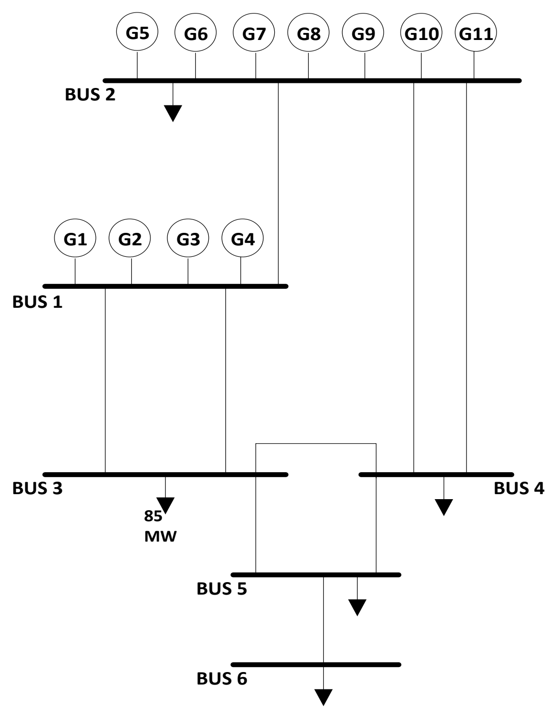



Figure 3-4 Single Line Diagram of the Roy Billinton Test System (RBTS)

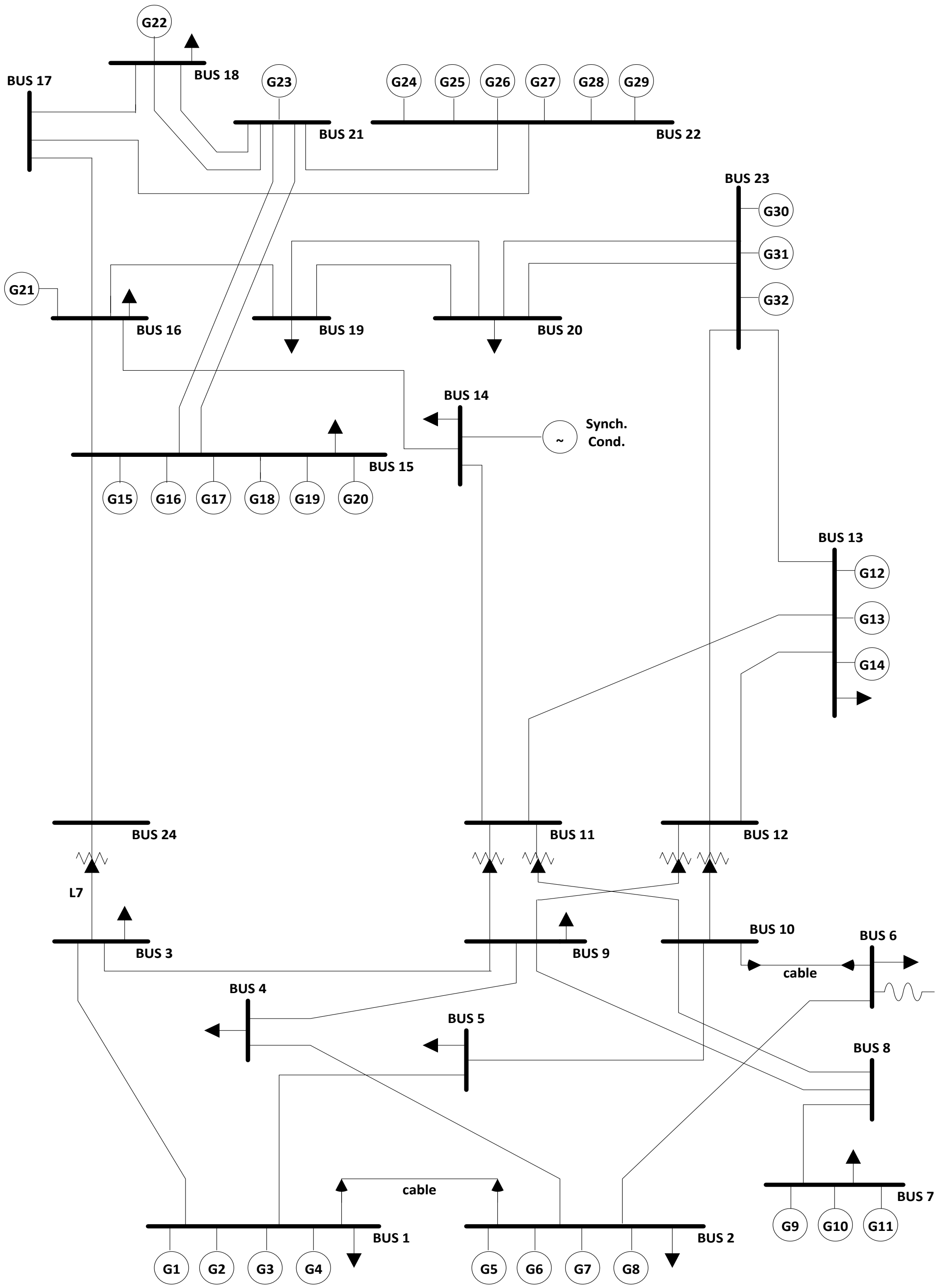



Figure 3-5 Single Line Diagram of the IEEE Reliability Test System (IEEE-RTS)

The RBTS is a relativity small test system developed by the power research group at the University of Saskatchewan to serve the students and researchers. The generation model in RBTS consists of 11 conventional generators with different capacities ranging from 5 MW to 40MW and having a total installed capacity of 240 MW. It has an annual peak load equal to 185 MW. In contrast, the IEEE-RTS is a relatively large test system developed by an IEEE Task Force, and it has been intensively used in different electric power areas. The generation model in IEEE-RTS comprises 32 conventional generators with different capacities ranging from 12 MW to 400MW and having a total installed capacity of 3405 MW. It has an annual peak load equal to 2850 MW. The relevant reliability data (*FOR*, *MTTF*, *MMTR*, etc.) for the conventional generators in the RBTS and the IEEE-RTS are available in Appendix A.

The IEEE-RTS load model [39] is used on an hourly basis in this thesis for applying the probabilistic methods in both the RBTS and the IEEE-RTS. This hourly load model is given as per unit or as percentage from the annual load peak of the given system. Once the annual peak load is determined (i.e., 185 for RBTS and 2850 for IEEE-RTS), the chronological hourly load model (8760 hours) can be developed. Figure 3-6 shows the chronological hourly load for the IEEE-RTS with an annual peak load of 2850 MW. The relevant data for the load models are given in Appendix B.

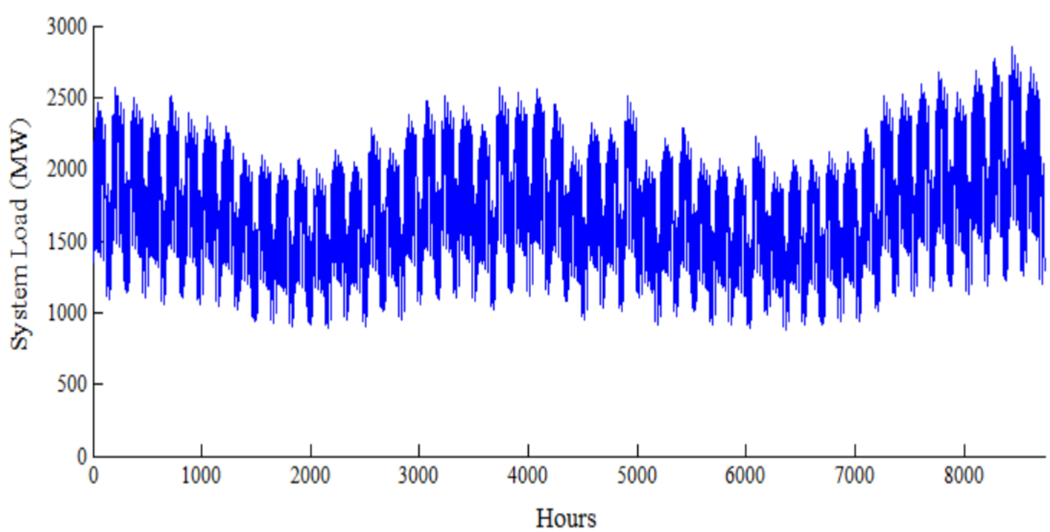



Figure 3-6 Chronological Hourly Load for IEEE-RTS over One Year

## 3.4 Results and Analysis

The main objectives of the study presented in this chapter can be summarized as follows:

1. Evaluate the adequacy of the generation capacity of the considered systems by examining the data related to their supply and demand systems.
2. Validate and verify the results obtained using three probabilistic techniques: analytical, sequential MCS, and non-sequential MCS with the ones available in the literature.
3. Compare the performance and efficiency of the three evolution techniques to each other considering different aspects.

All generating units are represented by a two-state model (fully-rated or failed state). The chronological IEEE-RTS load model is used on an hourly basis for applying the sequential MCS method into both systems, whereas the LDC model is used on an hourly basis for the analytical method. The LDC is rounded to 100 equally spaced levels and used in the non-sequential MCS techniques.

In the presented study, the stopping criteria for both MCS methods are as follows:

1- For the non-sequential MCS techniques, the simulation is terminated whenever it reaches either 1,000,000 as a maximum number of samples or 0.05 as a coefficient of variation tolerance for the LOEE index.

2- For the sequential MCS techniques, the simulation is ended whenever it reaches either 10,000 sampling years or the pre-specified coefficient of variation tolerance for the LOEE index, which is 0.05.

All considered probabilistic techniques applied in the test systems were programmed and executed in the MATLAB environment. A personal computer with 2.8 Ghz of speed processor and 8GB of RAM was used.

### 3.4.1 Reliability Indices Using Different Techniques and Different Systems

This subsection shows the obtained reliability indices for applying the described methods to the RBTS and IEEE-RTS. Also, the obtained results are verified with the ones available in the literature. In order to evaluate the adequacy of the generation capacity of the presented systems, the LOLE index is supposed to be less than 2.4 hours per year, as stated in [40].

The reliability indices for both systems are computed using the described analytical method and the results are presented in Table 3-2. The results show that the LOLE index obtained for the RBTS is about 1.09 hours per year, which is considered to be within the acceptable margin limits, while the LOLE index for the IEEE-RTS is almost four times the stated value. The computed indices are also verified with the results available in the literature. It can be observed that the computed indices are identical to the results in the literature due to their dependency on the same procedures of recursive algorithms.

Table 3-2 Adequacy Evaluation Indices Using Analytical Technique

| Reliability Indexes | RBTS | | IEEE-RTS | |
|---|---|---|---|---|
| | Computed | Published in [15] | Computed | Published in [14] |
| LOLE (hrs/yr) | 1.0916 | 1.0916 | 9.3936 | 9.3941 |
| LOEE (MWh/yr) | 9.8641 | 9.8613 | 1176.0 | 1176.0 |
| Elapsed Time (s) | 7.9343 | ----- | 12.235 | ----- |

Table 3-3 provides the reliability indices (i.e., LOLE and LOEE) obtained based on a non-sequential method. Besides, elapsed time, and number of samples are included as well. It can be noted that the computed results are not quite similar to the ones available in the literature due to diversities in simulation assumptions such as load steps and number of samples. However, even using the same load steps and number of samples as in the literature, the MCM methods would never provide exact results because of the different behavior of random numbers being used in different simulations. As observed from the table, a small system, RBTS, may require a very large number of samples to converge due to its small value of *FORs*. In contrast, when the value of *FOR* increases, as in IEEE-RTS, the required number of samples decreases. Therefore, the MCS methods are more efficient for a large application. A sensitivity analysis is carried out to assess the impact of variation of the indices in response to the number of samples, which is presented in Table 3-4. Each index has a different coverage rate, and it can be seen that the *LOEE* has the lowest rate of convergence.

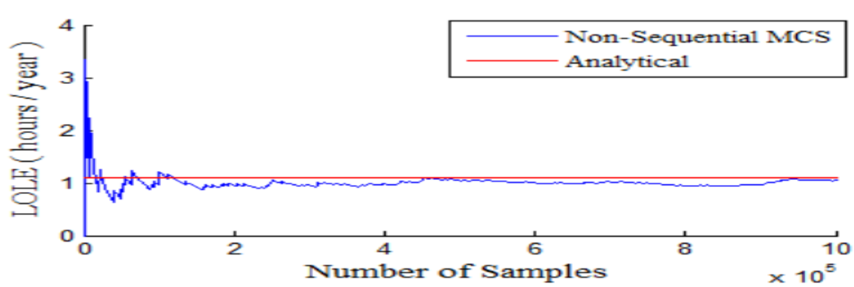
Table 3-3 Adequacy Evaluation Indices Using Non-sequential MCS technique

| Reliability Indexes | RBTS | | IEEE-RTS | |
|---|---|---|---|---|
| | Computed | Published in [21] | Computed | Published in [14] |
| LOLE (hrs/yr) | 1.0483 | 1.1516 | 9.3450 | 9.2185 |
| LOEE (MWh/yr) | 9.2747 | 11.780 | 1169.8 | 1147.3 |
| Elapsed Time (s) | 3576.2 | ----- | 961.50 | ----- |
| No. of samples | 1,000,000 | ----- | 281,086 | ----- |

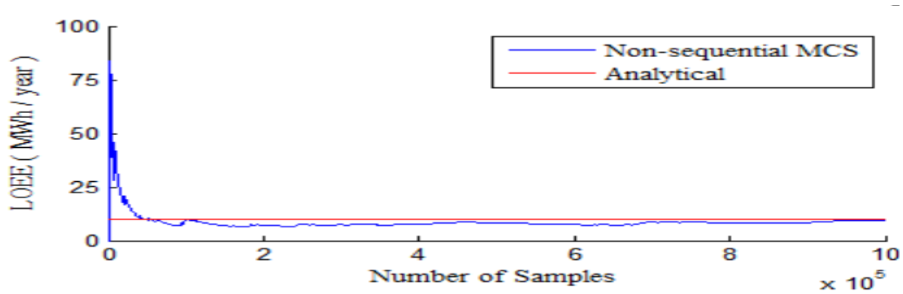
Table 3-4 Adequacy Evaluation Indexes vs. Number of Samples Using Non-sequential MCS technique

| | | | | | | |
|---|---|---|---|---|---|---|
| RBTS | No. of samples | 200,000 | 400,000 | 600,000 | 800,000 | 1,000,000 |
| | LOLE (hrs/yr) | 0.9610 | 0.9828 | 1.0046 | 0.9500 | 1.0483 |
| | LOEE (MWh/yr) | 7.2083 | 7.6347 | 7.5058 | 8.3216 | 9.2747 |
| | Coff. of var. | 0.1973 | 0.1342 | 0.0878 | 0.0656 | 0.0512 |
| IEEE-RTS | No. of samples | 50,000 | 100,000 | 150,000 | 200,000 | 250,000 |
| | LOLE (hrs/yr) | 8.5613 | 9.6970 | 9.2602 | 9.2165 | 9.3450 |
| | LOEE (MWh/yr) | 965.70 | 1233.5 | 1199.5 | 1154.8 | 1169.8 |
| | Coff. of var. | 0.2384 | 0.1309 | 0.0897 | 0.0645 | 0.0558 |

The LOLE and LOEE indices plotted against number of samples using a non-sequential method are shown in Figures 3-7 and 3-8, respectively. It can be observed that the indices for the early samples fluctuate, and they then begin to converge after more samples are tested. It is worth noting that the non-sequential method produces very close to the analytical values, as shown in the figures.

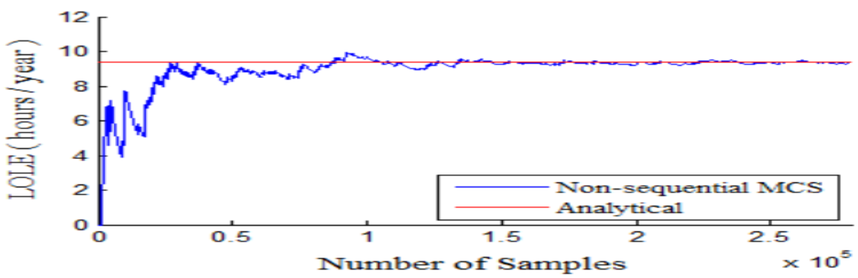



(a) LOLE

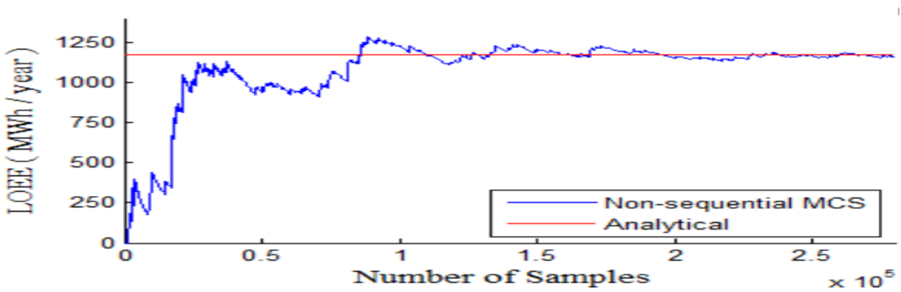



(b) LOEE

Figure 3-7 LOLE (a) and LOEE (b) for the RBTS Using Non-sequential MCS Method




(a) LOLE




(b) LOEE

Figure 3-8 LOLE (a) and LOEE (b) for IEEE-RTS Using Non-sequential MCS Method

A wide range of indices, presented in Table 3-5, are computed with sequential MCS for both power systems. Results available in the literature are included as well, but unfortunately a complete comparison of the results cannot be provided due to a lack of information in the literature. A close agreement can be observed between the results computed and the ones in the literature. However, some differences may be expected due to the random nature of the MCS methods. In Table 3-6, further case is conducted to examine the impact of variation of the indices with respect to number of samples. As earlier discussed, a large system, IEEE-RTS, requires a smaller number of sampling years compared to a small system, RBTS, where a large number of sampling years is required. Table 3-6 supports the fact that the more samples used, the less the coefficient of variation becomes, and hence the more accurate the results should be.

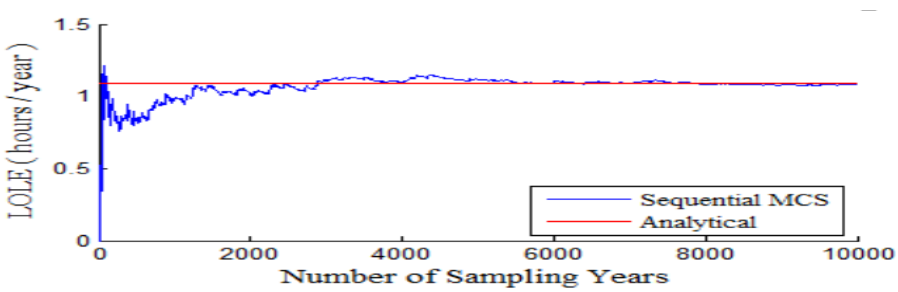
Table 3-5 Adequacy Evaluation Indices Using Sequential MCS technique

| Reliability Indexes | RBTS | | IEEE-RTS | |
|---|---|---|---|---|
| | Computed | Published in [15] | Computed | Published in [14] |
| LOLE (hrs/yr) | 1.0849 | 1.0901 | 9.3600 | 9.3716 |
| LOEE (MWh/yr) | 9.9083 | 9.9268 | 1,192.5 | 1,197.4 |
| LOLF (occ/yr) | 0.2174 | 0.2290 | 1.9606 | 1.9192 |
| ENSINT (MWh/ int) | 44.356 | ----- | 608.76 | ----- |
| DNSINT (MW/int) | 9.1321 | ----- | 127.14 | ----- |
| EDPI (hour/int) | 4.8568 | ----- | 4.7836 | ----- |
| No. of samples (yrs) | 10,000 | ----- | 2,733 | 2,500 |
| Elapsed Time (s) | 20,036 | ----- | 6,904 | ----- |

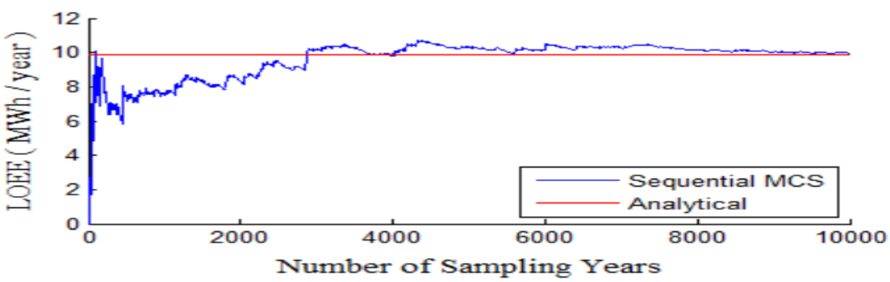
Table 3-6 Adequacy Evaluation Indexes vs Number of Samples Using Sequential MCS technique

| | | | | | | |
|---|---|---|---|---|---|---|
| RBTS | No. of sample years | 2,000 | 4,000 | 6,000 | 8,000 | 10,000 |
| | LOLE (hrs/yr) | 1.0150 | 1.1035 | 1.0968 | 1.0858 | 1.0849 |
| | LOEE (MWh/yr) | 8.2576 | 9.8334 | 10.2630 | 10.1060 | 9.9083 |
| | LOLF (occ/yr) | 0.2105 | 0.2245 | 0.2230 | 0.2199 | 0.2174 |
| | Coff. of var. | 0.1236 | 0.0909 | 0.0803 | 0.0685 | 0.0598 |
| IEEE-RTS | No. of sample years | 500 | 1,000 | 1,500 | 2,000 | 2,500 |
| | LOLE (hrs/yr) | 10.2324 | 9.8702 | 9.7294 | 9.4849 | 9.2897 |
| | LOEE (MWh/yr) | 1302.7 | 1335.5 | 1292.4 | 1238.0 | 1192.9 |
| | LOLF (occ/yr) | 2.1327 | 2.0028 | 1.9981 | 1.9609 | 1.9390 |
| | Coff. of var. | 0.1164 | 0.0860 | 0.0705 | 0.0605 | 0.0533 |

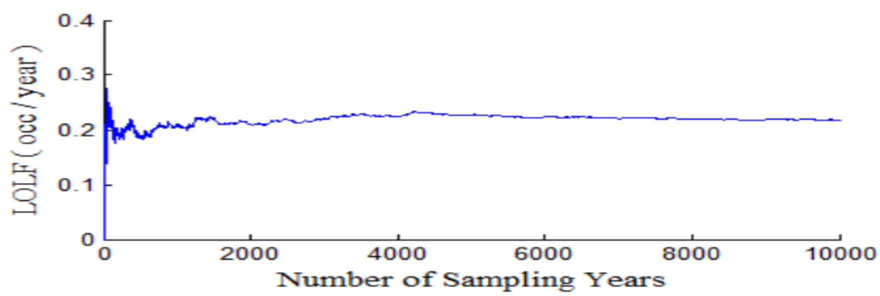
Figures 3-9 and 3-10 demonstrate the LOLE, LOEE, and LOLF indices for both power systems, respectively, over pre-specified sampling years using the sequential MCS. It can be observed that the computed results of the LOLE and LOEE indices fluctuate considerably for small sample sizes; however, they eventually settle around the analytical results. Whereas, the LOLF cannot be provided using analytical method.




(a) LOLE

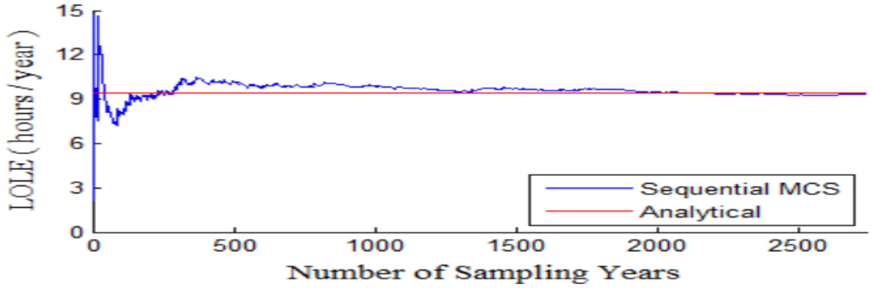



(b) LOEE

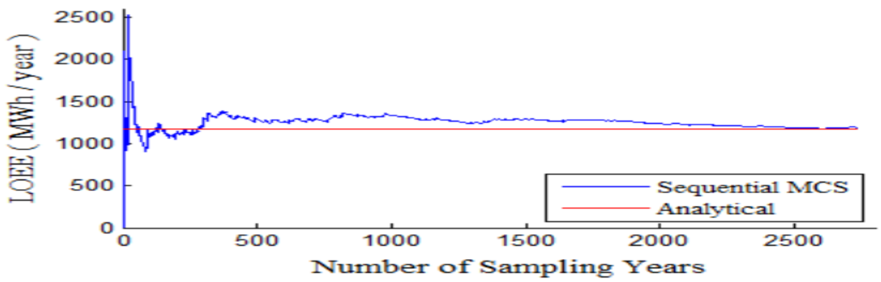



(c) LOLF

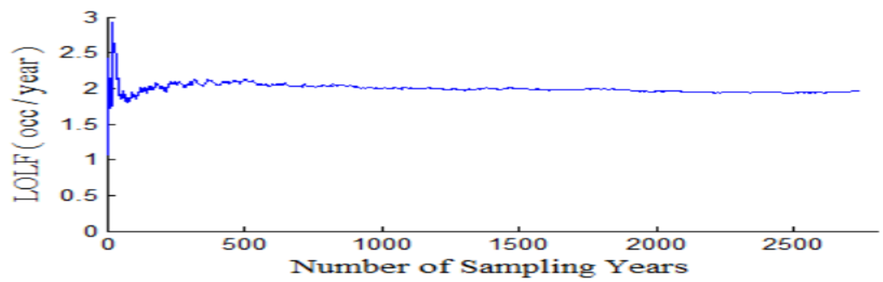
Figure 3-9 LOLE (a), LOEE (b) and LOLF(c) for RBTS Using the Sequential MCS Method




(a) LOLE



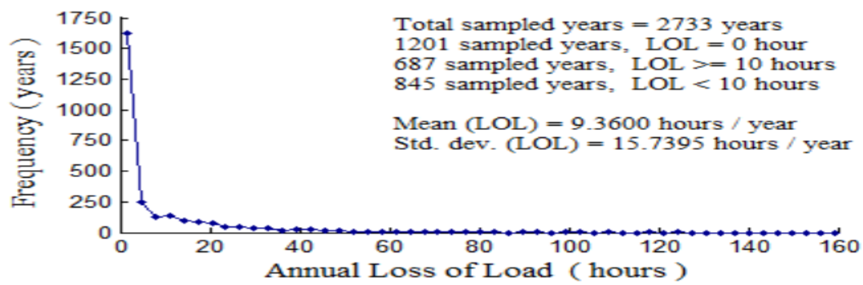

(b) LOEE



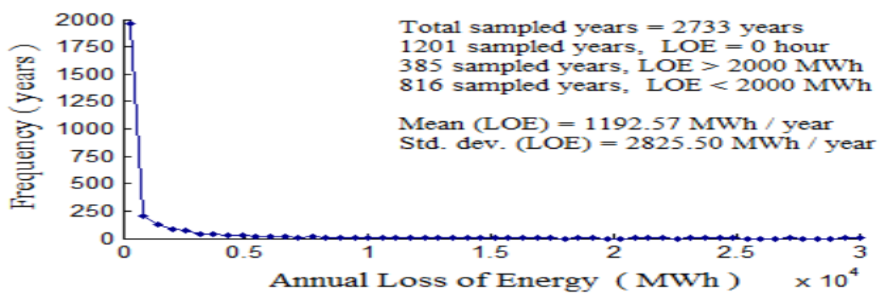

(c) LOLF

Figure 3-10 LOLE (a), LOEE (b) and LOLF(c) for IEEE-RTS Using the Sequential MCS Method

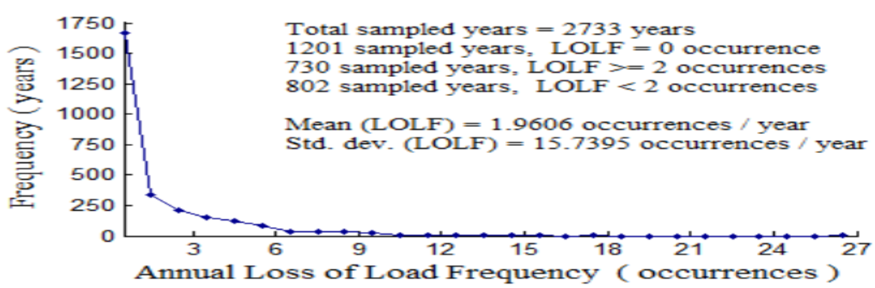
The sequential MCS method can also provide the probability distribution function of the indices. Figure 3-11, for example, shows the probability distribution function of three indices of the IEEE-RTS, which are: a) loss of load LOL, b) loss of energy LOE, and c) loss of load frequency LOLF. It can be noted that the system experienced no loss of load in 1201 years of the total sampled years. The number of sampled years in which the system encounters a shortage generation capacity is about 1532, 687 of which have a loss of load estimated by 10 hours or greater, while 845 years have a loss of load estimated by less than 10 hours. This interpretation can also be applied to b) LOE, and c) LOLF.




(a) Annual Distribution of the LOL




(b) Annual Distribution of the LOE




(c) Annual Distribution of the LOLF

Figure 3-11 Annual Distribution of LOL (a), LOE (b) and LOLF(c) for IEEE-RTS

### 3.4.2 A Comparison of Probabilistic Techniques

This subsection pertains to a comparison of three probabilistic evolution techniques considering their required procedures, accuracy of computed indices, and computational times. The comparison of the reliability indices computed using the presented methods for the studied systems are provided in Table 3-7.

Table 3-7 Adequacy Evaluation Indexes Using Three Probabilistic Methods

| Reliability Indexes | RBTS | | | IEEE-RTS | | |
|---|---|---|---|---|---|---|
| | Analytical | Non-sequential MCS | Sequential MCS | Analytical | Non-sequential MCS | Sequential MCS |
| LOLE (hrs/yr) | 1.0916 | 1.0483 | 1.0849 | 9.3936 | 9.3450 | 9.3600 |
| LOEE (MWh/yr) | 9.8641 | 9.2747 | 9.9083 | 1176.0 | 1169.8 | 1,192.5 |
| LOLF (occ/yr) | ------ | ------ | 0.2174 | ------ | ------ | 1.9606 |
| ENSINT (MWh/ int) | ------ | ------ | 44.356 | ------ | ------ | 608.76 |
| DNSINT (MW/int) | ------ | ------ | 9.1321 | ------ | ------ | 127.14 |
| EDPI (hour/int) | ------ | ------ | 4.8568 | ------ | ------ | 4.7836 |
| No. of samples | ------ | 1,000,000 | 10,000 | ------ | 281,086 | 2,733 |
| Elapsed Time (s) | 7.9343 | 3,576.2 | 20,036 | 12.235 | 961.50 | 6,904 |

Generally speaking, all of these methods are effective and efficient for evaluating the adequacy of conventional generating capacity. Several important points should be noted about these probabilistic techniques, which are as follows:

1- In the case of an adequacy assessment of conventional generation where units are represented by 2-state, the analytical technique is very efficient since it requires very short computational time compared to MCS techniques.

2- However, the analytical method is not appropriate for a complicated system where variable energy sources such as wind and solar generation are included and usually represented by multi-states units, and hence further approximations are required.

3- Furthermore, the analytical method cannot provide frequency and duration indices or interruption indices since it does not consider the chronology being in the nature of generation and load.

4- Unlike the analytical method, MCS methods are not likely to provide exact results because of their dependency on the random number generator being used.

5- When it comes to system size, MCS methods are found to be efficient and effective for a large and complicated system.

6- In MCS methods, a small size of samples cannot guarantee accurate results, and therefore the number of samples should be well defined, which is usually controlled by stopping criteria.

7- In MCS methods, the LOEE index has the lowest rate of convergence. Hence, choosing its coefficient of variation, as stopping criteria, can guarantee reasonable accuracy for other indices.

8- The non-sequential MCS method has very simple, straightforward procedures with respect to other techniques.

9- In the case of adequacy assessment for conventional generation, the non-sequential MCS method does not offer recognized benefits over the analytical method, since it requires a relatively large computational time.

10- Moreover, the non-sequential MCS method suffers from the same weakness as the analytical method, in which the chronology being in the nature of generation and load are not considered. Thus, frequency and duration indices and interruption indices cannot be computed.

11- The sequential MCS method recognizes the chronology of events and the stochastic behavior of system elements, so it provides additional and meaningful data about the behavior of a system such as time-based indices (frequency and duration indices) and the indices' probability distributions.

12- The major disadvantage of the sequential MCS method is the need for a large computational time compared with other methods.

## 3.5 Summary

This chapter has illustrated the application of a variety of probabilistic reliability techniques for the evaluation of adequacy of generating capacity of the RBTS and the IEEE-RTS. Three common techniques were used in order to evaluate the power systems under study: analytical, non-sequential Monte Carlo (state sampling), and sequential Monte Carlo (sampling duration). In each method, the required procedures to present generation and load models have been described in details. Particular attention is paid to verify the calculated results of the presented approaches with the ones available in the literature. According to our findings, it can be concluded that the analytical method produces results identical to the ones available in the literature, while MCS methods cannot generate exact results due to the random nature of the simulation process, but similar results can be provided.

A range of basic reliability indices for each system was obtained with the use of these techniques. The results show that the LOLE index computed for the RBTS is considered within the acceptable margin limits stated by NERC (2.4 hours per year), while the LOLE index for the IEEE-RTS is almost four times the stated value. A further study was conducted in order to compare the performance and efficiency of the three evolution techniques, taking into account different aspects such as the complexity of required procedures, accuracy of computed indices, and computational times. Among these techniques, the sequential MCS method can comprehensively evaluate the reliability of power systems by providing a wider range of indices with respect to the analytical and non-sequential MCS methods, such as time-based indices (frequency and duration indices), and the indices' probability distributions.

The major advantages of the sequential MCS method result from its ability to consider the chronology of events and the stochastic behavior of system elements, which are considered essential features for evaluating a power system that includes non-conventional generation such as wind and solar, which are time-dependent and correlated.

Moving forward, the next chapter will present a framework assessment for the adequacy of overall generating capacity by combining the conventional generation capacity obtained using the sequential MCS technique with the wind generation capacity obtained using the MCMC model.

# Chapter 4
# Inclusion of Wind Farm Modeling into the Conventional Generation Adequacy Evaluation

## 4.1 Introduction

In the previous chapter, the required models and calculations to evaluate adequacy assessment for conventional generation are presented using the most common probabilistic techniques (analytical, sequential MCS, and non-sequential MCS). These techniques are applied to two test systems (RBTS, and IEEE-RTS) and the obtained results are compared to each other and are also verified with the available results in the literature. In this chapter, the work is extended to study the contribution of wind generation to overall system reliability and to ensure the adequacy of generation capacity.

As discussed in Section 2.4 of Chapter 2, there are some issues imposed when implementing wind generation into the adequacy assessment of generating systems, the most significant of which is the availability of wind, which is random and intermittent in nature. Modeling wind generation in the reliability assessment requires a large historical wind speed/power measurement to accurately capture the stochastic nature and random behavior of the wind at a particular site. However, the unavailability of sufficient data calls for reliable stochastic wind simulation techniques. Such synthetic wind power/speed models should preserve the main characteristics of the historical measurement data (e.g., distributional and temporal variations of the wind speed). Most of the available models in the literature can be classified into two categories: the ARMA and Markov Chain models. Studies are widely available in the literature assess the overall adequacy of generating systems by combining the synthetic wind power time series based on the ARMA model with the sequential MCS method for conventional generation [32-36]. In this chapter, the application of the MCMC model is investigated to evaluate the adequacy of generating capacity. MCMC is used to generate synthetic wind power time series considering the recommendations in the literature such as developing a synthetic wind model in the power domain, selecting the appropriate states of Markov Chain discretization, and creating transition Markov Chain matrices on monthly basis.

In this chapter, the main procedures of the methodology of stochastic wind power simulation based on the MCMC model are first presented. Then, the synthetic wind power time series model is verified with the measured data in three statistical aspects, which are probability distribution functions, autocorrelation functions, and monthly variations. Afterward, a 20 MW wind farm is connected to the RBTS, and a 400 MW wind farm is connected to the IEEE-RTS in order to study the contribution of wind energy to the overall adequacy generating capacity. A further case study is conducted to compare the reliability indices obtained using the MCMC model with those obtained using the ARMA model in order to show the validation and efficiency of the proposed methodology.

## 4.2 Methodology of Stochastic Wind Power Simulation Model

In this section, the MCMC model used for generating synthetic wind power time series is illustrated. The main procedures of the stochastic wind power simulation model are summarized, as shown in Figure 4-1. In the following subsection, the procedures are discussed in details.

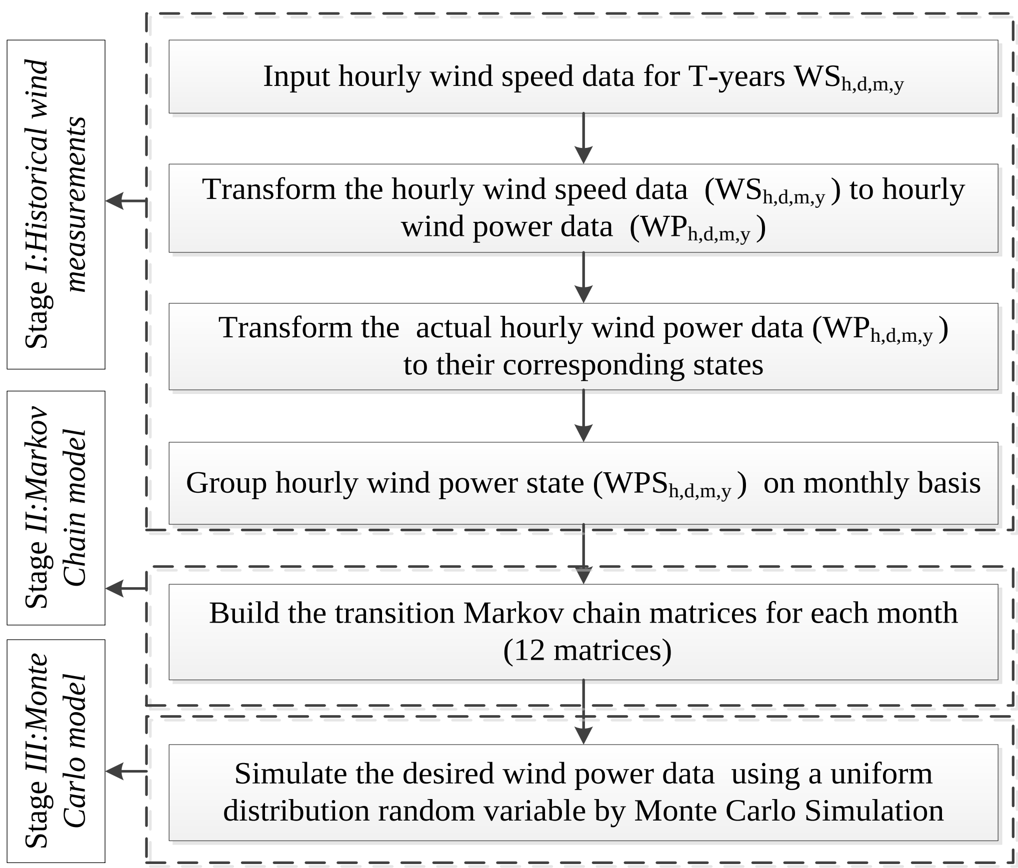



Figure 4-1 The Main Procedures of MCMC Model

### 4.2.1 Historical Wind Measurements

The hourly observed wind speed data over 8 years (Jan. 1, 1986 to Dec. 31, 1993) for the Bonavista site located in the Province of Newfoundland, Canada were downloaded from Environment Canada and used in this thesis [41]. As recommended in [29], the development of a synthetic wind power model from measured wind power data is more appropriate and offers basic advantages over a model based on measured wind speed data. Thus, the first step is to transform the measured wind speed data to wind power data through the wind power curve of the wind turbine generator, as given by (3.1) [31].

$$P(\omega) = \begin{cases} 0 & 0 \leq \omega \leq \omega_1 \\ (a_1 + a_2\omega + a_3\omega^2)P_{rated} & \omega_1 < \omega < \omega_r \\ P_{rated} & \omega_r \leq \omega \leq \omega_{cut-out} \\ 0 & \omega > \omega_{cut-out} \end{cases} \qquad 3.1$$

The constant terms $a_1$, $a_2$, and $a_3$ can be expressed in terms of the cut-in speed ($\omega_1$) and the rated wind speed ($\omega_r$), as given by (3.2)-(3.4):

$$a_1 = \frac{1}{(\omega_1 - \omega_r)^2}\left[\omega_1(\omega_1 + \omega_r) - 4\omega_1\omega_r\left(\frac{\omega_1 + \omega_r}{2\omega_r}\right)^3\right] \qquad 3.2$$

$$a_2 = \frac{1}{(\omega_1 - \omega_r)^2}\left[4(\omega_1+\omega_r)\left(\frac{\omega_1 + \omega_r}{2\omega_r}\right)^3 - (3\omega_1 + \omega_r)\right] \qquad 3.3$$

$$a_3 = \frac{1}{(\omega_1 - \omega_r)^2}\left[2 - 4(\omega_1+\omega_r)\left(\frac{\omega_1 + \omega_r}{2\omega_r}\right)^3\right] \qquad 3.4$$

Using (3.1), the output power characteristic is developed for a wind turbine generator of 2 MW. For all case studies presented in this chapter, the following wind speed data are used: $\omega_1$= 14.4 km/h, $\omega_r$ = 36 km/h and $\omega_{cut-out}$ = 80 km/h.

The fundamental step prior to creating transition matrices is to cluster the measured wind power data into a finite number of states. Accordingly, a clustering technique called K-means is used due to its simplicity and the reasonable accuracy it provides. The K-means clustering technique is discussed in detail in [42], and its procedures are summarized as follows:

1- Select the initial cluster means (centroids) $M_k$ of the clusters, where $k$ is the number of clusters. The eleven centroids (i.e. k=11) are initially selected in this study; this is determined by dividing the output power of WTG (2MW) equally into 0.2 steps (i.e. $k$=0, 0.2, …... ,2).

2- Calculate the distance $D_{ki}$ from each wind power value $W_i$ to each centroid $M_k$ , as given in equation 3.5.

$$D_{ki} = |M_k - W_i| \qquad 3.5$$

3- All the wind power data are then assigned to the nearest centroid.

4- Calculate new cluster means or centroids using equation 3.6, where the average of wind power data in cluster $k$ is divided by the total number of data points in the same cluster $N_k$.

$$M_k = \frac{\sum_{W_i \epsilon N_k} W_i}{N_k} \qquad 3.6$$

5- Repeat steps 2 to 4 until the centroids remain unchanged after a number of iterations.

Figure 4-2 shows a piece of the actual wind output power curve along with the curve obtained after 11 clustering states. Thereafter, the hourly historical wind power data is clustered into 12 groups, one for each month. Each group contains a number of 24-hour daily profiles which are equal to the number of days in a particular month multiplied by the number of available years.

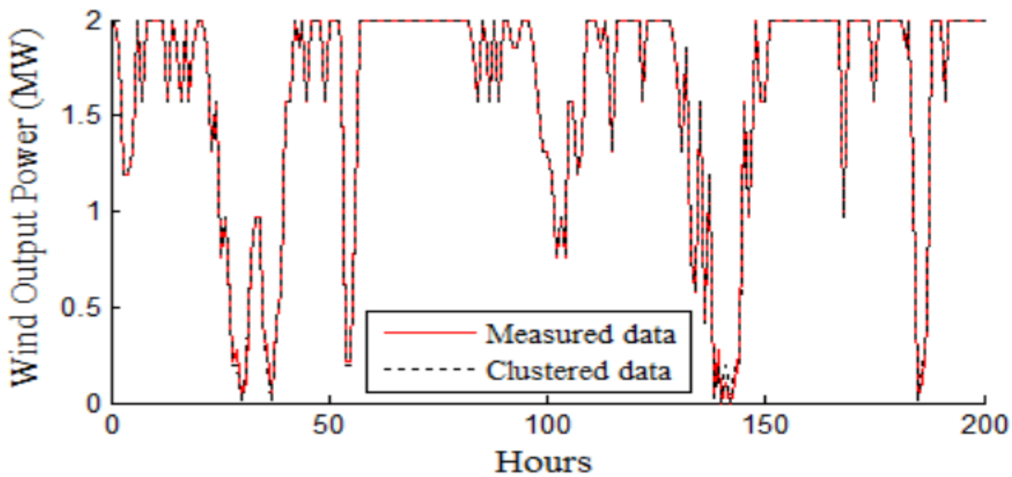



Figure 4-2 Piece of Time Series of the Actual Wind Output Power Curve along with the Curve Obtained After 11 Clustering States

### 4.2.2 Transition Matrices of Markov Chain

For the Markov Chain process, the probability of the given state in the given instant can be deduced from information about the preceding state. A Markov chain represents a system of elements moving from one state to another over time. A first-order Markov chain model has frequently been used for the modeling and simulation of wind speed or power data. The transition matrices of the Markov chain are used to mimic the pattern of hourly changes of historical wind power data so that the simulated wind power data track that pattern.

Let *X(t)* be a stochastic process having a discrete state space *S*={*1,2,…, K*}. Thus, the conditional probabilities $\Pr\{X(t) = j | X(t-1) = i\} = P_{ij}$ are called transition probabilities from state *i* to state *j* for all indices $1 \le (i, j) \le k$. For *k* states, the first-order transition matrix $P_{ind}$ with a size of *(k*k)* can be created and takes the form shown in (3.7). Each row of the matrix relates to the current state, while each column relates to the possible next state.

$$P_{ind} = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots\cdots & p_{1,k} \\ p_{2,1} & p_{2,2} & \cdots\cdots & p_{2,k} \\ . & & & \\ . & & & \\ . & & & \\ p_{k,1} & p_{k,2} & \cdots\cdots & p_{k,k} \end{bmatrix} \quad 3.7$$

The state probabilities at time $t$ can be estimated from the relative frequencies of the $k$ states. If $n_{ij}$ is the number of transitions from state $i$ to state $j$ in the sequence of wind power data, the maximum likelihood estimates of the transition probabilities is (3.8):

$$p_{ij} = \frac{n_{ij}}{\sum_j n_{ij}} \quad 3.8$$

After the individual transition matrix $P_{ind}$ is constructed based on individual probabilities, the cumulative probability transition matrix $P_{cum}$ can be constructed so that the $i_{th}$ row in $P_{cum}$ ends with one. For example, Tables 4-1 and 4-2 show the actual individual and cumulative transition matrix for the month of January, respectively. In this study, Markov chain transition matrices are formed on a monthly basis, resulting in 12 matrices, aiming to include the monthly variation so that the probability distribution and chronological correlation are further improved, as suggested in [30].

Table 4-1 Individual Transition Probability Matrix of the hourly wind power data for January

| State | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.485 | 0.250 | 0.044 | 0.015 | 0.000 | 0.044 | 0.000 | 0.000 | 0.015 | 0.015 | 0.132 |
| 2 | 0.276 | 0.293 | 0.155 | 0.121 | 0.069 | 0.034 | 0.000 | 0.017 | 0.034 | 0.000 | 0.000 |
| 3 | 0.074 | 0.370 | 0.074 | 0.259 | 0.037 | 0.037 | 0.037 | 0.037 | 0.037 | 0.000 | 0.037 |
| 4 | 0.038 | 0.115 | 0.038 | 0.000 | 0.115 | 0.115 | 0.115 | 0.077 | 0.154 | 0.038 | 0.192 |
| 5 | 0.000 | 0.280 | 0.120 | 0.160 | 0.080 | 0.120 | 0.080 | 0.040 | 0.040 | 0.000 | 0.080 |
| 6 | 0.023 | 0.000 | 0.140 | 0.023 | 0.116 | 0.070 | 0.163 | 0.140 | 0.093 | 0.070 | 0.163 |
| 7 | 0.053 | 0.000 | 0.026 | 0.079 | 0.079 | 0.132 | 0.132 | 0.132 | 0.184 | 0.079 | 0.105 |
| 8 | 0.019 | 0.019 | 0.019 | 0.000 | 0.019 | 0.115 | 0.135 | 0.058 | 0.192 | 0.038 | 0.385 |
| 9 | 0.008 | 0.000 | 0.008 | 0.008 | 0.015 | 0.069 | 0.062 | 0.115 | 0.185 | 0.108 | 0.423 |
| 10 | 0.000 | 0.025 | 0.000 | 0.000 | 0.038 | 0.013 | 0.038 | 0.038 | 0.213 | 0.075 | 0.563 |
| 11 | 0.012 | 0.001 | 0.000 | 0.002 | 0.001 | 0.007 | 0.002 | 0.017 | 0.063 | 0.053 | 0.841 |

Table 4-2 Cumulative Transition Probability Matrix of the hourly wind power data for January

| State | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.4853 | 0.7353 | 0.7794 | 0.7941 | 0.7941 | 0.8382 | 0.8382 | 0.8382 | 0.8529 | 0.8676 | 1 |
| 2 | 0.2759 | 0.5690 | 0.7241 | 0.8448 | 0.9138 | 0.9483 | 0.9483 | 0.9655 | 1.0000 | 1.0000 | 1 |
| 3 | 0.0741 | 0.4444 | 0.5185 | 0.7778 | 0.8148 | 0.8519 | 0.8889 | 0.9259 | 0.9630 | 0.9630 | 1 |
| 4 | 0.0385 | 0.1538 | 0.1923 | 0.1923 | 0.3077 | 0.4231 | 0.5385 | 0.6154 | 0.7692 | 0.8077 | 1 |
| 5 | 0.0000 | 0.2800 | 0.4000 | 0.5600 | 0.6400 | 0.7600 | 0.8400 | 0.8800 | 0.9200 | 0.9200 | 1 |
| 6 | 0.0233 | 0.0233 | 0.1628 | 0.1860 | 0.3023 | 0.3721 | 0.5349 | 0.6744 | 0.7674 | 0.8372 | 1 |
| 7 | 0.0526 | 0.0526 | 0.0789 | 0.1579 | 0.2368 | 0.3684 | 0.5000 | 0.6316 | 0.8158 | 0.8947 | 1 |
| 8 | 0.0192 | 0.0385 | 0.0577 | 0.0577 | 0.0769 | 0.1923 | 0.3269 | 0.3846 | 0.5769 | 0.6154 | 1 |
| 9 | 0.0077 | 0.0077 | 0.0154 | 0.0231 | 0.0385 | 0.1077 | 0.1692 | 0.2846 | 0.4692 | 0.5769 | 1 |
| 10 | 0.0000 | 0.0250 | 0.0250 | 0.0250 | 0.0625 | 0.0750 | 0.1125 | 0.1500 | 0.3625 | 0.4375 | 1 |
| 11 | 0.0117 | 0.0128 | 0.0128 | 0.0149 | 0.0160 | 0.0234 | 0.0255 | 0.0426 | 0.1053 | 0.1585 | 1 |

### 4.2.3 MCMC for the Simulated Wind Power Time Series

Using the Monte Carlo and Markov chain transition matrices, a desired number of sequences of hourly wind power samples is simulated for each month; the main procedures are clarified in Figure 4-3. The initial state is selected randomly and a random value between 0 and 1 is then produced by using a uniform random number generator. To determine the next wind power state in the Markov process, the value of the random number is compared with the elements of the $i_{th}$ row of the cumulative probability transition matrix determined by the preceding state. If the random number value is greater than the cumulative probability of the preceding state but less than or equal to the cumulative probability of the succeeding state, the succeeding state is chosen to represent the next state.

The same procedures are sequentially repeated to simulate the required hourly wind power data for each month. For example, the simulated data for the month of January should be equal to 24hours * 31 days =744 hours. By doing so, the hourly wind power time series is obtained for a year (1, 2, 3…8760). The loop is repeated for a desired or pre-specified number of years.

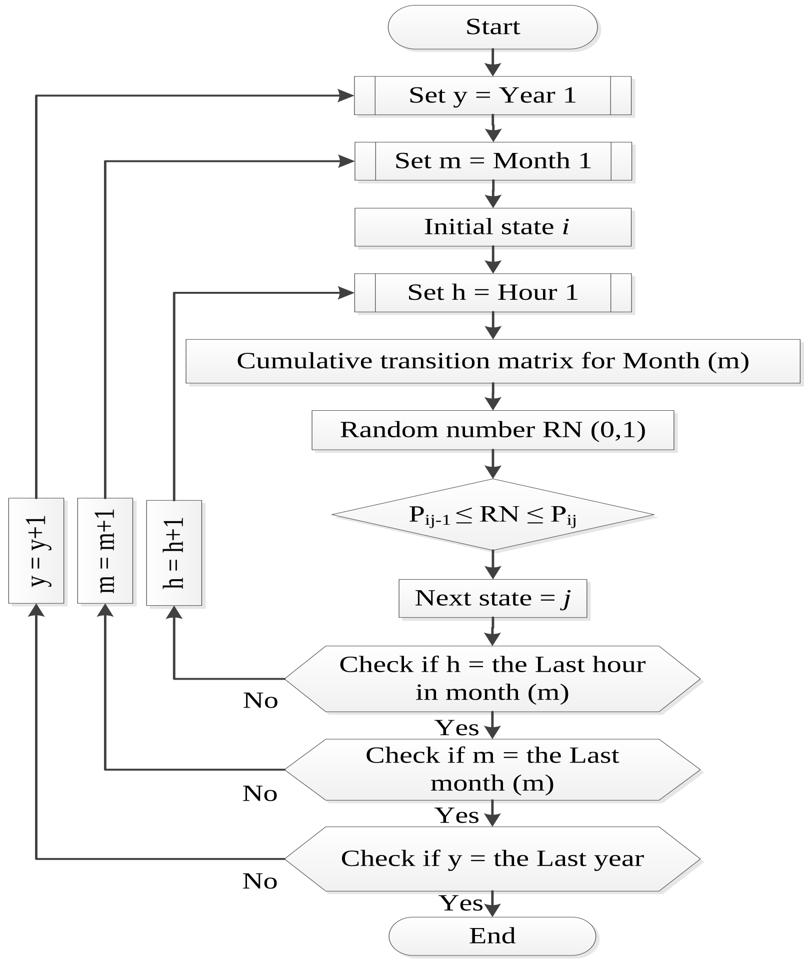



Figure 4-3 The Main Procedures of Monte Carlo Model

## 4.3 Model Verification

A synthetic wind power time series based on MCMC model is verified by considering various statistical aspects, which are probability distribution functions, autocorrelation functions, and monthly characteristics. For verification purposes, a thousand years (8,760,000 hrs.) of synthetic wind power time series is simulated and compared with the eight available years (70,080 hrs.) of measured data.

The higher wind speeds that may occur in wintertime might be quite different than those in the summertime. Hence, using one transition matrix for the measured data can be in conflict with the fact that the wind varies in all time scales (seasonally, monthly, and hourly). With regard to this issue, 12 transition Markov Chain matrices are created in the presented model, one for each month, aiming to include the monthly variations. Table 4-3 presents the monthly mean and standard deviation for both the simulated and measured data. It can be observed that the results are very similar; the percentage error in the mean varies between 0.31% and 1.2%, while it ranges from 0% to 0.52% in the standard deviation. These results are fairly reasonable and acceptable, as the simulation model depends on the measured data and random number generation.

Table 4-3 A Comparison of Monthly Mean and Standard Deviation

| Month | Mean (MW) | | Standard Deviation (MW) | |
|---|---|---|---|---|
| | Measured data | Generated data | Measured data | Generated data |
| Jan | 1.5414 | 1.5466 | 0.6873 | 0.6842 |
| Feb | 1.4065 | 1.4109 | 0.7602 | 0.7582 |
| Mar | 1.4198 | 1.4247 | 0.7400 | 0.7378 |
| Apr | 1.1233 | 1.1303 | 0.8055 | 0.8056 |
| May | 1.1141 | 1.1247 | 0.7943 | 0.7936 |
| Jun | 1.0183 | 1.0274 | 0.7980 | 0.7984 |
| Jul | 0.8308 | 0.8408 | 0.7649 | 0.7679 |
| Aug | 0.9728 | 0.9805 | 0.7673 | 0.7690 |
| Sep | 1.0869 | 1.0950 | 0.7945 | 0.7945 |
| Oct | 1.2458 | 1.2570 | 0.7747 | 0.7724 |
| Nov | 1.4475 | 1.4531 | 0.7231 | 0.7207 |
| Dec | 1.4989 | 1.5061 | 0.7206 | 0.7168 |

The probability density function (PDF) is often used for a qualitative comparison in time series models. When the PDFs of the real data and simulated data are perfectly matched, such a model can be considered as providing a good representation of the measured data. From Figure 4-4 it can be noted that the PDF of the simulated data almost fits with the PDF of the measured data, which shows how accurate the MCMC model is in capturing the variable characteristics of the measured wind data, and it distributes the simulated data accurately.

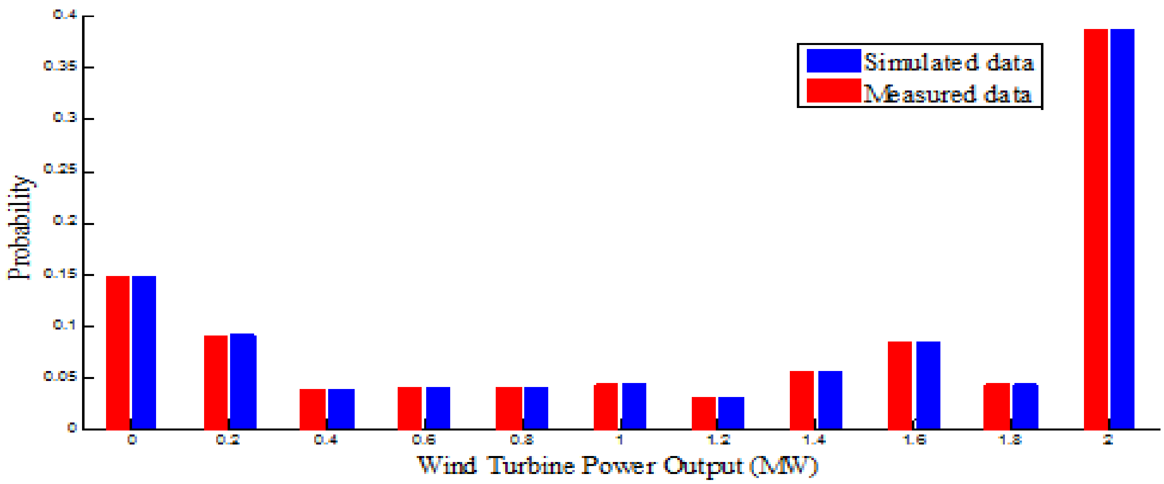



Figure 4-4 A Comparison of PDF of the Measured and Simulated Data

A certain degree of dependence appears between the wind speed condition at a given instant and the adjacent instants. The autocorrelation function (ACF) is usually used as relevant aspect of validating wind power time series by measuring the chronological persistence of processes at different points in time. The mathematical expression for ACF is given by equation 4.8:

$$ACF = \frac{E[(Y_t - \mu_Y)(Y_{t+K} - \mu_Y)]}{\sqrt{E[(Y_t - \mu_Y)^2]E[(Y_{t+K} - \mu_Y)^2]}} \tag{4.8}$$

where k is the time lag and $\mu_Y$ is the mean of wind power time series ($Y_t$, t=1,2,….N). The ACF are calculated here for both measured and simulated wind power time series considering up to time lag of 100, as depicted in Figure 4-5. It can be recognized that there is close agreement between the ACFs. Although the ACF of the simulated data is a bit lower, it has the same slope as that observed in the measured data. A higher-order scheme of a Markov Chain model and weekly transition matrices can further improve the results, and they represent areas for future investigation.

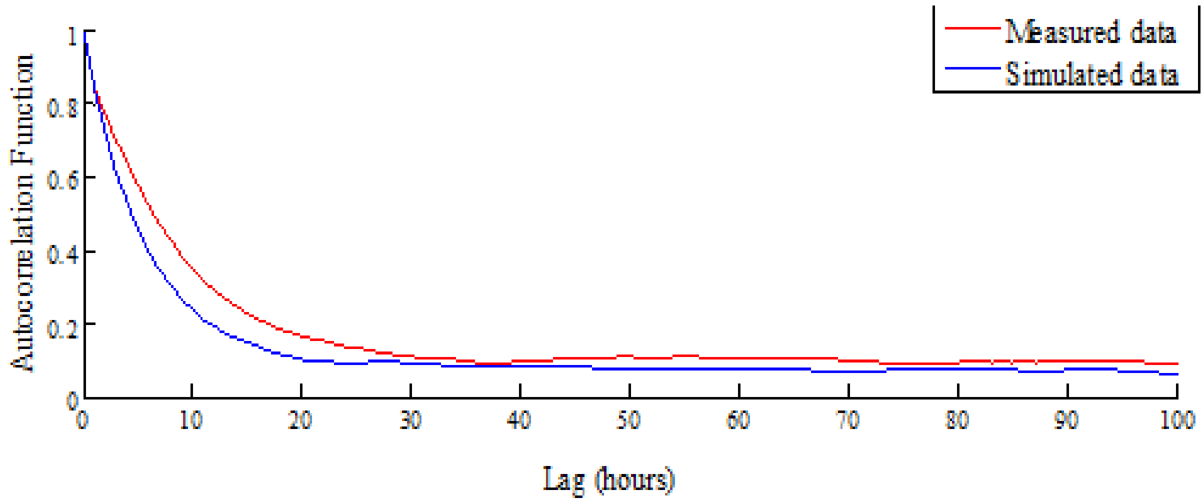



Figure 4-5 A Comparison of the CDFs of the Measured and Simulated Data

### 4.4 Generating Capacity Adequacy Assessment Including Wind Power Generation

To assess the overall generating capacity adequacy including wind energy using a sequential MCS technique coupled with the MCMC model, the following steps are considered:

*Step 1*: Generate the yearly synthetic wind power time series using MCMC discussed in Section 4.2.

*Step 2*: Create the total available capacity of the generation system by combining the synthetic generated wind power time series and the chronological conventional generation model built in Section 3.2.3 of Chapter 3.

*Step 3*: Superimpose the total available capacity of the generation system on the hourly chronological IEEE-RTS load model on hourly basis (8,760 hrs.).

*Step 4*: Calculate the wide range of reliability indices which can be calculated for N sampling years. These indices are viewed as two categories: annual system indices and interruption indices, as presented in Section 3.2.3 of Chapter 3.

## 4.5 Results and Analysis

In the study presented in this chapter, the previously described wind power time series based on the MCMC model is incorporated in generating capacity adequacy assessment, considering the same test systems (RBTS and IEEE-RTS) presented in Chapter 3. A small 20 MW wind farm consisting of 10 identical 2MW WTGs is added to the conventional generation of the RBTS. A large wind farm consisting of 200 identical 2MW WTGs is connected to the conventional system IEEE-RTS. The WTGs are considered to be 100% available. For the purpose of comparison, the sample space for both systems is specified to be the same as the previous cases conducted in Chapter 3.

### 4.5.1 Model Validation

This subsection pertains to comparing the obtained reliability indices using the MCMC model with those of the ARMA model to show validation and efficiency of the proposed methodology. To achieve a precisely comparison, the considered case study in [36] is used in this chapter. Thus, the reliability indices (LOLE, LOEE, and LOLF) computed by the ARMA model in [36] are considered to be criterion values. As reported in the literature [32-36], the ARMA model can provide a comprehensive representation of the actual wind regime, and is considered as the most suitable model for use in a sequential simulation process. Table 4-4 shows a comparison of reliability indices obtained by the MCMC and ARAM models. The results show that the reliability indices using the MCMC model are quite similar to those computed using the ARMA model in terms of all considered indices. With respect to the ARMA model, it can be concluded that the MCMC model efficiently simulates wind power time series, which can be coupled the with sequential MCS process to assess overall generating capacity.

Table 4-4 Comparison of Reliability Indices Obtained by MCMC and ARMA models

| Wind models | | LOLE (hrs/yr) | LOEE (MWh/yr) | LOLF (occ. /yr) |
|---|---|---|---|---|
| ARMA | Developed in [36] | 0.3349 | 2.81 | 0.1052 |
| MCMC | Proposed Model | 0.3283 | 2.79 | 0.0994 |

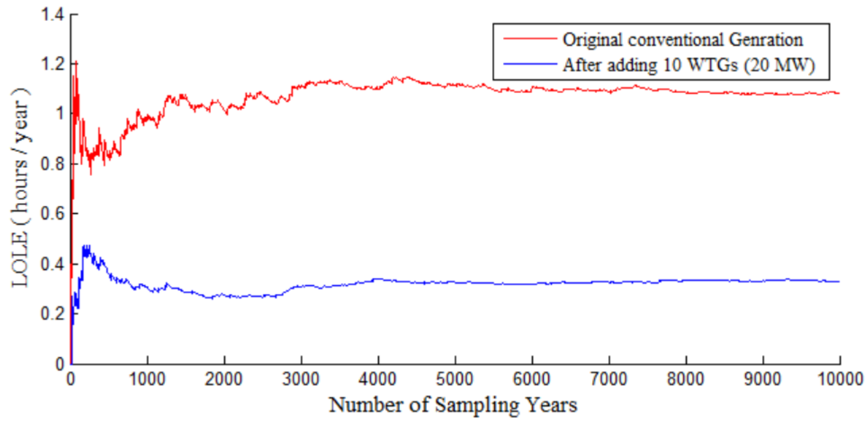
### 4.5.2 Reliability Indices for RBTS and IEEE-RTS Including Wind Power Generation

To assess the contribution of wind energy to the overall adequacy generating capacity, Table 4-5 shows a comparison of the reliability indices before and after adding the 10 WTGs to the conventional units of RBTS. The results show that the adequacy indices are improved with the addition of a 20MW wind farm. The LOLE and LOEE indices are usually used to judge the degree of benefit in the assessment of wind energy. For example, it can be seen from the table that LOLE and LOEE are reduced approximately by one-third when compared to no WTGs are added. In the sense of the adequacy assessment, this is considered as a significant reduction, and it actually reveals that the selected site has a good wind regime.

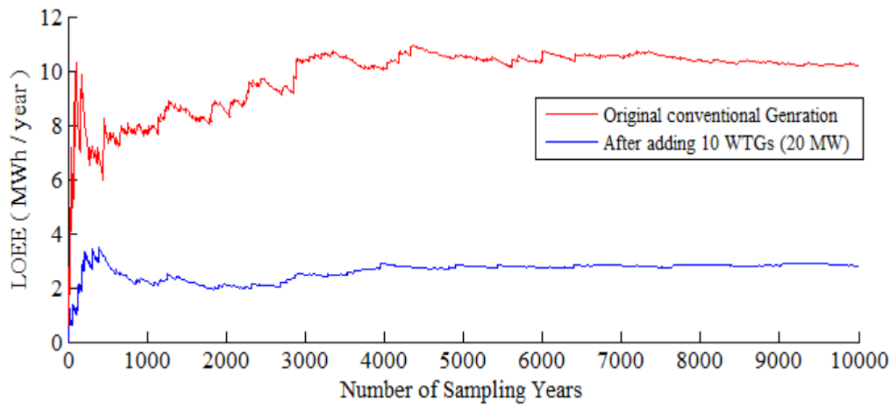
Table 4-5 A Comparison of Reliability Indices Before and After Adding 20MW Wind Farm to RBTS

| Reliability Indices | Conventional units only | Conventional units, and 20 MW wind farm |
|---|---|---|
| LOLE (hrs/year) | 1.0849 | 0.3283 |
| LOEE (MWh/year) | 9.9083 | 2.7978 |
| LOLF (occ. /year) | 0.2174 | 0.0994 |
| ENSPI (MWh/int.) | 44.356 | 28.147 |
| DNSPI (MW/int.) | 9.1321 | 4.8272 |
| EDPI (hrs/int.) | 4.8568 | 3.3028 |

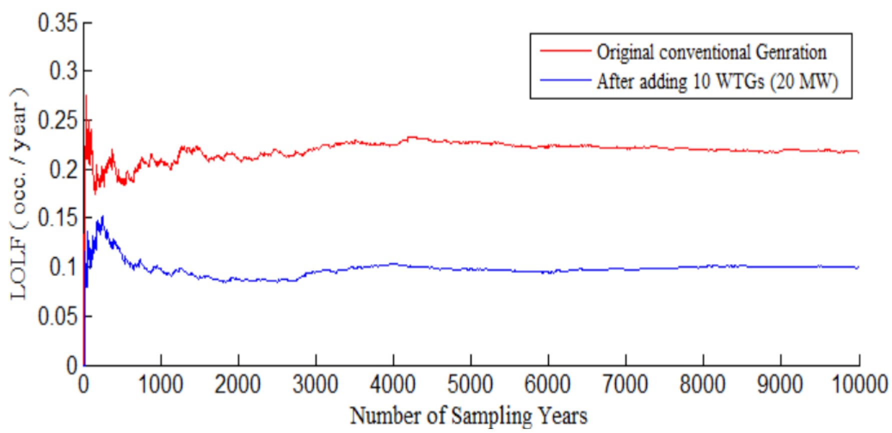
Figure 4-6 illustrates the adequacy indices LOLE, LOEE, and LOLF respectively for RBTS over pre-specified sampling years both with and without considering wind power generation. It can be observed from the figure that after adding 10 WTGs (20 MW), the estimated indices begin to stabilize faster than in the original conventional scenario.




(a) LOLE




(b) LOEE



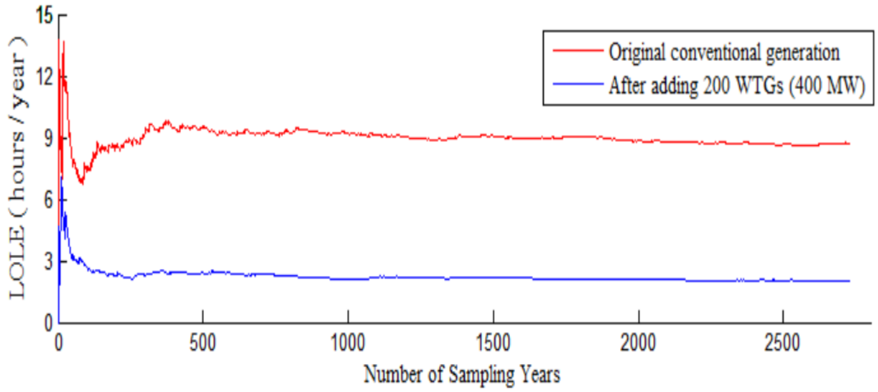

(c) LOLF

Figure 4-6 LOLE (a), LOEE (b) and LOLF(c) for RBTS

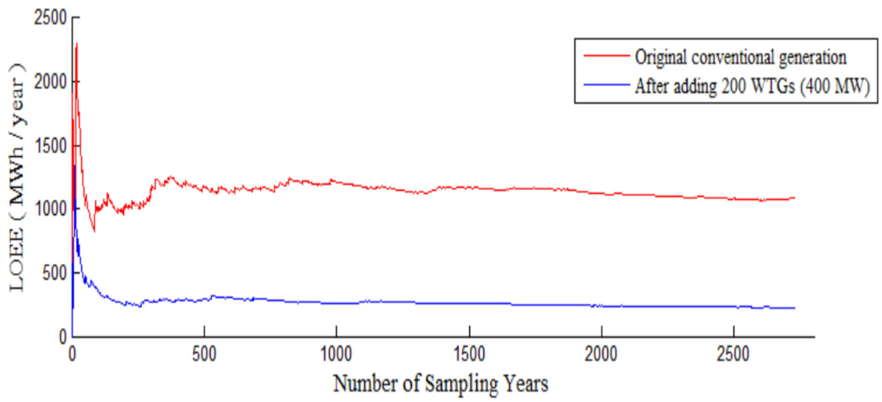
It is crucial and beneficial to study the impact of wind generation on the reliability performance of large systems, and hence IEEE-RTS is considered. Table 4-6 presents the reliability indices after adding 200 WTGs (400 MW) with those obtained when only conventional generation. As observed from the table, the LOLE is 2.0249 hours/year after 400MW is added to the system, which is reduced by 7.33 hours from the base case. This supports the fact that having a good wind regime at a selected site can result in a significant reduction in the reliability indices. Furthermore, referring to [40], the LOLE index is about 9.3 hours/year, which is greatly beyond the acceptable margin limits (2.4 hours/year). On the other hand, after adding a wind generating capacity of 400 MW to the system, the LOLE index is found to be within the acceptable level, which shows a positive contribution of wind power generation to system reliability. The LOLE, LOEE, and LOEF indices plotted against number of samples, with and without 400 MW of wind power generation, are shown in Figures 4-7 respectively.

Table 4-6 A Comparison of Reliability Indices Before and After Adding 400MW Wind Farm to IEEE-RTS

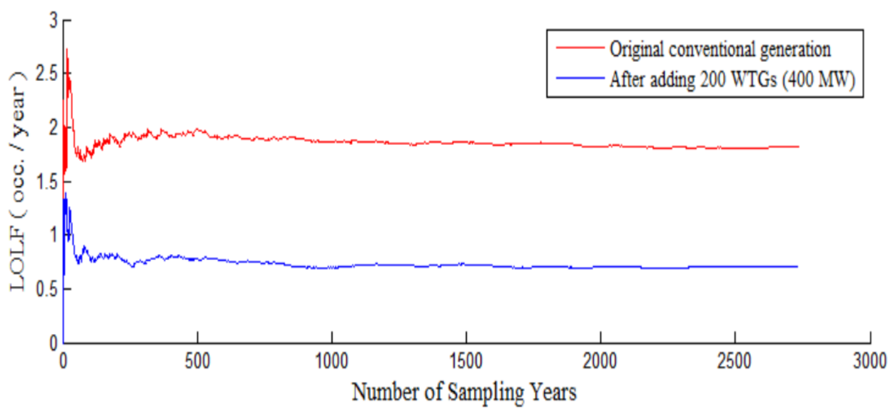
| Reliability Indices | Conventional units only | Conventional units, and 400 MW wind farm |
|---|---|---|
| LOLE (hrs/year) | 9.3600 | 2.0249 |
| LOEE (MWh/year) | 1192.5 | 225.98 |
| LOLF (occ. /year) | 1.9606 | 0.7007 |
| ENSPI (MWh/int.) | 608.76 | 322.5192 |
| DNSPI (MW/int.) | 127.14 | 63.9668 |
| EDPI (hrs/int.) | 4.7836 | 2.8898 |




(a) LOLE




(b) LOEE




(c) LOLF

Figure 4-7 LOLE (a), LOEE (b) and LOLF(c) for IEEE-RTS

## 4.6 Summary

This chapter dealt with simulating a wind power time series based on MCMC, which is necessary to be considered in reliability assessment when sufficient measurements are not available. Some statistical aspects, including probability distribution functions, autocorrelation functions, and monthly characteristics, are used to verify the simulated wind power time series with the measured one. The results show that the MCMC model is efficient in simulating a wind power time series, considering the randomness of the wind along with keeping the main characteristics of the measured data.

The contribution of wind energy to the overall adequacy of generating capacity is evaluated and reflected by a wide range of reliability indices, considering two test systems which are RBTS and IEE-RTS. A 20 MW wind farm was connected to the RBTS, while a 400 MW wind farm was connected to the IEEE-RTS. The reliability indices obtained using MCMC are compared with those computed by the ARMA model often used in reliability studies. The results showed very close agreements between these models, and therefore it can be concluded that the MCMC model efficiently simulates a wind power time series, which can be coupled with the sequential MCS process to assess overall generating capacity.

As well, a comparison of reliability indices before and after adding the two farms to the considered systems was carried out. The simulation results illustrate that the adequacy of generating capacity for both systems is considerably improved with the connection of wind farms. It can be revealed that the selected farms' sites have good regimes, and hence a significant reduction in reliability indices is achieved. Indeed, this supports the fact that the contribution of wind power generation to system reliability is mainly restricted by the wind conditions at a particular site.

# Chapter 5
# Summary, and Future Work

## 5.1 Summary

The significant increase in the penetration of wind generation introduces various challenges for both the planning and operation of power systems. This is mainly due to the fact that wind power generation is characterized by its variability and uncertainty. One of the great challenges of integrating wind facilities into utility grids can be seen from the reliability point of view. Hence, developing appropriate models to involve wind generation capacity into overall generation capacity assessment is a major concern which often raises research questions. The overall goal of the study presented in this thesis is to develop a reliable and appropriate model to assess the planning generation adequacy of power systems which have a significant portion of wind generation. In particular, an application of adequacy evaluation models for conventional generating systems and the inclusion of wind farm modeling into conventional generation adequacy evaluation are addressed.

In Chapter 1, the motivations and objectives of the research presented in this thesis were discussed. Chapter 2 presented a literature review pertaining to the related concepts and available techniques of generating system adequacy assessment and the previously developed models, with regard to wind energy in particular. Generally speaking, deterministic and probabilistic techniques are widely used to evaluate the generating capacity adequacy of power systems. However, with the availability of applicable reliability data and advancements in computational technologies, the use of probabilistic techniques has recently been preferred due to their essential feature of considering the inherent stochastic power systems. The most developed probabilistic techniques can be categorized into two general types: analytical and MCS techniques (sequential or non-sequential). As is also clarified in this chapter, each method has its own advantages and drawbacks, so the appropriate method is determined depending not only on the type of evaluation desired, but also the nature of the problem.

The generation adequacy problem when wind generation is integrated is also discussed. Since the most significant issue is the availability of wind, an essential task in the reliability analysis of wind generation is developing an appropriate and accurate wind speed model to cope with wind variability. As reported in the literature, the most commonly used approaches are the

ARMA and Markov Chain models, and hence their descriptions, advantages, and disadvantages have been discussed. Moreover, the multi-state and load adjustment models which are mostly used for involving wind generation capacity in adequacy assessment analysis are described and discussed in Chapter 2. The multi-state model cannot consider the chronological characteristics of the wind speed along with the inaccuracy and complexity associated with the discretization process, and therefore the load adjustment model is more desirable.

In Chapter 3, the applications of three common probabilistic techniques (analytical, sequential MCS, and non-sequential MCS) to evaluate the adequacy of conventional generation are presented. These methods are applied to two well-known test systems (RBTS and IEEE-RTS) that are often used in reliability studies. The results obtained using these techniques are validated with the ones available in the literature. The findings show that the analytical method produces results identical to the ones available in the literature, while MCS methods cannot generate exact results due to the random nature of the simulation process, but can provide similar results.

Furthermore, the computed results using these techniques are compared with each other to evaluate the performance and efficiency of the three evolution techniques in considering different aspects, such as the complexity of required procedures, accuracy of computed indices, and computational times. Among these techniques, the sequential MCS method can comprehensively evaluate the reliability of power systems by providing a wider range of indices, such as time-based indices (frequency and duration indices), and the indices' probability distributions. The major advantages of the sequential MCS method result from its ability to consider the chronology of events and the stochastic behavior of system elements, which are considered essential features for evaluating a power system that includes non-conventional generation such as wind and solar, which are time-dependent and correlated.

Chapter 4 proposed an assessment framework to include wind farm modeling into conventional generation adequacy evaluation. The main idea is to combine the simulated wind power time series from the MCMC model with the chronological conventional generation data from the sequential MCS technique. A synthetic wind power time series based on the MCMC model verified with the measured one by considering some statistical aspects. The results indicate that the MCMC model can efficiently simulate a wind power time series, considering the randomness of the wind along with keeping the main characteristic of the measured data.

Wind farms with capacities of 20 MW and 400 MW are connected to the RBTS and IEEE-RTS respectively to study the contribution of wind energy to overall generating capacity adequacy. In order to show the validation and efficiency of the proposed methodology, the computed results using the MCMC model are compared with those obtained using the ARMA model. Since very close agreement between the results of these models is found, it can be concluded that the MCMC model efficiently simulates wind power time series that is coupled with the sequential MCS process to assess overall generating capacity.

## 5.2 Future Work

Based on the research reported in this thesis, the possible extensions are as follows:

I. The developed model can be extended to include more relevant factors of wind farms and evaluate their impact on system reliability, such as:
   a. Wake effects
   b. Different wind turbine technologies
   c. Different wind speeds at the installation site
   d. Power collection grid in the wind farm
   e. Correlation of output power for different wind farms
   f. Grid connection configurations
   g. Offshore and onshore wind farms

II. The MCMC model can be applied to simulate solar power time series to be used in the reliability analysis.

III. The presented work can be extended to include transmission facilities to evaluate bulk power systems.

IV. A higher-order scheme of a Markov Chain model and weekly transition matrices can be considered for further improvements.

# Appendix A

# Generation Data

Table A.1 Generators Data for the RBTS [38]

| No. of Units | Unit Size (MW) | Unit Type | Forced Outage Rate | MTTF (Hour) | MTTR (Hour) | Scheduled Maintenance |
|---|---|---|---|---|---|---|
| | | | | | | Weeks per year |
| 2 | 5 | Hydro | 0.010 | 4380 | 45 | 2 |
| 1 | 10 | Thermal | 0.020 | 2190 | 45 | 2 |
| 4 | 20 | Hydro | 0.015 | 3650 | 55 | 2 |
| 1 | 20 | Thermal | 0.025 | 1752 | 45 | 2 |
| 1 | 40 | Hydro | 0.020 | 2920 | 60 | 2 |
| 2 | 40 | Thermal | 0.030 | 1460 | 45 | 2 |

Table A.2 Generators Data for the IEEE-RTS [39]

| No. of Units | Unit Size (MW) | Unit Type | Forced Outage Rate | MTTF (Hour) | MTTR (Hour) | Scheduled Maintenance |
|---|---|---|---|---|---|---|
| | | | | | | Weeks per year |
| 5 | 12 | Oil/Steam | 0.02 | 2940 | 60 | 2 |
| 4 | 20 | Oil/CT | 0.10 | 450 | 50 | 2 |
| 6 | 50 | Hydro | 0.01 | 1980 | 20 | 2 |
| 4 | 76 | Coal/Steam | 0.02 | 1960 | 40 | 3 |
| 3 | 100 | Oil/Steam | 0.04 | 1200 | 50 | 3 |
| 4 | 155 | Coal/Steam | 0.04 | 960 | 40 | 4 |
| 3 | 197 | Oil/Steam | 0.05 | 950 | 50 | 4 |
| 1 | 350 | Coal/Steam | 0.08 | 1150 | 100 | 5 |
| 2 | 400 | Nuclear | 0.12 | 1100 | 150 | 6 |

# Appendix B

# IEEE-RTS Load Data

Table B-1 Weekly Peak Load in Percent of Yearly Peak [39]

| Week | Peak Load | Week | Peak Load |
|---|---|---|---|
| 1 | 86.2 | 27 | 75.5 |
| 2 | 90.0 | 28 | 81.6 |
| 3 | 87.8 | 29 | 80.1 |
| 4 | 83.4 | 30 | 88.0 |
| 5 | 88.0 | 31 | 72.2 |
| 6 | 84.1 | 32 | 77.6 |
| 7 | 83.2 | 33 | 80.0 |
| 8 | 80.6 | 34 | 72.9 |
| 9 | 74.0 | 35 | 72.6 |
| 10 | 73.7 | 36 | 70.5 |
| 11 | 71.5 | 37 | 78.0 |
| 12 | 72.7 | 38 | 69.5 |
| 13 | 70.4 | 39 | 72.4 |
| 14 | 75.0 | 40 | 72.4 |
| 15 | 72.1 | 41 | 74.3 |
| 16 | 80.0 | 42 | 74.4 |
| 17 | 75.4 | 43 | 80.0 |
| 18 | 83.7 | 44 | 88.1 |
| 19 | 87.0 | 45 | 88.5 |
| 20 | 88.0 | 46 | 90.9 |
| 21 | 85.6 | 47 | 94.0 |
| 22 | 81.1 | 48 | 89.0 |
| 23 | 90.0 | 49 | 94.2 |
| 24 | 88.7 | 50 | 97.0 |
| 25 | 89.6 | 51 | 100.0 |
| 26 | 86.1 | 52 | 95.2 |

Table B-2 Hourly Peak Load in Percent of Daily Peak [39]

| | winter weeks | | summer weeks | | spring/fall weeks | |
|---|---|---|---|---|---|---|
| | 1 -8 & 44 - 52 | | 18 -30 | | 9-17 & 31 - 43 | |
| Hour | Wkdy | Wknd | Wkdy | Wknd | Wkdy | Wknd |
| 12-1 am | 67 | 78 | 64 | 74 | 63 | 75 |
| 1-2 | 63 | 72 | 60 | 70 | 62 | 73 |
| 2-3 | 60 | 68 | 58 | 66 | 60 | 69 |
| 3-4 | 59 | 66 | 56 | 65 | 58 | 66 |
| 4-5 | 59 | 64 | 56 | 64 | 59 | 65 |
| 5-6 | 60 | 65 | 58 | 62 | 65 | 65 |
| 6-7 | 74 | 66 | 64 | 62 | 72 | 68 |
| 7-8 | 86 | 70 | 76 | 66 | 85 | 74 |
| 8-9 | 95 | 80 | 87 | 81 | 95 | 83 |
| 9-10 | 96 | 88 | 95 | 86 | 99 | 89 |
| 10-11 | 96 | 90 | 99 | 91 | 100 | 92 |
| 11-noon | 95 | 91 | 100 | 93 | 99 | 94 |
| Noon-1pm | 95 | 90 | 99 | 93 | 93 | 91 |
| 1-2 | 95 | 88 | 100 | 92 | 92 | 90 |
| 2-3 | 93 | 87 | 100 | 91 | 90 | 90 |
| 3-4 | 94 | 87 | 97 | 91 | 88 | 86 |
| 4-5 | 99 | 91 | 96 | 92 | 90 | 85 |
| 5-6 | 100 | 100 | 96 | 94 | 92 | 88 |
| 6-7 | 100 | 99 | 93 | 95 | 96 | 92 |
| 7-8 | 96 | 97 | 92 | 95 | 98 | 100 |
| 8-9 | 91 | 94 | 92 | 100 | 96 | 97 |
| 9-10 | 83 | 92 | 93 | 93 | 90 | 95 |
| 10-11 | 73 | 87 | 87 | 88 | 80 | 90 |
| 11-12 | 63 | 81 | 72 | 80 | 70 | 85 |

Table B-3 Daily Peak Load in Percent of Weekly Peak [39]

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

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