Reliability management of power systems with wind power generation and energy storage

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**NANYANG
TECHNOLOGICAL
UNIVERSITY**

**RELIABILITY MANAGEMENT OF POWER
SYSTEMS WITH WIND POWER GENERATION
AND ENERGY STORAGE**

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SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING**

2013

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SCHOOL OF ELECTRICAL AND ELECTRONIC ENGINEERING

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SUMMARY

With increasing concerns of sustainable development of energy resources, many countries have planned to incorporate large percentages of renewable energy into their electrical power systems. Wind energy draws most attentions because it can be produced at acceptable cost with relatively mature technologies. Due to the intermittent and unpredictable nature of wind speed, power output from wind turbine generators (WTGs) is highly variable and uncontrollable. Many problems such as reliability and security issues will arise when existing power systems are integrated with high wind power penetration. New methods and techniques should be proposed to evaluate and solve these problems. This thesis focuses on investigating the impacts of integration of large amounts of wind power generation on power system reliability, and investigating optimal battery energy storage sizing techniques. The thesis focuses on operational reliability evaluation of power systems with wind energy and energy storage, and energy storage sizing techniques considering ramp rates of conventional generating units based on cost/worth analysis. Basic reliability evaluation techniques have also been introduced for easy understanding of power system reliability evaluation issue.

Reliability evaluation techniques for conventional power systems have been developed and used for many years [1-10]. The basic idea of reliability evaluation is to evaluate reliability indices using certain reliability evaluation methods. These methods can be classified into analytical and simulation methods. Analytical methods represent a power system using mathematical models and evaluated reliability indices using direct numerical solutions [9]. They can provide expectation indices with less computation but require assumptions to simplify the problem and produce an analytical model of the system. Simulation methods, on the other hand, evaluate reliability indices by simulating the actual process and random behaviors of a power system. Expectation values as well as probability distribution of indices can be obtained using simulation techniques but a lot of computation time is required. The analytical techniques are used in the study.

One of the most important parts of reliability evaluation is component modeling. Incorporation of large amounts of wind generation into conventional power systems gives rise to many new challenges on component modeling. Many methods have been proposed to model wind speed and wind power generation [11-17]. Different load models and wind speed models as well as corresponding wind power output models are discussed in details in Chapter 2. Other important system components, such as reliability of generators, generation system and energy storage, are modeled separately in each chapter for different applications.

The general reliability evaluation techniques for conventional power systems are reviewed and summarized. Reliability of a conventional generating unit can be represented by a two-state or a four-state model and the generation system is modeled as a capacity outage probability table. Popular used reliability indices such as loss of load probability and loss of load expectation are introduced and evaluated by applying the basic technique to a small test system, the IEEE-RBTS. Many sensitivity analyses are conducted to investigate the ways that different factors impact the power system reliability performance. The introduction of the general reliability evaluation procedure aims to provide basic concept for easy understanding more complicated techniques where wind generation and energy storage are integrated into the system.

Wind power output from a WTG is highly fluctuated due to intermittent and unpredictable wind speed. Reliability contribution of wind energy is limited and it may lead to system security issues when the wind power penetration level is high. Battery energy storage has been broadly used to solve such problems. Incorporation of wind energy and energy storage can increase the complexity of the power system significantly. More indices have to be proposed and defined to represent and describe various aspects of power system reliability. In addition to some popular used wind-related indices, a new index named expected energy not used (EENU) is proposed to represent wasted wind energy. It is an energy-based index which can be used to assess the wind energy utilization efficiency. The IEEE-RTS is modified to incorporate wind farms and energy storage. The general reliability evaluation technique is improved and extended to this modified test system to evaluate the EENU and other reliability indices. Case studies show the impacts of wind power generation and energy storage on the power system reliability and wind energy utilization efficiency.

The time span for a power system can be classified into the long-term planning phase and short-term operation phase. Load and wind speed are assumed to be constant within each time interval for long-term planning studies. Committed conventional generators (CGs) and spinning reserve (SR) provided by CGs are assumed to be able to pick up load immediately when required. However, these assumptions are not applicable for power system operation studies because of the short time interval and higher accuracy requirements. The wind speed and load level within each time interval should not be constant and are assumed to change linearly from one level to another. Generating units cannot be modeled by the two-state reliability model as in power system planning studies, in which mutual transitions between the two states are possible. During the short lead time in power system operation, CGs and WTGs are modeled by a two-state non-repairable reliability model, in which units can only move from up state to down state and unit repair is not possible. The forced outage rate (FOR) of a unit is also replaced by the outage replacement rate (ORR) in operational studies. Due to the incorporation of large amounts of wind power generation, CGs have to be ramped up and down or even started up and shut down more frequently to incorporate the variations of wind power output and load. Ramp rates of CGs become very important and cannot be ignored in operational studies, especially for micro grids with less dispatchable capacity. There may have power shortage or surplus if system ramp rates are not fast enough. The indices such as the expected energy not supplied (EENS), unit commitment risk (UCR) and EENU can still be used to represent the system reliability and wind energy utilization efficiency but their calculation formulae have to be modified to incorporate the operational considerations. For comparison, the modified IEEE-RTS is also used to illustrate the operational reliability evaluation. The accuracy is improved with the operational considerations and the impacts of such considerations on power system reliability performance are illustrated by a large amount of sensitivity studies.

As mentioned earlier, a power system with high wind power penetration or a micro grid with less dispatchable capacity may suffer power surplus or shortage if the committed CGs do not have sufficient reserve or fast response speed to account for variations of wind power output and load. Energy storage systems (ESSs) have been used to smooth out wind power fluctuations and improve system reliability. It is well known that the basic function of a power system is to satisfy the system load and

energy requirements as economically as possible and with a reasonable assurance of continuity and quality [9]. The size of ESSs has to be determined optimally because it is closely related to the cost for reliability improvements. A technique is proposed to determine the optimal size of the battery storage system (BSS) for power systems with high wind power penetration, based on reliability cost and worth of adding a BSS, and with operational considerations. Reliability worth is represented by the benefit from reduced EENU and the benefit from system reliability improvement after adding the BSS. Reliability costs include capital costs and operation and maintenance cost, which are all functions of the size of the BSS, i.e. capacity rating and power rating (charging/discharging rate). The objective function is to maximize the total system net benefit with an optimal size of BSS, subjected to some operation constraints and limitations. Many optimization techniques can be used to optimize the size of BSS and the *golden section search method* (GSSM) is adopted in the thesis.

In the future work, the proposed operational reliability evaluation and BSS sizing technique will be extended to transmission/distribution systems and micro grids with wind power generation and energy storage. More components such as distributed generators, transmission lines, transformers, feeders, switches, fuses and etc will be modeled and new indices will be defined to describe different aspects of those systems. More operational considerations, such as the changing unavailability of components due to aging or external factors, generator start up failures, unit outage postponability, will be incorporated into the current technique. More energy storage parameters will be considered in the reliability evaluation, such as the life cycle of batteries and different operating strategies. The Monte Carlo Simulation techniques may also be employed to investigate the reliability performance for more complicated power systems in the future work.

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LIST OF ABBREVIATIONS

ARMA	Autoregressive moving average
BSS	Battery storage system
CAES	Compressed air energy storage
CC	Capacity credit
CF	Capacity factor
CG	Conventional generator
COPT	Capacity outage probability table
CO ₂	Carbon dioxide
DNSINT	Demand not supplied per interruption
DOD	Depth of discharge
ECGC	Equivalent conventional generator capacity
ED	Economic dispatch
EDNS	Expected demand not supplied
EDPI	Expected duration per interruption
EENS	Expected energy not supplied
EENU	Expected energy not used
EGWE	Expected generated wind energy
EIR	Energy index of reliability
ELCC	Effective load carrying capacity
ENCG	Equivalent number of conventional generator
ENS	Energy not supplied
ENSINT	Energy not supplied per interruption
ENU	Energy not used
ESS	Energy storage system
EWEU	Expected wind energy utilized
FLOL	Frequency of loss of load
FOR	Forced outage rate

GSSM	Golden section search method
H ₂	Hydrogen
HLI	Hierarchical level I, i.e. generation level
HLII	Hierarchical level II, i.e. generation and transmission level
HLIII	Hierarchical level III, i.e. generation, transmission and distribution level
HVLM	Hourly variable load model
IWE	Installed wind energy
IWP	Installed wind power
LDC	Load duration curve
LOLE	Loss of load expectation
LOLP	Loss of load probability
MCS	Monte Carlo simulation
MTBF	Mean time between failures
MTTF	Mean time to failure
MTTR	Mean time to repair
NP	Net system load
O&M	Operation and maintenance
ORR	Outrage replacement rate
PDF	Probability density function
PJM	Pennsylvania-New Jersey-Maryland
RBTS	Roy Billinton test system
RTS	Reliability test system
SMES	Superconducting magnetic energy storage
SOC	State of charge of batteries
SR	Spinning reserve
TSB	Total system benefit
UCR	Unit commitment risk
UC	Unit commitment
VOLL	Value of lost load
WGAF	Wind generation availability factor

WGICB	Wind generation interruption cost benefit
WGIEB	Wind generation interrupted energy benefit
WTG	Wind turbine generator

LIST OF SYMBOLS

Chapter 2:

$\bar{v}$	Mean wind speed.
v	Real time wind speed.
v_i	Wind speed obversation i .
v_0	Wind speed at the reference hub height H_0 .
H_0	Reference hub height.
H	Hub height.
β	Terrain friction coefficient.
$f(v)$	Distribution density function.
$F(v)$	Cumulative distribution density function.
n_i	The number of wind speed obversations.
C_{WB}	Weibull distribution scale parameter.
K_{WB}	Weibull distribution shape parameter.
v_t	Real time wind speed at time t .
μ_t	Mean value of simulated wind speed.
σ_t	Standard deviation of simulated wind speed.
y_t	Time series data set.
φ_i	Autoregressive parameter of ARMA model.
θ_j	Moving average parameter of ARMA model.
α_t	A normal white noise process.
M	The number of simulated wind speed data in the step v_t .
P_t	Probability of each step v_t .
N_y	Number of sample years.
$P(v)$	Power output of a WTG at wind speed v .
$P(v)_{\max}$	Maximal wind power output at wind speed v .
V_{ci}	Cut in wind speed.
V_{co}	Cut out wind speed.
V_r	Rated wind speed.
P_r	Rated wind power output of a WTG.

m	Mass flow rate.
A_s	Sweeping area of wind stream.
ρ	Density of air.
η	Efficiency of wind energy tranformation.
η_{max}	Theoretical efficiency of wind energy tranformation.
j	Operating period index (subscript).
P_{Lj}	System load at time period j .
P_{Lj}^{ave}	Average system load at time period j .
δ_{PLj}	Standard deviation of P_{Lj} .

Chapter 3:

i	State index (subscript).
b	Battery storage system index (subscript).
W	WTG index (subscript).
C	Conventional generator index (subscript).
c	Component index (subscript).
λ_c	Failure rate of a component c .
μ_c	Repair rate of a component c .
U_c	Unavailability of a component c .
A_c	Availability of a component c .
m_c	Mean time to failure of component c .
r_c	Mean time to repair of component c .
Δt_j	Time duration of time step j .
T	Cycle time.
f	Cycle frequency.
T_s	Average reserve shut-down time.
D_s	Average in-service time.
P_s	Probability of starting failures.
n_c	Number of components c .
C_c	Rated capacity of component c .
FOR_c	Forced outage rate of component c .
$P(X_c)$	Cumulative probability of X_c MW out of service before C_c is added.
C_{oi}	Capacity outage at state i .
P_L	System load.

P_C	Conventional generation capacity.
$t_i(P_{Ci} < P_L)$	Time during which P_{Ci} is less than P_L .
ENS_i	Energy not supplied at state i .
E	Total energy under the LDC.
p_i	Probabiolity of state i .

Chapter 4:

E_b	Rated BSS capacity.
P_b	Rated charging/discharging rate the a BSS.
P_{bj}	Charging/discharging rate during j .
η_c, η_d	Charging and discharging efficiency of a BSS.
E_b^{min}	Mininum capacity of a BSS.
E_b^{max}	Maximum capacity of a BSS.
E_{cj}	Maximal energy to be charged during j .
E_{dj}	Maximal energy to be discharged during j .
SOC_j	SOC of a BSS during j .
P_{with}	Total system capacity with additional wind power P_w .
$P_{w/o}$	Total system capacity without additional wind power P_w .
P_{Cij}	Power output from CGs at the beging of j .
P_{Cij}^m	The maximum generation capacity of CGs.
P_{wij}	Power output from WTGs of state i during j .
P_{Lj}	System load during j .
p_{ij}	Probability of state i during j .
N_i	Number of the contingency states considered.
N_j	Number of invertals considered.
AG_{ij}	Total available capacity of state i during j .
A_{cG}	Availability of CGs.
A_{cW}	Availability of WTGs.
U_{cG}	Unavailability of CGs.
U_{cW}	Unavailability of WTGs.
N_{Goi}	Number of CGs operating at state i .
N_G	Total number of CGs operating at state i .
N_{Woi}	Number of WTGs operating at state i .
N_W	Total number of WTGs operating at state i .

Chapter 5:

r_{uij}	System ramp up rate of state i during j .
r_{dij}	System ramp down rate of state i during j .
SOC_j'	SOC of the BSS at the beginning of j .
SOC_j''	SOC of the BSS at the end of j .
$U_c(\Delta t_j)$	Unavailability of unit c for period Δt_j .
ENU_{ij}	Energy not used of state i during j .
ENS_{ij}	Energy not supplied of state i during j .
d_{ij}	Required time for the system to change output.
NP_{Lj}	Net system load during j .
NP_{Lj-1}	Net system load during $j-1$.

Chapter 6:

E_b^{opt}	Optimal BSS capacity rating in MWh.
$EENS_{aj}$	EENS after adding the BSS during j .
$EENS_{bj}$	EENS before adding the BSS during j .
$EENU_{aj}$	EENU after adding the BSS during j .
$EENU_{bj}$	EENU before adding the BSS during j .
E_{Dj}	Discharged energy of a BSS during j .
ENS_{ij}'	Modified ENS_{ij} .
P_b^{opt}	Optimal BSS power rating in MW.
TSB^{opt}	Optimal TSB in US dollar (\$).
C_{cap}	Capital cost of the installation of a BSS.
$C_{O\&M}$	Operation and maintenance costs of a BSS.
d	Discount rate.
ε	Convergence tolerance.
k_C	Investment cost of E_b (\$/MWh) for a BSS.
k_{fy}	Average energy price in year y (\$/MWh).
k_{Fy}	O&M power cost (\$/MW) in year y for a BSS.
k_P	Investment cost of P_b (\$/MW) for a BSS.
k_{Vy}	O&M energy cost (\$/MWh) in year y for a BSS.
t_{j-1}	Time at the beginning of interval j .
t_j	Time at the end of interval j .
T_b	Life-span of a BSS.

r_{fj}	Energy price during j (\$\$/MWh).
TC_{ES}	Total cost of energy storage.
TSB^{opt}	The optimal TSB.

Chapter 1. Introduction

1.1 Motivation

The basic function of an electric power system is to provide all customers with electricity. Modern society has come to expect the electrical supply to be always available with a reasonable degree of quality. However, it is neither economically nor technically feasible to build an absolutely reliable power system due to uncontrollable factors, such as the random failures of components. Over-investment can provide high reliability but results in excessive operating cost. On the other hand, under-investment may cause a large number of power system faults, and therefore leads to much more economic losses. The reliability and economic constraints compete obviously. This dilemma leads to difficult management decisions at both the planning and operating phases [9].

To resolve the dilemma between economic, operating and reliability constraints, every utility or country has developed its own reliability criteria in design and operational regulations. A wide range of deterministic and probabilistic criteria and techniques have been developed for power system reliability evaluation [18-21]. Typical deterministic criteria include:

- (a) Generating reserve capacity must not be less than a certain percentage of the peak system load;
- (b) Parallel transmission lines must be used for certain customers;
- (c) Installed capacity equals the expected maximum demand plus a fixed percentage of the expected maximum demand;

The essential weakness of deterministic techniques is that they are all experience-based and lack rigorous scientific proofs. They do not and cannot account for the probabilistic or stochastic nature of system behaviors. The probabilistic approaches recognize the stochastic behavior of power systems and treat system parameters as probabilistic variables. Typical probabilistic aspects include:

- (a) Forced outage rates of generating units are known to be a function of unit size and type and therefore a fixed percentage reserve cannot ensure a consistent risk;
- (b) The failure rate of a transmission line depends on its length, location and environment and therefore the same number of circuits may not result in the same risk of supply interruption.

Over the past decades, deterministic techniques have gradually been replaced by probabilistic techniques. Probabilistic techniques for power system reliability evaluation can be divided into two basic aspects of system adequacy and system security. System adequacy relates to the availability of sufficient generation, transmission and distribution facilities within the system to satisfy the consumer demand. Adequacy is therefore considered to be associated with static conditions. System security, on the other hand, is associated with the ability of the system to respond to disturbances arising within the system, and is therefore associated with system dynamics [22-24].

The system adequacy performance can be evaluated using analytical techniques or simulation techniques. Analytical techniques represent the system by a mathematical model and evaluate the reliability indices from this model using direct numerical solutions. They generally provide expectation indices in a relatively short computing time. Simulation techniques, however, estimate the reliability indices by simulating the actual process and random behavior of the system. The method therefore treats the problem as a series of real experiments. It estimates the reliability indices by counting the number of times that an event occurs [9].

A modern power system is complex, highly integrated, and very large. It is not necessary to analyze a power system as a whole. Power systems are usually divided into appropriate subsystems which can be analyzed separately. The most convenient method to divide the power system is to use its main functional zones: generation systems, transmission systems and distribution systems. Reliability evaluation can be conducted in each of these functional zones or in the combinations that gives the hierarchical levels [25]. Reliability assessment at hierarchical level I (HLI) is concerned only with the generation facilities, hierarchical level II assessment includes both

generation and transmission facilities, and hierarchical level III evaluation includes all three functional zones.

The power system becomes even more complicated when renewable energy is used to provide electric power generation all over the world, due to the global environmental concerns associated with conventional energy sources [26-29]. Wind energy can be produced nowadays at acceptable cost with relatively mature technologies and therefore draws most of the attentions. The wind turbine system, however, is an intermittent and uncertain energy source as wind speed is highly variable and site specific. The wind behavior is quite different from that associated with conventional energy sources. Therefore the incorporation of wind power into existing power systems will affect the power system reliability in a different manner. A proper wind speed model should be developed and new indices have to be proposed and defined to represent and describe all aspects of system reliability performance. Conventional reliability evaluation techniques need to be improved and modified to incorporate the impact of wind generation. As many utilities have been on the way to significantly increase the percentage of wind power generation in their power grids and even in micro grids with less dispatchable capacity, it becomes particularly important to evaluate and deal with the impact of wind generation on the overall system reliability.

Most existing reliability evaluation techniques for power systems with WTGs focus on planning phase [11-17]. When wind power generation is incorporated into existing power systems, SR from CGs becomes very important in power system operation to incorporate wind speed uncertainty, fast wind power output variation, load forecast uncertainty and possibilities of failure of generating units. CGs have to be started up/shut down or ramped up/down more frequently to incorporate the variations of wind speed and load. However, the committed CGs cannot take up load immediately as in power system planning and have to gradually pick up load in real time operation. When the wind power penetration level is low, the system has large enough load following capacity to match load and wind generation variation. When the wind power penetration level is high or in a micro grid with less dispatchable capacity, the load following capacity of the system will not be sufficient and the effects of ramp rate of CGs on system operation reliability become very significant. Therefore, considering

ramp rate of CGs and other operational factors in reliability evaluation is necessary for power systems with WTGs.

To solve the reliability and security problems caused by wind power fluctuation, energy storage has been used broadly to smooth out high variability of wind power, increase wind energy utilization efficiency and consequently to improve the system reliability [30-33]. Different energy storage technologies are applicable to different applications. Selection of suitable energy storage depends on many factors, such as response time, energy density, easiness of capacity expansion, site constraints as well as financial matters. As mentioned earlier, reliability and economy should be balanced and therefore adding energy storage to benefit system reliability and wind energy absorption has to consider the rationality and suitability of the investment. The size of energy storage needs to be optimal determined in order to maximize the benefit from integration of wind power generation and energy storage. Some researchers have proposed battery sizing techniques but few of them consider from reliability aspects, and ramp rate of CGs and other operational factors are ignored [31-33]. A sizing technique based on reliability with consideration of operational factors is beneficial and necessary for power system planners and wind farm owners.

1.2 Objectives

Reliability evaluation of power systems has traditionally been an integral part of planning and operation of electric power systems. The integration of large amount of wind power generation into existing power systems can have considerable impact on the system reliability performance. It is therefore to develop reliability evaluation techniques which can be used by power system planners and wind farm owners to assess the effects of wind generation on system adequacy and to make relatively optimal planning and operation decisions. WTGs can provide electric energy to customers but capacity credit from a given WTG may be far below its rated value because of the intermittent characteristic of wind speed. Energy storage can be incorporated into the power system with WTGs to smooth out the wind power output fluctuations, increase wind energy capacity credit and improve system reliability. The impacts and benefits of adding WTGs and energy storage systems on system reliability

and economics are to be evaluated during the decision-making process at the planning and operation phase. This information would enable objective planning and operation decisions to be made regarding the relative merits of installing how many WTGs, or how large energy storage or conventional generating capacity.

This thesis aims to investigate the reliability performance of power systems with wind energy and energy storage, both in planning and operation viewpoints. Energy storage sizing problem will also be covered based on reliability cost and worth analysis. Analytical techniques are adopted and the studies focus on generation system level, i.e. HLI. The detailed objectives can be addressed as follows:

1.2.1 Component modeling for planning and operation

Component modeling plays a very important part in reliability evaluation. A component should be modeled differently in planning and operating phase, which have different time scales, accuracy and other requirements. For a power system with WTGs and energy storage, the models of wind speed, wind power output of a WTG, wind farms, load, generator reliability (both CGs and WTGs), generation system and energy storage should be reviewed and modified according to respective requirements of planning and operation studies.

1.2.2 New indices

Many indices have been used to represent and describe varied aspects of reliability performance of conventional power systems. With incorporation of wind power generation and energy storage, new indices should be proposed and defined to represent special aspects related to wind generation and energy storage. Different system conditions and respective requirements of power system planning and operation studies should be considered when formulating these indices.

1.2.3 Improved reliability evaluation techniques

For easy understanding, the basic reliability evaluation techniques for conventional power systems should be reviewed and illustrated with test systems. These techniques need to be improved to incorporate the impact of wind power generation and energy

storage. Power system planners or wind farm owners would find solutions for planning and operation problems using the improved techniques.

1.2.4 Operational considerations

Most existing reliability evaluation techniques for power systems with wind power generation focus only on the planning phase and no operational factors are considered. In a power system with highly fluctuated wind power generation, operational considerations such as the ramp rates of CGs become very important and cannot be ignored. Operational adequacy analysis will be conducted considering short lead time, time-varying wind speed and load, ramp rates of CGs and energy storage. Sensitivity studies should be done to show the impacts of such factors on the system reliability performance.

1.2.5 Energy storage sizing problem

Using energy storage to improve the power system reliability and wind energy capacity credit has to consider the cost of installing such an energy storage system. Optimal sizing of energy storage can maximize the benefit. An energy storage sizing technique will be proposed based on the reliability cost and worth analysis. In order to increase accuracy, the sizing technique will also be conducted considering operational factors.

1.3 Major contributions

The highlights of the research work done and major contributions are summarized as follows:

1.3.1 Modeling

Four main wind speed models as well as their advantages/disadvantages, four wind power output models, and three load models as well as their advantages/disadvantages, are reviewed and summarized in the thesis. When doing reliability evaluation in operational time scales, the wind speed and load model are modified to change linearly

from one interval to another. The reliability of a generator is represented by a two-state non-repairable model because generating units cannot be repaired during a short lead time. The system generation is also modeled as a ramp function due to the ramp rate consideration of conventional units. These modifications on modeling can lead to more practical and precise reliability evaluation results.

1.3.2 Indices

A new index, EENU, is proposed to represent the wind energy produced but not used to supply load due to insufficient energy storage and slow ramp down rate of CGs. This index can be used to reflect the different wind energy utilization efficiencies with different system conditions, such as the peak load, SR allocation policies, generator types, unit commitment policies, wind speed patterns, ramp capabilities of generators, energy storage sizes and operation strategies, and etc. The EENU is also used in the reliability cost and worth-based sizing technique to find the optimal battery storage capacity rating and power rating.

1.3.3 Formulation of EENU and EENS

For a power system with WTGs and energy storage, the calculation of EENU and EENS becomes more complicated, especially when considering operational factors. Wind speed and load variation, the number of the committed CGs and their ramp rates, SOC of energy storage and forced outage rate (FOR) of CGs have to be considered in the formulation of EENU and EENS. Their formulae under different system conditions are developed and classified with the help of graphical illustrations. Other indices can also be formulated using similar methods.

1.3.4 Operational adequacy studies

In a power system with high renewable power penetration, uncertain and intermittent characteristics of renewable energy resources become major concerns of system planning and operation. In such a power system, conventional thermal or hydro units have to be dispatched, shut down or started up more frequently to incorporate load, renewable resource variation and system failures. Slow ramp up (or down) of

conventional units may cause energy shortage (or surplus) in power systems with high wind power penetration or in isolated micro grids with limited dispatchable capacity. A technique to evaluate operational reliability and energy utilization efficiency is proposed for power systems with high wind power penetration. The short time intervals, varying wind speed and load, and ramp rates of CGs are considered in the proposed technique. More accurate results can be obtained for power system planners, operators and wind farm owners to understand the power system reliability performance better using the proposed technique.

1.3.5 Sizing technique of battery storage

For a power system or a micro grid with high wind power penetration, the dynamic response of CGs to load and wind power variation is an important operation issue. An energy storage system plays an important role in solving the problem. Although ESSs can significantly reduce the response time of SR and to improve system reliability and reduce energy surplus, the cost of installing BSS should also be considered. A technique to determine the optimal size of BSS is proposed on reliability and economical benefit and cost of adding BSS with consideration of ramp rates of CGs and wind speed variation. The accuracy of the proposed technique is increased because the load and wind speed variation for an operating period is modeled as a linear function instead of a constant wind speed and load level used in most existing techniques. The GSSM is applied to search the optimal size of BSS under the maximum total system net benefit.

1.4 Thesis organization

This thesis focuses on investigating the impacts of large amount of wind generation and energy storage on power system reliability, and studying battery energy storage technologies to mitigate or eliminate these impacts. The thesis starts from basic reliability evaluation for conventional power systems to power systems with wind power and energy storage, and then emphasizes on operational adequacy analysis and optimal sizing technique of battery storage. Chapter 1 provides a brief summary of the motivation and lists the major contributions made in this research. Chapter 2 reviews

the models of wind speed, power output of a WTG, and system load. Their respective advantages and disadvantages and suitable applications are also discussed in this chapter.

The basic reliability evaluation procedure and reliability indices are introduced in Chapter 3. The conventional reliability indices including loss of load probability (LOLP), loss of load expectation (LOLE), expected energy not supplied (EENS), and energy index of reliability (EIR) are introduced. The general reliability evaluation procedure is illustrated by applying it to a smaller test power system, the IEEE-RBTS. The impacts of peak load, FORs of CGs, generator capacities and spinning reserve (SR) provided by CGs on the LOLP, LOLE, EENS and EIR are investigated.

In Chapter 4, the reliability evaluation procedure is extended to power systems with WTGs and energy storage. Different energy storage technologies are reviewed and the battery storage is selected to be used in this research. Many indices related to wind power generation are introduced, such as wind energy capacity credit (CC), expected generated wind energy (EGWE), capacity factor (CF), wind generation availability factor (WGAF), etc. A larger test power system, the IEEE-RTS, is used to show the impact of wind generation and energy storage on reliability indices.

In Chapter 5, an operational adequacy study is conducted for power systems with wind power generation and energy storage. Under short lead time in operation, the reliability of a generator has to be modeled as a two-state non-repairable model. To improve accuracy, the ramp rate of CGs is considered, and the hourly wind speed and load are considered to change within each time period. The EENS and EENU are formulated considering ramp rate, state of charge (SOC) of battery storage, variation of wind speed and load. The IEEE-RTS is used to illustrate the technique and its results are compared with those obtained in planning studies.

In Chapter 6, a reliability cost/worth-based energy storage sizing technique is proposed considering ramp rates of CGs. The costs of adding battery storage include initial capital cost and operation and maintenance cost. The reliability benefit or worth consists of benefit from reduced EENU and benefit from improved reliability. They all are functions of EENS and EENU. An optimization technique, the *golden section*

search method (GSSM) is introduced and used to find the optimal size of battery storage. The IEEE-RTS is used to investigate the factors which impact the optimal sizing results.

Conclusions and recommendations for future work are given in Chapter 7.

Chapter 2. Energy Resources and Demand Modeling

Wind is one of the most feasible renewable energy resources and has been utilized broadly to increase the percentage of renewable power capacity in total power generation. The stochastic and uncontrollable characteristics of wind speed have significant impacts on the operation of power systems with wind power generation. Load is also with stochastic characteristics but can be predicted more accurately and be controlled in certain degree. The load model is combined with the generation system model to assess reliability indices. It is necessary to establish accurate and suitable wind speed models and load models in reliability assessment. Several basic wind speed models and load models are investigated in this chapter. Their respective suitable applications and advantages/disadvantages are also discussed.

2.1 Wind speed modeling

Estimating the potential energy of a wind farm requires a large amount of wind speed data. The best way of assessing wind speed is by actual measurements. Wind speed increases significantly with the height above ground, depending on the roughness of terrain. Therefore, correct wind speed measurements must consider the hub height (H) of WTGs and the roughness of terrain of the wind site. If measurements are difficult at high elevations, an approximate empirical formula (2.1) can be used to estimate wind speed at high elevations by using wind speed measured at a lower reference elevation, typically 10 meters [34].

$$\left(\frac{v}{v_0} \right) = \left(\frac{H}{H_0} \right)^\beta \quad (2.1)$$

where v is the real time wind speed; v_0 is the wind speed at the reference hub height H_0 (usually 10 m) and β is the terrain friction coefficient (e.g. for smooth hard ground and calm water, β is 0.10).

In reliability evaluation of power systems with WTGs, wind speed data are usually represented by different wind speed models to ease calculations. This section introduces several widely used wind speed models including the probabilistic models such as the Weibull distribution model, the mean wind speed model, the multi-state wind speed model, and the ARMA time-series model. The selection of wind speed models depends on many factors, such as the applications, availability of wind speed data, accuracy required, etc.

2.1.1 Mean wind speed model

The potential wind power production can be estimated using the mean wind speed, which is obtained from measurements over a period of time. The time period cannot be too short, such as one month or three months. Data collection of years of wind speed is necessary because wind speed has seasonal characteristics. The mean wind speed can be in hourly, daily or yearly value. The mean wind speed $\bar{v}$ can be calculated using equation (2.2):

$$\bar{v} = \frac{\sum_{i=1}^{n_i} v_i}{n_i} \quad (2.2)$$

where v_i is the wind speed observation i and n_i is the number of the observations.

The estimated wind power production based on the mean wind speed model may be quite inaccurate since it cannot reflect the real wind speed distribution. Sizing of a wind power plant based on such wind speed model would be underestimated in most cases. However, it is quite simple and fast to estimate a wind site when accuracy requirement is not high.

Wind speed is typically a stochastic variable and therefore mathematical wind speed models based on statistic methods are used widely, as introduced in the following paragraphs.

2.1.2 Weibull probabilistic wind speed model

The Weibull distribution is the most well recognized mathematic description of wind speed frequency distribution. Other statistic models such as normal distribution, Rayleigh distribution, Gamma distribution, Pearson distribution, Lognormal distribution and Gumbel distribution [35], can be employed in fitting the distribution of wind speed but the two-parameter Weibull distribution is most widely used [36]. The two-parameter Weibull probability distribution function (PDF) is given by equation (2.3):

$$f(v) = \frac{K_{WB}}{C_{WB}} \left(\frac{v}{C_{WB}} \right)^{K_{WB}-1} \exp \left[- \left(\frac{v}{C_{WB}} \right)^{K_{WB}} \right] \quad (2.3)$$

where $f(v)$ is the distribution function of the Weibull probability distribution, C_{WB} is the Weibull scale parameter, in wind speed units and K_{WB} is the unitless Weibull shape parameter. The corresponding cumulative distribution function $F(v)$ is given by equation (2.4) [36]:

$$F(v) = 1 - \exp \left[- \left(\frac{v}{C_{WB}} \right)^{K_{WB}} \right] \quad (2.4)$$

with $F(0) = 0$ and $F(\infty) = 1$.

Historical hourly wind speed data for the wind farm site collected over a significant time period are normally required to obtain the two Weibull parameters: C_{WB} and K_{WB} . Figure 2.1 shows a histogram for describing the PDF of a particular hour's wind speed data series which follow the Weibull distribution [37].

Given a series of wind speed data, the C_{WB} and K_{WB} can be estimated using many methods, such as the maximum likelihood method and the popular graphical method [35]. Using the maximum likelihood method, the shape parameter K_{WB} and scale parameter C_{WB} can be estimated using equations (2.5) and (2.6).

Figure 2.1: A Histogram describing PDF for Weibull distribution wind speed data.

$$K_{WB} = \left(\frac{\sum_{i=1}^n v^{K_{WB}} \ln(v)}{\sum_{i=1}^n v^{K_{WB}}} - \frac{\sum_{i=1}^n \ln(v)}{n} \right)^{-1} \quad (2.5)$$

$$C_{WB} = \left(\frac{\sum_{i=1}^n v^{K_{WB}}}{n} \right)^{1/K_{WB}} \quad (2.6)$$

where n is the number of nonzero wind speed data points. Equation (2.5) has to be solved using an iterative procedure with a suitable initial guess value, such as the Newton method, Secant method, and Inverse Interpolation method [38]. Using the graphical method, a relation (2.7) can be developed from equation (2.4):

$$\ln \{ -\ln[1 - F(v)] \} = K_{WB} \cdot \ln v - K_{WB} \cdot \ln C_{WB} \quad (2.7)$$

A plot of $\ln \{ -\ln[1 - F(v)] \}$ versus $\ln(v)$ presents a straight line with a slope of K_{WB} and a y-intercept of $-K_{WB} \cdot \ln C_{WB}$. This logarithmic transformation is the basis of the graphical method. The line of best fit can be drawn by hand or determined using a least square regression method.

If the K_{WB} and C_{WB} parameters are known at height H_1 , wind speeds at height H_2 can be estimated using equation (2.1) based on terrain friction coefficients. With approximated wind speed data at height H_2 the corresponding K_{WB} and C_{WB} parameters

can be derived using any of the methods discussed above. Although the accuracy may not be very high, it could be a possible way when no enough wind speed data at a height are available for estimating the Weibull parameters.

The two-parameter Weibull distribution model is more general than the single-parameter Rayleigh distribution model but less complicated than the five-parameter bivariate normal distribution model. It can provide a good fit to observed wind speed data and can be used to evaluate the wind resource, forecast wind energy production and investigate the effects of integration of wind power generation. However, the most obvious deficiency of the Weibull probabilistic model is that the chronological characteristics of wind speed and its effects on wind power output cannot be reflected.

2.1.3 ARMA time-series wind speed model

Wind speed is typically a time sequence, featured by tendency and stochastic characters. Another widely used wind speed model, Autoregressive Moving-average (ARMA) time-series model, is very suitable to describe a stable stochastic sequence [33, 39-40].

Wind speed varies with time and space and at a specified hour is related to the wind speed of previous hours. The ARMA time-series wind speed model can be developed based on measured wind speed data at a specific site. In the ARMA time-series model, the simulated wind speed at time $t(v_t)$ can be obtained from the mean wind speed (μ_t) and its standard deviation (σ_t) at that time. With the wind speed series data set y_t , the simulated wind speed v_t can be calculated using equation (2.8):

$$v_t = \mu_t + \sigma_t y_t \quad (2.8)$$

The time-series data set y_t can be expressed as equation (2.9) [40]:

$$y_t = \sum_{i=1}^n \varphi_i y_{t-i} + \alpha_t - \sum_{j=1}^m \theta_j \alpha_{t-j} \quad (2.9)$$

where φ_i and θ_j are the autoregressive and moving average parameters, respectively. α_t is a normal white noise process with zero mean and a variance of σ^2 . To determine φ_i

and θ_j , a large amount of historical wind speed data and calculations are required [41]. Generally, they can be estimated using the least mean square algorithm, which can be summarized into the following steps [42]:

1. Calculate the difference between the observations and prediction values based on history data (also called error);
2. Square the error to make all values positive (square process);
3. Calculate the average (mean process);
4. Find the parameters that make the error the smallest (least mean square).

The ARMA time-series wind speed model can reproduce the high-order autocorrelation, seasonal and diurnal distribution of the actual wind speed. It does not require any assumption about the wind speed distribution. Therefore, it can be used in reliability studies of power systems with WTGs to simulate the actual wind speed with high accuracy. The ARMA time-series model can also be used to forecast future wind speed based on certain assumptions [43]. However, the wind speeds at any time point in the ARMA time-series model are also fixed values and cannot reflect the random nature of wind speed. As a result, the impact of random nature of wind speed on the power system reliability cannot be reflected. Furthermore, the process for obtaining the proper parameters is quite complex compared with the mean wind speed model. The ARMA time-series model is also specific to the geographic location of the wind farm.

2.1.4 Multi-state wind speed model

The Weibull probabilistic wind speed model and ARMA time-series wind speed model require quite a large number of historical wind speed data and computations to estimate model parameters. Complex techniques are not readily applied in a practical world. The multi-state wind speed model is a simple probabilistic model that can be obtained by statistics.

For a wind site with annual mean wind speed μ_t and the standard deviation σ_t , the distribution considering wind speed up to $10\sigma_t$ can include almost all possible wind

speed values. According to the accuracy required, the distribution can be divided into M number of interval steps, and each step has a length of $10\sigma_i/M$. The midpoint value of wind speed at each interval step (v_i) can be calculated using equation (2.10) [44]:

$$v_i = \begin{cases} \mu_i + (10\sigma_i / M)(i - 0.5M) & \text{for even } M \\ \mu_i + (10\sigma_i / M)(i - 0.5(M + 1)) & \text{for odd } M \end{cases} \quad (2.10)$$

The probability of each step p_i ($i = 1, \dots, N_v$) can be calculated using equation (2.11):

$$p_i = N_v / (8760 \times N_y) \quad (2.11)$$

where N_v is the number of simulated wind speed data in the step v_i , and N_y is the number of sample years.

An eleven-state wind speed model is built using the wind speed data of Ijmuiden city in year 2000 as an example. Table 2.1 lists the main statistical characteristics of 20 years of wind speed data for the wind site [45]. The eleven-state wind speed model is shown as Table 2.2.

Table 2.1: Main statistical characteristics of real wind speed data at a wind site

Year	Mean wind speed μ_i (m/s)	Standard deviation σ_i (m/s)	Year	Mean wind speed μ_i (m/s)	Standard deviation σ_i (m/s)
1982	6.57	3.41	1995	7.08	3.37
1984	6.21	3.25	1996	6.74	3.36
1987	6.38	3.22	1997	6.57	3.32
1988	7.31	3.36	1998	7.49	3.65
1989	6.51	3.31	2000	7.23	3.55
1990	7.16	3.69	2001	7.01	3.38
1991	6.47	3.37	2002	6.92	3.61
1992	6.89	3.24	2003	6.18	3.03
1993	6.73	3.30	2004	6.67	3.49
1994	6.96	3.46	2005	6.55	3.25

In Table 2.2, the mean wind speed μ_t is 7.23 m/s and the standard deviation σ_t is 3.55 m/s. The wind speed of the first three interval steps are negative and are converted to zeroes since negative wind speed has no physical meaning. Therefore, the eleven-state wind speed can be actually changed to a nine-state wind speed model.

The multi-state wind model can be used in an analytical method for reliability evaluation of power systems containing WTGs. Although this wind speed model is simple and with reasonable accuracy, it masks the chronological characteristics of wind speed and its effects on wind power output cannot be considered.

Table 2.2: Eleven-state wind speed model

Probability p_t	Wind speed (μ_t and σ_t)	Wind speed v_t (m/s)
0	$\mu_t - 4.5\sigma_t$	0
0	$\mu_t - 3.6\sigma_t$	0
0.0002	$\mu_t - 2.7\sigma_t$	0
0.0858	$\mu_t - 1.8\sigma_t$	0.84
0.174	$\mu_t - 0.9\sigma_t$	4.04
0.255	μ_t	7.23
0.156	$\mu_t + 0.9\sigma_t$	10.43
0.131	$\mu_t + 1.8\sigma_t$	13.62
0.102	$\mu_t + 2.7\sigma_t$	16.82
0.095	$\mu_t + 3.6\sigma_t$	20.01
0.001	$\mu_t + 4.5\sigma_t$	23.21

2.1.5 Selection of wind speed model

Selection of wind speed models depends strongly on their applications (power system planning or operation, etc), availability of wind speed data, and required accuracy. The introduction and comparison of the four wind speed models are for the sake of power system engineers to choose a suitable wind speed model according to their specific requirements when doing reliability evaluation.

2.2 Power output model of a WTG

The power output characteristics of a WTG are quite different from those of a conventional generating unit, which depends strongly on the wind regime as well as

the performance characteristics of the generator. Several wind power output models, including power curves, mathematical expressions for power curves and the kinetic theory method, are introduced in this section. Probabilistic wind power output is also discussed.

2.2.1 Power curves

Power curves from wind turbine generator manufactures are plots of output power against wind speed, which can be used to determine the power output with high accuracy. A power curve for Nordex N80 (2.5 MW) is shown in Figure 2.2 [46].

As shown in Figure 2.2, the wind power output curve is nonlinear to the change of wind speed. The cut-in, rated, and cut-out wind speeds are about 3 m/s, 13 m/s and 23 m/s, respectively. Power output of a WTG can be obtained accurately from power curves but they are not always available. Several approximation methods are introduced in the following sections.

Figure 2.2: Power curve for Nordex N80.

2.2.2 Mathematical expressions for power curves

A mathematical relationship between wind speed and power output from WTGs can be used to approximate the power output of a WTG when power curves from WTG manufactures are not available. With the assumption of the relation as shown in Figure

2.3, a mathematical expression (2.12) for power curves is used widely [47-48]. The accuracy obtained by this method is acceptable for reliability evaluation.

$$P(v) = \begin{cases} (A + B \times v + C \times v^2) \times P_r & V_{ci} \leq v < V_r \\ P_r & V_r \leq v \leq V_{co} \\ 0 & \text{otherwise} \end{cases} \quad (2.12)$$

where V_{ci} is the cut-in wind speed in (m/s); V_r is the rated wind speed in (m/s); V_{co} is the cut-out wind speed in (m/s); P_r is the rated power (MW) of the WTG and A , B , C are constant parameters, which can be obtained using equations (2.13)-(2.15) [49]:

Figure 2.3: Assumption of the relation between wind speed and power output.

$$A = \frac{1}{(V_{ci} - V_r)^2} \times \left[V_{ci}(V_{ci} + V_r) - 4(V_{ci}V_r) \left[\frac{V_{ci} + V_r}{2V_r} \right]^3 \right] \quad (2.13)$$

$$B = \frac{1}{(V_{ci} - V_r)^2} \times \left[4(V_{ci} + V_r) \left[\frac{V_{ci} + V_r}{2V_r} \right]^3 - (3V_{ci} + V_r) \right] \quad (2.14)$$

$$C = \frac{1}{(V_{ci} - V_r)^2} \times \left[2 - 4 \left[\frac{V_{ci} + V_r}{2V_r} \right]^3 \right] \quad (2.15)$$

2.2.3 Kinetic theory method

A Kinetic theory method is also used to obtain power output from a WTG [26, 49-50]. From the kinetic theory, the total power $P(v)$ of a wind stream is equal to the rate of the incoming kinetic energy of that stream, or

$$P(v) = \frac{1}{2}mv^2 \quad (2.16)$$

where m is the mass flow rate, which can be obtained by the continuity equation:

$$m = \rho A_s v \quad (2.17)$$

where A_s is the sweeping area of the wind stream and ρ is the density.

Thus the total power $P(v)$ from wind can be calculated as:

$$P(v) = \frac{1}{2}\rho A_s v^3 \quad (2.18)$$

It has been proved that due to the Betz' limits [26], the total power from wind cannot all be converted to mechanical power. There is a maximum power $P(v)_{max}$ which can be obtained from the wind as shown by equation (2.19) [26]:

$$P(v)_{max} = \frac{8}{27}\rho A_s v^3 \quad (2.19)$$

The ideal or maximum, theoretical efficiency η_{max} (also called the power coefficient) of a wind turbine is the ratio the maximum power obtained from the wind to the total power of the wind, i.e. 0.5926. In other words, a wind turbine is capable of converting no more than 60% of the total wind power to useful mechanical power.

Many factors can affect the practical efficiency of a wind-turbine wheel. One main factor is the rotor speed. If the rotor rotates too slowly, more wind will pass through the swept area without generating any thrust on the blades. On the other hand, if the wheel turns too fast, the effect of one blade on wind will be increasingly disturbed by the other blade that follows. Other factors include mechanical losses, turbulence

caused by other wind-turbine wheels in the same wind farm, temperature and pressure on air density, and etc. Therefore, practical turbines can only achieve some 50% to 70% of the ideal efficiency. The real efficiency η is the ratio of actual to total power:

$$P(v) = \frac{1}{2} \eta \rho A_s v^3 \quad (2.20)$$

where η varies between 30% and 40% for real turbines.

2.2.4 Probabilistic wind power output

Power output of a WTG can be obtained based on varied wind speed models. If the wind speed model is a probabilistic model, the corresponding power output is also a probabilistic variable. It has been mentioned in Section 2.1.2 that many statistical models can be used to fit the distribution of wind speed for a specific wind site, such as Rayleigh distribution, Gamma distribution, Pearson distribution, Lognormal distribution and etc. However, for a large wind farm, it may cover several diverse geographic locations (with different wind conditions). In this case, the normal distribution is usually used to represent the wind speed model of these wind farms [44] as shown in Figure 2.4. The PDF of the normal distributed wind speed is split into many groups of wind speeds according to certain wind speed intervals. Each group of wind speed is represented by the average wind speed in its interval as well as associated average probability. The mathematical expressions for power curves in Section 2.2.2 are used to build the power output model as shown in Figure 2.4.

The wind speed in shading areas cannot produce power output because it is either smaller than cut-in wind speed or larger than cut-out wind speed. The developed probabilistic wind power output model is a multi-state power output model as shown in the table at the right side in Figure 2.4.

The four methods of obtaining wind power output from wind speeds are only applicable to a single WTG. When there are many dispersed WTGs located in a large wind farm, every WTG will experience different wind speeds from that measured at the meteorological tower. Determination of the spatial-temporal relationship of wind

speeds for dispersed WTGs becomes very important for calculating the power output of the wind farm. Another factor which impacts the accuracy of estimating wind power output is the wake effects of adjacent WTGs. The wake effects will result in wind power losses and may have big impact on the overall wind power system reliability as discussed in [51].

2.3 Load modeling

Load modeling plays an important role in power system reliability evaluation. Building a load model is actually trying to find the mathematical function of the load variation with respect to other factors, such as time [52]. The constant load

Figure 2.4: Development of a probabilistic wind power output model of a large wind farm.

models, time varying load models and probabilistic load model are introduced in this section.

2.3.1 Constant load model

The constant load model includes annual constant load model and daily constant load model, which the load is constant during a year and a day, respectively. In practice, a periodic constant load model is often used, which the energy consumption is relatively

constant during a period of hours with very little weather dependent variation [53]. The demand for electrical energy is quite stable from day to day and season to season. The load level changes one, two or three times over 24 hours depending on different shift operation and production. For example, the load profile for a day with three shifts is shown in Figure 2.5.

Large users and many industrial customers belong to the periodic constant load class. This model has relatively high accuracy and can reflect the seasonal and diurnal characteristic of load in certain level, comparing to the annual constant load model and daily constant load model.

In general, the constant load model is very simple to be developed and can save much computations. The low accuracy and lack of chronological information of the system load are the main disadvantages of the constant load model.

Figure 2.5: Load profile for a periodic constant load.

2.3.2 Time varying load model

The load may change its load level from hour to hour, from minute to minute and from second to second. In practice, an hourly variable load model (HVLM) is usually used. It is assumed that load level in an hour is constant in this load model, which the load level can be obtained from load forecast. The load information provided in the IEEE-RTS [54] is a typical hourly variable load for a year, as shown in Figure 2.6.

The HVLM can reflect the chronological characteristic of the system load and is usually used in operational reliability evaluation. One of the main disadvantages of the

hourly variable load model is the excessive computational effort required especially when used in Monte Carlo simulation.

If the hourly load data are organized in descending order of magnitude (not chronological), it forms the load duration curve (LDC) [55], as shown in Figure 2.7. The area under the load duration curve represents the total energy supplied by the utility's generation.

Figure 2.6: The hourly variable peak load model of the IEEE-RTS.

Figure 2.7: The load duration curve of the IEEE-RTS.

As shown in Figure 2.7, a LDC can be divided into three parts: the based load to be supplied 100% of the time, the peak load to be supplied during very short periods, and the intermediate load [56]. The three load categories are usually fed by different types

of generating equipment. Hence, one of the main applications of a LDC is to establish the types of generating stations to be constructed and their operating schedules.

One major disadvantage of the LDC is the loss of chronological information of the system load and therefore it is not possible to represent some aspects of time dependant by nature, such as the frequency and duration characteristics. Furthermore, LDCs have to be approximated by some functions, such as the smooth functions, step functions, and piecewise functions, especially in the context of energy supply modeling and utility scheduling [56]. The step and piecewise functions gain accuracy at the expense of simplicity while the smooth functions are quite complex. A tradeoff has to be made when using the LDC.

2.3.3 Probabilistic load model

Even in the time varying load model, such as the model in Figure 2.6, the load level in an hour is assumed to be constant at a value of the forecasted or statistical average value. However, it is not accurate using these average values due to the load forecast uncertainty. Load forecast uncertainty can be described by a probability distribution whose parameters can be estimated from past experience and future considerations. However, it is extremely difficult to obtain sufficient historical data to determine the distribution type and the most common practice is to describe the uncertainty by a normal distribution with a given standard deviation [9]. Hence, the forecast uncertainty of load P_{Lj} for period j can be represented by the normal distribution (2.21):

$$f(P_{Lj}) = \frac{1}{\sigma_{Pj}\sqrt{2\pi}} \exp\left(-\frac{(P_{Lj} - P_{Lj}^{ave})^2}{2\sigma_{Pj}^2}\right) \quad (2.21)$$

where P_{Lj}^{ave} is the mean load level for period j and σ_{PLj} is the standard deviation of P_{Lj} .

To evaluate reliability indices using the probabilistic load model in analytical techniques, the normal distribution load can be represented using N-step approximation [57] as shown in Figure 2.8.

The load level, P_{Lj} , is assumed to be constant for load step j . Load P_{Lj} of step j can be calculated using equation (2.22):

$$P_{Lj} \approx f(P_{Lj})(P_{Lj+1} - P_{Lj}) \quad (2.22)$$

Using the above described method, the constant load model and time varying load model can be changed to the probabilistic load model when the load forecast uncertainty is considered. Figure 2.9 show a probabilistic load model based on the hourly varying load model. The load level for each time interval (hour) is no longer a constant value but a probabilistic distribution, whose parameters can be estimated using historical data. It should be noted that the probabilistic distributions at all steps could be different as shown in Figure 2.9.

Figure 2.8: Normal distribution of a load.

Figure 2.9: A probabilistic hourly variable load model.

It is very important to consider the load forecast uncertainty for electric power utilities. Other probabilistic distributions can also be used to describe the load forecast

uncertainty if there have sufficient historical data. The N-step approximation method can be adopted when calculating reliability indices. Higher accuracy can be achieved when use the probabilistic load model to evaluate the reliability indices. However, much more computations may be required, especially when used in Monte Carlo simulations. Therefore, selection of a load model in reliability evaluation requires ponderation according to accuracy requirement, time constraints, and etc.

2.4 Summary

Different wind speed models including the Weibull distribution wind speed model, the mean wind speed model, the multi-state wind speed model and the ARMA time-series wind speed model are reviewed and discussed in this chapter. They have different advantages and suitable applications. Selection of wind speed models depends on many factors, including their applications, availability of wind speed data and required accuracy.

Power output from a WTG depends strongly on the wind regime as well as the performance characteristics of the generator. Power curves from WTG manufactories are most accurate but they are not always available. Mathematical expressions for power curves are used widely to approximate the power output of a WTG. The kinetic theory method is also introduced which can be used to roughly estimate wind energy potential of a wind site. When the wind speed model is a probabilistic model, the corresponding power output is also a probabilistic variable. Such a model has been developed as an example.

The load model plays an important role in power system reliability evaluation. The constant load model, time varying load model and probabilistic load model are also introduced in this chapter. These models will be used in the following chapters according to their respective features and different requirements of reliability studies.

Chapter 3. Reliability Evaluation of a Power System

Reliability evaluation of a power system is to find the risk indices (reliability indices) by a reliability evaluation procedure. Load models are combined with generation system model to assess reliability indices and have been introduced in Chapter 2. Generation system model, reliability indices and basic reliability evaluation procedure are presented in this chapter. An illustrated example of reliability evaluation of a test power system is also given.

3.1 Introduction

Reliability evaluation can be categorized into the deterministic and probabilistic techniques [9]. Deterministic techniques are based on deterministic criteria, such as assigning spinning reserve equal to a fixed percentage of the expected maximum demand or the capacity of the largest generating unit, and planning network capacity based on well known (n-1) or (n-2) criterion, etc. The deterministic techniques are direct and simple but they cannot account for the stochastic and probabilistic nature of system behaviors, customer demands or component failures such as intermittent wind speed. Probabilistic reliability evaluation techniques fit for the modern complex power system and are used broadly in power system operation and planning [7, 58-64].

There are two types of probabilistic reliability techniques: analytical techniques and simulation techniques. Analytical techniques [65-66] represent the system by a mathematical model and evaluate the reliability indices from this model using mathematical solutions. They require less computing time and can provide sufficient information to system planners and designers to make objective decisions. Simulation techniques [33, 62, 65] (refer to stochastic simulation techniques in this thesis) estimate the reliability indices by simulating the actual process and random behavior of the system, and therefore treat the problem as a series of real experiments. Although the simulation techniques need quite a large amount of computing time, there is increasing interest to use them because of their ability to model system behaviors more

comprehensively and to provide more informative set of system reliability indices and their probability distributions. The basic technique will be introduced in the following sections.

3.2 Generation system model

The basic approach to evaluate reliability of a power system requires generation model, load model and risk model. Load models have been introduced in Chapter 2 because they are seldom modified in different reliability evaluation techniques. All the generating units are lumped together to form a total system generation at hierarchy level I (HLI).

3.2.1 Reliability model of a generating unit

A generation system may consist of many generating units. A base load generating unit can be represented by a two-state reliability model in which the unit has relatively long operating cycles, as shown in Figure 3.1 [9]. The generating unit can move from operating state to failure state at failure rate (λ_c) and return to operating state at repair rate (μ_c) after the unit is repaired.

Figure 3.1: The two-state reliability model of a generating unit.

Two basic parameters of generating units are used in static reliability evaluation: unit availability (A_c) and unit unavailability (U_c). The availability A_c is defined as the probability of a unit being in the operating state while the unavailability U_c is defined as the probability of a unit being in the failure state. The unit unavailability is known as the unit forced outage rate (FOR) in power system applications historically. The A_c and U_c of a generating unit can be calculated using equations (3.1) and (3.2) [9].

$$\text{Unavailability (FOR)} = U_c = \frac{\lambda_c}{\lambda_c + \mu_c} = \frac{r_c}{m_c + r_c} = \frac{r_c}{T} = \frac{f}{\mu_c} \quad (3.1)$$

$$\text{Availability} = A_c = \frac{\mu_c}{\lambda_c + \mu_c} = \frac{m_c}{m_c + r_c} = \frac{m_c}{T} = \frac{f}{\lambda_c} \quad (3.2)$$

where

m_c = mean time to failure = MTTF = $1/\lambda_c$

r_c = mean time to repair = MTTR = $1/\mu_c$

T = cycle time = $1/f$

f = cycle frequency = $1/T$

$m_c + r_c$ = mean time between failures = MTBF = $1/f$

When the operating cycles are relatively short and for peaking or intermittent operating units, multiple state models can be used to provide more precise estimation. A four-state unit reliability model has been proposed to represent peaking generating units by the IEEE Subcommittee on the Application of Probability Methods [67], as shown in Figure 3.2. For intermittent energy generating units, such as WTGs and solar PVs, multiple steps capacity models have been proposed in [68].

Figure 3.2: The four-state reliability model of a generating unit.

The probabilities of residing in each state in terms of the state transition rates P_0 , P_1 , P_2 , P_3 , and conventional FOR can be calculated using equations (3.3) to (3.7) [68].

$$P_0 = \frac{\mu_c T_s [D\lambda_c + 1 + D(\mu_c + 1/T_s)]}{A} \quad (3.3)$$

$$P_1 = \frac{D\lambda_c + P_s}{A} \quad (3.4)$$

$$P_2 = \frac{D\mu_c (1 - P_s + \mu_c D + D/T_s)}{A} \quad (3.5)$$

$$P_3 = \frac{D(\mu_c + 1/T_s)(D\lambda_c + P_s)}{A} \quad (3.6)$$

$$FOR = \frac{P_1 + P_3}{P_1 + P_2 + P_3} \quad (3.7)$$

where $A = (D_s\lambda_c + P_s)[(\mu_c T_s + 1) + (\mu_c + 1/T_s)D_s] + [(1 - P_s) + D_s(\mu_c + 1/T_s)](\mu_c T_s + \mu_c D_s)$; T_s is average reserve shut-down time between periods of need, D_s is average in-service time per occasion of demand and P_s is probability of starting failure.

3.2.2 Generation system reliability model

A generating unit can be represented by the two-state or four-state model or other models while a generation system has many system states when considering random failures of generating units. A well-known generation system model in analytical power system reliability evaluation techniques is the capacity outage probability table (COPT) [9]. A COPT includes all possible system states, available capacities, capacity outages, individual state probabilities and cumulative state probabilities. Two methods used to build a COPT are introduced in this section.

The first method is using the binomial distribution as shown in equation (3.8), for n identical generating units. The identical generating units refer to those with identical capacities, and identical probabilities of success and therefore of failure. The number of terms in equation (3.8) represents the possible system states and each term's value is the individual state probability. The available capacity for a system state can be obtained according to the power of A_c , e.g. the available capacity of the second term is $(n_c - 1)$ multiplying the capacity of the generating unit.

$$(A_c + U_c)^n = A_c^{n_c} + nA_c^{n_c-1}U_c + \frac{n_c(n_c-1)}{2!}A_c^{n_c-2}U_c^2 + \dots + U_c^{n_c} = 1 \quad (3.8)$$

The binomial coefficients can be obtained by many methods, such as direct hand evaluation, Pascal's triangle, Stirling's formula and special binomial distribution tables [65]. They all have certain limitations for application. For example, the direct hand evaluation method can only be used when the factorial is small and the special binomial distribution tables can only be used for a certain range of data. With the advance in computer techniques, computer software can provide pre-programmed functions to calculate the binomial coefficients, such as the MatLab software.

If the generating units are not identical, the binomial distribution cannot be used directly to form the COPT. A procedure can be used: first, combine together all identical units using the binomial distribution; second, combine together, one at a time, these groups of tables by identifying all possible system states and evaluating the probability of each state. The COPT of a generation system with two non-identical generating units is created with this procedure, as shown in Table 3.1. C_1 and C_2 , and FOR_1 and FOR_2 are the rated capacities and forced outage rates of the two units, respectively.

Table 3.1: Procedure to form COPT using basic probability method

State	Capacity in service	Individual probability
Step 1: Unit 1 is added		
1	C_1	$1-FOR_1$
2	0	FOR_1
Step 2: Unit 2 is added		
1	C_1+C_2	$(1-FOR_1) \cdot (1-FOR_2)$
2	$0+C_2$	$FOR_1 \cdot (1-FOR_2)$
3	C_1+0	$(1-FOR_1) \cdot FOR_2$
4	$0+0$	$FOR_1 \cdot FOR_2$

The final COPT for the generation system with two non-identical units is shown as Table 3.2.

The second method to build a COPT is using a recursive algorithm as described in [9, 69-70]. This method is suitable for computer programming and can be used for multi-state units as well as two-state units. For the case of two-state units considered, the cumulative probability $P(X_c)$ of a particular capacity outage state of X_c MW after a unit of capacity C_c MW and forced outage rate FOR_c is added is given by equation (3.9) [9]:

$$P(X_c) = (1 - FOR_c)P'(X_c) + (FOR_c)P'(X_c - C_c) \quad (3.9)$$

where $P'(X_c)$ and $P(X_c)$ denote the cumulative probabilities of the capacity outage of X_c MW before and after the C_c unit is added. Equation (3.9) is initialized by setting $P'(X_c) = 1.0$ for $X_c \leq 0$ and $P'(X_c) = 0$ otherwise. For the case of multi-state considered, the cumulative probability $P(X_c)$ can be calculated using equation (3.10) [9]:

$$P(X_c) = \sum_{i=1}^{N_i} p_i P'(X_c - C_{oi}) \quad (3.10)$$

where N_i is the number of unit states, C_{oi} is the capacity outage of state i for the unit being added, and p_i is the probability of existence of the unit state i . A COPT example for a general generation system is shown in Table 3.3.

Table 3.2: COPT for a generation system with two non-identical units

State	Unit 1	Unit 2	Capacity in service	Capacity out of service	Individual probability	Cumulative probability
1	Up	Up	$C_1 + C_2$	0	$(1 - FOR_1) \cdot (1 - FOR_2)^{\#4}$	$\#1 + \#2 + \#3 + \#4$
2	Up	Down	C_1	C_2	$(1 - FOR_1) \cdot FOR_2^{\#3}$	$\#1 + \#2 + \#3$
3	Down	Up	C_2	C_1	$FOR_1 \cdot (1 - FOR_2)^{\#2}$	$\#1 + \#2$
4	Down	Down	0	$C_1 + C_2$	$FOR_1 \cdot FOR_2^{\#1}$	$\#1$

In Table 3.3, it is assumed that $C_1 > C_2 > \dots > C_i > \dots > C_{n-1} > C_n$ since the values in column “capacity in service” are organized in descending order. The COPT can be truncated by omitting states of which the cumulative probability is less than a specified amount, e.g. 10^{-8} . This can save considerable computation time. In practice, the

probability of more than two components failing simultaneously is very low. Therefore, for a large power system, system states can be reduced significantly by only considering up to two or three components failures.

Table 3.3: COPT for a general generation system

State	Capacity in service	Individual probability	Cumulative probability
1	C_1	p_1	$P_1 = p_1 + \dots + p_i + \dots + p_{n-1} + p_n$
2	C_2	p_2	$P_2 = p_2 + \dots + p_i + \dots + p_{n-1} + p_n$
:	:	:	:
i	C_i	p_i	$P_i = p_i + p_{i+1} + \dots + p_{n-1} + p_n$
:	:	:	:
$n-1$	C_{n-1}	p_{n-1}	$P_{n-1} = p_{n-1} + p_n$
n	C_n	p_n	$P_n = p_n$

3.3 Reliability indices

Reliability indices are used to indicate the system reliability performance and the main aspects of reliability include the frequency, duration, and magnitude of interruptions to electricity service or to maintaining proper reserve levels. Many reliability indices are proposed and used in different utilities and techniques. Several important indices are introduced in this section.

3.3.1 Loss of load probability

The loss of load probability (LOLP) is in units of *percent*, representing the probability of system not having enough capacity available to meet a given load [71]. The LOLP is usually represented by the following equation (3.11) in both the analytical and simulation reliability evaluation techniques.

$$LOLP = P(C_o > P_C - P_L) \quad (3.11)$$

where P_L is the load demand, P_C is the total available capacity and $P(C_o > P_C - P_L)$ is the probability of having a capacity outage C_o greater than the margin $(P_C - P_L)$, the conditions when a loss of load would occur in the power system.

The LOLP does not reflect the frequency of events because simulations with one or multiple loss of load occurrences are counted equally. It also provides no information regarding duration or magnitude of loss of load events.

3.3.2 Loss of load expectation

The loss of load expectation (LOLE) is in units of days per year, representing days of the system with loss of load event [9]. The LOLE can be calculated using equation (3.12) in analytical techniques:

$$LOLE = \sum_{i=1}^{N_i} p_i \times t_i(P_{Ci} < P_L) \quad (\text{hours / year}) \quad (3.12)$$

where $t_i(P_{Ci} < P_L)$ is the time during which available capacity P_{Ci} is less than load P_L .

When the load model is the load duration curve (LDC), the LOLE can be obtained using the relationship between the state available capacity P_{Ci} and time t_i , as shown in Figure 3.3.

Figure 3.3: Relationship between load and capacity.

The capacity outage C_{oi} and the corresponding individual state probability p_i for state i can be determined from the COPT. The outage time t_i ($P_{Ci} < P_L$) for state i during which the available capacity P_{Ci} is less than load P_L can be determined from Figure 3.3. The mathematical function of the LDC is normally not available. In practice, the LDC is represented by one or more straight lines to reduce calculations.

This index indicates the frequency of occurrence for days with loss of load events while is not a frequency measure for individual events because multiple events can occur during a single day and a single event can last longer than one day. Historically, many utilities used a “one day in ten year” threshold to design their power system. LOLE provides a different measure of reliability than the LOLP but neither provides any indication of duration nor magnitude.

3.3.3 Expected energy not supplied

As stated in previous sections, LOLP and LOLE are metrics more closely associated with the frequency aspect of reliability. Neither provides any indication of the size or magnitude of potential loss of loads nor of the duration of loss of loads. Expected energy not supplied (EENS) is a loss of energy index defined to provide some measure of the magnitude of loss of load events [9]. It is calculated as the sum of all unsupplied energy (in megawatt-hours) over an evaluation period (one year in most cases).

In analytical techniques, the EENS can be calculated using the LDC as shown in Figure 3.4. The shaded area in Figure 3.4 is the energy curtailed ENS_i , i.e. energy not supplied, for a system state i . For a given load curve, the ENS_i can be calculated using (3.13):

$$ENS_i = \int_0^{t_i} (P_L - P_{Ci}) dt \quad (3.13)$$

where t_i is the time during which the P_{Ci} is smaller than P_L at system state i .

After determining the ENS_i for each system state i , the total EENS can be calculated using equation (3.14):

$$EENS = \sum_{i=1}^{N_i} p_i \times ENS_i \quad (3.14)$$

where N_i is the number of system states and p_i is the probability of state i .

3.3.4 Energy index of reliability

The total energy under the load duration curve in Figure 3.4 is designated as E and the energy index of reliability, EIR, can be calculated using EENS and E using equation (3.15) [9]:

$$EIR = 1 - \frac{EENS}{E} \quad (3.15)$$

Figure 3.4: Relationship between load, capacity and unsupplied energy.

Numerous other indices can be defined to address different aspects of reliability, such as EDNS (expected demand not supplied), FLOL (frequency of loss of load), ENSINT (energy not supplied per interruption), DNSINT (demand not supplied per interruption) and EDPI (expected duration per interruption) [72]. As stated earlier, the three key parameters of loss of load events are frequency, duration and magnitude. Any number of reliability indices can be defined using some combination of these three key parameters, LOLP, LOLE and EENS. The three reliability indices are the most commonly used metrics but they do not fully describe the characteristics of loss

of load events. Each utility or region must decide what factors are most important for its own reliability planning.

3.4 Reliability evaluation procedure

The basic procedure for calculating reliability indices of power systems, regardless in analytical techniques or simulation techniques, can be summarized by the following steps [73].

- Step 1: Develop a suitable load model from the estimated data over the period of study;
- Step 2: Select the appropriate generating unit model, depending on the characteristics of each unit;
- Step 3: Develop a generation system model;
- Step 4: Combine the generation system model with the load model to obtain the reliability indices of the system and the expected energy supplied by each generating unit.

3.5 System studies

The IEEE-RBTS [74] is evaluated using the analytical techniques in this section. There are 11 conventional generating units providing total capacity of 240 MW and the annual peak load in the IEEE-RBTS is 185 MW. All generating units are assumed to be committed during the whole study period. SR is assigned to be the system capacity margin, which is the difference between the total installed generation capacity and load level. The FOR and other reliability data of the 11 conventional generating units are shown in Table 3.4. The study focuses only on the generation system level, i.e. HLI, and the study period is one year (8760 hours).

The generating unit is represented by the two-state reliability model and the generation system is modeled by the COPT, as shown in Table 3.5. The LDC for 8760 hours and for the IEEE-RBTS is shown in Figure 3.5. The four main reliability indices LOLP, LOLE, EENS and EIR are assessed using the LDC by the analytical method mentioned above.

3.5.1 Basic study

Combining the load model (LDC) in Figure 3.5 and the COPT in Table 3.5, the reliability indices of the IEEE-RBTS can be calculated as shown in Table 3.6.

Table 3.4: Generating unit reliability data

Unit size (MW)	Type	No. of unit	FOR	MTTF (hours)	MTTR (hours)	μ	λ
5	Hydro	2	0.010	4380	45	198.0	2.0
10	Thermal	1	0.020	2190	45	196.0	4.0
20	Hydro	4	0.015	3650	55	157.6	2.4
20	Thermal	1	0.025	1752	45	195.0	5.0
40	Hydro	1	0.020	2920	60	147.0	3.0
40	Thermal	2	0.030	1460	45	194.0	6.0

Figure 3.5: The IEEE-RBTS LDC.

It can be concluded from Table 3.6 that the IEEE-RBTS is a very reliable power system. There is a possibility of 0.0125% which the “loss of load” events occur, as shown by LOLP. The LOLE is also smaller than the popular used criteria “one day in ten years” ($\text{LOLE} \leq 2.4$ hours/year). An EIR of 0.9999 also means that the generation system is very reliability and with high adequacy. The basic reliability evaluation can only be used to estimate the general reliability of a power system. To improve certain aspects of system reliability performance or selecting a better way to increase the system reliability most efficiently, a large amount of sensitive studies will have to be conducted in the following sections.

3.5.2 Effect of peak load

From the basic study in Section 3.5.1, it has been found that the IEEE-RBTS is quite a reliable power system. In order to investigate the effects of peak load on the system reliability indices, the system peak load is changing from 90 percent to 150 percent of its original values. Other system conditions do not change. The results are shown in Figure 3.6 through Figure 3.9.

Table 3.5: COPT of the IEEE-RBTS

State	Capacity out (MW)	Capacity in (MW)	Individual probability	Cumulative probability
1	0	240	0.81285961	1.0
2	5	235	0.01642141	0.18714039
3	10	230	0.01667191	0.17071898
4	15	225	0.00033513	0.15404707
5	20	220	0.07035854	0.15371194
6	25	215	0.00142135	0.08335340
7	30	210	0.00144303	0.08193205
8	35	205	0.00002901	0.08048902
9	40	200	0.06926973	0.08046001
10	45	195	0.00139939	0.01119028
11	50	190	0.00142073	0.00979090
12	55	185	0.00002856	0.00837017
13	60	180	0.00582845	0.00834161
14	65	175	0.00011803	0.00251316
15	70	170	0.00011962	0.00239513
16	75	165	0.00000239	0.00227550
17	80	160	0.00200114	0.00227312
18	85	155	0.00004043	0.00027197
19	90	150	0.00004104	0.00023154
20	95	145	0.00000169	0.00019050
21	100	140	0.00015862	0.00018881
22	105	135	0.00000322	0.00003019
23	110	130	0.00000326	0.00002696
24	115	125	0.00000006	0.00002370
25	120	120	0.00002119	0.00002364
26	125	115	0.00000049	0.00000245
27	130	110	0.00000040	0.00000196
28	135	105	0.00000003	0.00000155
29	140	100	0.00000141	0.00000152
30	145	95	0.00000011	0.00000011

Table 3.6: Values of reliability indices

Reliability indices	LOLP (%)	LOLE (hours/year)	EENS (MWh/year)	EIR
Values	0.0125	1.0911	9.8124	0.9999

Figure 3.6: Effect of peak load on the LOLP.

Figure 3.7: Effect of peak load on the LOLE.

Figure 3.8: Effect of peak load on the EENS.

Figure 3.9: Effect of peak load on the EIR.

It can be seen from Figures 3.6 to 3.8 that all LOLP, LOLE and EENS are increasing with the increases of system peak load. When the system peak load is smaller than 110% of its original value, the increase of those reliability indices is very slow and the power system is very reliable with the increased load. On the other hand, when the system peak load is over 120% of its original value, the increase of those indices becomes very fast, i.e. the system reliability deteriorates quickly. The increased peak load has an inverse impact on the EIR, as shown in Figure 3.9. Although the EIR decreases very fast when the peak load exceeds certain value, its value is still quite high because of the unsupplied energy with the increased peak load is very small comparing to the system total required energy.

The sensitivities of the four reliability indices to the peak load can also be calculated. When the peak load increases by 0.5 times from its original value, the LOLP, LOLE and EENS increase by 502 times, 502 times and 874 times respectively while the EIR is reduced by 5.8%. The EIR and EENS have the least and largest sensitivity to the peak load, respectively.

These studies also provide useful information for system planners when making system expansion decision. For example, if the planner wants to integrate more customers (load) into the existing power system without adding new generating units, these studies can tell how much load that can be added without violating system reliability requirement. As shown by Figure 3.7, less than 5% load or 9.25 MW load can be added into the IEEE-RBTS without violating the popular LOLE threshold of “one day in ten year”.

3.5.3 Effect of FORs

Different power systems consist of different combinations of generating units which are with varied FORs. In order to investigate the effect of FORs on the power system reliability, it is assumed that FORs of all generating units in the IEEE-RBTS are changed in the same time from 100% to 250% of their original values without changing other system conditions. The results are shown in the following figures.

Figure 3.10: Effect of generating unit FORs on the LOLP.

Figure 3.11: Effect of generating unit FORs on the LOLE.

Figure 3.12: Effect of generating unit FORs on the EENS.

Figure 3.13: Effect of generating unit FORs on the EIR.

It can be seen from Figures 3.10 to 3.13 that with the increase of generating unit FORs, i.e. decreased generating unit availability, the LOLP, LOLE and EENS are increased with small acceleration. The EIR is reduced slowly when the FORs of generating units is increased. When the FORs are increased by 0.5 times from its original values, the LOLP, LOLE and EENS are increased by 1.46 times, 1.46 times and 1.71 times respectively while the EIR is reduced by 0.00017%. The EIR is very insensitive to the change of generating unit FORs. Comparing to the studies in Section 3.5.2, it can be found that the reliability indices are with far more insensitive to changes of generating unit FORs than to changes of peak load. In other words, the FORs of generating units will not impact the power system reliability significantly.

3.5.4 Effect of generator capacities

The IEEE-RBTS is a strong power system as shown in previous sections. In order to show the impact of generator capacities on power system reliability clearly, the peak load is first increased by 10%. In this case, the LOLE and EENS are calculated to be 4.7131 hours/year and 50.5246 MWh, respectively. The capacity of each generator is then increasing from 100% to 120% of their original value and the results are shown in Figures 3.14 to 3.15.

Figure 3.14: Effect of generator capacities on the LOLE.

Figure 3.15: Effect of generator capacities on the EENS.

It can be seen from Figures 3.14 and 3.15 that both the LOLE and EENS are decreased with the increase of generator capacities. With the continuous increase of generator capacities, the reduction rate of LOLE and EENS becomes slow and finally to be very close to 0 at certain generator capacity level.

This study can also help the system planners to decide the amount of generation capacity that needs to be put into service to realize certain reliability requirement. For example, if the test system with increased peak load is required to recover to its original LOLE level, 1.0911 hours/year, its capacity will be 17 MW by putting a new generator with a FOR of 0.02 into operation, as shown in Figure 3.16. Comparing to the increased peak load of 18.5 MW, it can be found that a same increase of generation capacity and system peak load decrease will not result in the same impact on system reliability. The curves in Figure 3.16 will be different if an existing generator is replaced with bigger capacity to achieve the original LOLE level. Therefore, to realize certain reliability requirement should consider many factors such as FORs, unit loading priority orders, and so on.

3.5.5 Effect of SR

The current SR is allocated to be the capacity margin for each time interval. To study the impact of SR on the power system reliability, SR is assumed to be a fixed

percentage of the peak load for each time interval. In this case, the generating unit loading priority order is shown in Table 3.7.

Figure 3.16: LOLE variation with changing capacity of added generators.

Table 3.7: Loading priority order of generating units

Unit size (MW)	5	5	10	20	20	20	20	20	40	40	40
Loading priority order	11	10	9	5	7	6	8	4	3	2	1

When the SR is changing from 0 to 20% of peak load at each time interval, the effects of SR on the LOLE and EENS are shown by Figures 3.17 to 3.18.

It can be seen from Figures 3.17 to 3.18 that both the LOLE and EENS decrease rapidly with the increase of SR. The LOLE and EENS values are relative higher than that using capacity margin as SR due to the following two reasons. Firstly, the allocated SR in this case is smaller. Take the SR of 20% of peak load as example. The total SR for 8760 hours is 1.9911×10^5 MWh and 1.1068×10^6 MWh when using capacity margin as SR. Secondly, the specified load priority order of generating units commits larger generators first. This results in big generation loss when any generator is out of service due to forced failure and therefore leads to a large energy not supplied.

Figure 3.17: Effect of spinning reserve on the LOLE.

Figure 3.18: Effect of spinning reserve on the EENS.

Therefore, it is obvious that different SR allocation policies impact the power system reliability performance in varying degrees. Under-allocation of SR will result in low system reliability while over-allocation of SR costs high. Optimal determination of the value of SR is necessary and important in power system planning and operation but this is beyond the scope of the thesis.

3.6 Conclusion

The basic analytical reliability evaluation techniques for conventional power systems have been introduced in this chapter. Generating units are modeled as a two-state or four-state model and the generation system is modeled by COPT, which can be formed based on generating unit model using the binomial distribution method or a recursive algorithm. Several main reliability indices such as the LOLP, LOLE, EENS and EIR are introduced and evaluated.

A small test power system, the IEEE-RBTS, is employed to illustrate the analytical reliability evaluation techniques. The generation system model COPT is built using the recursive algorithm using MatLab software and the load is modeled by a LDC which is converted from the peak load variation curve of the test system. It is found that the IEEE-RBTS has very low LOLP, LOLE, EENS and very high EIR, i.e. the power system is very reliable. Many sensitivity studies are conducted to provide the power system planners much useful information when making decision. Both the increased system peak load and FORs of generating units have negative effects on system reliability and the former has relatively bigger impact. Incorporating new generation and assigning more SR can improve system reliability but the amount of reliability improvement depends on many factors, such as the FORs of generators, loading priority order, SR allocation policies, and etc. And most importantly, these methods to improve system reliability cost much. A balance between cost and reliability should be made all the time.

Chapter 4. Reliability Evaluation of Power Systems with Wind Farms and Energy Storage

The general reliability evaluation techniques for conventional power systems have been introduced in Chapter 3. In this chapter, those techniques are improved and extended to power systems with wind power generation and energy storage. Wind speed and wind power output models have been reviewed in Chapter 2 and will be used to build the power system generation system model together with conventional generating units. More reliability and economic indices are introduced and defined because of the incorporation of wind energy and energy storage. Illustrated system studies are also presented to investigate the impacts of the intermittent and uncontrollable wind power on system reliability and wind energy utilization.

4.1 Introduction

Clean and sustainable characteristics of wind energy attract many countries to install more and more WTGs to replace their conventional generators. Worldwide a total nameplate capacity of 238351 MW of WTGs has been put into operation till the end of 2011 [75]. China became the world leader of installed wind power capacity in 2010, and many large wind farms are under construction [76]. However, integration of a large number of WTGs may impact the reliability and stability of the existing power system significantly if no suitable measures are taken. Incorporation of energy storage into power system with wind energy is one of the most efficient and popular measures to smooth out wind power output fluctuation and increase wind power capacity credit. Different energy storage technologies will be introduced and the battery is selected as energy storage in this study.

Integration studies of wind power generation into conventional power systems have been carried out widely and covered varied issues such as the reliability, stability, security, and etc [43, 77-83]. Generating capacity adequacy of power systems with

wind energy is studied in [79]. Both the reliability contribution from conventional generating units and WTGs are evaluated and compared, and the wind power's contribution to system adequacy is found to be highly dependent on the wind site conditions. The adequacy evaluation is extended to the bulk systems with wind power using the well-being analysis framework [81]. The effects of wind power on reliability indices and well-being indices at bulk system were investigated. Transmission capacity may limit the system capability to absorb more wind power when a large-scale wind farms is connected to a weak transmission area. The authors in [80] proposed potential transmission reinforcement schemes based on reliability cost and worth analysis. Four new indices, the wind generation interrupted energy benefit (WGIEB), the wind generation interruption cost benefit (WGICB), the equivalent number of conventional generators (ENCG) and the equivalent conventional generator capacity (ECGC), are defined in [77] to provide direct reliability benefit information on the addition of WTGs, which can be used by system planners to select a wind site and the number of WTGs. The authors in [43] proposed a method to evaluate the contribution of wind power for the load carrying capability of a power generating system in an operating scenario. Unit commitment risk analysis is extended to incorporate the variation of wind energy and a consistent approach to calculate the operating risk in power system with wind power is provided. Reference [78] provides experience of wind power integration in some high wind penetration areas. The impacts of wind generation on the operation and development of the UK electricity systems are studied in [83]. Many issues, including the cost of installation and operation of wind farms, cost of real time balancing, fuel savings and network costs, value of fault ride through capability and capacity benefits of wind generation, are investigated. A new simulation method is proposed to assess the impacts of large-scale wind power on system operations from cost, reliability and environmental perspectives [82]. To simulate actual operation and short-term planning activities for power systems with high wind penetration, the UC and ED tool have to allow revising conventional generation unit schedules frequently based on information on current wind energy production and forecasts for the next 36 hours.

Many researchers have adopted batteries as energy storage in their researches to improve the wind power output performance [30-31, 33, 84-86]. A Monte Carlo

simulation (MCS) method is used in [33] to evaluate reliability of power system containing wind power and energy storage. The wind energy dispatch level is restricted during simulation because of consideration of system stability. The operation strategies of different energy storage are found to be the main factors which impact its benefit to the power system. An overview of battery energy storage technology, their applications and limitations for power systems is introduced in [30]. The utilization of battery storage is discussed in terms of many aspects, including the electricity market prices, balancing power price and wind power variation, power quality improvement, black start capacity, deferral of transmission and distribution costs, island mode operation and ancillary service. In [31], a probabilistic method was proposed for predicting the ability of battery storage to increase the penetration of wind generation on weak power systems. Different energy storage technologies are compared for different application and under different time scales. The amount of absorbed wind energy is found to be increased slightly by incorporating of short-term storage. The value of bulk energy storage to manage wind power output fluctuation is evaluated by improved system operation efficiency and wind power absorption, saved fuel cost and reduced CO₂ emissions in [84]. The impact of uncertain wind forecasts is considered and the benefit of energy storage is found to be more significant in power systems with low generation flexibility and with high wind power penetration levels. When energy storage is used as standing reserve, it introduces a higher value in servicing the highly frequent smaller imbalances of wind power fluctuation. The benefits and costs of utility energy storage were estimated in three applications on the Niagara Mohawk Power Corporation systems [86]. Batteries are not cost-efficient for the industrial case when a high quality reliable power is required and as a long-time storage for thermal overloaded transmission system. If environmental and siting problem are considered, batteries can be used with diesel generators to provide cost-efficient energy storage for important commercial load at the end of a radial feeder.

4.2 Energy storage technologies

Main energy storage technologies and their applications are introduced in this section. Due to the fast response time, acceptable cost and relative mature technology of batteries, they are used as energy storage in this thesis.

Existing energy storage technologies include pump station, flywheel, compressed air energy storage, battery, capacitor, electrolysis hydrogen production device, and heat or cold storage. They can be integrated into power systems to add values in different ways as summarized in Table 4.1 [31].

Table 4.1: Storage technologies and applications

Full Power Duration of Storage	Application	Hydrogen Electrolysis + fuel cell	Compressed Air Energy Storage	Pumped Hydro	Redox Flow Cells	Battery Technologies	Flywheel	Superconducting Magnetic Energy Storage	Super Capacitor	Conventional Capacitor or Inductor
4 months	Annual smoothing of loads, PV, wind and small hydro	√	×	×	×	×	×	×	×	×
3 weeks	Smoothing weather effects: loads, PV, small hydro	√	×	×	×	×	×	×	×	×
3 days	Weekly smoothing of loads and most weather variations	√	√	√	√	×	×	×	×	×
8 hours	Daily load cycle, PV, wind, transmission line repair	√	√	√	√	√	×	×	×	×
2 hours	Peak load lopping, standing reserve, wind power smoothing	√	√	√	√	√	×	×	×	×
20 minutes	Spinning reserve, wind power smoothing, cloud on PV	√	√	√	√	√	√	×	×	×
3 minutes	Spinning reserve, wind power smoothing of gust	√	×	√	√	√	√	×	×	×
20 seconds	Line of local faults, voltage and frequency control, governor controlled generator	×	×	×	√	√	√	√	√	√

Generally, the short duration application of energy storage can be used to smooth out the fluctuation of power output from WTGs and to facilitate a higher installed capacity (i.e. penetration level) without exceeding local voltage limits. On the other hand, the long duration application of energy storage could shift power output from WTGs during a high wind period to a high load period. Advantages and disadvantages of these energy storage technologies are introduced in the following sections.

4.2.1 Hydrogen based energy storage technology

The hydrogen based energy storage consists of an electrolysis unit which can use electrical power generated in high wind speed and low demand period to produce hydrogen (H₂). The stored chemical energy in hydrogen can be converted back to electrical power using fuel cells when required [87]. The main advantages of hydrogen based energy storage are without CO₂ emissions, cheap and long last storage, high energy density as well as facilities to implement in different sizes up to several MW. On the other hand, hydrogen energy storage has some disadvantages, such as hydrogen is highly flammable, the construction cost is high at present, and the round trip efficiency is relatively low.

4.2.2 Compressed air energy storage technology

The compressed air energy storage (CAES) usually works with conventional gas turbines. It stores the electrical energy during low demand periods in the form of elastic potential energy of compressed air which is kept for peak period use. To extract the stored energy, compressed air is expanded through a high pressure turbine and then mixed with fuel. The high pressure fuel-air mixture is combusted with the exhaust expanded through a low pressure turbine. Both the high and low pressure turbines are connected to a generator to produce electricity. The advantages of CAES are its very high energy and power capacity and long life time [88]. Its disadvantages include low energy conversion efficiency due to relatively large heat losses, slow response and fewer environmentally acceptable siting opportunities.

4.2.3 Pumped hydro storage technology

The pumped hydro storage can use excess electricity produced in periods of low demand to pump water to a deposit situated at a certain height. The water with potential energy can be recovered through a turbine at high demand periods [89]. The advantages of pumped hydro storage include very high energy and power capacity, moderate access time, and very long life time. The disadvantages include difficulty of finding topographically suitable sites and enough water, adverse impact on environment caused by reservoirs, and the moderate efficiency.

4.2.4 Redox flow cell technology

A flow battery is a rechargeable fuel cell in which electrolyte containing one or more dissolved electroactive species flows through an electrochemical cell that reversibly converts chemical energy directly to electricity. The Redox flow cell is the representative of the flow batteries, in which all electroactive components are dissolved in the electrolyte. The advantages of the Redox flow cell battery include high power rating, long duration, decoupled power rating and energy rating, easily replacing of electrolytes, fast response and transition from charge to discharge modes, and no self-discharge problem [30]. The major disadvantage of the Redox flow cell is the high capital and running costs associated with the operation of a chemical plant which consists of pump systems, sensors and other accessories.

4.2.5 Flywheel storage technology

A flywheel is an electromechanical storage system in which energy is stored by a rotating mass as kinetic energy [89]. Flywheel energy storage is a “green” facility that has long cycle life, insensitive to the depth of discharge (DOD). The advantages of flywheel energy storage are high peak power capacity without overheating concerns, high round trip energy efficiency, rapid response capability, much higher charging/discharging rate, durability, ability to provide other ancillary services, and low overall costs [89-90]. The major disadvantage of flywheel energy system is the danger of explosive shattering of the massive wheel due to overload. The immature

suspension techniques and containment vessel are also problems of flywheel storage technologies.

4.2.6 Superconducting magnetic energy storage technology

The superconducting magnetic energy storage (SMES) can store electrical energy in a magnet field of conducting coil without conversion to chemical or mechanical forms [88]. The advantages of a SMES are extremely short response time with high power, no degradation in performance over the life of the system, capability of keeping at remote locations, long life (at least 20 years), as well as high efficiency. The major disadvantage is that the superconducting coil must be kept at a very low temperature to maintain its superconducting capability. This greatly limits the application of SMES technology from the economic point of view. Another disadvantage is the immaturity of the large-scale SMES systems capable of bulk storage [88-89].

4.2.7 Super capacitor technology

The super capacitor has very high energy density compared to common capacitors. The advantages of super capacitors comparing to batteries include less weighty than that of battery of the same energy storage capacity, fast access to the stored energy, allowable of fully discharge, high charging/discharging cycles ($>10^6$ times), fast charging speed, storage capacity independent of number of charging/discharging cycles, and high efficiency (95%) [91-92]. The main disadvantage of super capacitors comparing to batteries is the very poor energy density. The discharging time of a super capacitor system is very short and therefore it is only viable for improving power quality or to assist batteries.

4.2.8 Battery technology

Batteries are composed of one or more electrochemical cells, which each cell consists of a liquid or solid electrolyte having a positive and a negative electrode. The battery can be charged during off-peak or using energy from renewable resources. When power is needed, batteries can discharge its energy to the grid [93]. The main

advantages of battery storage include very quick response time (high charging/discharging rate), high energy density and efficiency, and ready factory-built modules. The main disadvantages include high cost, potential adverse environmental impact, and the need of periodic maintenance.

The main characteristics of several batteries [94] are listed in Table 4.2, in terms of energy density, cycle life, operating temperature, etc. As shown in Table 4.2, the NiCd battery is a battery which uses nickel and cadmium as its electrodes. The NiMH battery is a nickel metal hydride battery similar to NiCd batteries, but made with more affordable and environmentally friendly components. The lead acid battery has a very low energy-to-weight ratio and low energy-to-volume ratio, but its ability to supply high surge currents and low cost make it very popular. The Li-ion battery is one of rechargeable batteries in which lithium ions move from the negative electrode to the positive electrode during discharge, and reversely when charging. The Li-ion polymer battery is technologically evolved from Li-ion batteries. The primary difference is that lithium-salt electrolyte is not held in an organic solvent but in a solid polymer composite such as polyethylene oxide. The reusable alkaline battery is another one of rechargeable batteries dependent upon the reaction between zinc and manganese dioxide (Zn/MnO₂).

Table 4.2: Characteristics of batteries [93]

Type Parameters	NiCd	NiMH	Lead Acid	Li-ion	Li-ion polymer	Reusable Alkaline
Gravimetric Energy Density (Wh/Kg)	45-80	60-120	30-50	110-160	100-130	80
Internal R (mΩ)	100-200	200-300	<100	150-250	200-300	200-2000
Cycle Life	1500	300- 500	200-300	500-1000	300-500	50
Fast Charge Time	1h typical	2-4h	8-16h	2-4h	2-4h	2-3h
Overcharge Tolerance	moderate	low	high	very low	low	moderate
Cell Voltage (Nominal)	1.25V	1.25V	2V	3.6V	3.6V	1.5V
Load Current (peak)	20C	5C	5C	>2C	>2C	0.5C
Operating Temperature (discharge only)	-40~ 60°C	-20~ 60°C	-20~ 60°C	-20~ 60°C	0~ 60°C	0~ 65°C
Commercial Use since	1950	1990	1970	1991	1999	1992

Among all these batteries, the lead acid battery is the oldest and most mature technology, which has been used for majority power system applications. The Li-ion, NiMH and NiCd batteries seem to represent the leading technologies in high-power-density battery applications. Li-ion possesses the greatest potential for future development and optimization. In addition to small size and low weight the Li-ion batteries offer the highest energy density and storage efficiency close to 100%, which makes them ideally suited for portable devices. However, some of the major drawbacks of Li-ion technology are its high cost and the detrimental effect that deep discharging has on its lifetime. Although NiCd and lead acid batteries can supply excellent pulsed power, they are large, contain toxic heavy metals and suffers from severe self-discharge.

4.2.9 Selection of energy storage

The criteria for selecting suitable energy storage technologies include power and energy capability, response time, cyclic capability and ramping capability [89]. The competing technologies could also have more credits for high energy density, low maintenance, long life and low cost. The ability to support fast response regulation service also helps to identify suitable technologies. Ease of siting, ability to provide other ancillary services and other specified project requirements are also considered.

Battery is chosen as energy storage while the type of a battery used in this thesis is not specified. In power system security analyses, most of the battery parameters should be considered, such as the cycle time, energy density, charging/discharging rate, operating temperature, storage capacity, charging/discharging efficiency, and charging/discharging limit. In reliability evaluation, only several main parameters have big impact on the reliability of power systems with WTGs and energy storage, and will be introduced in the following chapters.

4.3 System modeling

The model of a generation system and reliability of generators have been introduced in Chapter 3 and will be used in this chapter. The LDC is normally used in reliability

evaluation for a conventional power system. The wind speed and energy storage model as well as the load model used for power systems with wind energy are introduced.

4.3.1 Wind speed and load model

The wind speed model used in this research is an hourly mean wind speed model as shown in Figure 4.1. Twenty years of wind speed data for the city Ijmuiden, Dutch obtained from the "KNMI HYDRA Project" by Royal Netherlands Meteorological Institute are used to form the hourly mean wind speed model [45]. The main statistical characteristics of the twenty years wind speed data for Ijmuiden City are shown in Table 4.3. The mathematical expressions for power curves in Section 2.2.2 are used as wind power output model. The hourly peak load variation curve in Figure 2.6 is used as the load model. The time interval for the study is one hour and the wind speed and load level is assumed to be constant within each time interval.

Figure 4.1: The hourly mean wind speed model for Ijmuiden city.

4.3.2 Energy storage model

Battery energy storage has been chosen in this research. The important battery parameters, which may affect power system operation, include rated charging and discharging rate P_b (MWh/hour), charging/discharging limit (E_b^{min}/E_b^{max}), rated storage capacity E_b (MWh), charging/discharging efficiency (η_{bc}/η_{bd}), state of charge

Table 4.3: Main statistical characteristics of the wind speed data for Ijmuiden city

Year	Mean wind speed μ_t (m/s)	Standard deviation σ_t (m/s)	Year	Mean wind speed μ_t (m/s)	Standard deviation σ_t (m/s)
1982	6.57	3.41	1995	7.08	3.37
1984	6.21	3.25	1996	6.74	3.36
1987	6.38	3.22	1997	6.57	3.32
1988	7.31	3.36	1998	7.49	3.65
1989	6.51	3.31	2000	7.23	3.55
1990	7.16	3.69	2001	7.01	3.38
1991	6.47	3.37	2002	6.92	3.61
1992	6.89	3.24	2003	6.18	3.03
1993	6.73	3.30	2004	6.67	3.49
1994	6.96	3.46	2005	6.55	3.25

(SOC) and depth of discharge (DOD) [33]. DOD (MWh) shows the energy discharged from the full capacity. Battery storage can be controlled to charge or discharge in constant or variable rate based on system operation requirements. SOC (MWh) represents the remaining electric energy in a battery and it has the relationship with other parameters as follows:

$$SOC_j = \begin{cases} SOC_{j-1} + \eta_{bc} \cdot E_{cj} & \text{in charging states} \\ SOC_{j-1} - \frac{1}{\eta_{bd}} \cdot E_{dj} & \text{in discharging states} \end{cases} \quad (4.1)$$

$$E_b^{\min} \leq SOC_j \leq E_b^{\max} \quad (4.2)$$

$$DOD_j = E_b - SOC_j \quad (4.3)$$

$$0 \leq P_{bj} \leq P_b \quad (4.4)$$

where SOC_j is the state of charge at time step j ; SOC_{j-1} is the state of charge at time step $(j-1)$; DOD_j is the depth of discharge at time step j ; P_{bj} is the charging/discharging

rate at j ; and E_{cj} and E_{dj} are the maximal energy to be charged and discharged at time step j , respectively.

In charging states, the maximal wind energy to be charged E_{cj} may not be equal to the produced wind energy since some of wind energy may be used to supply system load. Only the excess wind energy is available to charge the energy storage (batteries). The excess wind energy may not be fully utilized because of the limits of the charging rate. On the other hand, in discharging states, the remaining energy in batteries may not be fully discharged due to the limit of discharging rate. In any state, the DOD of battery ESS must be within the maximum and minimum storage capacities.

The η_{bc}/η_{bd} and E_b^{min}/E_b^{max} are actually associated with the charging/discharging rate and storage rated capacity, respectively. They just scale down the charging/discharging rate and storage rated capacity to certain levels. To simplify calculations, the charging/discharging efficiency is assumed to be 100% and the energy storage is assumed that can be fully charged and discharged. The two parameters to characterize an energy storage unit are charging/discharging rate and storage capacity, which are exactly the two main parameters to determine the price of energy storage units. With these assumptions, the formulae (4.1)-(4.2) are modified as shown in formulae (4.5)-(4.6):

$$SOC_j = \begin{cases} SOC_{j-1} + E_{cj} & \text{in charging states} \\ SOC_{j-1} - E_{dj} & \text{in discharging states} \end{cases} \quad (4.5)$$

$$0 \leq SOC_j \leq E_b \quad (4.6)$$

4.3.3 Operating strategy of energy storage

In addition to the parameters mentioned above, the operating strategy is also an important factor of characterizing a battery ESS [31]. The factors that impact the operating strategy include the objectives of using energy storage, such as peak load shaving, WTG output fluctuation smoothing and maximizing wind power utilizing, and priority of wind power, i.e. the wind power is with or without priority to supply

load. Different operating strategies have varied impacts on the reliability evaluation of power systems with WTGs and energy storage. In this chapter, the basic operating strategy of the battery ESS is to offset the deficiency of the available generation and absorb excess wind generation in some states, and the wind power has no priority to supply load. The operating strategy is shown in details as follows.

- 1) If the committed CGs in a time step can supply system load, all the wind energy produced in that time step is available to be stored in energy storage. This available energy cannot always be stored in the energy storage due to the limits of SOC and charging rate of the battery storage.
- 2) If the committed CGs in a time step cannot supply system load, the wind energy produced will be incorporated. When the total generation from WTGs and CGs is adequate to supply system load, the excess wind energy is available to be stored and the storing process is also limited by the constraints of SOC and charging rate of the battery storage.
- 3) If the committed CGs and WTGs cannot supply system load, the battery storage will be discharged to the grid.
- 4) If all the energy from the CGs, WTGs and battery storage still cannot supply the system load, load curtailment is required to balance supply and demand.

According to the above operating strategy, the maximal energy to be charged E_{cj} and the maximal energy to be discharged E_{dj} can be calculated using equations (4.7) and (4.8):

$$E_{cj} = \begin{cases} P_{wj} \cdot \Delta t_j & \text{if } P_{Cj} \geq P_{Lj} \\ (P_{Cj} + P_{wj} - P_{Lj}) \cdot \Delta t_j & \text{if } P_{Cj} < P_{Lj} \end{cases} \quad (4.7)$$

$$E_{dj} = SOC_{j-1} \quad (4.8)$$

where P_{wj} is the available capacity from WTGs at time step j and Δt_j is the time duration of time step j .

In some charging states, the produced wind energy cannot be fully utilized to supply load and charge batteries. The surplus wind energy should be evaluated by the certain indices. On the other hand, in some discharging states, the remaining energy in batteries may not fully discharge due to the limit of discharging rate. This will affect the value of EENS. A new index will be defined and used to represent the wind energy utilization efficiency in the following sections.

4.4 Indices

When the wind power generation is incorporated into the reliability evaluation, a set of indices has been presented to reflect the specific aspects of the wind farm performance [95]. A new index, expected energy not used (EENU), is proposed to represent the wind energy produced but not used to supply load which can be used to measure the wind energy utilization efficiency.

4.4.1 Wind-related indices

4.4.1.1 Installed wind power

The installed wind power (IWP) is defined as the sum of the rated power of all the WTGs in the system. The IWP can be expressed as a percentage of the peak load of the system, and in this alternative form it is usually named wind power penetration level [96].

4.4.1.2 Installed wind energy

The installed wind energy (IWE) is defined as the product of the IWP and the number of hours in a year. It represents the theoretical maximum amount of wind energy that could be generated in a year.

4.4.1.3 Expected generated wind energy

The expected generated wind energy (EGWE) is defined as the expected maximum amount of energy that the WTGs would produce in a year subjected to the real wind if dispatched, load demand, and the transmission system would not impose any limitation to its production. It is calculated as the sum of the energies that all the available WTGs can produce throughout the simulation period, under real simulated wind intensity and unit availability, divided by the number of simulated years.

4.4.1.4 Expected wind energy utilized

The expected wind energy utilized (EWEU) is defined as the expected amount of wind energy which is actually consumed in a year by the composite system, taking into account all factors that may limit its use. These factors may be transmission system limitations, load level, and generation dispatch order effects. It is calculated as the sum of the energy outputs of the WTGs actually consumed by the system along the simulation, divided by the number of simulated years. If the load demand is big enough, the difference between EWEU and EGWE is entirely due to transmission inadequacies.

4.4.1.5 Capacity factor

The capacity factor (CF) is defined as the actual energy output of the wind generation system over a period of time divided by the maximum possible energy output over the same period.

4.4.1.6 Wind generation availability factor

The wind generation availability factor (WGAF) is defined as the ratio between the EGWE and the IWE. It indicates the maximum wind energy capacity factor of the system, which could be obtainable if demand were big enough to consume all the expected generated wind energy, and the transmission system, if present, would not limit its transport.

4.4.1.7 Capacity credit of wind power

The capacity credit (CC) (sometimes called capacity value) of wind power can be defined as the amount of firm conventional generation capacity which can be replaced with wind generation capacity, while maintaining the existing level of security of supply [97]. Although there are several methods used to calculate wind capacity credit, most of them are based on power system reliability evaluation techniques. Researchers have used many different capacity credit metrics for evaluation capacity credit, such as the LOLE in [98], LOLP in [99] and effective load carrying capability (ELCC) in [43, 100]. It is generally agreed that the most comprehensive way to evaluate wind capacity credit is to determine the ELCC [97, 101]. The capacity credit determination processes using those metrics, however, are the same by comparing two systems, one system with, and another without, the additional wind power capacity and expanding both systems to obtain the same capacity credit metric. Then the capacity credit can be established using equation (4.9):

$$CC = 1 - \frac{P_{with} - P_{w/o}}{P_W} \quad (4.9)$$

where P_W is the additional wind power capacity, P_{with} is the total power system capacity with additional P_W , and $P_{w/o}$ is the total power system capacity without additional P_W .

4.4.2 Expected energy not supplied

As introduced in Section 3.3.3, the expected energy not supplied (EENS) is one of the most important and widely used loss of energy indices in generating capacity adequacy evaluation. It declares the cumulative amount of energy that is not provided to customers [9] and can be calculated by the integral of the difference between system generation and load whenever generation is less than demand. Because the incorporation of wind farms and energy storage, the formula of EENS (3.14) for a time period should be modified to equation (4.10):

$$EENS = \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} p_{ij} \times (P_{L_j} - AG_{ij}) \times \Delta t_j \quad (4.10)$$

where p_{ij} is the individual probability of state i at time step j ; P_{Lj} is the load level at step j ; AG_{ij} is the total available capacity of state i at time step j ; and N_i, N_j are the number of system states and time steps, respectively. The p_{ij} and AG_{ij} are calculated using equations (4.11) and (4.12).

$$p_{ij} = \prod_{c=1}^{N_{Goi}} A_{cG} \prod_{c=N_{Goi}+1}^{N_G} U_{cG} \prod_{c=N_G+1}^{N_G+N_{Woi}} A_{cW} \prod_{c=N_G+N_{Woi}+1}^{N_G+N_W} U_{cW} \quad (4.11)$$

$$AG_{ij} = \sum_{c=1}^{N_{Goi}} P_{Cij} + \sum_{c=N_G+1}^{N_G+N_{Woi}} P_{Wij} + E_{dij} \quad (4.12)$$

where A_{cG} , A_{cW} , U_{cG} and U_{cW} are availability of conventional generating units, availability of WTGs, unavailability of conventional generating units and unavailability of WTGs, respectively; P_{Cij} and P_{Wij} are available capacity of conventional generating units and WTGs, respectively; E_{dij} is the maximal energy to be discharged of state i at time step j ; N_{Goi} is the number of conventional generating units being operating at state i ; N_G is the total number of conventional generating units; N_{Woi} is the number of WTGs being operating at state i ; and N_W is the total number of WTGs.

4.4.3 Expected energy not used

A new index, expected energy not used (EENU), is defined to represent the wind energy produced by WTGs but not used to service system load. The EENU may result from the low response speed of conventional units to fast reduction of load or increase of wind power generation, or insufficient energy storage size, and etc. This index can be used to measure the wind energy utilization efficiency and estimate the system increase in wind energy absorption due to incorporation of energy storage. It can also be converted into increased benefit easily in reliability cost and worth analysis for sizing energy storage in Chapter 6. The EENU in this case results from the operating strategy of the wind farm. Only when the CGs cannot supply system load, the wind generation will be incorporated to supply the system load together with the CGs. If the

battery storage is fully charged when there is excess wind energy, there will be EENU. The EENU for a time period can be calculated using equation (4.13).

$$EENU = \begin{cases} \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} P_{ij} \times (P_{wij} \cdot \Delta t_j - E_{cj}), & \text{if } P_{cij} \geq P_{Lj} \\ \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} P_{ij} \times (P_{wij} \cdot \Delta t_j + P_{cij} - P_{Lj} - E_{cj}), & \text{if } P_{cij} < P_{Lj} \end{cases} \quad (4.13)$$

where E_{cj} is the wind energy absorbed by energy storage at time step j which is subject to the following constraints (4.14) and (4.15).

$$0 \leq E_{cj} \leq P_b \cdot \Delta t_j \quad (4.14)$$

$$0 \leq E_{cj} \leq (E_b - DOD_j) \quad (4.15)$$

4.5 Evaluation procedure

The analytical evaluation technique for evaluating the EENU and EENS consists of the following steps:

- Step 1: Pre-process the historical wind speed data and form the hourly mean wind speed model using equation (2.2).
- Step 2: Obtain the power output model of a single WTG using the relationships (2.12 - 2.15).
- Step 3: Combine the WTG two-state reliability model and the power output model from Step 2 to form the WTG power output reliability model.
- Step 4: According to the types of WTGs in the wind farm, form the wind farm reliability model.
- Step 5: Obtain the hourly peak load model.
- Step 6: Calculate the capacity outage probability table (COPT) for conventional generating units in the power system using the recursive algorithm in [46].

- Step 7: For every time step j , add the wind farm to the generating unit list and form new $COPT_j$.
- Step 8: Determine the energy storage model and its operating strategy.
- Step 9: For a time step j , combine the load at this time step, $COPT_j$ and the operating strategy of energy storage, to calculate the $EENU_j$ and $EENS_j$.
- Step 10: Repeat Step 9 for all time steps, obtain the EENS and EENU for whole time period.
- Step 11: Adjust the power system parameters, such as the parameters of conventional generating units, the wind conditions, the parameters of WTGs and wind farm, and the parameters of energy storage. Repeat steps 1-10.

4.6 System studies

The proposed procedure is applied to the modified IEEE-RTS [101]. The total installed capacity in the IEEE-RTS is 3405 MW provided by 32 conventional generating units as shown in Table 4.4. The peak system load is 2850 MW. A wind farm with 50 identical 10.0-MW WTGs is incorporated into the IEEE-RTS. The cut-in, rated, and cut-out speeds of these wind turbines are 3 m/s, 14 m/s and 25 m/s, respectively. The capacity of the wind farm is 500MW, which accounts for about 13% of the total power system capacity, i.e. the wind power penetration level is 13%. The FORs of WTGs are assumed to be 0.05. The battery ESS has a capacity of 100 MWh and a charging/discharging rate of 100 MW, respectively. It is assumed that the battery ESS has no initial stored energy, i.e. $SOC = 0$. The study period is assumed to be one year.

4.6.1 Base case

For the IEEE-RTS without considering WTGs and battery ESS, the EENS is 1.17×10^3 MWh and there is no EENU since it only represents the unused wind energy. When the wind farm is considered, the EENS is decreased 40.7% to 694.08 MWh. The wind farm can produce 7.38×10^5 MWh wind energy over one year and the EENU is 6.98×10^5

MWh. The value of EENU is quite large comparing to the total expected wind energy. The reason is because that the generation system of the IEEE-RTS is very reliable and with high adequacy. There have very low probabilities for wind generation to offset the deficiency of the conventional generation. When both the battery ESS and WTGs are considered, the EENU and EENS are changed to 6.81×10^5 MWh and 68.53 MWh, respectively. Comparing to the values without considering the battery ESS, the EENU and EENS decrease 2.4% and 90.1%, respectively. It is obvious that adding battery ESSs improves both the system reliability and wind energy utilization efficiency while the storage has a bigger impact on the EENS.

Table 4.4: Generating unit reliability data of the IEEE-RTS

Unit size (MW)	Unit type	Number of units	FORs	MTTF (hours)	MTTR (hours)
12	Oil/steam	5	0.02	2940	60
20	Oil/CT	4	0.10	450	50
50	Hydro	6	0.01	1980	20
76	Coal/steam	4	0.02	1960	40
100	Oil/steam	3	0.04	1200	50
155	Coal/steam	4	0.04	960	40
197	Oil/steam	3	0.05	950	50
350	Coal/steam	1	0.08	1150	100
400	nuclear	2	0.12	1000	150

4.6.2 Effect of rated capacity of battery

The impact of rated capacity of the battery ESS on reliability indices is studied. Assume that the rated capacity of battery ESS increases from 0 MWh to 1000 MWh, the corresponding EENS and EENU variations are shown in Figure 4.2.

It can be seen from Figure 4.2 that the EENU decreases almost linearly with the increase of rated capacity of the battery ESS. More excess wind energy can be stored and shifted to other time periods with larger battery ESSs. On the other hand, the EENS decreases sharply when the capacity of battery storage is increased from 0 MWh to 150 MWh and then keeps constant at 68.53 MWh when the its capacity is over 200 MWh. This unchanged EENS in this case results from the failure events of conventional

generating units. Therefore, from the EENS point of view, a battery ESS with rated capacity of 150 MWh is more economic than the one used in the study since a larger battery will cost more. However, determination of an optimal size of the battery ESS needs to consider many factors, not solely the required reliability level. An optimization of battery size based on cost and worth is meaningful.

Figure 4.2: Impact of the battery ESS rated capacity on the EENU and EENS.

4.6.3 Effect of charging/discharging rate

In order to investigate the effect of charging/discharging rate of the battery ESS on the EENS and EENU, the charging/discharging rate is changed from 0 MWh/hour to 1000 MWh/hour but the capacity keeps constant at 100 MWh. Figure 4.3 shows the changes of EENU and EENS with the changes of charging/discharging rate. It can be seen from Figure 4.3 that both the EENU and EENS are reduced with the increase of charging/discharging rate but it has smaller effect on the EENU than that on the EENS. Actually, the EENU is impacted mainly by the charging rate because wind energy that cannot be stored occurs during charging period while the EENS is impacted mainly by the discharging rate because insufficient discharging will lead to EENS. When the charging/discharging rate is over 300 MWh/hour, the decrease of EENU becomes slow due to the limitation of battery rated capacity. The lower curve in Figure 4.3 indicates

that when the charging/discharging rate is over 100 MWh/hour, the EENS will not benefit more with a bigger battery power rating.

Figure 4.3: Impact of charging/discharging rate of the battery ESS on EENU and EENS.

4.6.4 Effect of wind power penetration level

The effect of wind power penetration levels on the EENU and EENS is studied by changing it from 3% to 23% as shown in Figure 4.4. Other system conditions do not change. It can be seen from Figure 4.4 that the increase of wind power penetration level leads to quite large increase of EENU but results in a small reduction of EENS. Hence, for the test system, increasing of wind power penetration level cannot produce much reliability benefit and on the other hand it leads to a large amount of wind energy wasted. It is not economic to improve system reliability by solely integrating more wind generation. To solve this problem, some measures should be taken to make the grid absorbing more wind energy produced. The two curves in Figure 4.4 are not straight lines because the power output of wind farm is not changing continuously with the increase of wind speed.

Figure 4.4: Impact of wind power penetration level on EENU and EENS.

4.7 Conclusion

The basic reliability evaluation technique is extended for analyzing power systems with wind farms and energy storage. The battery is selected to be the energy storage in the study. A new index EENU is proposed to represent the wind energy produced but to not to be used to supply load. It can also be used to estimate the wind energy utilization efficiency. The improved reliability evaluation technique is applied to the IEEE-RTS with a 500MW wind farm and a battery ESS whose rated capacity and charging/discharging rate are 100 MWh and 100 MWh/hour, respectively. Both the EENU and EENS are improved by adding the battery storage. Sensitivity studies revealed the impacts of the rated battery capacity and charging/discharging rate and the wind power penetration level on the EENU and EENS. At the meantime, these studies also make it clear that the size of the battery ESS used is not suitable and should be optimized. This is the target of Chapter 6.

Chapter 5. Operational Adequacy Studies of Power Systems with Wind Farms and Energy Storage

As mentioned in previous chapters, the time span for a power system study is classified into planning phase and operation phase. Chapter 3 and Chapter 4 evaluated power system reliability for the planning phase, which the time period considered is relatively long. Both the CGs and WTGs can be represented by the two-state reliability model. During the long time period, generating units can be repaired. Load and wind speed are assumed to be constant within each time interval since it will not violate the accuracy requirement of power system planning. Committed CGs and SR provided by CGs are assumed that they can pick up load immediately when required. However, in power system reliability evaluation for operation, the above assumptions and approximations would not be applicable any longer due to a relatively short time period considered and a higher accuracy required. The operational adequacy evaluation for HLI of power systems with wind farms and energy storage is investigated in this chapter.

5.1 Introduction

As mentioned in previous chapters, high wind power penetration impacts significantly on system stability and reliability due to the intermittent and uncertain characteristics of wind speed. Since wind speed changes very fast, the operational reliability of a power system with high wind power penetration should also be considered.

For normal operation of a power system, the total load must be equal to the total generation at any time. Reserved generation must also be scheduled in order to account for load uncertainty, possible outages of generating units, and other uncertainties. The reserve capacity that is spinning, synchronized and ready to take up load is known as spinning reserve (SR) [9]. Some utilities include not only the SR but also one or more interruptible loads, assistance from interconnected systems, and

voltage/frequency reductions. These additional factors and the effective SR are known as operating reserve. When wind power generation is incorporated into conventional power systems, SR from CGs becomes very important in power system operation to incorporate wind speed uncertainty as well as load forecast uncertainty and possibilities of failure of generating units. CGs have to be ramped down or ramped up more frequently to incorporate the variations of wind speed and load. In extreme cases such as periods of low load and very high wind speed, some CGs will even be shut down in order to utilize as much wind power as possible. In periods of high load and low wind speed or generator failures, more CGs (including SR and uncommitted units) have to be started up to supply system demand. However, the committed CGs cannot take up load immediately as in power system planning and have to gradually pick up load in real time operation. When wind power penetration level is low, the ramp capacity of committed CGs is large enough to match load and wind variation. However, when the wind power penetration is high, the load following capacity will not be sufficient and the effects of ramp rates of CGs on system operational reliability become more significant. The response time of the committed CGs must be considered when the system experiences sudden and large percent of changes of wind speed and load, which are caused by random failures of generators and gust of wind. When the wind speed reduces suddenly or generators fail, there may have power shortage if the system ramp up rate is not fast enough. On the other hand, when there are sudden wind speed increases or load decreases, power surplus may occur if system ramp down rate is low. The effects of ramp rates on system operational reliability should be an important issue for systems with high wind power penetration or micro grids with less dispatchable capacity. Other operational factors such as spinning reserve policy, generator start-up failure and time, and outage postponability also play an important role in operational reliability [102].

Generating flexibility for incorporating wind speed uncertainty has been investigated for power systems with WTGs in [43, 79, 103-110]. In [104], the authors built a new probabilistic method based on Monte Carlo Sequential simulation to assess system generating flexibility indices considering the long-term planning. Reserves are categorized according to their different starting time and are estimated by a set of new defined indices. An offline approach based on cost and benefit analysis is presented in

[105] to set the SR requirements. Different from other methods used to schedule SR, the presented approach determines the SR requirement in an auxiliary process prior to the optimization of unit commitment. Computation time is reduced significantly but a similar accuracy of the results is maintained. Both the load following capacity and spinning reserve penalties for power systems with intermittent generation are investigated in [107]. The unit commitment risk analysis is extended to power system operation and the contribution of wind power to load carrying capability of a power system is evaluated in [43]. The authors drew a conclusion that the operating benefits associated with the incorporation of wind generation are the initial wind speed and wind pattern at that wind site.

Adequacy of large interconnected systems and small isolated systems with WTGs has been studied extensively [44, 66, 79, 100, 110-112]. Impacts of high wind power penetration on the reliability of distribution systems have been investigated in [77, 113-115]. Reliability cost and worth of adding WTGs to existing power systems have been studied from reliability point of view [113, 116]. Different modeling techniques and indices were proposed to analyze various aspects of system reliability. Load carrying capacity benefit ratio and equivalent capacity rate were introduced and defined to indicate wind capacity benefit and credit of wind farms [100]. However, most of those works focus only on long term power system planning. Real time operational adequacy problems caused by wind speed and load variation have seldom been considered in those techniques. The effects of the ramp rates of CGs as SR to incorporate fast wind power and load change have not been considered. Energy surplus and utilization efficiency due to the oversize of wind farms and lack of energy storage have been ignored.

This chapter proposes a technique to evaluate operational adequacy and energy utilization efficiency of power systems with high wind power penetration and energy storage. The EENS is used to represent system reliability. The EENU is used to represent system energy surplus and utilization efficiency. The EENS and EENU with considering the ramp rates of CGs under various resources, load conditions and contingencies are formulated. The facts which affect EENS and EENU are investigated using the proposed technique. Section 5.2 describes modeling of wind

speed, load, and generation. Two reliability indices are defined and introduced in Section 5.3. Energy Not Used (ENU) and Energy Not Supplied (ENS) for different system operating conditions and contingency states are formulated in Section 5.4. The proposed evaluation procedure is introduced in Section 5.5. In Section 5.6, the IEEE-RTS is used to illustrate the proposed technique. A conclusion is presented in Section 5.7.

5.2 System modeling

When considering operating reliability evaluation, system component models should be based on shorter time period, i.e. in operational time scale. Wind speed and load model, reliability of a generation and system generation, and ramp rate of a generator are introduced in this section.

5.2.1 Wind speed and load model

The time varying wind speed model and hourly variable load model in Sections 2.1 and 2.3 are used. The ARMA time series wind speed model for a wind site is shown in Figure 5.1 [45]. The time interval for the wind speed model and load model is selected to be 1 hour. In order to improve accuracy, it is assumed that the wind speed and load level change linearly from one level to another, i.e. from the beginning to the end of one time interval. Most wind speed data values recorded by practical wind farms and weather stations are the average wind speeds for a given period such as 10, 30 or 60 minutes. Shorter time intervals such as 5 minutes or 1 minute could be used to obtain more accurate simulation results. The reason of selecting 1 hour as the time interval is that both the wind speed data and load data used hourly data.

5.2.2 Reliability of system generation

In power system operation, lead time for unit commitment is usually from 15 to 60 minutes. In such short time, unit repair is not possible. Therefore reliability of a CG or a WTG cannot be represented by the two-state or four-state reliability model in Figure

3.1 and 3.2. In this chapter, the reliability of a generator is modeled as a two-state non-repairable model [9] as shown in Figure 5.2.

Figure 5.1: The ARMA time series wind speed model for a wind site.

Figure 5.2: Two-state non-repairable model for a generator in operation.

It was shown in [65], that the failures and repairs of a system component are distributed exponentially. Unit unavailability U_c for period Δt_j , i.e. the probability of a generator in down state, can be calculated using equation (5.1) [9].

$$U_c(\Delta t_j) = P(\text{down}) = \frac{\lambda_c}{\lambda_c + \mu_c} - \frac{\lambda_c}{\lambda_c + \mu_c} e^{-(\lambda_c + \mu_c)\Delta t_j} \quad (5.1)$$

Since repairs during lead time T is not possible, i.e. μ_c is zero, equation (5.1) should be modified to equation (5.2).

$$U_c(\Delta t_j) = P(\text{down}) = 1 - e^{-\lambda_c \Delta t_j} \quad (5.2)$$

Finally, for the short period Δt_j of up to several hours, $\lambda_c \Delta t_j \ll 1$ and U_c of a generator can be calculated by equation (5.3).

$$U_c(\Delta t_j) \cong \lambda_c \Delta t_j \quad (5.3)$$

The $U_c(\Delta t_j)$ in equation (5.3) is known as the outage replacement rate (ORR) in power system, which represents the probability that a unit (generator) fails and is not replaced during the lead time Δt_j . The ORR is directly analogous to the FOR used in planning studies but the former is dependent on both the failure rate λ_c and lead time Δt_j .

The reliability of system generation is modeled as a COPT using the similar method in Section 3.2.2. The only difference is that the FORs are replaced by ORRs during calculations. A COPT based on ORRs will be shown in Section 5.3.

5.2.3 Ramp rates of a generator

In reliability evaluation for planning studies, the operating cycles of a generation system are modeled as a step function as shown in Figure 5.3. The basic assumption for this model is that CGs can be committed or shut down immediately when required. However, a CG being shut down or taking up load needs a ramping process. When a unit is starting up, a pre-warming process is necessary because of physical limitations of the turbine and generator. On the other hand, when a unit is shutting down, a cooling down process is also unavoidable. Therefore, the generation system operation has to be following the dot lines as shown in Figure 5.4, and limited by the ramp rates of CGs as shown by equation (5.4). The ramp rates of CGs may cause energy deficient or surplus. For a large power system with low wind power penetration, the effect of ramp rates can be ignored. However, for a power system with high wind power penetration or a micro grid with limited capacity from CGs, the impact of ramp rates may become significant and should be considered in analyses.

$$\begin{cases} [P_{Cj} - P_{Cj-1}] \leq r_{uj} \\ [P_{Cj-1} - P_{Cj}] \leq r_{dj} \end{cases} \quad (5.4)$$

where P_{Cj} is the power output of CGs at time j , P_{Cj-1} is the power output of CGs at time $j-1$, r_{uj} is the ramp up rate of CGs at time j and r_{dj} is the ramp down rate of CGs at time j .

Figure 5.3: Operating cycles of system generation modeled as a step function.

Figure 5.4: Operating cycles of system generation modeled as a ramp function.

5.2.4 Energy storage model

Detailed energy storage models have been introduced in Chapter 4. Batteries are selected as an energy storage system (ESS) in this chapter. The charging/discharging rate P_b (MWh/hour), rated storage capacity E_b (MWh), state of charge (SOC) and depth of discharge (DOD) are considered because they may affect power system operation. DOD (MWh) shows the energy discharged from the full capacity while SOC (MWh) represents the remaining electric energy in a battery. Battery storage can be controlled to charge or discharge at a constant or variable rate based on system operation requirements. The advantages of battery ESS include fast charging/discharging rate and ease of capacity expansion, which can satisfy power system operation requirement.

5.3 Reliability and energy efficiency indices

The unit commitment risk (UCR), EENS and EENU for operation adequacy analysis are introduced in this section. The ENS and ENU are formulated considering ramp rates of CGs.

5.3.1 Indices

In power system operation, SR has to be scheduled in order to account for load and wind speed uncertainties and possible outages of generation units. Historically, SR requirements for a power system have been done by rule-of-thumb methods, such as a spinning generating reserve equal to one or more largest units in operation. The Pennsylvania-New Jersey-Maryland (PJM) interconnection included SR in their assessment of system adequacy using probabilistic methods. Since then, the PJM method [71] has been used as a basic method for evaluating unit commitment risk (UCR) which is defined as the probability of the committed units (including all units which produce electricity and are used as SR) just satisfying or failing to satisfy the demand in the system failures during the period of time or lead time that generation cannot be replaced by other units [9].

The UCR can be deduced directly from the generation system model COPT, which is created for power system operation studies as introduced in Section 5.2. An example is given to show the determination of UCR, maximum demand that the system can meet as well as SR using the COPT as shown in Table 5.1.

If the load is maintained at 14 MW during lead times, the UCRs for lead times of 1, 2 and 3 hours can be read from the COPT and are 0.00012584, 0.00025168 and 0.00037752, respectively. If an acceptable UCR level of 0.0001 is predefined by system planners, the maximum loads for the three lead times are 12 MW, 8 MW and 8 MW, respectively. When the SR is given to be the capacity margin (assuming all units are committed), the SRs for the acceptable UCR level of 0.0001 are 8 MW, 12 MW and 12 MW, respectively. □

Various indices are used to represent power system reliability as described in Section 3.3 and the EENS is used for operational adequacy analysis. A power system may experience load variation and generation variation caused by power system failures and wind speed changes. Those changes may lead to inadequate power (ENS) if the ramp up rates of CGs are slow. The total system EENS in this case can be calculated using equation (5.5).

$$EENS = \sum_{j=1}^{N_j} \sum_{i=1}^{N_i} p_{ij} ENS_{ij} \quad (5.5)$$

where ENS_{ij} is the energy not supplied for state i and period j .

When a power system experiences a load reduction or an increase of wind speed, there is energy surplus (ENS) before the committed CGs are ramped down and replaced by WTGs. The energy efficiency index designated as EENU is defined in the following equation (5.6) to evaluate energy surplus in this study.

$$EENU = \sum_{j=1}^{N_j} \sum_{i=1}^{N_i} p_{ij} ENU_{ij} \quad (5.6)$$

where ENU_{ij} is the energy not used for state i and period j .

Table 5.1: COPT for power system operation studies

Capacity		Cumulative probability for the lead time of		
Out (MW)	In (MW)	1 hour	2 hours	3 hours
0	20	1.00000000	1.00000000	1.00000000
2	18	0.00135684	0.00271368	0.00407052
4	16	0.00056235	0.00112470	0.00168705
6	14	0.00012584	0.00025168	0.00037752
8	12	0.00009856	0.00019712	0.00029568
10	10	0.00006351	0.00012702	0.00019053
12	8	0.00002589	0.00005178	0.00007767
14	6	0.00000987	0.00001974	0.00002961
16	4	0.00000632	0.00001264	0.00001896
18	2	0.00000023	0.00000046	0.00000069
20	0	0.00000001	0.00000002	0.00000003

5.3.2 Formulations of ENS and ENU

As shown by equations (5.5) and (5.6), the main part of EENS and EENU determination is to formulate the ENS and ENU. When considering changes of load and wind power generation, CGs may have to be ramped up or down to reduce energy shortage or surplus respectively. The ENU and the ENS for a contingency state depend on many factors such as the number of the committed CGs and their ramp rates, variations of wind speed and load, SOC of the battery energy storage and etc. Those factors should be considered in simulations. The ENS_{ij} and ENU_{ij} for state i and period j under various system conditions are formulated as three cases in this section. It is assumed that the ramp rates are constant for an operating period. The wind speed and load are assumed to change linearly.

5.3.2.1 Generation from CGs only

In this case, a power system consists of only CGs. The total generation is balanced with the load at the beginning of period j . When the load is decreasing in period j , the output of the CGs should be reduced to match the load as shown in Figure 5.5. The ENU_{ij} considering the ramp down rate is represented as the shade area as shown in Figure 5.5. In system operation, the rate of load variation is usually smaller than the ramp rate, and therefore $ENU_{ij} = 0$. In case of $r_{dij}\Delta t_j < P_{Lj-1} - P_{Lj}$, i.e. the ramp down rate of CGs is smaller than the load decreased, ENU_{ij} can be calculated using equation (5.7).

$$ENU_{ij} = \frac{\Delta t_j}{2} (P_{Lj-1} - P_{Lj} - r_{dij}\Delta t_j) \quad (5.7)$$

When load is increasing in period j , the output of the CGs should increase to match the load as shown in Figure 5.6. If there is a sudden loss of CGs, the load has to be curtailed if necessary to maintain power balance. The ENS_{ij} considering the ramp up rate and capacity limit of CGs is also shown in Figure 5.6 and can be calculated by the following equations for different conditions.

If $P_{Cij}^m < P_{Lj}$,

$$ENS_{ij} = \begin{cases} \frac{\Delta t_j}{2} (NP_{Lj} + P_{Lj-1} - 2P_{Cij-1} - r_{uij}\Delta t_j) & \text{if } r_{uij}\Delta t \leq (P_{Cij}^m - P_{Cij-1}) \\ \frac{\Delta t_j}{2} (P_{Lj} + P_{Lj-1} - 2P_{Cij-1}) - (P_{Cij}^m - P_{Cij-1}) \left(1 - \frac{d_{ij}}{2}\right) & \text{otherwise} \end{cases} \quad (5.8)$$

where $d_{ij} = (P_{Cij}^m - P_{Lj-1}) / r_{uij}$ is the required time for the system to increase its power from P_{Lj-1} to P_{Cij}^m .

Figure 5.5: ENU_{ij} for generation from CGs only.

Figure 5.6: ENS_{ij} for generation from CGs only.

If $P_{Cij}^m \geq P_{Lj}$,

$$ENS_{ij} = \begin{cases} \frac{\Delta t_j}{2} (P_{Lj} + P_{Lj-1} - 2P_{Cij-1} - r_{uij} \Delta t_j) & \text{if } r_{uij} \Delta t_j \leq (P_{Lj} - P_{Cij-1}) \\ \frac{d_{ij}}{2} (P_{Lj-1} - P_{Cij-1}) & \text{otherwise} \end{cases} \quad (5.9)$$

where $d_{ij} = (P_{Cij-1} - P_{Lj-1}) \Delta t / (P_{Lj} - P_{Lj-1} - r_{uij} \Delta t)$ is the required time for the system to increase its power output to match the load change.

5.3.2.2 Generation from CGs and WTGs

In this case, a power system consists of both CGs and WTGs. Wind power output variation due to wind speed changes is considered as negative load and the different between the load and wind power output is defined as net system load (NP). The NP is calculated based on the rates of load and wind power output variation. When the net system load is decreasing (or increasing), the output of the committed CGs should be reduced (or increased), and ENU_{ij} (or ENS_{ij}) will occur correspondingly. NP_{Lj} and NP_{Lj-1} should be determined as:

$$\begin{cases} NP_{Lj} = P_{Lij} - P_{Wij} \\ NP_{Lj-1} = P_{Lij-1} - P_{Wij-1} \end{cases} \quad (5.10)$$

The ENU_{ij} and ENS_{ij} are calculated using equations (5.7), (5.8) and (5.9) respectively.

5.3.2.3 Generation from CGs, WTGs and ESS

In this case, a power system consists of CGs, WTGs and battery ESS. The ENU_{ij} is first calculated based on Section 5.3.2.2 and then modified for different system conditions.

If the battery ESS is fully charged at the beginning of period j , the ENU_{ij} will be kept the same as in Section 5.3.2.2. If not, the ENU_{ij} in Section 5.3.2.2 should be modified to ENU'_{ij} for the following cases.

If $P_b \geq P_{Cij} - NP_{Lj}$ and $P_{Cij} - NP_{Lj} > 0$,

$$\begin{cases} ENU'_{ij} = 0; & SOC''_j = SOC'_j + ENU_{ij} & \text{if } ENU_{ij} \leq DOD_j \\ ENU'_{ij} = ENU_{ij} - DOD_j; & SOC''_j = E_b^{\max} & \text{otherwise} \end{cases} \quad (5.11)$$

If $0 < P_{Cij} - NP_{Lj}$ and $P_b < P_{Cij} - NP_{Lj}$,

$$\begin{cases} ENU'_{ij} = ENU_{ij} - E_{cj}; & SOC''_j = SOC'_j + E_{cj} & \text{if } E_{cj} \leq DOD_j \\ ENU'_{ij} = ENU_{ij} - DOD_j; & SOC''_j = E_b^{\max} & \text{otherwise} \end{cases} \quad (5.12)$$

If $P_{Cij} - NP_{Lj} \leq 0$, the ENU_{ij} will be zero because there is no energy surplus.

Figure 5.7: ENU_{ij} for generation from CGs, WTGs and ESS.

The ENS_{ij} considering the ramp up rates, capacity limits of the CGs, WTGs and ESS is shown in Figure 5.8. If the ESS is fully discharged at the beginning of period j , the ENS_{ij} will be the same as in Section 5.3.2.2. Otherwise, the ENS_{ij} in Section 5.3.2.2 should be modified to ENS'_{ij} for the following cases.

If $P_b \leq NP_{Lj} - P_{Cij}^m$,

$$\begin{cases} ENS_{ij}' = ENS_{ij} - E_{dj}; SOC_j'' = SOC_j' - E_{dj} & \text{if } E_{dj} \leq SOC_j' \\ ENS_{ij}' = ENS_{ij} - SOC_j'; SOC_j'' = 0 & \text{otherwise} \end{cases} \quad (5.13)$$

where $E_b' = P_b \Delta t - 0.5 P_b^2 / r_{uij}$ is the maximal energy that needs to be discharged within Δt .

If $P_b > NP_{Lj} - P_{Cij}^m$,

$$\begin{cases} ENS_{ij}' = 0; SOC_j'' = SOC_j' + ENS_{ij} & \text{if } ENS_{ij} \leq SOC_j' \\ ENS_{ij}' = ENS_{ij} - SOC_j'; SOC_j'' = 0 & \text{otherwise} \end{cases} \quad (5.14)$$

It is noted that the linearized hourly wind speed and load models are used to illustrate the proposed technique. The accuracy of the results also depends on operating time intervals used. The results based on hourly wind speed and load models are less accurate. In order to simulate more realistic load and wind speed variation, the data for short time intervals such as 5 minutes or less has to be measured and used. The shorter the time interval is, the more accurate the results are.

Figure 5.8: ENS_{ij} for generation from CGs, WTGs and ESS.

5.4 Evaluation procedure

The proposed procedure for operational adequacy evaluation considering ramp rates, resource variation and system failures includes the following eight steps:

Step 1: Input wind speed, load level, reliability data for WTGs and CGs to create system component models.

Step 2: Initialize SOC of the battery ESS.

Step 3: For the operating period j , determine the combinations of committed CGs based on unit loading priority order.

Step 4: For system contingency state i , calculate state probabilities.

Step 5: Calculate ENS_{ij} and ENU_{ij} using the developed formulas based on the load, generation conditions, and update the total EENS and EENU.

Step 6: If all the states are considered go to Step 7 otherwise go to Step 4.

Step 7: If all the periods are considered go to Step 8 otherwise go to step 3.

Step 8: Output the results.

Three priority orders are used only to illustrate the impact of the ramp rates on system reliability in the following system studies. However, it is noted that all the committed CGs including SR units determined by loading priority orders must be economically justified nowadays in practical systems. Optimization techniques should be at the basis of these justifications in order to relate EENS and EENU to system cost. Many research works such as the techniques in [117] have been done and can be used in Step 2 to commit CGs.

5.5 System studies

The proposed procedure is applied to the modified IEEE-RTS [101]. The total installed capacity of CGs is 3405 MW and the annual peak load is 2850 MW. In order to illustrate the impact of WTGs and ESSs, the peak load of the IEEE-RTS is increased 10% to 3135 MW. The lead time is assumed to be 1 hour. Three loading

priority orders and the ramp rates of the CGs are shown in Table 5.2. CGs for priority order I are committed sequentially from nuclear units, coal units, hydro to oil units, and larger units of the same type will be committed first. In priority orders II and III, CGs are committed based on ascending and descending order in terms of ramp rates. The number of the committed units is determined based on the load level and spinning reserve. The system states with the probability being less than 10^{-7} are truncated during the simulation. The hourly wind speed model in Figure 5.1 is modified to be used. Both the load and wind speed curves in a period are assumed to change linearly to represent their variation. The monthly EENS and EENU for June under three different generation and storage conditions are calculated using the modified time varying peak load model and wind speed model.

Table 5.2: Generator data and loading priority orders

Unit Group	Unit Type	Unit Size (MW)	ORR	Ramp Rate (MW/h)	Priority Order I	Priority Order II	Priority Order III
U12×5	Oil	12	3.4×10^{-4}	60	28-32	1-5	28-32
U20×4	Oil	20	2.2×10^{-3}	180	18-21	10-13	20-23
U50×6	Hydro	50	5.1×10^{-4}	3000 [#]	22-27	28-32	1-6
U76×4	Coal	76	5.1×10^{-4}	120	8-11	6-9	24-27
U100×3	Oil	100	8.3×10^{-4}	420	15-17	23-25	9-11
U155×4	Coal	155	1.0×10^{-3}	180	4-7	14-17	16-19
U197×3	Oil	197	1.0×10^{-3}	180	12-14	18-21	13-15
U350×1	Coal	350	8.7×10^{-4}	240	3	22	12
U400×2	Nuclear	400	9.1×10^{-4}	1200	1-2	26-27	7-8

The ramp rate of hydro units is not provided in [54] and is assumed to be 3000MW/h in simulations.

5.5.1 System with only CGs

The UCR, EENS and EENU are calculated for the following two cases.

Case 1: In this case, the ramp rates of CGs are not considered, i.e. the ramp up/down is modeled as a step function. Priority order I is used for unit commitment. The

economic generation dispatch is based on the operating costs of the units. The spinning reserve is 15% of the peak load.

The UCR for lead time of 1 hour is calculated for the whole month as shown in Figure 5.9. The load variation during each time interval cannot impact the UCR much and therefore the load is assumed to be constant at average value of individual time period when calculating the UCR. Although the values of UCR for different time differ significantly, the average UCR keeps a very low value of 4.89×10^{-7} .

Figure 5.9: UCR curve for June without considering ramp rates of CGs.

The monthly EENS and EENU in this case are 0.25 MWh and 0 MWh respectively. There is no energy surplus when the CG has no ramp rate constraints.

Case 2: The ramp rates of 10% of committed generation capacity are considered in this case.

The EENS and EENU depend on the number and types of the power output of the committed units. When the ramp capacity is provided only by spinning units, the monthly EENS is 126.32 MWh and the EENU is 7981.68 MWh because of the low system ramp rates. If the system ramp capacity can be provided by all committed units in a period, the EENS and EENU are reduced to 6.25 MWh and 1356.89 MWh, respectively. The UCR curve is changed as shown in Figure 5.10. It can be seen that the variation pattern of the UCR curve is very similar to the one without considering

the ramp rate of CGs. The average value of UCR is increased to 8.14×10^{-5} . Consideration of ramp rates of CGs reduces the power system operational reliability.

Figure 5.10: UCR curve for June with considering ramp rates of CGs.

It is assumed that the ramp capacity is provided by all committed units in the following simulations. However, the different ramp capacity based on system operating conditions can be implemented in the proposed technique.

5.5.2 System with both CGs and WTGs

A wind farm is incorporated into the test system and sensitive studies are conducted in this section.

5.5.2.1 Base case

A wind farm with 100 identical 5-MW WTGs is added into the system in Section 5.1, i.e. the wind power penetration level is about 12.8%. The unreliability U_c of a WTG is assumed to be 0.01. The cut-in, rated and cut-out wind speeds are 3 m/s, 14 m/s and 25 m/s, respectively. The total wind energy output of the wind farm in June is 1.23×10^5 MWh. With consideration of ramp rates of CGs, the EENS is reduced 43% from 6.25 MWh without WTGs to 3.59 MWh and the EENU is increased 44% from 1356.89 MWh to 2054.34 MWh. The average UCR is reduced from 8.14×10^{-5} to 3.20×10^{-6} .

The operational adequacy and unit commitment risk of the system is improved. However, the energy surplus is increased at the same time with the addition of WTGs.

5.5.2.2 Effect of ramp rate of CGs

The system ramp rate depends on the number of committed CGs, percentage of system spinning reserve and priority order of generation dispatch. The EENS, EENU and average UCR for three loading priority orders are shown in Table 5.3.

The results show that different loading priority orders lead to different EENS and EENU but very similar average UCR. The average UCR is not sensitive to generator loading priority orders. The loading priority order III results in the least EENS and EENU because the units with highest ramp rates are committed first. However, a loading priority order resulting in the better reliability and less surplus is not necessary to have the less operating cost. Therefore the EENS, EENU and operating cost related to fuel price should be considered when determining the unit loading priority order in a practical system.

Table 5.3: EENS, EENU and average UCR for the three loading priority orders

Priority Indices \ Order	Priority Order I	Priority Order II	Priority Order III
EENS (MWh)	3.59	9.28	3.11
EENU (MWh)	2054.34	2012.51	1839.49
Average UCR	3.20×10^{-6}	3.19×10^{-6}	3.20×10^{-6}

Assuming that priority order I is used to dispatch generators, the ramp rates of CGs are changing from 90% to 110% of their original values and the corresponding variations of the EENS and EENU are shown in Figure 5.11.

Figure 5.11: Effect of ramp rate of CGs on EENS and EENU.

The figures show that both the EENU and EENS decrease with the increase of the ramp rate of CGs. When the ramp up/down rate increases from 90% to 100%, the monthly EENS decreases 73% from 13.12 MWh to 3.59 MWh. When the ramp up/down rate increases from 100% to 110%, the monthly EENS decreases 15% from 3.59 MWh to 1.64 MWh. The EENS changes with ramp rate nonlinearly. The EENU can be zero if the conventional generators can ramp up/down immediately, which arrives at the similar conclusion as in Section 5.1.

The average UCR cannot be impacted sensitively by the ramp rate of CGs, as shown in Figure 5.12. It can be seen that the average UCR is distributed discretely, i.e. certain changes of ramp rate will lead to the same average UCR. It should be noted that the same average UCRs do not always mean the same UCR curves, such as those in Figures 5.9 and 5.10. The UCR curves may be changed with different ramp rates but these changes cannot make the average UCR changes much and therefore they are ignored.

Figure 5.12: Effect of ramp rate of CGs on average UCR.

5.5.2.3 Effect of wind power penetration level

The impact of wind power penetration levels on system EENS, EENU and average UCR is simulated in this case. When wind power penetration level increases from 5% to 25% of the total CG capacity to supply the same load in Section 5.5.1, the curves of EENU and EENS are shown in Figure 5.13. Although the EENS is reduced from 6.34 MWh to 3.12 MWh, the EENU is significantly increased from 1415.32 MWh to 2913.88 MWh. The results indicate that less reliability improvement can be made but more wind energy is wasted. In other words, it is not worth (economical) to add more WTGs to improve reliability for this system.

The impact of wind power penetration on the average UCR is shown in Figure 5.14. It can be seen from the figure that the average UCR decreases quickly with the increase of wind power penetration level and it becomes zero when the wind power penetration level is over 22%. The average UCR is quite sensitive to the wind power penetration. From previous analyses, the IEEE-RTS is a very reliable power system with very low UCR and adding more wind generation makes the generation system more reliable. The average UCR become zero is because that all system states with probability lower than 1×10^{-8} are truncated.

Figure 5.13: Effect of wind power penetration level on EENS and EENU.

Figure 5.14: Effect of wind power penetration level on average UCR.

5.5.2.4 Effect of SR

When the SR increases from 5% to 25% based on the system operating condition in Section 5.5.1, the corresponding curves of EENU and EENS are shown in Figure 5.15.

It is obvious that the EENS decreases with the increase of SR. When SR is over 15%, the reduction rate of EENS becomes smaller for a same percentage increase of SR. The EENS is almost constant when SR reaches 19%. However the EENU increases almost linearly with the increase of SR, which means that it is not economic to continuously increase the SR to improve system reliability.

Figure 5.15: Effect of SR on EENS and EENU.

The impact of SR on the average UCR is shown in Figure 5.16. It can be seen that the average UCR decreases as the percentage of the SR increases. In this research, the wind power output can response to a wind speed change immediately while the SR has ramp rate limitation. This assumption makes the average UCR relatively less sensitive to the SR than to wind power penetration levels.

Figure 5.16: Effect of SR on average UCR.

5.5.2.5 Capacity credit of a WTG

It is well known that a 5-MW WTG cannot replace the same size CG due to the intermittent characteristics of wind speed. Capacity credit of a WTG has been defined

to represent the number of WTGs required to replace a given number of CGs for the same system reliability [118-119]. To replace two 50- MW CGs for the system in Section A, 152×5-MW WTGs are required to achieve the same EENS of 6.25 MWh/month. It is obvious that a WTG cannot provide the same capacity credit as a same size CG. On the other hand, the EENU increase significantly from 1356.89 MWh to 1789.56 MWh.

The capacity credit of a WTG is closely related to the wind speed model in a wind farm. If the wind farm has the higher average wind speed of 14 m/s and less intermittency as shown in Figure 5.17, 40×5-MW WTG units is required to replace two 50 MW CGs for the same EENS. The EENU is reduced from 1789.56 MWh to 1701.28 MWh. The wind capacity credit can only shows the available generation capacity of a WTG from reliability point of view and does not represent its economic aspect. Therefore, the EENU is proposed in this paper to evaluate economical aspect of replacing a CG by WTGs for the same reliability. The simulation results show that it is not worth to directly add WTGs in a power system from both reliability and economic aspects. The related ESS or sufficient SR should be added with WTGs at the same time.

5.5.3 System with CGs, WTGs and ESS

The capacity credit improvement of adding battery ESS and the impacts of the ESS parameters on system EENS and EENU are investigated in this section.

Figure 5.17: Hourly wind speed model for a better wind site.

Case 1: A 100-MWh battery ESS is added into the system based on the system condition in Section 5.5.2.1. The charging/discharging rate is 100 MW (100 MWh/hour). The monthly EENS is reduced 86% from 3.59 MWh (without the ESS) to 0.41 MWh (with the battery ESS). The monthly EENU is reduced 16% from 2054.34 MWh to 1723.91 MWh. The battery ESS also reduces the system EENU due to its fast ramp (charging/discharging) rates compared with CGs.

Case 2: For the fixed discharging rate 100 MW, the effects of the ESS capacity on the EENS and EENU are investigated. When the EES capacity changes from 10 MWh to 200 MWh, the EENU and EENS are shown in Figure 5.18.

Figure 5.18: Effect of ESS capacity on EENS and EENU.

It can be seen from Figure 5.18 that both the EENS and EENU decrease with the increase of the battery EES capacity. Before 60 MWh, the EENS reduces significantly with a capacity increase. After 60 MWh, the EENS reduces slowly. After 100 MWh, the EENS become constant. This is due to the limitation of discharging rate of 100 MW. Before 100 MWh the EENU decreases significantly. After 100 MWh, the EENU decreases slowly.

Case 3: Figure 5.19 shows that the required WTG capacity to replace two 50 MW CGs for different ESS capacities under a given EENS.

It can be seen that the required WTG capacity decreases sharply with the increase of ESS capacity. Compared with 152×5-MW WTGs without ESSs, the required WTG capacity is reduced to 37×5-MW WTGs when the ESS is 100 MWh. This means that wind capacity credit increases tremendously after adding ESS.

Figure 5.19: WTG capacity for replacing 2×50-MW CGs.

The required WTG capacity is reduced slowly when the ESS capacity is over 40 MWh. This means that wind capacity credit improvement becomes not economic. The ESS required depends on the size of a wind farm and its wind speed model.

5.6 Conclusion

This chapter proposed a technique to evaluate the operational reliability and wind power utilization efficiency. In power system operation, the generating units become not repairable over short lead times. CGs have to be ramped up/down or even started up/shut down more frequently to account for the variations of wind power outputs and load. The calculation of EENU and EENS become complicated because of consideration of these operational factors. With the help of graphic analysis, formulae for the EENU and EENS have been derived for various system conditions.

The IEEE-RTS is used to illustrate the proposed technique. The EENS and EENU are increased with consideration of ramp rates of CGs. The average UCR is found to be not very sensitive to generator loading priority and ramp rates of CGs while it is very sensitive to wind power penetration levels and SR. The incorporation of wind farms without the battery ESS leads to very limited system reliability improvement but results in large amount of energy surplus. ESSs can significantly improve the wind

power capacity credit of a wind farm. However, there is maximum size of ESSs for a given size of the wind farm and a given wind speed model. Reliability and associated cost should be balanced when selecting the ESS. The proposed method and indices can be used to provide useful information to sizing a wind farm and required ESSs.

Chapter 6. Cost/Worth-Based Energy Storage Sizing Considering Ramp Rates of Conventional Generators

As shown in Chapter 5, considering operating factors in reliability evaluation can improve the result accuracy. Although battery storage system (BSS) can significantly reduce the response time of SR and to improve system reliability and reduce energy surplus, the cost of installing BSS should also be considered. This chapter is investigating the technique of optimal sizing the BSS to make maximum net benefit of adding energy storage. The wind speed model, load model, reliability of a generator and BSS model are similar to those in Chapter 5.

6.1 Introduction

Due to the intermittent and unpredictable nature of wind speed, a power system with high wind penetration or a micro grid with less dispatchable capacity may suffer power shortage and power surplus if committed CGs do not have sufficient operating reserve and fast response time to incorporate wind power fluctuation. ESSs have been proposed for compensating wind variability, shifting wind generation, energy arbitrage and grid balancing, and to act as an operating reserve [31, 84, 120-123]. Different energy storage technologies are compared for their operational suitability over different time scales, and wind speed probability distribution is considered using a simple stochastic method [31]. The size of bulk energy storage for managing wind power fluctuations has been investigated with considering flexibility of standing and spinning reserve provided by CGs [84]. A probabilistic method is proposed in [120] for designing ESSs for wind farms to reduce the uncertainty of short-term wind power forecasts. The expected unserved energy that may be dumped or sold at a lower price is adopted as the sizing criterion. The focus of the proposed technique is on the benefit of an individual wind farm instead of reliability and economical benefit of an entire generation system. A national assessment of grid-connected ESSs for the U.S. grid has been conducted to

address two specific ESS applications: energy balancing application and energy arbitrage [121]. Different energy storage technologies have been investigated and compared based on the two applications for four sub-regions' grids under the Western Electricity Coordinating Council. The authors in [122] presented field results and analyses quantifying the value of Sodium Sulfur battery storage toward shifting wind generation, limiting the ramp rate of local wind power outputs, participating in energy markets and being an operating reserve. The ramp rate and reliability of generators, and wind speed variation were not considered in those techniques.

The operating consideration of generators such as SR commitment, start-up failure, and outage postponability were investigated [102]. In real time operation of a power system with high wind power penetration, CGs, which provide power and SR, have to be frequently ramped up/down or started up/shut down to incorporate system failures and wind speed and load variations. It is assumed in existing techniques that SR can immediately take up load when required. However, a SR generator needs response time to change its power output. The effects of ramp rates of CGs on sizing of energy storage have not been considered in existing techniques. The BSS as an additional energy source for energy and SR will be investigated in this paper.

Reliability cost/worth, which is a very important factor for making optimal investment decisions, has been broadly used in power system planning and operation [72-73, 109, 124-130]. Although ESSs can significantly reduce the response time of SR and to improve system reliability and reduce energy surplus, the cost of installing BSS should also be considered. This paper proposes a technique to determine the optimal size of BSS for power systems with high wind penetration based on reliability and economical benefit and cost of adding BSS with consideration of ramp rates of CGs and wind speed variation. In order to increase result accuracy of the proposed technique, load and wind speed variation for an operating period are modeled as linear function instead of a constant wind speed used in most existing techniques. The EENS is used to determine reliability benefit and the EENU, which shows energy surplus from unused wind energy, is used to determine economical benefit due to addition of a BSS. The golden section search method (GSSM) is applied to search the optimal size of a BSS under the maximum total system net benefit.

6.2 System modeling

The proposed BSS sizing technique considers operational factors and therefore many system component models are similar to those in Chapter 5. The reliability model of generation system in operational studies and ramp rates of a generator have been introduced in Chapter 5 and will not be covered in this chapter. Wind speed, load and BSS will be discussed with small modifications.

6.2.1 Wind speed and load model

The wind speed in a practical wind farm is usually measured in several minutes to one hour. Average wind speed obtained from the practical wind speed data is usually used to obtain wind power output P_W for most power system reliability evaluation. This means that P_W is assumed constant as a solid line shown in Figure 6.1 during an operating period. The accuracy of the wind speed model is the most important factor to obtain the optimal size of BSS. In order to capture the ramps of wind power, the wind power output in an operation interval is assumed to change linearly as shown by the dotted line in Figure 6.1. The power output of a WTG can be calculated using mathematical equations (2.12)-(2.15) based on wind speed [12]. The slope of the linear line for a period should be determined based on the average wind power for the same period to guarantee that the total wind energy produced is the same for the two models. The operation intervals for wind speed can be reduced for obtaining higher accuracy.

Similarly, in order to capture possible load variation, a linearized load model is used in this study. The load intervals will be also reduced for high accuracy. Linear interpolation methods may be used if the time interval of available load data is less than 1 hour.

6.2.2 BSS model

Energy storage systems with fast response for resource and load variation play important role in solving energy surplus and deficiency problems caused by wind speed fluctuation and failures in generation system. Battery energy storage is also used in this

chapter due to its fastest response time among all ESSs and future development of vehicle-to-grid implementation of electric vehicles. In addition to the three important parameters introduced in Chapter 5, several more parameters are considered in this chapter to improve the accuracy of the BSS model. The important parameters of a BSS

Figure 6.1: WTG power output model using linear approximation.

considered are the rated storage capacity (E_b), charging/discharging rate (P_b), charging/discharging limits (E_b^{min}/E_b^{max}), charging/discharging efficiency (η_{bc}/η_{bd}), real time state of charge (SOC) and depth of discharge (DOD). E_b^{max} (MWh) is the maximal energy that can be stored and E_b^{min} (MWh) is the minimum energy that must be kept in the storage. SOC (MWh) represents the remaining energy in a BSS. DOD (MWh) shows the energy has been used from its full capacity E_b and $DOD_j = E_b - SOC_j$. P_b (MW) is the power charging/discharging capability of a BSS. The size of a BSS is measured by its P_b and E_b [131]. The SOC of a BSS is modeled as a function of time as shown in Figure 6.2 and should be accurately determined at anytime during system operation.

Figure 6.2: Real time SOC of a BSS.

The basic operating strategy of a BSS is to store the excess wind energy when wind speed is high and load level is low and supply energy to the system when there is a generation shortage. It is assumed that wind energy has priority to supply load.

6.3 Reliability and efficiency indices

Integration of a BSS into a power system with WTGs can increase wind power utilization efficiency and improve system reliability. The efficiency improvement can be calculated by the reduction of wind energy surplus representing by reduced EENU and the reliability improvement can be calculated based on the reduction of EENS. The EENU and EENS for a period j are calculated using equations (6.1) and (6.2).

$$EENS_j = \sum_{i=1}^{N_i} p_{ij} ENS_{ij} \quad (6.1)$$

$$EENU_j = \sum_{i=1}^{N_i} p_{ij} ENU_{ij} \quad (6.2)$$

The ENU_{ij} and ENS_{ij} are calculated using the similar formulae in Chapter 5. As more BSS parameters have been considered in this chapter, those formulae are used with modifications.

6.3.1 ENU_{ij} formulation

When a power system experiences a fast increase of wind power or load decrease for a contingency state, the output of conventional generators has to be reduced to increase utilization of wind energy and balance demand and supply. In this case, there may have energy surplus if the ramp down rate of CGs is slower than the wind power ramp up. The energy surplus may be fully or partially absorbed by a BSS, depending on its rated capacity, charging rate and DOD. Therefore there will be ENU under some operating conditions. The ENU_{ij} for failure state i and interval j under different operating conditions are formulated by the following cases. The interval j starts from the time t_{j-1} and ends at time t_j . In order to simplify ENU formulations, a net system load is calculated as load minus wind power output.

Case 1: In this case, the BSS is fully charged at the beginning of interval j . The ENU_{ij} is represented by the shade areas as shown in Figure 5.5. If the reduction rate of the net system load is smaller than the ramp down rate of the CGs, P_{Cij} is below NP_{Lj} at t_j and $ENU_{ij} = 0$. If the ramp down rate of CGs is slower than the reduction rate of the net system load, ENU_{ij} can be calculated using equation (5.7).

Case 2: The BSS is not fully charged at the beginning of interval j . In this case, the energy surplus can be partially or fully absorbed by the BSS. The ENU_{ij} in equation (5.7) should be modified to ENU_{ij}' as the shade area shown in Figure 5.7. The ENU_{ij}' are calculated based on ENU_{ij} , SOC_j and P_{bj} .

If $P_{bj} \geq P_{Cij} - NP_{Lj} > 0$, i.e. the charging rate of the BSS is larger than the difference between generation and net system load, the ENU_{ij}' for different SOC conditions are calculated using equations (6.3) and (6.4).

$$\begin{cases} ENU_{ij}' = 0; SOC_j'' = SOC_j' + ENU_{ij}\eta_c & \text{if } ENU_{ij}\eta_c \leq DOD_j \\ ENU_{ij}' = ENU_{ij} - DOD_j/\eta_c; SOC_j'' = E_b^{\max} & \text{otherwise} \end{cases} \quad (6.3)$$

If $P_{Cij} - NP_{Lj} > P_{bj} > 0$, i.e. the charging rate of the BSS is smaller than the difference between generation and net system load, the ENU_{ij}' for different SOC conditions are calculated using

$$\begin{cases} ENU_{ij}' = ENU_{ij} - E_{cj}/\eta_c; SOC_j'' = SOC_j' + E_{cj} & \text{if } E_{cj} \leq DOD_j \\ ENU_{ij}' = ENU_{ij} - DOD_j/\eta_c; SOC_j'' = E_b^{\max} & \text{otherwise} \end{cases} \quad (6.4)$$

where $E_{cj} = P_b\Delta t - 0.5P_b^2/r_{dij}$ is the maximal energy that needs to be charged within Δt .

If $P_{Cij} - NP_{Lj} \leq 0$, the ENU_{ij} will be zero because there is no energy surplus.

6.3.2 ENS_{ij} formulation

When a power system experiences a fast decrease of wind power or load increase for a contingency state, the output of conventional generators has to be increased to balance demand and supply. In this case, it may have energy insufficient if the ramp up rate of the CGs is slower than the increase of net system load. The BSS may be discharged to offset the shortage of system generation. In some operating conditions, there will be insufficient generation and load has to be curtailed. The ENS_{ij} for failure state i and interval j under different system conditions are formulated by the following cases. The ENS_{ij} considering the ramp up rate and capacity limit of CGs is represented by the shade areas in Figure 5.6. If the increase rate of net system load is smaller than the ramp up rate of CGs, $ENS_{ij} = 0$.

Case 1: The SOC of the BSS is zero at the beginning of interval j . When the increase rate of the net system load is faster than the ramp up rate of CGs, the ENS_{ij} under different operating conditions are represented by the two shade areas and can be calculated based on the maximum generation capacity P_{Cij}^m of the CGs. If $P_{Cij}^m < NP_{Lj}$, the ENS_{ij} for high and low ramp rates of CGs can be calculated using equation (5.8). If $P_{Cij}^m \geq NP_{Lj}$, the ENS_{ij} for high and low ramp rates of CGs can be calculated using equation (5.9).

Case 2: The SOC of the BSS is not zero and there is energy to be discharged at the beginning of interval j , the ENS_{ij} is represented by the upper shade area in Figure 5.8. The ENS_{ij} should be modified to ENS_{ij}' which is formulated as the following two cases:

If $P_{bj} \leq NP_{Lj} - P_{Cij}^m$, i.e. the discharging power of the BSS is lower than the shortage of generation, the ENS_{ij}' is calculated using equation (6.5).

$$\begin{cases} ENS_{ij}' = ENS_{ij} - E_{dj}; SOC_j'' = SOC_j' - E_{dj}/\eta_d & \text{if } E_{dj} \leq SOC_j'\eta_d \\ ENS_{ij}' = ENS_{ij} - SOC_j'\eta_d; SOC_j'' = 0 & \text{otherwise} \end{cases} \quad (6.5)$$

where $E_{dj} = P_b \Delta t - 0.5 P_b^2 / r_{uij}$ is the maximal energy that needs to be discharged within Δt .

If $P_{bj} > NP_{Lj} - P_{Cij}^m$, i.e. the discharging power of the BSS is larger than the shortage of generation, the ENS_{ij}' is calculated using equation (6.6).

$$\begin{cases} ENS_{ij}' = 0 ; SOC_j'' = SOC_j' + ENS_{ij} / \eta_d & \text{if } ENS_{ij} \leq SOC_j' \eta_d \\ ENS_{ij}' = ENS_{ij} - SOC_j' \eta_d ; SOC_j'' = 0 & \text{otherwise} \end{cases} \quad (6.6)$$

6.4 Problem formulation

The optimal size of a BSS is selected based on the reliability and economic benefit and cost for adding BSS to a power system.

6.4.1 Reliability and economic benefit

When a BSS is added to a power system, wind energy surplus during high wind speed periods can be stored in the BSS and ENU due to slow ramp down rate of CGs will be reduced, which means that more wind energy can be absorbed. On the other hand, the system EENS will be reduced due to the fast discharge of the BSS, which means a low customer interruption cost.

The benefit B_{EENU} from the reduced EENU can be calculated using equation (6.7) based on the additional wind energy utilized and energy price k_{fy} in the life span T_b of a BSS. The additional energy utilized during period j is the EENU difference before and after adding BSS.

$$B_{EENU} = \sum_{y=1}^{T_b} \sum_{j=1}^{T_n} (EENU_{bj} - EENU_{aj}) k_{fy} \frac{1}{(1+d)^{y-1}} \quad (6.7)$$

where $EENU_{bj}$ and $EENU_{aj}$ are the EENU before and after adding the BSS, respectively. Over the battery life-span, the benefit B_{EENU} in each year has been

converted into the value at the first year by considering the discount rate d using the present value method [132-133].

The benefit B_{EENS} is from system reliability improvement can be estimated by equation (6.8) based on the reduction of EENS and the associated interruption cost. The interruption cost is calculated using the value of lost load (VOLL) [134], which represents the average willingness of consumers to pay for avoiding an interruption for a given period. The VOLLs were determined by several methods [135-136]. A typical VOLL of \$15,000/MWh is used in this thesis.

$$B_{EENS} = \sum_{y=1}^{T_b} \sum_{j=1}^{T_n} (EENS_{bj} - EENS_{aj}) VOLL \frac{1}{(1+d)^{y-1}} \quad (6.8)$$

where $EENS_{bj}$ and $EENS_{aj}$ are the EENS values before and after adding the BSS, respectively. The B_{EENS} also has to be converted into the present values using similar method.

6.4.2 BSS cost

The total cost $TC_{ES}(P_b, E_b)$ of a BSS includes capital costs and operation and maintenance (O&M) cost. Both costs depend on storage capacity and charging/discharging rate. The one time capital cost $C_{cap.}(P_b, E_b)$ is defined as the summation of the rated capacity E_b times the cost rate k_C (\$/MWh) and the rated charging/discharging rate P_b times the cost rate k_P (\$/MW) [137] as:

$$C_{cap.}(P_b, E_b) = k_P P_b + k_C E_b \quad (6.9)$$

The O&M cost $C_{O\&M}(P_b, E_b)$ is required for each year during the life-span of the BSS and can be expressed by a fixed cost and a variable cost as [137]:

$$C_{O\&M}(P_b, E_b) = \sum_{y=1}^{T_b} \left(k_{Fy} P_b + k_{Vy} \sum_{j=1}^{T_n} E_{Dj} \right) \frac{1}{(1+d)^{y-1}} \quad (6.10)$$

The energy price k_{fj} , variable power cost k_{Fy} and variable energy cost k_{Vy} are on the yearly basis and the O&M cost has been converted to the present values.

The total cost of a BSS $TC_{ES}(P_b, E_b)$ is:

$$\begin{aligned} TC_{ES}(P_b, E_b) &= C_{cap.}(P_b, E_b) + C_{O\&M}(P_b, E_b) \\ &= r_P \cdot P_b + r_C \cdot E_b + \sum_{j=1}^{T_b} (r_{Fj} \cdot P_b + r_{Vj} \cdot E_{Dj}) \end{aligned} \quad (6.11)$$

6.4.3 Objective function

The objective of the problem is to find the optimal BSS size under the maximum total system benefit (TSB) which is the total benefit minus the total cost associated with the BSS. The objective function is:

$$Max \{TSB(P_b, E_b)\} = B_{EENS} + B_{EENU} - TC_{ES}(P_b, E_b) \quad (6.12)$$

subject to the following constraints:

Capacity constraint of CGs:

$$0 \leq P_{Cj} \leq P_{Cij}^m \quad (6.13)$$

Ramp rate constraints of CGs:

$$\begin{cases} P_{Cj} - P_{C(j-1)} \leq r_{uj} & \text{as generation increases} \\ P_{C(j-1)} - P_{Cj} \leq r_{dj} & \text{as generation decreases} \end{cases} \quad (6.14)$$

SOC limit of BSS:

$$\begin{cases} E_b^{\min} \leq SOC_j' \leq E_b^{\max} \\ E_b^{\min} \leq SOC_j'' \leq E_b^{\max} \end{cases} \quad (6.15)$$

Charging rate limits:

$$0 \leq P_{bj} \leq P_b \quad (6.16)$$

6.5 Solution technique

The proposed BSS sizing procedure involves reliability evaluation, cost/worth assessment and optimization procedure. The time frame is the life span of the selected BSS. The EENU and EENS are calculated using the formulae developed in this chapter.

The net benefit is the total benefit from the reliability improvement and the reduction of energy surplus minus the total cost of BSS. The cost of BSS increases with BSS size linearly and the growth rate of the total benefit will gradually reduce. Therefore the net benefit increases with increase of BSS size at certain range until the net benefit reaches the maximum at the optimal size of BSS followed by net benefit reduction after the optimal point. This means that the net benefit is a convex function. Therefore A direct search method can be used to solve the problem. The *golden section search method* (GSSM) [138] is used to find the optimal BSS size because of the fast speed compared with other search methods. The GSSM is a technique to search the extremum (minimum or maximum) of a unimodal function by successively reducing the range of the search. The basic procedure of the GSSM is illustrated using Figure 6.3.

The basic search procedure to find the extremum of a univariate function $f(x)$ using the GSSM is illustrated in Figure 6.3. Within the initial search range of $[x_{min}, x_{max}] = [0, x_{max}]$, the two new points are chosen according to the golden ratio 0.618 as:

$$x_1 = x_{min} + (1 - 0.618) (x_{max} - x_{min}) = 0.382x_{max} \quad (6.17)$$

$$x_2 = x_{min} + 0.618 (x_{max} - x_{min}) = 0.618x_{max} \quad (6.18)$$

The $f(x_1)$ and $f(x_2)$ are then calculated. If $f(x_1)$ is larger than $f(x_2)$, the minimum must be within $[x_1, x_{max}]$. The $x_{min} = x_1$ and the search range is updated. Two new x_1 and x_2 are chosen based on equations (6.17) and (6.18) in the new search range. New $f(x_1)$ and $f(x_2)$ are calculated and compared, and the process is repeated until $[f(x_1) - f(x_2)]$ is smaller than a given convergence tolerance ε . The minimum can be found to be $f(x_1) = f(x_2)$.

Figure 6.3: Diagram of a golden section search.

The objective function (6.11) is a bivariate optimization problem related to P_b and E_b . As illustrated in Figure 6.4, the optimization procedure includes the following steps.

- Step 1: Set the initial range of E_b and P_b .
- Step 2: Determine two points E_{b1} and E_{b2} , based on the golden ratio.
- Step 3: Determine two initial points P_{b1} and P_{b2} based on the golden ratio.
- Step 4: Calculate the net benefits TSBs at points $[P_{b1}, E_{b1}]$ and $[P_{b2}, E_{b1}]$ for the fixed E_{b1} .
- Step 5: Compare the TSBs obtained in Step 4 and update P_{b1} and P_{b2} based on the GSSM, until $||TSB(P_{b1}, E_{b1}) - TSB(P_{b2}, E_{b1})|| < \varepsilon$ and then $P_b^{opt}(E_{b1})$ is obtained.
- Step 6: Repeat steps 2-4 to find $P_b^{opt}(E_{b2})$.
- Step 7: Compare the TSBs obtained in steps 5-6 and update E_{b1} and E_{b2} , until $||TSB(P_b^{opt}(E_{b1}), E_{b1}) - TSB(P_b^{opt}(E_{b2}), E_{b2})|| < \varepsilon$, and then P_b^{opt} & E_b^{opt} are obtained.
- Step 8: Output the optimal P_b^{opt} , E_b^{opt} and the maximum $TSB^{opt}(P_b^{opt}, E_b^{opt})$.

The main objective of adding BSS is to reduce EENU and EENS due to wind power fluctuations. The selection of the initial range of P_b and E_b should consider daily average wind power, the associated standard deviation and the maximum wind power. The range of E_b are selected based on the daily maximum wind energy $(0, E_W^{max})$ and the initial interval of P_b is set to be $[0, E_W^{max}/1h]$ in this chapter.

Figure 6.4: Procedure of selecting the optimal sizing of the BSS.

6.6 System analysis

The IEEE-RTS [54] is modified to illustrate the proposed BSS sizing technique. The system peak load is increased 15% to 3277.5 MW. The total installed capacity is 3405 MW and the generating unit data are extracted from [54]. Unreliability U and ramp rates of CGs are listed in Table 6.1. The SR from CGs is assumed to be fixed at 10% of the system peak load in each time interval. A wind farm consisting of 86 identical 7.0-MW WTGs is added to the test system. Twenty years wind speed data are extracted from [45] and used. The cut-in, rated, and cut-out wind speeds are assumed to be 3 m/s, 14 m/s and 25 m/s, respectively. The WTG unavailability is assumed to be 0.01. The operating interval is set to be 5 minutes and therefore the load and hourly wind speed model are modified accordingly using a linear interpolation method. The

contingency states with probability over 10^{-6} are considered. The convergence tolerance ε in the GSSM is set to be 10^{-6} .

Table 6.1: Conventional unit data

Unit	U12	U20	U50	U76	U100	U155	U197	U350	U400
$U (\times 10^{-3})$	0.3	2.2	0.5	0.5	0.8	1.0	1.0	0.9	0.9
Ramp Rate (MW/Min)	1	3	*50	2	7	3	3	4	20

*The ramp rate of hydro units is not provided in [22] and is assumed to be 50 MW/min in simulations

Assume that k_{vy} is \$30/MWh with 2% annual growth rate, and k_{fy} , k_P and k_C are \$50/MW, $\$5 \times 10^5/\text{MW}$ and $\$6 \times 10^5/\text{MWh}$, respectively. The VOLL is fixed at \$15,000/MWh [136]. The BSS life cycle is assumed to be 20 years. The energy price k_{fy} is assumed to be \$250/MWh with 5% annual growth rate [139]. A discount rate d is 0.03. BSS efficiency η_{bc} and η_{bd} are assumed to be 75%. The initial range of P_b and E_b are estimated as $[0, 14333 \text{ MWh}]$ and $[0, 14333 \text{ MW}]$, respectively. The large initial P_b and E_b are selected in this research to consider the situation of continuous high wind speed and low demand for several days followed by low wind speed and high demand for several other days. The reasonable initial values should be selected based on the maximum wind speed of the wind farms and the minimum load in the system and their maximum duration in a year from the historical data.

6.6.1 Base case

The annual EENU and EENS of the system without wind farms and BSS are 8854 MWh and 468.38 MWh respectively.

The wind farm is then added to the system without BSS and the linearized wind power and load models are used. The EENS decreases 89.3% from 468.38 MWh/year to 49.91 MWh/year. This is obvious because additional WTGs are added to the system. The system EENU increases 12.6% from 8854 MWh/year to 10127 MWh/year. This means that wind energy cannot be fully utilized although the system reliability increases. The computational time is 75 seconds.

6.6.2 Optimal BSS size

In this case, the optimal size of the BSS is selected using the proposed technique. The P_b^{opt} and E_b^{opt} of the BSS are 6.4 MW and 8.9 MWh respectively. The small size of the BSS is due to the high cost of BSS. The EENU are reduced 4% from 10127 MWh/yr to 9681 MWh/year. This means that a part of EENU from the wind farm is utilized due to the addition of BSS. The EENS is significantly reduced 79% from 49.91 MWh/year to 10.29 MWh/year because the capacity credit of the wind farm is increased by the BSS. This case shows the optimal BSS has larger impact on the EENS than on the EENU for the fixed ramp rate. The main reason is that the optimal capacity of the BSS is very small and cannot store more wind energy. On the other side, the addition of a 6.4 MW BSS will significantly reduce the load curtailment caused by generator failures. The benefits B_{EENU} and B_{EENS} are $\$2.68 \times 10^6$ and $\$9.11 \times 10^6$ respectively and the associated cost of the BSS over 20 years is $\$10.01 \times 10^6$. The corresponding maximum TSB is $\$1.78 \times 10^6$.

6.6.3 Effect of ramp rates

The ramp rates of CGs have significant impact on the EENU and EENS, and therefore on the optimal size of BSS. Table 6.2 shows the EENUs and EENSs with and without the optimal BSS for different ramp rates. The unit ramp rates in Table 6.2 are the percentages of the base ramp rates in Table 6.1, which means that 100% ramp rates in Table 6.2 are the base ramp rates in Table 6.1.

The EENS and EENU with or without BSS reduce with increase of the ramp rate. However, EENSs with BSS is reduced significantly compared to those without BSS because of the capacity (MWh) contribution from the BSS. However, percentage changes of EENUs with and without BSS are not significant when the ramp rates increase. This is because of limited capacity of the BSS. The energy surplus from the wind penetration of 602 MW wind farm cannot be stored during period of high wind speed. When the ramp rate is infinite (idea case), the EENU is zero with and without the BSS because CGs can absorb any wind energy surplus during high wind speed. Therefore it is not necessary to add BSS to the test system.

Table 6.2: EENU and EENS for different ramp rates

Ramp Rates	Without the BSS		With the BSS ($P_b = 6.4$ MW; $E_b = 8.9$ MWh)	
	EENU (MWh)	EENS (MWh)	EENU (MWh)	EENS (MWh)
50%	12134	59.32	11631	10.89
90%	10313	52.31	9985	10.44
110%	9780	46.01	9502	10.21
150%	9547	36.89	9339	9.69
200%	8898	23.66	8926	8.67
infinite	0	0.16	0	0.03

Figure 6.5 shows that both the optimal rated capacity and charging/discharging rate are reduced with the increase of the ramp rates. A higher ramp rate makes the power system more flexible to cope with variations of wind generation and load. Therefore a smaller size of BSS is needed to store and shift excess wind energy. When the ramp rate is over 200%, the reduction rate of P_b^{opt} and E_b^{opt} becomes very small, which means it is not necessary to increase the size of BSS. The information can help the system planners to decide the optimal combination of BSS and SR from CGs based on the ramp rates.

It can be seen from the results and formulations of ENS and ENU that the power rating of the BSS is sized based mainly on the EENS and therefore a larger power rating can reduce more EENS and interruption cost. On the other hand, the rated capacity is mainly determined by energy surplus during high wind speed periods and therefore a larger BSS rated capacity can reduce the EENU more.

6.6.4 Effect of wind speed pattern

The optimal size of BSS depends on wind speed patterns and the corresponding wind power output variations. An offshore high wind speed model (Model 1) and an island

low wind speed model (Model 2) [140] as shown in Figure 6.6 and Figure 6.7 are used in the analysis. Model 1 has a high average wind speed with slow variation. Model 2 has a small average wind speed with fast variation. The other system parameters are the same as those in the basic case.

Figure 6.5: The optimal size for different ramp rates.

Figure 6.6: An offshore high wind speed model and its power outputs (Model 1).

Figure 6.7: An island low wind speed model and its power outputs (Model 2).

The optimal sizes of BSS and corresponding TSB^{opt} for the three wind speed models are shown in Table 6.3.

Table 6.3: Optimal size with different wind speed patterns

Wind speed model	P_b^{opt} (MW)	E_b^{opt} (MWh)	TSB^{opt} (\$)
Base model	6.4	8.9	1.78×10^6
Model 1	5.0	6.6	2.82×10^6
Model 2	11.4	11.7	1.95×10^6

It can be seen from Table 6.3 that Model 1 results in the smaller BSS size than the base case in Section 6.6.2. The reason is that a slow wind power variation leads to smaller ENS_{ij} and ENU_{ij} for the same ramp rate of CGs. Consequently, a smaller BSS capacity is needed to store energy surplus and a smaller discharging rate to reduce EENS. The TSB for the Model 1 is also relatively higher than the base case because of the less investment cost and larger benefit from less EENU.

The results show that a larger BSS is obtained for Model 2. The reason is that high fluctuation of wind power requires the CGs to ramp up and down more frequently. Therefore higher storage capacity and charging/discharging rate are required to reduce

the EENU and EENS. With such a larger BSS, the net benefit is lower than that for Model 1. It can be concluded that wind speed and wind power generation fluctuations are important factors that should be considered when determining the optimal size of BSS.

6.6.5 Effect of spinning reserve

Both CGs and BSS can serve as spinning reserve during generator failures, wind speed decrease and load increase. Because the response speeds and economic cost of CGs and BSS are different, the ratio of BSS to CGs as SR is an important issue. This section investigates the relationship between BSS and the SR from CGs. The impacts of the SR from CGs with the fixed ramp rates on the optimal BSS size and the maximal TSB are shown in Figure 6.8. It can be seen that the size of BSS reduces with the increase SR from the CGs. When the SR reaches to 25% of the system peak load, the further increase of SR will have no impact on the size of BSS and the associated TSB. This means that the further increase of the SR from CGs cannot replace BSS because their limited ramp rates.

Figure 6.8: Impact of SR on the maximal TSB and optimal BSS size.

Figure 6.9 shows the BSS rated capacity for replacing the required SR from CGs for the same EENS. It can be seen from Figure 6.9 that the BSS capacity increases nonlinearly with the increased SR. Only less than 30 MWh BSS is required to replace 1% of SR at the beginning of the curve. However, over 150 MWh BSS is required to replace 1% of SR when it increases from 5% to 6%. In this case, it is not economic to use more BSS

to replace the same amount of SR. Therefore the suitable ratio of SR from CGs to BSS have to be decided based on both economic and reliability requirements.

Figure 6.9: The optimal size of BSS for replacing SR (%) from CGs.

6.7 Conclusion

This chapter proposed a new technique for sizing energy storage for a power system with wind farms based on the reliability cost/worth assessment. The ramp rates of CGs are considered in the formulation of reliability indices for more accurate and reasonable sizing results. Wind speeds and loads within each time interval are assumed to change linearly from one level to another. Reliability evaluation is performed at each interval to provide inputs for the reliability cost/worth assessment. The GSSM is used to search the optimal BSS size and maximal TSB.

The proposed BSS sizing technique is applied to the modified IEEE-RTS. System studies show that BSS costs and reliability cost/worth parameters have significant impacts on the optimal BSS size. The BSS size also depends on ramp rate of CGs, wind speed models, load variation and spinning reserve. Compared to the existing methodologies on energy storage sizing, the proposed technique includes both the response of CGs and system reliability considerations. System planners can obtain the better information from the proposed method to make optimal decisions.

Chapter 7. Conclusions and Future Work

7.1 Conclusions

Integrating large amounts of wind power generation into conventional power systems has created many new reliability issues in planning and operation. Battery energy storages are broadly used to increase wind power capacity credit, improve system reliability performance, and augment wind energy utilization efficiency. The thesis reviewed and summarized the general reliability evaluation procedure for conventional power systems, extended it to power systems with wind farms and energy storage, investigated operational adequacy of power systems and proposed an optimal sizing technique for energy storage considering operational factors.

In reliability evaluation of conventional power systems, a generating unit can be represented using a two-state or multi-state model and is repairable if the operation cycles are relatively long. The generation system consists of many conventional generating units and can be modeled as a capacity outage probability table (COPT). By convolving the COPT with the system load model, an analytical procedure can be used to estimate reliability indices of the power system. A small test system, the IEEE-RBTS has been used to illustrate the basic reliability evaluation technique. From sensitivity studies, the generation system of the IEEE-RBTS is proven to be very reliable according to various reliability indices. Even when the system peak load is increased by 10-15%, the system LOLP, LOLE, EENS and EIR do not change obviously. On the other hand, the spinning reserve and FORs of generating units have big impacts on the system reliability. Reduction of spinning reserve or larger FORs can deteriorate the system reliability significantly.

The basic reliability evaluation technique is extended to assess the reliability performance of power systems with wind farms and energy storage. A WTG can also be represented by the two-state model but its power output varies tremendously both in frequency and in magnitude, due to the wind speed fluctuations. A time varying wind

power output model is therefore adopted. The generation system consists of both CGs and WTGs and still can be modeled using the COPT concept. However, the COPTs for each time interval have to be changed due to the varied wind power outputs in different intervals. Energy storage technologies are broadly used along with wind farms to smooth out wind power output fluctuations and increase the wind energy utilization. A new index EENU is therefore defined to measure the utilization efficiency of wind energy. The EENU and other reliability indices are evaluated using a large test power system the IEEE-RTS. From the system studies, it is obvious that adding a wind farm to the test system can improve the system reliability. Unfortunately, not all wind energy produced can be absorbed by the system because there have many system states where the total generation from CGs and WTGs is larger than the system load while the CGs cannot reduce their outputs quickly. Wind energy in these cases has to be truncated or dumped. Incorporation of a BESS into the system can reduce these wind energy wastes by shifting a part of wind energy from off-peak periods to on-peak periods. Due to the fast discharging speed of BESSs, the system EENS can also be improved. The sensitivity studies of the BESS rated capacity and charging and discharging rates versus the EENU and EENS reveal that an optimization procedure is required to avoid over sizing or under sizing of energy storage.

The power output of wind farms changes very fast and therefore the capability of the generation system to supply system load will vary in short time. The operational reliability evaluation of power systems with high wind power penetration levels becomes necessary and very important. In power system operation, the generating units including both CGs and WTGs become not repairable over short lead times. Furthermore, CGs have to be ramped up or down more frequently to account for the variations of wind power outputs and load. Hence, the impacts of ramp rates of CGs (including reserve units) cannot be ignored. The calculation of EENU and EENS become complicated because of consideration of these operational factors. With the help of graphic analysis, formulae for the EENU and EENS have been derived for various system conditions. From system studies, the EENS and EENU of the IEEE-RTS are increased with consideration of ramp rates of CGs. The sensitivities of system indices to spinning reserve, ramp rates, and wind power penetration levels have also been evaluated in operational time scales. The capacity credit of WTGs is improved

significantly with an added BESS and the size of the energy storage must be determined carefully for optimal system operation.

An energy storage sizing technique based on reliability cost and worth analysis with consideration of operational factors has been proposed. In order to capture the ramps of wind power, the power output for each interval is assumed to be change linearly. The charging/discharging efficiency and charging/discharging limits have to be considered for the battery storage system (BSS) model as they have big impacts on the sizing of the storage. In the sizing of energy storage, both the cost and worth of adding a BSS are assumed to be functions of the rated capacity and charging/discharging rate of the BSS. The golden section search method is used to find the maximal total system benefit. From system studies, it can be found that the optimal size of the BSS added to the IEEE-RTS with WTGs is relatively small. The ramp rates of CGs, spinning reserve and wind speed patterns have been found to have big impacts on the optimal size of BSSs but the high costs of adding a BSS are the main factors which affect the maximal total system benefit.

The thesis presents a series of reliability evaluation techniques and an energy storage sizing technique for power systems with WTGs. System planners and engineers may make use of them to obtain useful information when evaluating and designing a power system.

7.2 Future work

In view of the progress described in the previous chapters, the following directions are suggested as possible areas for future work.

The current research focuses only on the generation level, i.e. HLI. It is more practical that a wind farm connects to the transmission and distribution systems. In the future, the proposed operational reliability evaluation concept and BSS sizing technique will be extended to transmission and distribution system and micro grids with wind power generation and energy storage. Many more components can affect the system reliability performance, such as distributed generators, transmission lines, transformers,

feeders, switches, fuses and etc. They should be modeled in the operational point of view due to the same reason as in the current research. For reliability evaluation at transmission or distribution system levels, the power flow analysis may be necessary to calculate some reliability indices. Take the EENS for example. If one generator is lost, the others should pick up its load and there should be no energy not supplied provided the generation system has sufficient reserve capacity. However, it may not be true if the capacity required to take up the load of the lost generator exceeds the transmission line capacity limits. Such information can be provided by power flow analyses. The reliability evaluation in this case becomes very complicated and certain state selection techniques [130] and network equivalent techniques [60, 129, 131-132] need to be employed to reduce computations.

One of the main challenges of incorporating wind energy as well as other renewable energy resources into existing power systems is the variability of their power outputs. When considering composite generation and transmission reliability, the geographical diversity of wind farm locations can be used to managing the variability. Energy storage systems can shift wind energy from off-peak periods to on-peak periods while interconnected several wind farms at diverse locations with different weather conditions can shift wind power outputs spatially. The integrated wind power output is more reliable with less variability because wind always blows somewhere. In such a wind generation system, energy storage may also be adopted but its size for per MW WTGs will be smaller comparing to that for a single wind farm. There requires an optimization procedure to determine the size of energy storage based on different wind farm locations, wind conditions, correlations among different wind sites, and etc.

The value of wind and other renewable energy resources could be mutually enhanced by working together to provide a stable supply of electricity, i.e. coordination of different renewable energy resources. For example, solar PVs have no power output during night, rain and snow while wind usually blows more in these conditions. A hybrid renewable energy system consisting of WTGs, solar PVs and energy storage can be a viable way to achieve trade-off solutions in terms of both the reliability and cost. The percentages of WTG and solar PV capacity should be determined based on the correlations of their power outputs. And this is also an important factor of impacting the size of energy storage. Other renewable resources such as tidal and

wave energy may also be used together with wind and solar energy, and requires further studies.

Demand response is a mechanism to manage customer consumption of electricity in response to supply conditions. A power system with demand response programs has more flexibility that enable the power system to more easily integrate wind and solar and demand response programs may be the cheaper way than alternatives. It is therefore worthy to be further investigated for improving the reliability of power systems with renewable resources and optimally determining the size of energy storage.

In addition to the discussion of the possible directions to continue the research, there are also some specific aspects to improve the current work as described in follows.

In Chapters 4 and 5, only the capacity rating and power rating of energy storage are used to define the energy storage. In Chapter 6, the SOC limits and charging/discharging limits of battery storage are also considered in the optimal sizing procedure. Other energy storage parameters such as the life cycles can be incorporated into these studies to obtain more accurate result, especially for the optimal energy storage sizing. The number of charging and discharging cycles (life cycles) is limited for battery storage and replacement may cost much. Therefore it is necessary to control battery storage charging and discharging optimally. One of the factors which impacts the life cycle of a battery is its operating strategy. The energy storage operating strategy in all studies was simple: when there is wind energy surplus that cannot be absorbed by the system, the energy storage will be charged if it is not full-charged; when there is capacity shortage in the system, the energy storage will be discharged if it is not full-discharged. There are many operating strategies for energy storage, such as peak load shaving, smoothing out wind power output fluctuation, maximizing wind power utilizing. The operating strategy is a crucial factor that impacts the life cycle and size of energy storage and therefore needs to be studied further.

For the operational adequacy analysis in Chapter 5, more operational factors can be considered in the current techniques, such as the unit start up time, unit start up

failures, spinning reserve policies, unit outage posponability, and etc. The reliability indices will be modified to incorporate the impact of these factors and the reliability evaluation becomes very complicated. For transmission and distribution systems, the changing component unavailability due to aging or external factors should be considered in the reliability evaluation. For example, the failure rates of transformers or overhead lines located at desolate areas may be increased greatly because of abnormal weather conditions. Modeling of these factors is very challenging.

All the above mentioned considerations of power systems make reliability evaluation very hard to handle. There are some system problems for which the operation in current time interval has significant effect on the next interval, and this must have a consequential effect on the reliability indices being studied. The SOC time sequence of battery storage in Chapters 5 and 6 is one of these problems. Analytical techniques may not be easy to handle many such problems at the same time. The Monte Carlo Simulation techniques treat these problems as a series of real experiments and modeling of system components and system operation procedure are easier. The information recorded in simulations shows not only the expected values of reliability indices. Their frequency distributions can also be evaluated. Although the simulation technique requires large amounts of computations, the strong capability of modern digital computers and increasing interest of modeling the system behavior more comprehensively make it more practical and desirable. Monte Carlo Simulation techniques, therefore, would be employed in the future work to handle very complicated reliability evaluation problems.

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Research related to this thesis has resulted in the following publications:

- [1] P. Wang, Z. Y. Gao and L. Bertling, "Operational Adequacy Studies of Power Systems with Wind Farms and Energy Storages", *IEEE Trans. Power Syst.*, vol. 27, pp. 2377-2384, Nov. 2012.
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