TRANSMISSION EXPANSION PLANNING AND UNIT COMMITMENT WITH LARGE-SCALE INTEGRATION OF WIND POWER

by

ZHI WU

A thesis submitted to

The University of Birmingham

for the degree of

DOCTOR OF PHILOSOPHY

Department of Electronic, Electrical

and Systems Engineering

University of Birmingham

March 2016

To my parents

ACKNOWLEDGEMENT

Finally, I must express my greatest appreciation for my parents, Mr. Shangliang Wu and Mrs. Shoufang Qin, for their endless love and support in all my life.

ABSTRACT

The large-scale integration of wind generation into the power system brings great challenges to transmission expansion planning (TEP) and unit commitment (UC). The intermittence nature of wind generation needs to be fully considered in these two problems, which stimulates the research of this thesis.

The selection of candidate lines is the prerequisite for the TEP problem. Considering the limitations of manual selection approach, a method to select candidate lines automatically is proposed, which consists of five stages to reinforce existing corridors and new corridors. Results of the two test systems illustrate that the locational marginal price difference is neither sufficient nor necessary condition for candidate lines. The uncertainty of load demand and wind power is studied both in the TEP and UC problems. In the term of TEP, a two-stage stochastic formulation of TEP is proposed. The stochastic dual dynamic programming (SDDP) approach is applied to consider the uncertainty, and the whole model is solved by Benders decomposition (BD) technique. In the term of UC, the chance-constrained two-stage programming formulation is proposed for the day-ahead UC problem. The chance-constrained stochastic programming formulation is converted into an equivalent deterministic formulation by a sequence of approximation and verification.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AC   Alternating Current

BD   Benders Decomposition

CCP   Chance-Constrained Programming

CHA   Constructive Heuristic Algorithm

CVaR   Conditional Value at Risk

DC   Direct Current

DTEPM   Deterministic Transmission Expansion Planning Model

EENS   Expected Energy Not Supplied

ELNS   Expected Load Not Served

FACTS   Flexible AC Transmission System

GEP   Generation Expansion Planning

GA   Genetic Algorithm

GRASP   Greedy Randomised Adaptive Search Procedure

ISO   Independent System Operator

KKT   Karush-Kuhn-Tucker

LMP   Locational Marginal Price

LMPM   LMP Model

LOLE   Loss of Load Expectation

LOLP   Loss of Load Probability

LOWP   Loss of Wind Probability

LP	Linear Programming
MIP	Mixed-Integer Programming
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Nonlinear Programming
NSGA II	Non-Dominated Sorting Genetic Algorithm II
PDF	Probability Distribution Function
PSO	Particle Swarm Optimisation
RUC	Robust Unit Commitment
RES	Renewable Energy Sources
SAA	Sample Average Approximation
SDDP	Stochastic Dual Dynamic Programming
SUC	Stochastic Unit Commitment
TEP	Transmission Expansion Planning
TLOP	Transmission Line Overloading Probability
UC	Unit Commitment
VaR	Value at Risk

CHAPTER 1 INTRODUCTION

1.1   Background and Motivation

1.1.1   Large-Scale Integration of Renewable Energy Sources

The development of industry and improvement of life quality requires increasing energy consumption. From 1971 to 2012, the global total primary energy supply increased from 6106 to 13371 Mtoe by fuel[1]. According to the report from International Energy Agency, energy demand will increase another 37% by 2040, with an annual average growth rate of 1.1%[2]. To meet increasing power demands, the generation capacity also needs to be expanded. In the past, power generation was mainly from fossil energy, including coal, oil and gas. However, the problem with fossil energy is that it will be exhausted in the next several decades, which is bringing energy crisis to the human society. To lessen dependency on fossil energy, many other power generation techniques have being explored and developed, such as nuclear generation, hydro generation, ocean power generation, renewable generation, and so on. Compared with fossil energy, these new generation techniques are environmental friendly, which can reduce greenhouse gas emissions. The power generation from low-carbon fuels will cover three quarters of the total energy demand by 2040.

Among new generation techniques, renewable energy sources (RES) have been considered as the most favourite choice to replace fossil energy [3, 4]. RES generation generally refers to energy that comes from naturally resources, such as wind, solar, waves and geothermal heat. Figure 1-1 demonstrates the development of RES generation during the last fifteen years. It can be seen that wind generation and solar generation have been rapidly developed, and taken up over two thirds of the overall RES generation.
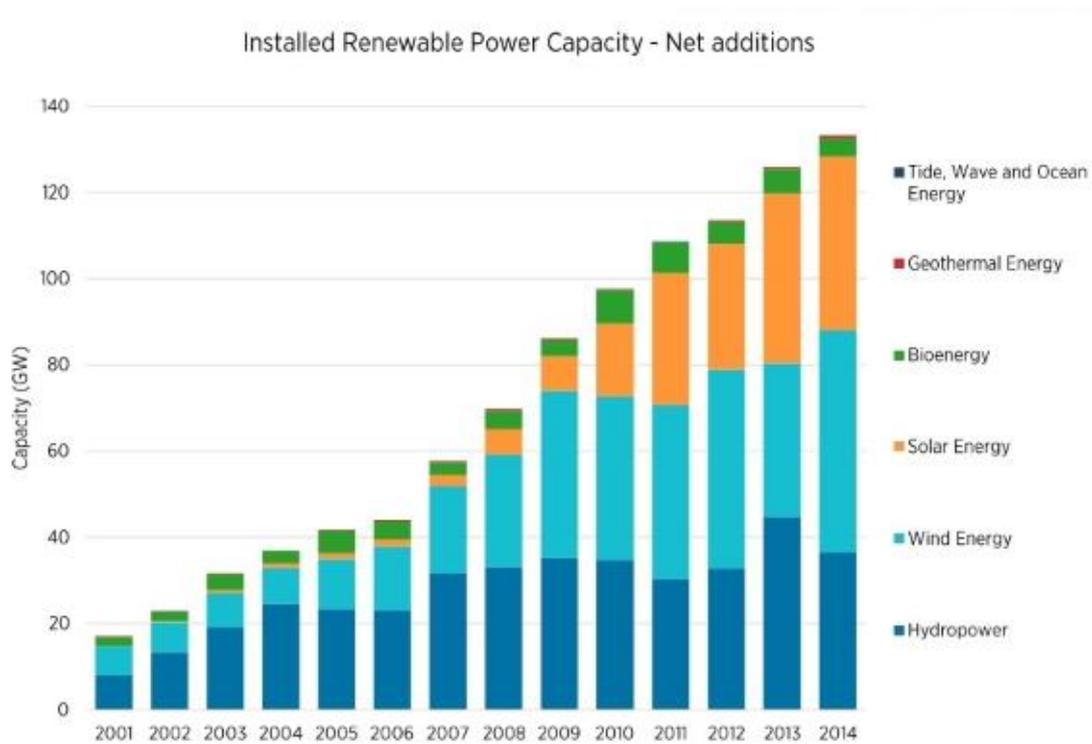
Figure 1-1 Global installed renewable power capacity

Stimulated by policies to enhance energy reliability and sustainability, newly installed capacity of RES in 2014 was 130GW, which contributed more than 45% of net

addition to global generation capacity in the power sector. Costs of renewable generation keep declining in many areas of world. It is expected that renewable energy will account for the largest part of net addition to generation capacity over the medium term. RES will take up almost two thirds of the new generation capacity by 2020. The share of RES in 2013 was 22%, which will increase to over 26% in 2020[5].

According to the report announced in 2012 by National Renewable Energy Laboratory (USA), 80% of total U.S. electricity generation in 2050 can be provided by renewable energy generation from current available technologies. Among 80% of renewable energy, nearly 50% can be from variable wind generation and solar generation[6].

In June 2009, EC/2009/28 was published by the European Commission. It is also known as Renewable Energy Directive. The purpose of the Directive is to establish the framework for supporting wind integration, so that European Union (EU) can achieve a 20% share of EU's energy from RES by 2020. In 2014, the projected share of renewable energy in the gross final energy consumption was 15.3%. Therefore, EU countries are well on the way to meeting the EU's target for 20% renewable energy in the overall energy supply by 2020 [7].

Each member was set to achieve a target. EU is expected to achieve 24% and 29% share of RES in the gross final energy consumption, in 2030 and 2050 respectively. In power generation particularly, the share of RES will reach 43% and 50% by 2030 and 2050 respectively[8].

China has established its renewable energy law to support the development of renewable energy, by the combination of mandatory targets, market incentives and direct subsidy. By 2015, renewable energy accounted for about 11.4% of total energy consumption, and the target by 2020 is expected to be 15%[9].

Among renewable generation, wind generation, solar generation and hydro generation account for the most of the part. From 1996 to 2014, the global wind power cumulative capacity increased from 6.1GW to 365.4GW, which was rapidly expanded during the past two decades. More advanced wind turbine designs continue to evolve to support the development of onshore and offshore wind generation, which enables a wide range of installation locations and operation conditions. Currently, cost for wind energy is the least, so new installations of wind farms continue to emerge in Asia, Africa and South America. Asia keeps the largest market led by China, which exceeds the total capacity in Europe. In several countries, the penetration level of wind generation has over 20% of total load demands, including Denmark, Nicaragua, Portugal and Spain.

Behind wind generation, solar generation takes up the second-largest source of new capacity in the adding renewable generation in 2014, driven by cost reductions. Figure 1-2 shows the U.S. solar installation capacity and solar price from 2005 to 2015. It can be seen that the solar installation capacity increases rapidly in recent years, while cost decreases from about 8 $/watt to less than 3 $/watt[10]. In 2014, another 40GW of solar generation was installed, with the global total cumulative capacity about 177GW. Solar installation hit 59GW in 2015 and 64GW to come in 2016 [11]. In some countries, solar generation has been taking up a considerable percentage in the overall generation. German has the largest solar capacity and contribution to the energy supply. China, Japan and U.S. account for the vast majority of the new solar installation[5].
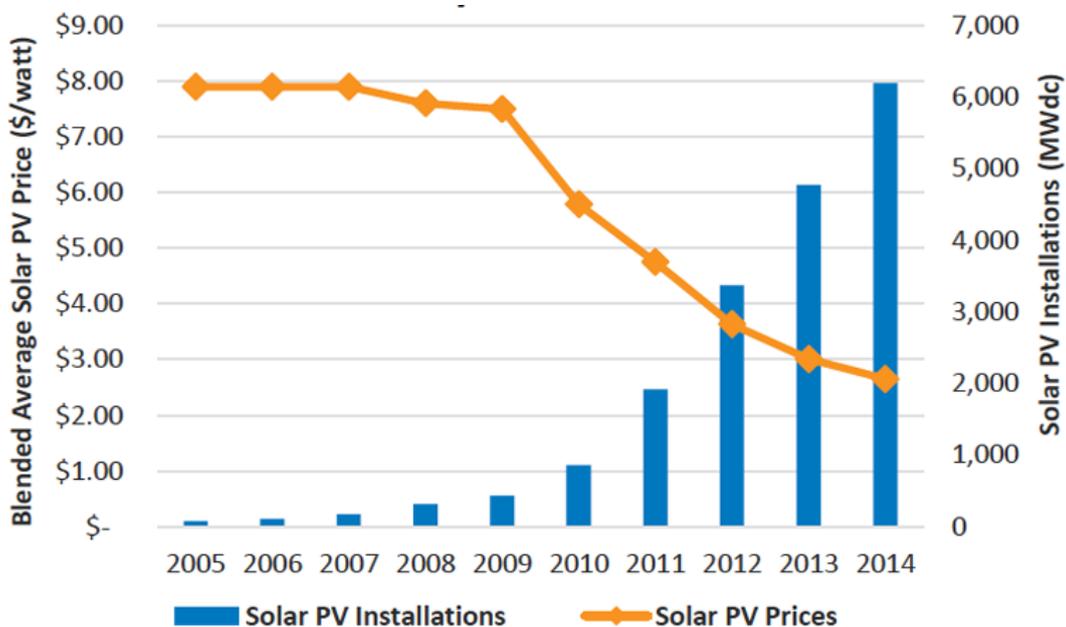
Figure 1-2 Solar installation capacity and solar price

1.1.2 Transmission Expansion Planning and Unit Commitment Considering Uncertainties

A typical electric power system includes generation, transmission, sub-transmission and distribution, which can be seen in Figure 1-3. The transmission system interconnects the generation stations to large substations near to the load centres.
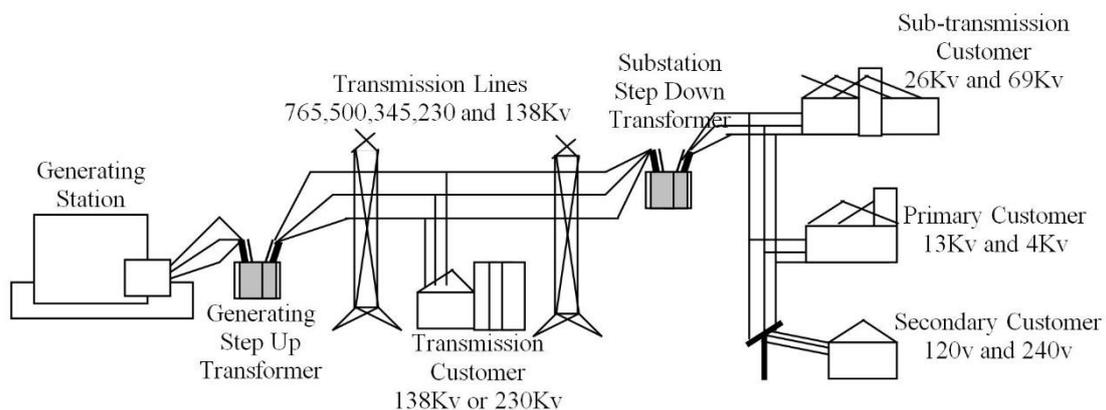
Figure 1-3 A typical electric power system[12]

Transmission expansion planning (TEP) is to determine when and where to build new lines to provide sufficient transmission capability, so that it can meet increasing load demands and generation capacity over a given time horizon. Unit commitment (UC) is to determine the optimal schedule and generation level of each generation unit over a given period of time period, while meeting various constraints (physical constraints, system-wide constraints, reliability constraints, etc.). There are two main uncertain sources both in TEP and UC problems: load demand and generation availability.

Generally, load demands increase annually with a certain rate, which might be affected by many factors, such as development of industry, improvement of human life, and so on. So load demands during the planning horizon can only be forecasted according to the historical data. Also, in the time scale of one day, load demands during the day time are quite different from those in the night; in the time scale of seasons, the average of load demands in each season also might vary in a quite large scope, which can be seen in Figure 1-4. So the forecast of load demands cannot be very accurate, which brings great uncertainties to problems of UC and TEP.
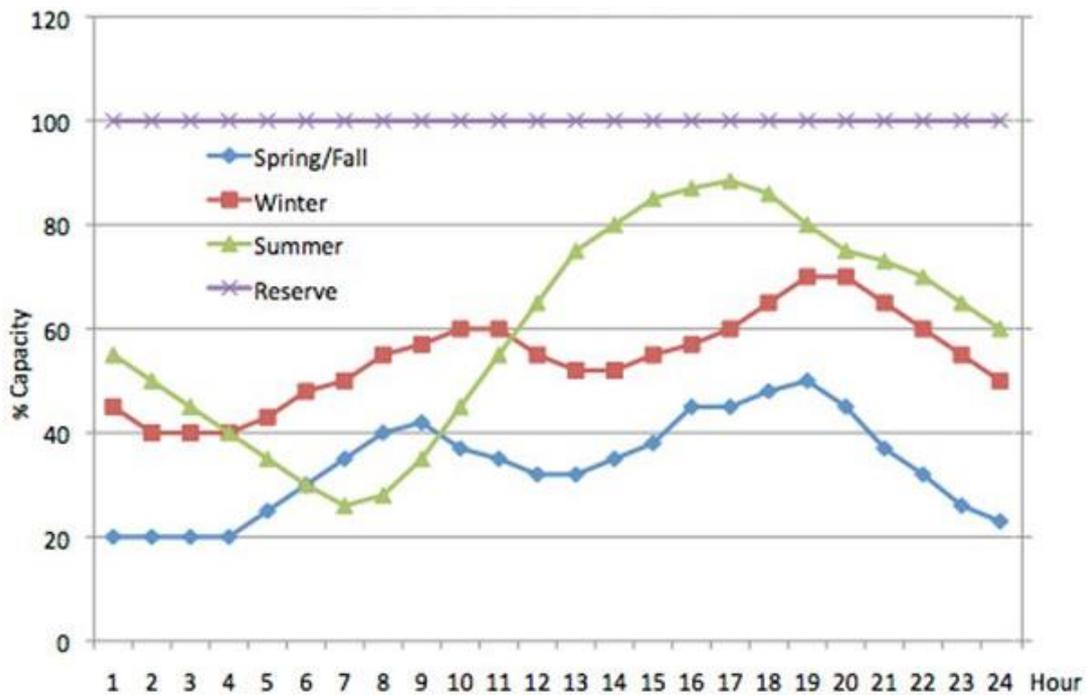
Figure 1-4 Typical demand patterns over the year[13]

Another uncertain source is the generation availability. Generation availability refers to the power that various generation can provide during a certain period. In a network, generation techniques might include conventional generation, renewable generation, nuclear generation, and so on. The power of conventional generation and nuclear generation are dispatchable. That is to say, these two generation techniques can adjust power generation from very low generation to the maximum install capacity. However, the power from renewable generation is not dispatchable. For example, wind generation is determined by the wind speed; solar generation is determined by the intensity of the sunlight. The generation availability of conventional generation techniques and nuclear generation is certain and dispatchable. The generation availability of renewable generation is uncertain and undispatchable. The uncertain generation availability affects both UC and TEP. To illustrate the importance of generation availability, two simple scenarios are taken as the example, and load demands in two scenarios are the same. In the first scenario, renewable generation is in a low level; while in the second scenario, renewable generation is in a high level. In many countries, renewable generation has the priority over conventional generation[14]. So in the second scenario, enough transmission capacity should be provided to support renewable generation. It is a great operation challenge for the grid operator when the penetration of undispatchable renewable generation is in a high level, but the remaining conventional generation and nuclear generation only has a

limited flexibility. Different scenarios of renewable generation might happen during the practical operation, so the transmission network should be able to accommodate various scenarios and to perform in a robust way. Also, the schedule of generation units should has a sufficient flexibility to accommodate the fluctuation of wind generation.

Besides uncertainties, another important issue brought by renewable generation is the trend of multi-regional interconnection. This is because areas rich of renewable energy are always far away from load centres. Take the situation in China as an example, the left part of Figure 1-5 shows the wind resource distribution in China, and it can be seen that wind-rich areas are mostly located at the northwest, north and northeast of China. However, load centres are located at the middle east of China. The right part of Figure 1-5 demonstrates China power grid expansion plan for 2020. Many transmission lines are going to be built to deliver huge wind generation to load centres. To enable the large-scale integration of renewable generation, multi-regional interconnection is an essential approach to secure system operations. So during the planning stage, a close cooperation between different regions is required. For example, in Texas, U.S., much effort has been undertaken to explore areas rich of wind resources and regions where new wind installation can take place (called Competitive Renewable Energy Zones). Corresponding transmission lines are going to be built to access those areas, so that wind generation can be connected to the grid shortly after

construction[6]. The multi-regional wind transmission also increases the complexity of UC. The limited flexibility of conventional generation should be optimal dispatched, so that the utilisation level of wind generation can be maximised.

In some cases, the facility might run on its own generation sources rather than the main grid. This situation refers to the term, islanding. It can either happen as the result of a power black-out or be set up intentionally. For example, a distinct island in the sea, away from the main grid. The power supply can be from wind generation or solar generation. Under such circumstance, the energy storage system becomes very important to ensure the stable power supply. The UC problem for an islanding system is quite different from the traditional UC problem.

Another important trend of power system is the development of interconnection between national electricity markets. Take the interconnection in EU for example, the target is that at least 10% of the electricity produced by each member state's power plants can be sent across its borders to neighbours[15]. The interconnection can bring a variety of benefits. Firstly, it can improve the reliability of supply and enable greater penetration of wind generation. The interconnection is an important tool to manage the fluctuation of wind generation, allowing countries such as UK to import electricity from hydropower in Norway, nuclear in France and so on. Secondly, the cost of electricity to consumers can be reduced by increasing use of the cheapest generation sources in the connected markets. Thirdly, the interconnection can also support

diversification of the energy mix and integration of low-carbon technologies. The trend of interconnection makes the work of TEP to be more complicated and more coordination is required to carry out TEP over a large power network, including many countries.
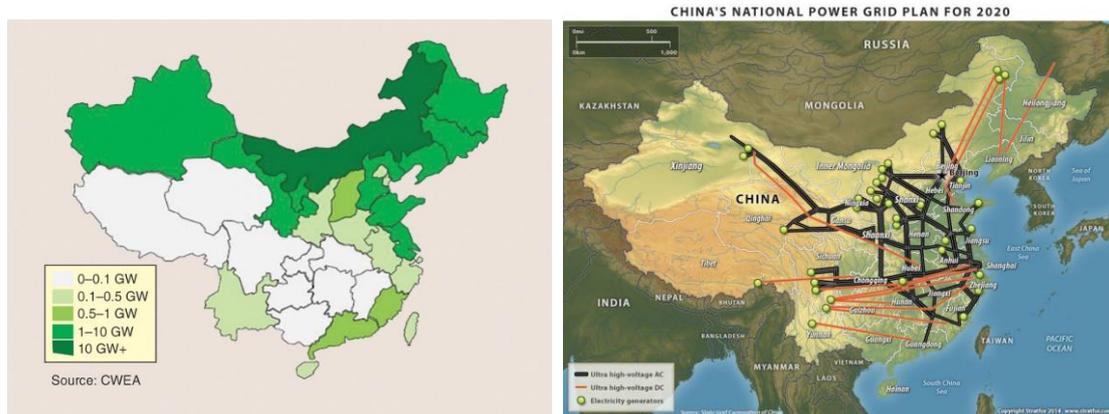
Figure 1-5 (left) Distribution of wind resource in China; (right) China power grid plan for 2020.

1.1.3   Motivation

The problems of TEP and UC are complicated and have been widely studied during the last several decades. Considering the great impact of uncertainties to the problems of TEP and UC, it is worthwhile to study TEP and UC with the consideration of uncertain load demand and wind generation. In the term of TEP problem, it is one of the most important tasks for the power system, because the transmission network provides connections between the generation and the load demand. With the large-scale integration of wind generation, the transmission network should have the capability to accommodate the intermittent wind generation. How to design such

transmission network in an optimal and robust way is quite challenging. In the term of UC problem, it is also very critical since it determines the profile for each generation unit to provide sufficient generation capacity to meet load demand. Due to the fluctuation of wind generation, it is also a challenging work to make the arrangement for generation units to ensure the load demand can be met in a stable and economic way.

Although lots of work has been done to address the problems of TEP and UC, the research work with the consideration of uncertainties still needs to be enhanced. For example, how to select the candidate lines for the TEP is still in its preliminary stage. Therefore, it is worthwhile to carry out studies about TEP and UC, from the aspects of: 1) the selection method of candidate lines for TEP; 2) the stochastic TEP problem with the certainties of load demand and wind generation; and 3) the chance-constrained day-ahead UC problem with the uncertainties of load demand and wind generation.

1.2   Research Focus, Objective and Contributions

1.2.1   Research Focus

Under the ongoing trend of large-scale integration of wind generation, more and more challenges are coming up, in terms of TEP, UC and so on. In this thesis, how to carry

out TEP and UC under uncertainties brought by the integration of wind generation is investigated from three main aspects.

Firstly, TEP is to determine when and where to build new lines, and it can be expressed as a mixed-integer programming (MIP) or mixed-integer linear programming (MILP). It is well known that the MIP or MILP problem is hard to solve, so that the problem should be controlled to be within a reasonable size. MIP and MILP are NP-hard problems. It is really difficult to measure the computational difficulty of the MIP or MILP. Currently, there are no practical complexity measurements for MILP formulations and instances. All lines connecting any two buses can be considered as candidate lines, and TEP selects some of those candidate lines to build. However, if all those possible lines are taken as candidate lines, then the size of the TEP might be beyond the computation capability. So the common way is that planners provide a set of candidate lines in advance, and TEP just needs to determine the expansion plan from the provided set of candidate lines. The completeness of the candidate set has a great influence on the performance of the expansion plan obtained by TEP. If some optimal lines are not included in the candidate set, then it cannot be selected by TEP. So the selection of candidate set is an essential work for TEP. However, up to now, only little research work has focused on this issue [16, 17]. Traditionally, the candidate set is manually selected by planners,

which is facing great challenges. So the first research focus is to propose an approach to select the candidate set automatically.

Secondly, when determining the expansion plan, it needs to consider both investment cost for building new lines and operation cost for generation. The best expansion plan should make a trade-off between investment cost and operation cost. Operation cost depends on the availability of various generation (dispatchable generation and undispatchable generation). However, wind generation has the characteristic of uncertainty, so operation cost is also uncertain. So how to determine the expansion plan under great uncertainties of wind generation and load demands is another research focus of this thesis.

Thirdly, under the vast fluctuation of wind generation, the limited flexibility provided by conventional generation might be not sufficient to provide up/down spinning reserve capacity. In some extreme scenarios, three constraints might be violated: (1) load shedding, because there is no sufficient up spinning reserve capacity; (2) the utilisation level of wind generation might be violated under some realisations of wind generation; (3) the power flow of transmission lines might exceed corresponding transmission capacity under some circumstance. However, it is not economic to provide excessive up/down spinning reserve amount to prevent the happening of some extreme cases, which only have a very small probability. A reasonable way is to permit the violation of some constraints under some extreme scenarios. So this

problem can be modelled by chance-constrained programming (CCP). How to establish and solve chance-constrained stochastic programming for UC is the third research focus of this thesis.

1.2.2 Objectives

According to the three research focuses mentioned above, the research objectives of this thesis can be summarised as follows:

Firstly, to deal with the shortcomings of the manual selection of candidate lines, this thesis is going to propose an approach to select candidate lines automatically. The set of candidate lines selected by the proposed approach should make a trade-off between the size of the set and the completeness of the set. The proposed approach should be applicable to facilitate the expert planners to carry out TEP.

Secondly, to deal with the increasing wind generation in the TEP, this thesis will propose an approach to determine the optimal TEP with the consideration of uncertainty of load demand and wind generation. The N-k reliability criteria need to be considered in the problem. Both the investment cost of new lines and operation cost of generation should be considered together.

Thirdly, because of the integration of wind generation, it is more realistic to allow some constraints can be violated in some extreme scenarios but with a very small probability. In this thesis, the method of CCP will be applied to model the UC

problem with chance constraints. A new approach to solve the CCP-based problem is also going to be proposed.

1.2.3   Contributions

According to the above three research focuses, main contributions of this thesis can be divided into three parts according to three research focuses, and summarised as follows:

Firstly, to deal with the shortcomings of manual selection of candidate lines, an automatic selection method of candidate lines for TEP is proposed. This method has the following contributions:

➢ The proposed selection method for candidate lines includes five stages, which are the combination of enforcing existing transmission corridors in the first two stages and exploring new corridors in the latter three stages.

➢ A method to determine candidate buses is proposed. Through the identification of candidate buses, the complexity to select new corridors is greatly reduced.

➢ N-k reliability criteria are well-considered during the process of selecting candidate lines.

➢ Linear relaxation is applied to improve the completeness of candidate lines, as well as to reduce the required computation time.

➢ The case study shows that the LMP difference is neither sufficient nor necessary

condition for the selection of candidate lines.

Secondly, a two-stage stochastic dual dynamic programming (SDDP) for the TEP problem is proposed, and the contributions of this method can be summarised as follows:

➢ A two-stage stochastic model for the TEP problem is established, with the overall objective to minimise the sum of investment cost and the expectation of operation cost, considering uncertainties of load demand and wind generation.

➢ Benders decomposition (BD) approach is applied to reduce the computation complexity, while to enable the capability to consider N-k reliability criteria into the TEP problem.

➢ SDDP algorithm is implemented to get the optimal expansion plan under uncertainties. This algorithm

Thirdly, to deal with the UC problem under uncertainties, the chance-constrained two-stage stochastic program for UC problem is proposed, including chance constraints for loss of load probability (LOLP), loss of wind probability (LOWP) and transmission line overloading probability (TLOP). A new approach is proposed to convert chance constraints into equivalent deterministic constraints. The main contributions of this method are summarised as follows:

➢ A chance-constrained two-stage stochastic program for UC problem is

formulated, subject to chance constraints for LOLP, LOWP and TLOP.

➢ A new approach to convert the proposed chance-constrained formulation into the equivalent deterministic formulation is proposed by a sequence of approximation and verification.

➢ Correlations between load demand and wind generation can be fully considered by the proposed method.

1.3 Thesis Outlines

Based on the above three research focuses, the content of each chapter is summarised as follows:

Chapter 2: A literature review about existing research about TEP and UC is carried out. According to the three research focuses, the corresponding review about each research focus is presented in detail.

Chapter 3: An automatic selection method for candidate lines is presented in this chapter, which explain the five stages of the selection method in detail. The concept of Locational marginal price (LMP) is brief introduced, and how to use LMP to select candidate lines is presented. To verify the performance of the proposed method, case studies are carried out on two test systems.

Chapter 4: This chapter presents a two-stage SDDP for TEP with large-scale integration of wind generation. A detail two-stage formulation of TEP is firstly presented, followed by the basic introduction of SDDP for a two-stage problem and the overall procedure of SDDP algorithm. The whole problem is solved by the application of BD. The proposed method is evaluated on two test systems. Expansion plans under the SDDP approach and the deterministic approach are compared.

Chapter 5: A new solving algorithm to the chance-constrained two-stage stochastic programme for UC with large-scale integration of wind is presented in this chapter. Firstly, the mathematical formulation of the chance-constrained two-stage stochastic UC problem is presented, with a detail introduction of first stage and second stage problem. Secondly, how to convert chance constraints into equivalent deterministic constraints is explained. Thirdly, a new solving algorithm for the proposed formulation is presented, followed by case studies on two test systems.

Chapter 6: The research work of this thesis is concluded in this chapter, together with the further research topics.

The main research work is presented in Chapter 3, 4 and 5, which deal with the three research focuses, respectively. Chapter 3 aims to select the set of candidate lines for the TEP problem. Uncertainties of load demand and wind generation are both

considered in the TEP problem and UC problem, which are the focus of Chapter 4 and

Chapter 5, respectively.

CHAPTER 2 LITERATURE REVIEW

2.1   Introduction

This chapter aims to give a comprehensive review related to the three research topics of this thesis. Firstly, the existing studies about the selection method of candidate lines in TEP are reviewed. Secondly, the review about the TEP, in terms of modelling, solving approaches, reliability and uncertainties, is carried out. Thirdly, the existing studies about UC, in terms of stochastic programming, robust optimisation and chance-constrained programming, are summarised.

2.2   Overview of Selecting Candidate lines

The TEP problem is generally modelled as a MIP or MILP problem, which poses challenges in solving, especially when the size of integer variables is large. In the TEP problem, integer variables represent decisions whether one transmission line should be built or not. For the sake of tractability of the problem, it is better not to consider all transmission corridors as candidate lines. Otherwise, the size of the problem would be too large to solve. For example, if there are 100 buses in one network, and the line between any two buses is considered as a candidate line, then the total candidate lines would be as many as 100*99/2=4950. If the TEP problem is formulated as a five-year dynamic planning, then the number of total integer variables would become 4950*5=24750. Although most possible lines can be eliminated for the reasons of

geographical condition, length of transmission line, and so on, many possible lines remain to be identified. So in practice, expert planners manually select a set of certain promising candidate lines and then TEP determines which lines should be built, by selecting from the given candidate set. The performance of the final expansion plan relies on the provided candidate set. However, the current common practice is that candidate lines are selected according to experts' experience or some reliability requirements. However, it is quite possible that some better candidate lines are not included into the candidate set, which leads to the suboptimality of the final expansion plan.

Currently, researches about how to select candidate lines are very limited. Only few papers focused on this problem. In [16], a candidate selection algorithm was proposed to select candidate lines automatically, without the intervention of expert planners. The potential candidate lines were selected according two aspects: the investment cost of one line and the potential benefit obtained if the line would be built. The potential benefit is approximated according to the LMP difference and the capacity of the line. If the potential benefit of one line is larger than the corresponding investment cost, then the line is selected as candidate lines. Considering the number of candidate lines selected according to the established approach can still result in an unmanageable size, a method was proposed in [16] to control the size of the candidate set by implementing the linear relaxation approach to remove unnecessary candidate lines.

In [17], candidate lines were also selected according to the LMP difference between any two buses. It states that the LMP difference is a necessary but not sufficient condition to select candidate lines. Both [16, 17] assume that the candidate lines can be fully explored according to the LMP difference. However, the potential benefit evaluated by the LMP difference might deviate from the real benefit, which leads to the failure of this assumption. For example, even the LMP difference between two buses is very large; the potential benefit might be small by building a new line between these two buses. Or, even though the LMP difference is small, the potential benefit might be greater than the investment cost.

The assumption in [16, 17] stated that the candidate lines can be selected according to the LMP difference. However, according to the case studies on two test systems, this assumption is not always feasible. In this thesis, an approach to select candidate lines is proposed, to overcome the disadvantage of the assumption mentioned above. The detail of this approach is presented in Chapter 3.

2.3   Overview of Transmission Expansion Planning

The power system expansion is one of the most important issues in the power system studies. Power system expansion can be divided into three categories: generation expansion planning (GEP), TEP and distribution expansion planning. Regarding TEP, it has been widely investigated in terms of different research focuses.

TEP is to determine the optimal expansion plan to meet the increasing transmission

capacity requirement. Different objective functions have been considered in the TEP, including investment cost, operation cost, congestion cost, reliability cost and so on. Constraints can be divided into two categories: mandatory constraints and optional constraints. Mandatory constraints include generation limits, transmission line power flow limits, no load shedding in normal operation and so on. Optional constraints vary from different research focuses, which include investment cost limits, reliability limits, wind utilisation level limits and so on. In the following part, a comprehensive review about the previous TEP studies will be carried out.

2.3.1   Static Planning and Dynamic Planning

From the perspective of planning horizon, TEP problem can be classified as static planning and dynamic planning. In the static planning, the factor of time is not included in the TEP model, and the expansion plan is determined for a single year. For example, TEP can determine the optimal transmission configuration for the fifth years from now on. In the static planning, it does not consider when to build those new lines over the five years. That is to say, the sequence to build new lines is not taken into account. The static TEP planning can provide an outlook of the further power grid, but further work needs to be done to determine which lines need to be built in each year.

In the dynamic planning, it determines the sequence of new lines to be built in each year over the planning horizon. Different sequences lead to different transmission

configurations in each year, which further affect the system operation. The expansion plan for each year is mutually coupled with each other, that is, the expansion plan for the current year affects the expansion plan for the following years. So the dynamic planning is more complex and time-consuming than the static planning. More researches about dynamic planning have been carried out to provide a clear view of the transmission network in each year over the planning horizon. However, considering the complexity of dynamic programming, advanced solving methods need to be applied, such as the decomposition technique to decompose the dynamic programing into several single stage problems [18, 19].

2.3.2 AC Model and DC Model

There are two general modelling methods for TEP problem, AC (alternating current) model [20] or DC (direct current) model [21]. As we all know, AC power flow is more complicated and accurate than the DC power flow. Both of these two models have been widely studied in TEP problem.

For the DC model, it is easy to compute the DC power flow, and it does not have the problem of convergence. However, there are some disadvantages for the DC model, which can be summarised as follows:

   1) In the DC model, the reactive power is neglected, as well as the amplitude of the voltage. As the result, only the approximated active power in each line and

the voltage angle at each bus are derived, rather than the exact system information in terms of active power, reactive power, voltage amplitude and voltage angle.

2) In most cases, the power loss in DC model is neglected, based on the assumption that the line loss is limited and can be ignored. However, this assumption might bring problems for the long term transmission expansion, where line losses might play a very important role over a long planning horizon, such as 20 years.

In [22, 23], a pricewise linearisation method was proposed to approximately represent the active power loss in the DC model.

3) The expansion plan obtained through DC model cannot be implemented directly into the practical construction. The obtained plan needs to be further verified and reinforced by the system simulation using AC model.

For the AC model, it is more accurate than the DC model. Advantages to use AC model can be summarised into the following aspects:

1) In the AC model, the reactive power can be considered. That is to say, the reactive planning can be carried out together with the TEP.

2) The power loss can be fully considered in the AC model. So the problem brought by neglecting power loss can be eliminated.

3) Other components such as FACTS (Flexible AC Transmission System) devices

can be considered in the AC model. FACTS devices have been widely applied in the current power grid, and will play an important role in the future network.

4) More studies can be carried out in the AC model, such as voltage stability analysis, reliability analysis and so on.

Although the AC model has many advantages over the DC model, it also has the following disadvantages, which are related to the computation complexity.

1) the AC model is a large and complex non-linear problem, which needs great efforts to solve it.

2) The AC model is time-consuming and has the problem of convergence. Efficient solving techniques are required.

3) AC model fails to deal with the disconnected systems. At the beginning of TEP, some buses have not been connected with other buses. For example, when a new generation or a new transformer station is established and considered as a new bus, then this bus has not been connected with other buses. In this situation, the AC model confronts the problem of disconnection[24].

2.3.3   Transmission Expansion Planning and Generation Expansion Planning

GEP, which is to determine the investment on new generation facilities to meet the increasing load demands, is another important expansion plan in the power system.

Different aspects need to be considered in the GEP problem, such as sizing, timing, and available technologies of new generation units. Also, investors consider the expected profits, risks and investment reversibility.

As the process of market liberalisation and restructuring, generation companies (GenCos) have the freedom to build new generation units, and their decisions are not directly affected by the transmission planners. That is to say, TEP and GEP are dependent on each other. However, in reality, both expansion plans need to be verified and confirmed by the independent system operator (ISO). ISO can provide collaboration between TEP and GEP. The main objective of TEP is to determine the optimal expansion plan, which can improve the competition level among all the power market participants. During the TEP process, it needs to incorporate with GenCos' decisions, so that the expansion plan for the transmission network can match with the expansion plan for the new generation units. TEP and GEP are strongly coupled with each other. Moreover, as the GEP and TEP can both be formulated as the MILP problem, it is possible to form a single objective function to consider both GEP and TEP simultaneously in a competitive market.

Many studies have been carried out based on the assumption that the GEP and TEP collaborate with each other [25-29]. In [25], a tri-level optimisation algorithm was presented with multi-objectives: maximising the social welfare, maximising the profit of generation companies and maximising the congestion cost in TEP. In [26], a

bi-level optimisation for coordination between TEP and GEP based on game approaches in a competitive market was proposed. The upper level is the TEP problem under different market incentives, while the lower level is to calculate the expected outcome of the market where generation firms compete with each other to determine their investment on new generation units. The whole problem was formulated as a mixed-integer nonlinear programming (MINLP) solved by the duality theory and Karush-Kuhn-Tucker (KKT) optimality conditions. In [27], an integrated GEP and TEP model was proposed, considering bus voltage limits, through the reactive power simplification. In [28], a multi-objective planning method for GEP and TEP was proposed to simultaneously minimise total costs of planning (including operation cost and investment cost), total emission (including NO_x and SO_2) and ELNS (Expected Load Not Served). In [29], a tri-level equilibrium model for the combined TEP and GEP was established. The lower level is the pool-based market operation, representing the equilibrium of ISO and GenCos; the intermediate level represents the generation investment to maximise GenCos profits; the high level is the transmission investment problem to minimise operation and investment cost. In the lower level, the KKT condition is applied, while Nash equilibrium[30] is applied at the second level. The whole problem is converted into a MILP problem.

2.3.4 Transmission Expansion Planning Solving Methods

The TEP problem is complex and there are many different planning objectives, which might even be in conflict with each other. To solve different TEP problems, many solving methods have been investigated, which can be classified into three groups: mathematical optimisation methods, heuristic methods and meta-heuristic methods.

1) Mathematical optimisation methods

Most of the popular mathematical optimisation methods have been studied in the TEP, which can be summarised as follows.

In [31], linear programming (LP) was utilised to transform the nonlinear problem into the linear problem. In [32], the penalty for load curtailment was calculated through LP. The most popular approach in the TEP studies is MIP, for the reason that the TEP problem itself is a binary problem. For example, in [22, 23, 31, 33], the TEP problem was modelled as a MIP problem. When considering the operation cost or penalty of load curtailment, the TEP is commonly modelled as a MILP problem, which is a combination of the LP and MIP problem.

Another widely applied approach is BD, which can decouple the original complicated MILP problem, into a master problem (MIP problem) and sub-problems (LP problem). BD has been successfully implemented in many literatures [34-37]. In [34], BD approach was used to create initial cuts for the DC model, and the cuts were passed

onto the second stage problem with the AC model. In [35], the Gomory cuts were considered in BD to improve the convergence performance. In [36], uncertainties of wind generation and loads demands were considered to establish a probabilistic TEP problem. The BD algorithm and Monte Carlo simulation were both applied to solve the problem. In [37], a two-stage stochastic program for TEP was proposed, considering the joint distribution of load demands and wind generation by using a Gaussian copula. The decomposition approach was applied to get the upper bound and lower bound of the problem with the help of a sample average approximation (SAA) algorithm.

Besides the BD approach, the branch-bound method is also widely applied in the TEP problem [38-41]. In [38], a branch-bound algorithm was applied to solve the TEP problem using the DC model, while considering transmission line losses. The overall problem was formulated as a MINLP problem and the nonlinear programming problem was solved by an interior-point method at each node of the branch-bound tree. In [39], the TEP problem was solved by a constructive heuristic algorithm embedded in a branch-bound structure.

Normally, the optimal solution obtained through mathematical optimisation methods needs many simplifications, which reduces the feasibility of results.

2) Heuristic methods

The constructive heuristic algorithm (CHA) is the most widely investigated heuristic methods in the TEP problem. In [39], the TEP problem was solved by CHA embedded in a branch-bound structure. In [42], CHA was used to identify the most promising lines from a given set of candidate lines to reduce the search space.

In [43], another heuristic algorithm, called greedy randomised adaptive search procedure (GRASP), was applied to reduce the search space of the multistage TEP problem, together with the concept of a binary numeral system to reduce the number of binary and continuous variables related to the candidate lines and other network constraints.

The heuristic methods are quite easy to understand and implement. However, the disadvantages with such methods are that they lack robustness to solve different problems and lack reliability for the complex problems.

3) meta-heuristic methods

The TEP problem is rather complicated, especially when the size of the problem is large. In some cases, it is hard to use mathematical methods and heuristic methods to get results, which is the motivation to explore the meta-heuristic methods. Various meta-heuristic methods have been investigated in the TEP problem.

Among so many meta-heuristic methods, genetic algorithm (GA) is the most widely studied one in the TEP problem. In [44], a controlled non-dominated sorting genetic

algorithm II (NSGA II) was applied to solve TEP, with two objectives: minimising investment cost for new lines and minimising expected energy not supplied (EENS). In [45], NSGA II was also utilised to solve a stochastic multi-stage multi-objective market-based TEP problem, considering investment cost, absorption of private investment and system reliability. The Pareto optimal solutions were obtained, which were then further selected by a compromise-solution method based on decision-maker preferences. In [46], GA was applied to solve the TEP problem, and the fitness function was calculated by using a linearised AC power flow model.

In [47], a meta-heuristic algorithm by the means of differential evaluation algorithm was proposed to solve the TEP problem, using accurate AC power flow models.

In [42], the particle swarm optimisation (PSO) method was applied to find the minimum investment cost for new lines, by using the heuristic information obtained from CHA method. In [48], a modified PSO method was applied to solve TEP problem, by using a new initialisation.

In [49-51], another meta-heuristic algorithm, called tabu search, was applied to solve the TEP problem. In [49, 51], the tabu search and GA algorithm was combined together to overcome the shortcomings of each individual method.

In [52, 53], a recently developed optimisation algorithm, called harmony search algorithm, which imitates the music improvisation process, was applied in the TEP problem.

In [54], a meta-heuristics optimisation algorithm based on Gas Brownian Motion and Turbulent Rotational Motion was developed to solve the TEP problem, where each molecule position represents a possible expansion plan, and all molecules travel in the feasible region of the problem, with the help of two motions.

Meta-heuristics can find optimal or suboptimal solutions even for large-scale problems, at the costs of high computation efforts. Despite computation effort, meta-heuristics approaches especially many hybrid approaches have been widely used in literature.

2.3.5   Consideration of Reliability in Transmission Expansion Planning

TEP projects can be categorised into three types according to the main task: 1) to enhance the reliability of the system; 2) to bring economic benefits to the whole system; 3) to improve regional interconnection. There are other tasks, such as public policy for the purpose of meeting renewable generation integration needs[55]. Any transmission project can improve the transmission capacity, as well as serves all these tasks to some extent. The overall benefits obtained from all these tasks should be fully considered to obtain the final expansion plan.

Among all these categories, the most common task is to enhance the reliability of the whole system and to meet relative reliability criteria. Considering the fact that the penetration level of wind generation is increasing so fast, to ensure the reliability of the system is becoming more and more complicated. Since the reliability is the priority of the system operation, so many TEP projects serve the task of the reliability. The other tasks can also be achieved, after ensuring the reliability criteria. For example, the transmission congestion can be reduced by upgrading the transmission grid.

Figure 2-1 shows the overall procedure for a typical power system planning [56]. The procedure can be summarised into two stages: macro stage and micro stage. In the macro stage, adequacy (the capability to meet the load demand) or other reliability standards are applied to select feasible plans from the various given draft plans determined based on the strategic policy. In the micro stage, the selected plans are examined in detail, in terms of N-k contingency analysis, fault analysis and stability analysis, to ensure the final expansion plan can accommodate the practical operation.
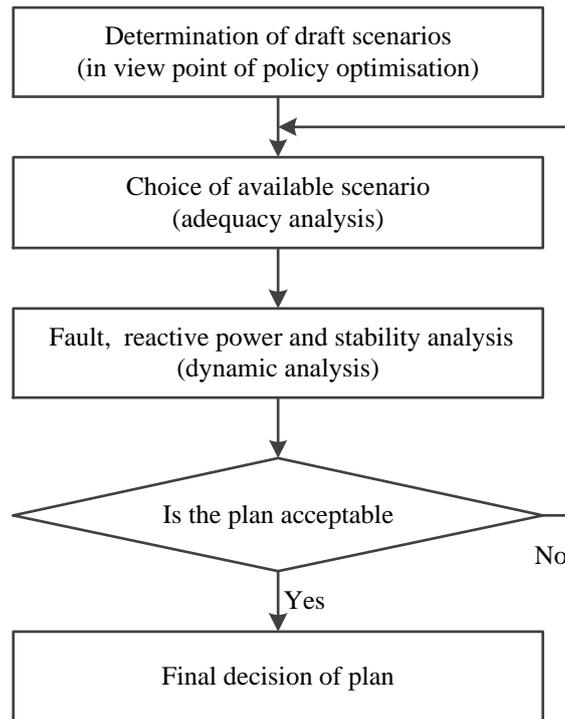
Figure 2-1 General procedure to carry out power system planning

Many different reliability indices have been considered in the TEP problem. In [57], two probabilistic reliability criteria were considered: the loss of load expectation (LOLE) for the whole system and the LOLE for each bus. In [44, 58, 59], EENS was considered as the reliability index for the transmission plans.

Also the reliability criteria can also be included in the TEP to ensure the network can operate in secure under contingencies. According to the transmission planning standards defined by the North American Electric Reliability Corporation (NERC), the system should be able to stabilise without any loss-of-load under the condition that only one element failure occurs (N-1 contingency). In the case of k contingencies (N-k contingency), the system should also restore stability, with the loss-of-load under

a given percentage [21]. In [21, 56, 60, 61], N-k contingency was considered as a constraint for the TEP problem. In [56], the N-k contingency was eliminated if the probability of the contingency is less than the specified probability limit. In [21], an approach was proposed to identify the worst-case loss-of-load for each contingency size by solving bi-level separation problems. In [61], the risk of blackouts was considered in the TEP, to achieve a set of best plans to avoid serious cascading blackouts. In [62], a filtering technique to select relevant contingencies (beyond N-1 criteria), was proposed to get the set of umbrella outages by undertaking a risk assessment of the expected post-fault costs.

2.3.6   Consideration of Uncertainty in Transmission Expansion Planning

Historically, the uncertainty within the TEP has not been widely considered, regarding future generation development and load demand growth. However, the rapid growth of renewable generation entails great uncertainty to the TEP, rendering it is unable to make fully-informed planning, such as unit commitment for the long-term projects. To investigate the impact of uncertainty for the TEP, many literatures have considered the uncertainty of renewable generation, load demands and regulatory policies in different aspects.

In [63], the value of flexible network technologies, including phase-shifting transformers, energy storage and demand side management to accommodate new

sources of renewable generation, was evaluated within a long-term planning strategy, considering the generation uncertainty.

In [64], a risk-control model was developed to avoid overload risks in the presence of large-scale integration of wind generation. The probabilistic power flow was calculated by using cumulants and Gram-Charlier series. Three risk-control strategies were proposed to specify the non-overload margin for all branches and the whole system.

In [65], a two-stage stochastic programming-based tool to support adaptive TEP under market and regulatory uncertainties (three scenarios with distinct renewable electricity mandates, emission policies, and fossil fuel prices) were proposed, and the case study for western electricity coordinating council was carried out.

In [66], the optimal expansion of the transmission network was studied with the consideration of active switching of transmission elements, to improve the capability of integration of large-scale wind generation. A two-stage stochastic model with transmission switching for the TEP problem was established, and solved with the Dantzig-Wolfe reformulation.

In [67], a two-stage stochastic model for the TEP problem was established, considering the uncertainties of wind generation and loads. The solving technique,

SAA, was applied to solve the problem, with the case of the Electric Reliability Council of Texas.

In [68], a multi-objective multi-stage TEP problem considering the life cycle cost was studied, to minimise the life cycle cost and conditional value-at risk of social welfare. Four uncertain factors including the conventional generation, load, transmission line and wind generation were considered.

In [69], two sources of uncertainties, including growth of load demand, the availability of generation capacity, were considered by the approach of an adaptive robust optimisation model, to get an optimal expansion plan by anticipating the worst case realisation of the uncertain parameters within an uncertainty set. The proposed model was formulated as a mixed-integer three-level optimisation problem. The approach of robust optimisation has been widely studied in many other literatures, such as [50, 60, 70-74].

Although the uncertainty has been widely studied in the TEP problem, however the consideration of N-k reliability criteria has not been comprehensively considered. So in this thesis, the problem of TEP under uncertainty considering N-k reliability criteria will be studied.

2.4   Overview of Unit Commitment

UC is one of the most important problems in the power system operations, and it refers to the problem to get an optimal schedule and the production level for each generation unit over a given period of time while meeting operation constraints for generation units (capacity limits and ramping limits), system-wide constraints (load balance, voltage limits, etc.), reliability constraints (N-k reliability) and so on[75]. In a deregulated electricity market, UC is often carried out by ISOs for the day-ahead market clearing, reliability assessment and intra-day operations[76]. The UC problem is a MILP problem, because variables that represent commitment (ON/OFF) of generation units are binary. It has been proved that UC problem is NP-hard, which is very difficult to solve, especially when the size of the problem is relatively large.

UC problem has been widely studied over the past half century[77]. Many different formulations and approaches have been applied to model and solve UC problem. The solution methodologies have evolved over the years. At the beginning, the popular methods were based on priority lists and dynamic programming. Recently, the most commonly ones are based on MILP. Although, UC problem has been well studied in various literatures, the large-scale integration of wind is bringing a great amount of interest to UC modelling and solution methodologies, with the consideration of uncertainties of wind and load demands. Because of the significant intermittence of wind, the system requires more flexibility to deal with the fast and large fluctuations

from load demands and wind generation. Considering the fact that the flexibilities provided by conventional generation units are limited due to physical constraints, so novel UC methods or new devices (e.g. energy storage systems) are required to arrange various generation units and storage devices more efficiently to ensure the secure operation of the system under large variations of wind generation.

Due to the large number of papers related to UC, only the literature addressing day-ahead UC problems considering uncertainties of load demands and wind generation is reviewed in this section.

2.4.1 Stochastic Programming for Unit Commitment

1) Two-stage formulation for stochastic unit commitment

Stochastic unit commitment (SUC) is one of the most popular approach to tackle UC problems involving uncertainties, such as [75, 77-81]. The idea of SUC is to represent uncertainties based on Monte Carlo simulations. A two-stage SUC model is commonly applied to capture uncertainties, and its general form is shown below[76]:

$$\min_{\mathbf{u} \in \mathbb{U}} \mathbf{c}^{\mathrm{T}} \mathbf{u} + E_{\xi} \left[F(\mathbf{u}, \xi) \right] \tag{2-1}$$

where **u** represents the first stage decisions, which are commitment decisions of the generation units. The commitment decisions **u** need to be decided in the day-ahead schedule, because of the physical limits. $\mathbb{U}$ represents the feasible region of the first stage decisions, which needs to satisfy constraints, such as the minimum ON/OFF

requirement[82]. The cost parameters (e.g. startup cost) are represented by $\mathbf{c}$. The second term of (2-1) is the expected cost of second stage real-time operations. ξ represents the uncertain vector with a known joint probability distribution.

For a given realisation s of the random vector ξ, the second stage problem can be represented as follows:

$$F(\mathbf{u}, s) = \min_{\mathbf{p}_s, \mathbf{f}_s} f(\mathbf{p}_s) \tag{2-2}$$

$$s.t. \quad \mathbf{A}_s \mathbf{u} + \mathbf{B}_s \mathbf{p}_s + \mathbf{H}_s \mathbf{f}_s \geq \mathbf{d}_s \tag{2-3}$$

where $\mathbf{p}_s$ represents the vector of second stage decisions, including both production and reserve levels of each unit over multiple time periods. $\mathbf{f}_s$ represents the vector of other second stage decisions (e.g. power flows, bus voltages, bus angles). The function $f(\cdot)$ represents the generation cost for each unit. According to different sources of uncertainties (e.g. equipment outage, wind generation, load demands), the expression of (2-3) can be modelled from different perspectives. For example, the left-hand-side matrices ($\mathbf{A}_s, \mathbf{B}_s, \mathbf{H}_s$) can be applied to model different contingencies (equipment outage [81]). The right-hand-side matrices ($\mathbf{d}_s$) can be used to modelled the uncertain load demands and wind generation [83, 84].

To calculate the expected cost of the second stage real-time operation, a large number of scenarios are required to simulate different realisations of uncertainties, which lead

to a problem with a quite large size. However, second stage problems under different realisations are not related to each other. Once the first stage decision **u** is made, the second stage problem can be solved independently, resulting in many small size individual problems. Because of this characteristic, the technique of decomposition has been widely applied to solve SUC problems. BD algorithm is generally applied when the problem ((2-2) and (2-3)) is a linear one [85, 86]. However, in practice, the objective function $F(\mathbf{u}, s)$ might not be convex or continuous when it includes integer variables. To deal with this dilemma, many other advanced methods have been proposed, such as integer L-shaped method[87], disjunctive cuts[88], convexification of second stage problem[89]. Another method, Langrangian relaxation, is widely applied to divide the original problem into small ones, by dualizing the coupling constraints between different scenarios [90, 91].

2) Stochastic unit commitment considering risk

In most of the literature related to the SUC, the objective is to obtain a minimisation of the expected costs under all realisations of uncertainties. However, under some realizations, they might improve the cost of the objective greatly. To control the risk, a risk-averse UC problem is considered, the objective of which includes both expected costs and risk costs. To control the relevant risk within a given level, some additional constraints are included into the SUC model. Or, another term, representing the cost of risk, is added into the objective function (2-2). Several different risk

measures have been considered, including ELNS [92, 93], variance of the total profit[94], Conditional Value at Risk (CVaR)[95].

ELNS also refers to the Expected Loss of Load, or Load Shedding. It can be calculated by adding up the product of net load unserved under each scenario and its corresponding probability. There are two methods to include ELNS into UC problems. One method is to include ELNS into the objective function as a penalty term, and another method is to consider it as a constraint. Considering ELNS is an expectation value, it cannot know the risk level of a certain schedule might be. So it comes up an idea to deal with this shortcoming, by considering ELNS and variance of profit relating to a set of UC solutions.

Another widely applied risk measure in UC problems is the CVaR, which is derived from Value at Risk (VaR). The meaning of VaR is shown by the following expression:

$$\text{VaR}_\varepsilon(l^\xi) = \inf\left\{l \,\middle|\, \text{Prob}\left(l \geq l^\xi\right) \geq 1 - \varepsilon\right\} \tag{2-4}$$

where l^ξ represents the amount of load shedding required to meet the power balance. ε is the small upper tail probability. $\text{VaR}_\varepsilon(l^\xi)$ is the maximum load shedding with the confidence level $1-\varepsilon$, which also means the probability that loss-of-load exceed $\text{VaR}_\varepsilon(l^\xi)$ is less than ε. However, VaR has several limitations. For instance, it fails to provide information about the extent of potential loss-of-load exceeding $\text{VaR}_\varepsilon(l^\xi)$.

Moreover, VaR is intractable when the problem is calculated based on scenarios. To overcome these disadvantages, CVaR, which is also called mean excess loss, provides a more consistent measure of risk than VaR. The expression of CVaR is shown as follows:

$$\text{CVaR}_{\varepsilon}(l^{\xi}) = \mathbb{E}\left[l^{\xi} \middle| l^{\xi} \geq \text{VaR}_{\varepsilon}(l^{\xi}) \right] \tag{2-5}$$

It can be seen that $\text{CVaR}_{\varepsilon}(l^{\xi})$ is the expectation of load shedding which is larger than the given $\text{VaR}_{\varepsilon}(l^{\xi})$. According to (2-5), $\text{CVaR}_{\varepsilon}(l^{\xi})$ is always greater than or equal to $\text{VaR}_{\varepsilon}(l^{\xi})$. UC solutions with low $\text{CVaR}_{\varepsilon}(l^{\xi})$ must also have the low $\text{VaR}_{\varepsilon}(l^{\xi})$ [96]. CVaR-based models are computationally tractable even when a large number of scenarios are considered [97, 98].

2.4.2   Robust Optimisation for Unit Commitment

In contrast to SUC models, robust unit commitment (RUC) tries to get an optimal solution without knowing the exact probability distributions of random variables, but the range of the uncertainty. In the SUC problem, it minimises the total expected costs under all possible scenarios. However, in the RUC problem, it minimises the worst-case cost regarding all possible realisations of the uncertainty within the given range. Compared with SUC models, solutions generated by RUC are more conservative, but can be obtained without a large number of scenarios.

The existing literature related to RUC problems mostly uses the two-stage RUC

models, which can be summarised as follows:

$$\min_{\mathbf{u} \in \mathbb{U}} \left\{ \mathbf{c}^{\mathrm{T}} \mathbf{u} + \max_{\mathbf{v} \in \mathbb{V}} \left[F(\mathbf{u}, \mathbf{v}) \right] \right\} \tag{2-6}$$

where $\mathbf{u}$ and $\mathbb{U}$ keep the same meaning as defined in the (2-1). $\mathbf{v}$ represents the

vector of uncertain variables, such as uncertain load demands, and uncertain wind

generation. $\mathbb{V}$ represents the vector of uncertainty set. $F(\mathbf{u}, \mathbf{v})$ is the real-time dispatch

cost function under the given first stage decision $\mathbf{u}$ and the given realisation of $\mathbf{v}$. In

the objective of SUC models, as defined by (2-1), the second term is the expected cost

under a large number of scenarios. In RUC models, the second term of the objective is

to maximise the dispatch cost under the given first stage decision $\mathbf{u}$ and within the

uncertainty set $\mathbb{V}$. The overall objective of RUC models is to minimise the total cost of

the worst-case scenario. $F(\mathbf{u}, \mathbf{v})$ can be defined as follows:

$$F(\mathbf{u}, \mathbf{v}) = \max_{\mathbf{p}, \mathbf{f}} \quad f(\mathbf{p}) \tag{2-7}$$

$$s.t. \quad \mathbf{A_v}\mathbf{u} + \mathbf{B_v}\mathbf{p} + \mathbf{H_v}\mathbf{f} \geq \mathbf{d_v} \tag{2-8}$$

Compared with the formulation of the SUC second stage problem, as defined by (2-2)

and (2-3), the formulation of RUC second stage problem is almost the same, except

that $\mathbf{A_v}$, $\mathbf{B_v}$, $\mathbf{H_v}$ and $\mathbf{d_v}$ are functions of the uncertain variables $\mathbf{v}$. RUC models

have been applied to address different uncertainties, mostly in terms of wind availability [99, 100] and power system component contingencies [101, 102].

2.4.3   Chance-Constrained Programming for Unit Commitment

In SUC and RUC models, constraints (such as power balance and transmission capacity) are enforced to be satisfied under all possible scenarios. However, such stringent constraints might result in too conservative UC solutions. For example, to avoid the possibility of load shedding, a large amount of up reserve might be needed. Or, to ensure the system operation reliability under all possible scenarios, there might be considerable amount of wind spillage. To deal with this problem, CCP is applied in some papers [103-109]. The general chance-constrained stochastic problem can be formulated as follows [105]:

$$\min_{\mathbf{x} \in \mathbb{X}} f(\mathbf{x}) \tag{2-9}$$

$$s.t. \quad \Pr\{\mathbf{G}(\mathbf{x}, \xi) \le \mathbf{0}\} \ge 1 - \varepsilon \tag{2-10}$$

where $\mathbf{x}$ represents the vector of decision variables, and $\mathbb{X}$ is the feasible region $\mathbb{X} \subset \mathfrak{R}^n$. ξ is the random variable and its probability distribution is supported on set $\Theta \subset \mathfrak{R}^d$. $\mathbf{G}(\mathbf{x}, \xi)$ represents the constraint mapping $\mathfrak{R}^n \times \mathfrak{R}^d \to \mathfrak{R}^m$. $\mathbf{0}$ represents a vector or zero with m dimensions. $\varepsilon \in (0,1)$ is a predefined probability that constraint $G(x, \xi)$ can be violated. This formulation represents that the objective $f(\mathbf{x})$ is minimised while satisfying the constraint with the confidence level no less than $1 - \varepsilon$.

Problems involving chance constraints cannot be solved directly. There are two main approaches to deal with chance constraints.

The first approach is to convert chance constraints into deterministic constraints, so that problems can be solved. One representative paper of applying this approach to solve the UC problem is [103], in which chance constraints were converted into deterministic ones, and the UC problem was solved iteratively in order to ensure chance constraints were satisfied by the specified confidence level. In [106], chance constraints were also converted into equivalent deterministic linear inequalities, by assuming that probability distributions of load demands were independent from each other.

Another approach is to solve the problem through scenario-based stochastic programming methods. In [105, 107, 109, 110], a chance-constrained two-stage stochastic program for UC was formulated, in which a chance constraint for the wind utilisation was included into the model. The proposed model was solved by the sample average approximation algorithm (SAA).

2.5   Summary

This chapter has reviewed previous research related to TEP and UC problems, which are two important research topics of this thesis. With the rapid development of wind generation, both TEP and UC problems are facing more and more challenges, because of significant uncertainties brought by wind availability and load demands.

This chapter firstly reviewed the existing literatures about TEP problems, in terms of model formulation, solving approaches, the selection of candidate lines and the handling of uncertainties. There are two issues about TEP problems. The first issue is how to select candidate lines for the TEP problem. The second issue is how to deal with uncertainties in the TEP problem.

Then, previous researches about UC problems, especially involving uncertainties, were summarised, in terms of SUC, RUC and CCP. UC is one of the most widely studied and important research topics in the power system. It is still worthwhile to investigate UC problems, aiming to provide optimal UC decisions, which can accommodate the large-scale integration of wind.

Based on the above review, this thesis will conduct further study the selection of candidate lines, TEP and UC problems with uncertainties. In the following chapters, the research topics of this thesis will be introduced one by one.

CHAPTER 3   AN AUTOMATIC SELECTION METHOD FOR CANDIDATE LINES IN TRANSMISSION EXPANSION PLANNING

3.1   Introduction

The TEP problem is to select optimal lines to be built from a given set of candidate lines. Because of the complexity of the TEP problem, which is generally formulated as a MILP problem, it is impossible to consider all possible corridors as candidate lines. When selecting candidate lines, many factors need to be considered. For example, it is not economic to build lines over mountain areas and the length of a transmission line should not be too long. By considering various factors, many possible lines could be eliminated. Even so, the size of the rest of lines is still beyond the capability of TEP to solve. As a result, it needs to identify the rest of candidate lines and control the size of candidate set to be within an acceptable scale. However, currently there are no well-established methods available for determining the candidate lines. Considering the complexity of TEP problem, if the candidate set is manually selected, it is quite possible that some promising candidate lines are missing from the candidate set. As a result, the final expansion plan is not a globally optimal one, but a suboptimal one. To address above deficiencies, an automatic candidate lines selection approach for TEP is presented in this chapter.

The remainder of this chapter is organized as follows. Firstly, the two-stage deterministic model for TEP problem is presented. Secondly, the solution approach based on BD for the deterministic TEP problem is introduced. Thirdly, a method to select candidate lines for TEP is proposed. Fourthly, the performance of the proposed method is verified on the revised IEEE 24-bus test system and IEEE RTS-96. Finally, the conclusion is presented.

3.2   Deterministic Model for Transmission Expansion Planning

3.2.1   Nomenclature

Sets and indices

B   Set of buses (indexed by i and j).

CL   Union of candidate lines selected in each stage.

CL$_m$ Set of candidate lines selected in *Stage m.*

CB   Set of candidate buses.

RC$_i$ Set of residual lines connected to bus i

E   Set of transmission lines (indexed by e).

E$_0$ Set of existing transmission lines (indexed by e).

E$_{\cdot i}$ Set of transmission lines oriented into bus i.

E$_{i\cdot}$ Set of transmission lines oriented out of bus i.

G$_t$ Set of generation units in year t (indexed by g).

$\mathbf{G}_{i,t}$ Set of generation units in year t at bus i (indexed by g).

d Index of the time interval in one year.

NT Total planning years.

(i, j) Line from bus i to bus j

i_e/j_e Tail/head (bus no) of line e.

$\mathbf{S}_k$ Set of all contingency states, over existing and candidate lines, with exactly k failures (indexed by s).

$\mathbf{S}$ Set of all contingency states, over existing and candidate lines, with k or fewer failures, $\mathbf{S} = \mathbf{S}_0 \cup \mathbf{S}_1 \cup \mathbf{S}_2 \cdots \cup \mathbf{S}_k$.

t Index of the year .

$\mathbf{W}_t$ Set of wind units in year t (indexed by w).

$\mathbf{W}_{i,t}$ Set of wind units in year t at bus i (indexed by w).

Parameters

K   Maximum size of contingency under consideration. In any contingency state, the number of line failures is between 0 and K.

r Discount factor.

C_{lolp} Loss-of-load penalty

C_{res} wind spillage penalty.

C_e Annualised investment costs for line e.

Δd Time length of each duration.

NT Total planning years.

ND Total time durations during one year.

$C_g(\cdot)$ Generation cost function for generator g.

c_g Cost parameter for generator g

B_e Electrical susceptance of line e.

$D^t_{i,d}$ Load demand at bus i in d^{th} interval of year t.

D^t_d Total load demand in d^{th} interval of year t.

$\tilde{h}^s_e$ Binary parameter that is 1 if line e is part of the contingency s.

$\overline{f}^s_e$ Maximum capacity of line e under contingency state s.

$\overline{p}^t_g$ Maximum capacity of generator g in year t.

σ Minimum utilisation level of wind generation.

$\overline{p}^t_{w,d}$ Maximum generation from wind w in d^{th} interval of year t.

ε_k Fraction of load demands that can be shed given contingency size k.

y Life time of line e in years.

$|s|$ Number of failed lines in contingency s.

Decision variables

x^t_e Binary variable that is 1 if line e is built in year t.

$p^{t,s}_{g,d}$ Power generation of generator g in d^{th} interval of year t under contingency s.

$f^{t,s}_{e,d}$ Power flow for line e in d^{th} interval of year t under contingency s.

$p^{t,s}_{w,d}$ Power generation of wind w in d^{th} interval of year t under contingency s.

$q^{t,s}_{i,d}$ Loss of load at bus i in d^{th} interval of year t under contingency s.

$\theta_{i,d}^{t,s}$ Phase angle of bus i in d^{th} interval of year t under contingency s.

L_w wind spillage amount of wind w .

3.2.2   Deterministic Model of Transmission Expansion Planning

The deterministic mathematical TEP model is presented in this section, with the consideration of N-k reliability criteria and wind utilisation. The DC model is applied in this section. In the DC model, the power losses are neglected and the reactive power is not considered because only the active power is considered in the calculation. Both investment costs and operation costs are considered in the objective function, to minimise the total costs. Both costing parameters can be obtained as given in [17]. The following formulation is referred to that in [21], and noted as **DTEPM** (Deterministic TEP Model).

$$\text{Min} \ \sum_{t=1}^{NT} 1/(1+r)^t \sum_{e \in \mathbf{E}} x_e^t \cdot C_e + \sum_{t=1}^{NT} 1/(1+r)^t \sum_{d=1}^{ND} \Delta d \sum_{g \in \mathbf{G}_t} C_g(p_{g,d}^{t,0}) \tag{3-1}$$

$s.t.$

$$\sum_{g \in \mathbf{G}_{i,t}} p_{g,d}^{t,s} + \sum_{e \in \mathbf{E}_{.i}} f_{e,d}^{t,s} - \sum_{e \in \mathbf{E}_{i.}} f_{e,d}^{t,s} + \sum_{w \in \mathbf{W}_{i,t}} p_{w,d}^{t,s} = D_{i,d}^t \ \forall i, \forall d, \forall t, \forall s \tag{3-2}$$

$$-B_e(\theta_{i_e,d}^{t,s} - \theta_{j_e,d}^{t,s}) \le -f_{e,d}^{t,s} + M_e(1 - x_e^t + \tilde{h}_e^s) \quad \forall e, \forall d, \forall t, \forall s \tag{3-3}$$

$$B_e(\theta_{i_e,d}^{t,s} - \theta_{j_e,d}^{t,s}) \le f_{e,d}^{t,s} + M_e(1 - x_e^t + \tilde{h}_e^s) \quad \forall e, \forall d, \forall t, \forall s \tag{3-4}$$

$$-\overline{f}_e^s x_e^t(1 - \tilde{h}_e^s) \le f_{e,d}^{t,s} \le \overline{f}_e^s x_e^t(1 - \tilde{h}_e^s) \quad \forall e, \forall d, \forall t, \forall s \tag{3-5}$$

$$0 \le p_{g,d}^{t,s} \le \overline{p}_g^t \quad \forall g, \forall d, \forall t, \forall s \tag{3-6}$$

$$\sigma \ \overline{p}_{w,d}^t \le p_{w,d}^{t,s} \le \overline{p}_{w,d}^t \quad \forall w, \forall d, \forall t, s = 0 \tag{3-7}$$

54

$$0 \le p_{w,d}^{t,s} \le \overline{p}_{w,d}^{t} \quad \forall w, \forall d, \forall t, \forall s \setminus s = 0 \tag{3-8}$$

$$x_e^t = 1 \quad \forall e \in E_0, \forall t \tag{3-9}$$

$$x_e^{t-1} \le x_e^t, x_e^t \in \{0,1\} \quad \forall e \in \mathbf{E} \setminus \mathbf{E}_0, \forall t \tag{3-10}$$

In the objective function (3-1), investment costs are annualised costs; investment costs for new transmission lines are also annualised costs, which are derived by applying the capital recovery factor $r(1+r)^y / ((1+r)^y - 1)$. As for operation costs, only generation costs for conventional generators are considered, and wind generation costs are assumed to be zero. Based on the annual load duration curve, each year is divided into several intervals according to load levels. The more time intervals one year is divided into, the more accuracy operation costs can be calculated with. However, the computation complexity increases quickly as the number of time intervals increases. To achieve a balance between the accuracy and the computation complexity, a proper number of time intervals should be implemented. For the sake of simplicity, cost functions are defined as linear functions: $C_g(p_{g,d}^{t,0}) = c_g p_{g,d}^{t,0}$.

Constraints for the **DTEPM** are shown in (3-2)-(3-10). The power balance at each bus is shown by (3-2), which includes scenarios under normal state (no-contingency state $s=0$) and contingency state. Here $s=0$ represents the normal state. (3-3) and (3-4) utilise the Big-M method to represent the DC power flow on each line. If $1 - x_e^t + \tilde{h}_e^s = 1$, it means $-f_{e,d}^{t,s} - M_e \le -B_e(\theta_{i_e,d}^{t,s} - \theta_{j_e,d}^{t,s}) \le -f_{e,d}^{t,s} + M_e$. Because M_e is a large positive value, so $\theta_{i_e,d}^{t,s}$ and $\theta_{j_e,d}^{t,s}$ are not bounded. If $1 - x_e^t + \tilde{h}_e^s = 0$, it means

$-f_{e,d}^{t,s} \leq -B_e(\theta_{i_e,d}^{t,s} - \theta_{j_e,d}^{t,s}) \leq -f_{e,d}^{t,s}$, so $f_{e,d}^{t,s} = B_e(\theta_{i_e,d}^{t,s} - \theta_{j_e,d}^{t,s})$. (3-5) ensures the power

flow on each line to be within its capacity.(3-6) represents the power generation of each

generator must be within its maximum capacity. (3-7) represents that the wind

utilisation level needs to be no less than the specified level under the normal state. (3-8)

shows that the wind utilisation level under contingency state is not restricted. (3-9)

shows that existing lines have been built. (3-10) represents that candidate lines remain

the existing state once they are selected to be built.

3.3 Solution Approach Based on Benders Decomposition

3.3.1 Benders Decomposition Algorithm for Two-Stage Problem

The general two-stage stochastic problem can be formulated as follows:

$$\min_{\mathbf{x} \in \chi} \mathbf{c}^{\mathrm{T}}\mathbf{x} + Q(\mathbf{x}) \tag{3-11}$$

where $\chi := \left\{\mathbf{x} \in \mathbb{R}^{n_1} : \mathbf{Ax} \leq \mathbf{b}, \mathbf{x} \geq 0\right\}$ and $Q(\mathbf{x})$ is the optimal value of the second stage

problem.

$$Q(\mathbf{x}) = \min_{\mathbf{y} \in \mathbb{R}^{n_2}} \mathbf{q}^{\mathrm{T}}\mathbf{y} \tag{3-12}$$

$$s.t. \quad \mathbf{Tx} + \mathbf{Wy} \geq \mathbf{h} \tag{3-13}$$

$$\mathbf{y} \geq 0 \tag{3-14}$$

This two-stage problem can be decomposed into the master problem and subproblems.

Master Problem

$$\min \mathbf{c}^{\mathrm{T}}\mathbf{x} + \alpha \tag{3-15}$$

$$s.t. \quad \mathbf{Ax} \geq \mathbf{b} \tag{3-16}$$

$$\alpha \geq \alpha(\mathbf{x}^{i}) - (\mathbf{x} - \mathbf{x}^{i})\mathbf{T}^{\mathrm{T}}\boldsymbol{\lambda}^{i} \tag{3-17}$$

$$\mathbf{x} \geq 0 \tag{3-18}$$

where:

➢ $\mathbf{x}^{i}$ is the trial decision obtained by the master problem in the ith iteration

➢ $\alpha(\mathbf{x}^{i}) = (\mathbf{h} - \mathbf{Tx}^{i})^{\mathrm{T}}\boldsymbol{\lambda}^{i}$ is the optimal value of the subproblem under the trial decision $\mathbf{x}^{i}$.

➢ $\boldsymbol{\lambda}^{i}$ is the dual variable associated with the solution to the subproblem under the trial decision $\mathbf{x}^{i}$.

Subproblem

The subproblem is the second stage problem under a given trial decision $\mathbf{x}^{i}$. In the ith iteration, the subproblem can be expressed as follows:

$$\alpha(\mathbf{x}^{i}) = \min_{\mathbf{y} \in \mathbb{R}^{n_2}} \mathbf{q}^{\mathrm{T}}\mathbf{y} \tag{3-19}$$

$$s.t. \quad \mathbf{Tx}^i + \mathbf{Wy} \geq \mathbf{h} \tag{3-20}$$

$$\mathbf{y} \geq 0 \tag{3-21}$$

The corresponding dual subproblem can be expressed as follows:

$$\alpha(\mathbf{x}^i) = \max_{\mathbf{y} \in \mathbb{R}^{n_2}} (\mathbf{h} - \mathbf{Tx}^i)^{\mathrm{T}} \boldsymbol{\lambda} \tag{3-22}$$

$$s.t. \quad \mathbf{W}^{\mathrm{T}} \boldsymbol{\lambda} \leq \mathbf{q} \tag{3-23}$$

$$\boldsymbol{\lambda} \geq 0 \tag{3-24}$$

The solving procedure of the BD algorithm can be summarised as follows[111].

Step 1: Initialise the iteration counter $i=1$, the lower bound $z_{lower}^i = 0$ and the upper bound $z_{upper}^i = +\infty$.

Step 2: Solve the master problem by available solvers (CPLEX[112] , Gurobi[113], etc.), which is shown in (3-15)-(3-18).

(3-17) is not included in the master problem in the first iteration $i=1$. Moreover, $\alpha \geq \alpha_{min}$ where α_{min} is the predefined lower bound of the second stage problem. Store the optimal solution of $\mathbf{x}$ as $\mathbf{x}^i$.

Step 3: Check the convergence by calculating the gap between the lower bound and the upper bound.

The lower bound is calculated by $z_{lower}^i = \mathbf{c}^{\mathrm{T}} \mathbf{x}^i + \alpha(\mathbf{x}^i)$.

where z_{lower}^i is the lower bound of the optimal solution in the ith iteration.

If $i=1$, then $z_{upper}^i = +\infty$.

Else calculate $z_{upper}^i = \mathbf{c}^T\mathbf{x}^i + Q(\mathbf{x}^i)$.

where z_{upper}^i is the upper bound of the optimal solution in the ith iteration.

Compare the gap between the upper bound and the lower bound.

If

$$\left| z_{upper}^i - z_{lower}^i \right| \le \varepsilon$$

Then the algorithm terminates with the optimal solution to be $\mathbf{x}^i$.

Else, continuou to **Step 4**.

Step 4: Update the counter $i \leftarrow i+1$. Solve the subrporblem (3-19)-(3-21), and the dual of the subproblem (3-22) to (3-24).

Step 5: The algorithm returns to **Step 2**.

The steps summerised above are also represented by Figure 3-1.
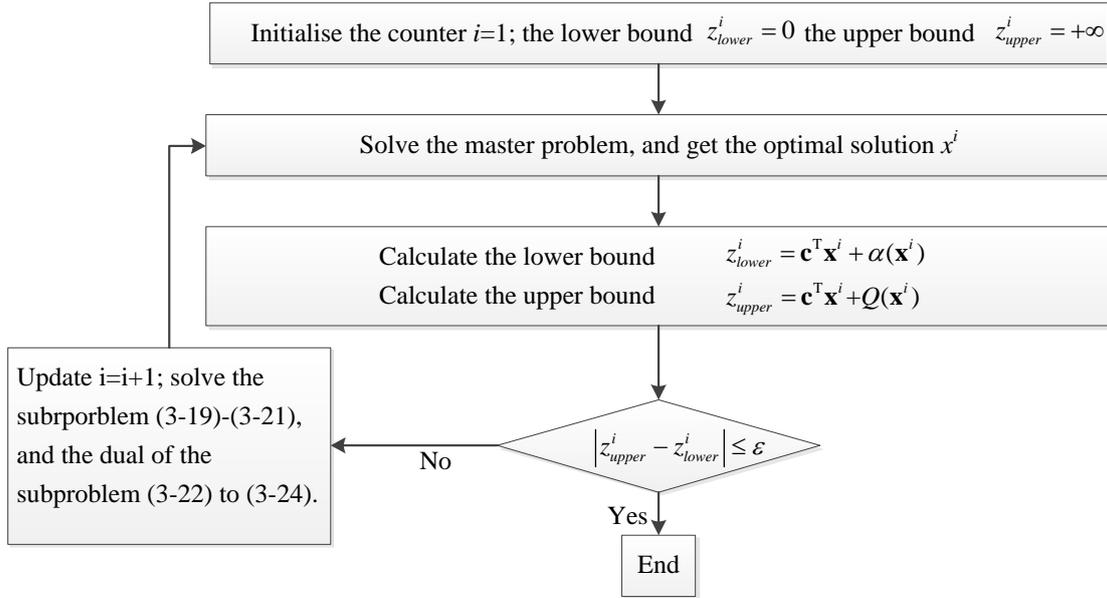
Figure 3-1 Steps for the BD algorithm

3.3.2 Application of Benders Decomposition Algorithm to TEP problem

According to the formulation of **DTEPM** considering the reliability criteria, the size of the problem increases quickly, making the problem to be intractable. In this section, the solution approach based on BD is presented, which can decompose the problem of **DTEPM** into the master problem and subproblems. The master problem is the investment problem, which is to decide the expansion planning. Subproblems are operation problems, which are to verify whether the expansion plan is flexible or not. The master problem is to decide when and where the lines need to be built, and variables to represent the expansion plan are binary. This problem is called as **MP**:

$$\text{Min} \ \sum_{t=1}^{NT} 1/(1+r)^t \sum_{e \in \mathbf{E}} x_e^t \cdot C_e + \alpha(x_e^t) \tag{3-25}$$

60

$$s.t \qquad \alpha(x_e^t) \geq \alpha_{min} \qquad\qquad\qquad (3\text{-}26)$$

(3-9) and (3-10)

The result of **MP** provides a predetermined expansion planning $\tilde{x}_e^t$, which needs to be verified by subproblems to determine whether it can meet the relative constraints, such as no load shedding, N-k reliability criteria and so on.

According to the rank of contingency state ($|s| = 0, 1, 2, \cdots, K$), subproblems can be divided into K+1 groups. The first group is the subproblem with $|s| = 0$, which means there is no contingency and can be called as **SP**-0. The rest K groups are those subproblems with different numbers of contingencies, called as **SP**-k.

For the first subproblem **SP**-0, the aim is to minimise the operation cost under given expansion planning $\tilde{x}_e^t$. The operation cost is the total cost over the planning horizon. The operation problem in different year t and different time interval d is not related with other time periods. So the problem **SP**-0 can be divided into **SP**-0(t, d) with each t and d, which is shown as follows:

$$\text{Min} \sum_{g \in \mathbf{G}_t} C_g(p_{g,d}^{t,0}) \qquad\qquad\qquad (3\text{-}27)$$

$$s.t. \ (3\text{-}2)\text{-}(3\text{-}8)$$

Under the given expansion planning $\tilde{x}_e^t$, the problem **SP**-0(t, d) might not be feasible, for the reason of load shedding or the low utilisation ratio of wind. If so, corresponding

feasibility cuts need to be created and added to the **MP** problem. If the problem is not feasible, optimality cuts are created and added to the **MP** problem. Since the BD approach has been widely introduced in many literatures, details about how to create feasibility and optimality cuts are not introduced here. Feasibility cuts are actually constraints on the **MP** variables. For a particular solution $\tilde{x}_e^t$, it needs to check whether it is feasible for all the subproblems. If any of the subproblem becomes infeasible, then a feasibility cut is generated and added to the **MP** problem. So that the particular solution can be removed from the solution set. Thus feasibility cuts are generated to make the subprolems feasible. Optimality cuts are constraints based on the **MP** variables and are generated only after all the feasibility cuts are generated. The idea of optimality cuts is to gradually take the solution towards the optimal solution.

For the subproblem **SP-**k with the contingency rank $|s| = k$ ($k \geq 1$), it is to calculate the minimum loss-of-load under the given expansion planning $\tilde{x}_e^t$ and with k failures. If the minimum loss-of-load exceeds the specified amount, then the expansion planning is not feasible. For each year t and each time interval d, the loss-of-load calculation is independent from other time periods. Under each combination of failures $\tilde{h}_e^s$ with total k failures, and each t, d, the problem is represented as **SP-**$k(t,d,\tilde{h}_e^s)$. The formulation is shown as follows:

$$\text{Min} \sum_{i \in \mathbf{B}} q_{i,d}^{t,s} \tag{3-28}$$

$$s.t. \qquad (3\text{-}3)\text{-}(3\text{-}6)$$

$$\sum_{g \in \mathbf{G}_{i,t}} p_{g,d}^{t,s} + \sum_{e \in \mathbf{E}_{\cdot i}} f_{e,d}^{t,s} - \sum_{e \in \mathbf{E}_{i\cdot}} f_{e,d}^{t,s} + \sum_{w \in \mathbf{W}_{i,t}} p_{w,d}^{t,s} + q_{i,d}^{t,s} = D_{i,d}^t \ \forall i \qquad (3\text{-}29)$$

$$0 \leq q_{i,d}^{t,s} \leq D_{i,d}^t \quad \forall i \qquad (3\text{-}30)$$

$$\sum_{i \in \mathbf{B}} q_{i,d}^{t,s} \leq \varepsilon_{|s|} D_d^t \qquad (3\text{-}31)$$

(3-30) restricts the loss-of-load at each bus cannot exceed the load demand at that bus.

(3-31) represents that the total loss-of-load under contingency s cannot exceed the

specified ratio $\varepsilon_{|s|}$. The problem (3-28)-(3-31) is to calculate the loss-of-load under the

given expansion decision $\tilde{x}_e^t$ and given failures $\tilde{h}_e^s$.

Under the given expansion decision $\tilde{x}_e^t$ and given failures $\tilde{h}_e^s$, problem (3-28)-(3-31)

might not be feasible, because the loss-of-load might be larger than the specified level

$\varepsilon_{|s|}$, just as the constraint (3-31) shown. Under the given rank of contingencies, there are

numerous combinations of failures. The worst-case loss-of-load scenario with the given

$\tilde{x}_e^t$ and given rank k can be found. As for how to achieve this task, please refer to [21].

Once the worst-case scenario $\tilde{\tilde{h}}_e^s$ is obtained, the subproblem **SP**-$k(t,d,\tilde{\tilde{h}}_e^s)$ is solved. If

the problem is not feasible, it can generate corresponding feasibility cuts and add them

to the **MP** problem. If the problem is feasible, it means the loss-of-load is smaller than

the specified level ε_k under any contingencies with the rank k.

3.3.3   Procedure of Transmission Expansion Planning

The general procedure to carry out TEP is shown in Figure 3-2, which includes four steps: selecting candidate lines, forming **DTEPM**, solving the model and obtaining the final plan. The left flow chart presents the traditional TEP procedure with all possible candidate lines or manually selected ones. The right flow chart shows the new procedure with the automatic selection of candidate lines, which is the focus of this chapter. The performance of these two procedures will be compared in terms of optimal cost and computation time.
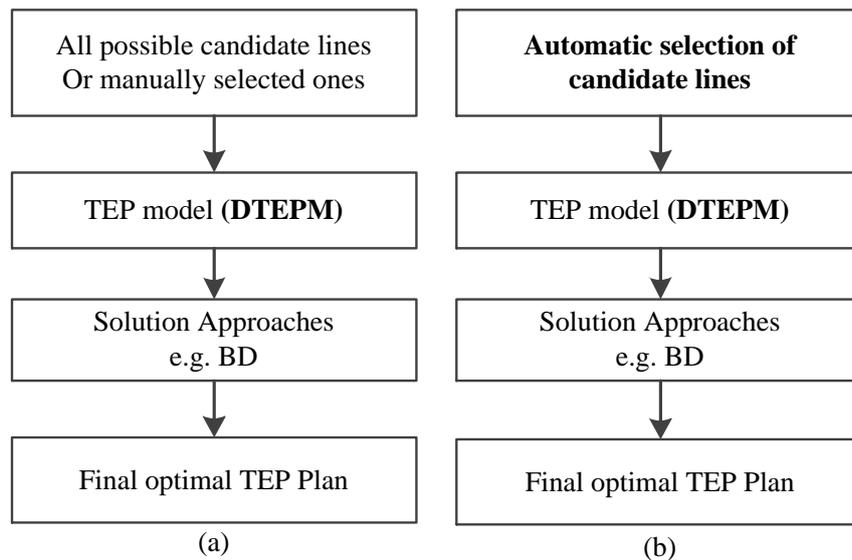
Figure 3-2 General procedure to carry out TEP, (a) traditional procedure, (b) new procedure.

3.4   New Selection Method for Candidate Lines

Over the planning horizon, the load demand and generation capacity at the last planning year is the largest, so the number of new lines needs to be built is also the largest. In this

section, the load demand and generation capacity at the last planning year is considered to select candidate lines. Before selecting candidate lines, the LMP of each bus LMP_i is calculated, which is the required information for the proposed selection method for candidate lines.

The problem to calculate LMP is called as **LMPM** (LMP model) and is formulated as follows:

$$\text{Min} \sum_{g \in \mathbf{G}_{NT}} C_g(p_g) + \sum_{i \in \mathbf{B}} C_{lolp} \cdot q_i + \sum_{w \in \mathbf{W}_{NT}} C_{res} \cdot L_w \tag{3-32}$$

$$s.t. \sum_{g \in \mathbf{G}_{i,NT}} p_g + \sum_{e \in \mathbf{E}_{\cdot i}} f_e - \sum_{e \in \mathbf{E}_{i\cdot}} f_e + \sum_{w \in \mathbf{W}_{i,NT}} p_w = D_i^{NT} \quad : \xi_i \tag{3-33}$$

$$f_e = B_e(\theta_{i_e} - \theta_{j_e}) \quad \forall e \in \mathbf{E}_0 \tag{3-34}$$

$$-\overline{f_e} \le f_e \le \overline{f_e} \quad \forall e \in \mathbf{E}_0 \tag{3-35}$$

$$0 \le p_g \le \overline{p}_g^{NT} \quad \forall g \tag{3-36}$$

$$\sigma \, \overline{p}_w^{NT} \le p_w + L_w \le \overline{p}_w^{NT} \quad \forall w \tag{3-37}$$

$$0 \le p_w \le \overline{p}_w^{NT} \quad \forall w \tag{3-38}$$

$$0 \le L_w \le \overline{p}_w^{NT} \quad \forall w \tag{3-39}$$

In the objective function (3-32), it includes generation cost, load shedding cost and wind spillage cost. The load shedding costs C_{lolp} and wind spillage cost C_{res} are set to be 5 times of the average generation costs[72]. These two parameters are only used to calculate the LMP at each bus.

The LMP at each bus is the dual variable for the constraint (3-33).The penalty of loss-of-load and wind spillage is much larger than generation cost. So the LMP at the bus with load shedding is a large positive value; and the LMP at the bus with wind spillage is a large negative value. Because if the load demand is increased by 1 unit at the bus with RES spillage, then the RES spillage at the corresponding bus can be reduced by 1 unit, which leads to the reduction of the objective with the value C_{res}. The LMP difference is a very important factor to explore new corridors. In [16, 17], LMP difference was used as the only criterion to select the new corridors. However, the LMP difference is neither necessary nor sufficient condition for selecting new corridors.

The selection method for candidate lines proposed in this chapter consists of five stages, which are carried out in sequence. The final candidate set provided by the selection method is **CL**, which is the union of candidate set $\mathbf{CL}_m (m = 1, 2, 4, 5)$ created in *Stage m*.

3.4.1   *Stage 1*-Enforcement of Existing Corridors

The TEP can be carried out for different reasons. For example, an existing transmission network may not be able to afford the increasing requirement of transmission capacity; or may not have the ability to meet the secure system operation. If new lines could not be built, then there would be congestion within the network. The congestion can be

reduced by enforcing the existing corridors. So the possible enforcement plan should be included into the candidate set. Here the set of candidate lines selected in *Stage m* is noted as CL_m. The union of CL_m is noted as CL, which is the final candidate set.

The approach to select possible enforcement lines is to solve the problem **LMPM**. After solving **LMPM**, it gives the power flow on each line, load shedding amount and wind spillage amount. If the power flow on a line reaches its corresponding capacity limit, then there is congestion in the line, and the corresponding line is selected and included into the candidate set CL_1. Then the **LMPM** is solved again with existing lines and those lines in CL_1. If there is still congestion in some lines, new lines are added into CL_1. Such a process continues until there is no congestion in the network. The whole process is shown in Figure 3-3. CL_1 is the set of candidate lines generated in this stage. At beginning, CL_1 is empty, and then candidate lines are added into CL_1 during the process. After *Stage 1*, CL becomes:

$$CL=CL_1.$$
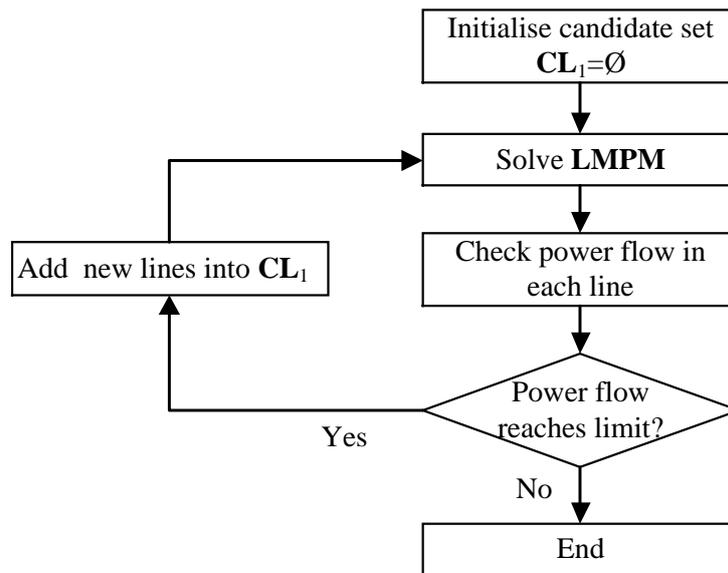
Figure 3-3 Process to enforce existing corridors

3.4.2   *Stage 2*-Reliability Criteria Check

In *Stage 1*, congestion is reduced by enforcing existing lines. Another important issue

for the TEP is to meet the reliability criteria, such as N-k contingencies. In *Stage 2*, a

possible enforcement plan for existing lines is selected to satisfy the requirement of N-k

contingencies. Take the N-1 contingency as an example, the common requirement is

that the loss-of-load should not happen under any N-1 contingency. For other N-k

contingencies, different ranks of contingencies have different limitations on the amount

of loss-of-load that can be shed. Under the given rank of k contingencies, the worst-case

loss-of-load should meet the specified limitation. According to the Transmission

Planning Standards (TPL-004-0 [114]), defined by the North Electric Reliability

Corporation (NERC), if only a single element is in failure (N − 1 contingency), there

should be no loss-of-load. In the case of k simultaneous failures (N − k contingency),

the loss-of-load should be no greater than a specified level. These requirements can also be formalized as $N-k\text{-}\varepsilon$ criterion [21], where ε represents the vector of the loss-of-load, under the contingency size k, as a fraction of total load demand. The process of *Stage 2* is shown in Figure 3-4. $\mathbf{CL}_2$ is the set of candidate lines created in this stage. After *Stage 2*, $\mathbf{CL}$ becomes:

$$\mathbf{CL} = \mathbf{CL}_1 \bigcup \mathbf{CL}_2$$
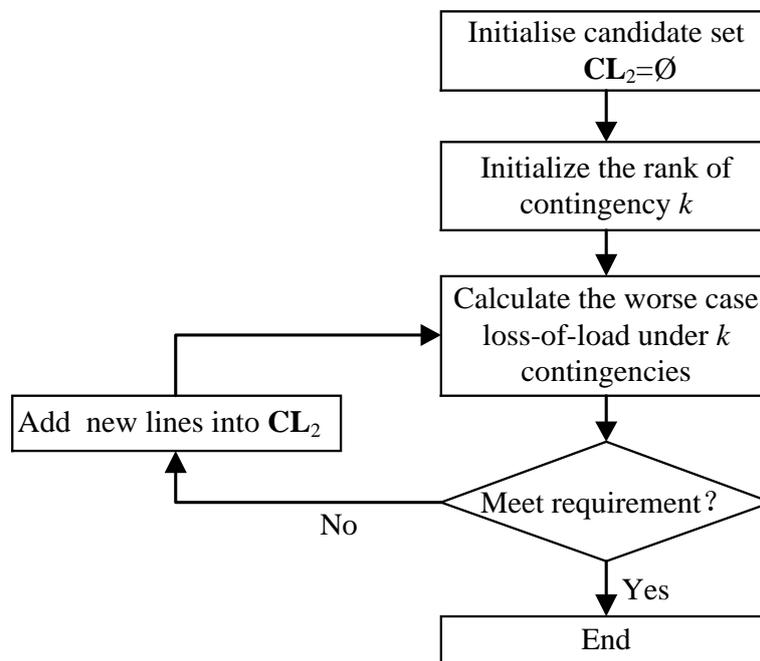
Figure 3-4 Process to consider N-*k* reliability criteria

3.4.3   *Stage 3*-Defining Candidate Buses

In the first two stages, candidate lines are selected to enforce existing corridors, so that the congestion can be reduced and the N-*k* reliability criteria can be met. However, it might not be the most efficient or economic way to meet the needs. It is quite possible

that a better choice is to construct new transmission corridors. The question is that how to select promising new corridors from a large number of possible corridors. Herein, an approach to select new corridors is presented.
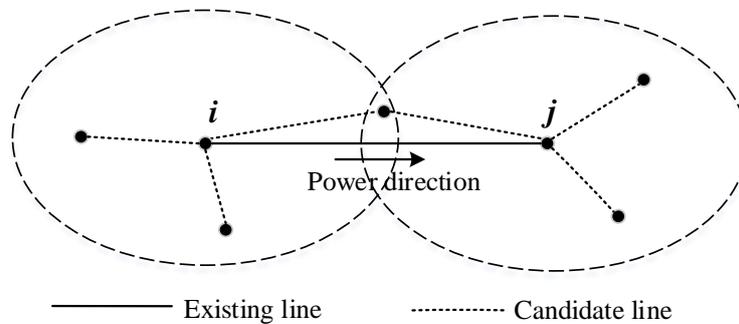
Figure 3-5 Illustration of exploring new corridors

The basic idea of selecting new corridors is illustrated in Figure 3-5. Suppose that there is an existing corridor between bus i and bus j, with the power flow direction from i to j. In the first two stages, the line is enforced for the purpose of reducing congestion and/or meeting reliability criteria. Except to build a new line between bus i to bus j directly, an alternative way is to build new corridors connected with these buses, which are identified as candidate buses. Basically, candidate buses are those with either very heavy power generation or load or power flows. The candidate buses are related to the following three possible scenarios:

➢ ***Candidate bus i as a generator bus:*** If bus i is a generation bus and a large amount of power needs to be dispatched through the line between i and j. By connecting bus i to other buses located in its vicinity, the power from bus i can be

dispatched through more lines, rather than just through the line between i and j, just as the left ellipse shows in Figure 3-5.

➤ **Candidate bus j as a load bus**: If bus j is a load bus and the load demand is mainly met through the line between bus i and bus j, the power flow in this line can also be reduced by connecting bus j to other nearby buses so that the load demand can be met through more corridors, just as the right ellipse shows in Figure 3-5.

➤ **Candidate bus i and bus j as interconnection buses**: If bus i and bus j are just interconnection buses or this line is required to be enforced for the purpose of meeting reliability criteria, the congestion or the reliability criteria can also be reduced or ensured, by connecting bus i or bus j to other buses.

Based on the above analysis, the candidate buses are formed. Buses connected to lines included in $\mathbf{CL} = \mathbf{CL}_1 \bigcup \mathbf{CL}_2$ are formed as candidate buses and denoted as the set **CB**.

$$\mathbf{CB} = \left\{ i \in \mathbf{B} \mid i \text{ connected to lines } e \in \mathbf{CL}_1 \bigcup \mathbf{CL}_2 \right\}$$

3.4.4 *Stage 4*-Exploring New Transmission Corridors

For each candidate bus $i \in \mathbf{CB}$, two factors are considered to select new corridors: the potential benefit and investment cost of new lines. The potential benefit brought by building a new line is estimated by the LMP difference and its capacity[16].

From the aspect of LMP difference, the larger the LMP difference between two buses is, the more benefit the new line may achieve. From the aspect of investment cost, new lines with lower investment cost are more attractive. These two aspects are both considered by the following index.

$$profit_{ij} = \left| LMP_i - LMP_j \right| \cdot \bar{f}_{ij} \quad i \in \mathbf{CB}, j \in \mathbf{CB}, i \neq j \qquad (3\text{-}40)$$

$$\kappa_{ij} = \frac{profit_{ij}}{inv_{ij}} \quad i \in \mathbf{CB}, j \in \mathbf{CB}, i \neq j \qquad (3\text{-}41)$$

The index κ_{ij} for each possible corridor is calculated according to the above formulation. From the above analysis, the corridor with larger κ_{ij} is more attractive. By sorting κ_{ij} in descending order, the first M corridors are selected and included into the candidate set $\mathbf{CL}_4$. M is a positive integer, and the larger M is, the larger the size of $\mathbf{CL}_4$ becomes. Although a large size of $\mathbf{CL}_4$ might improve the completeness of the candidate set, it also increases the computation complexity of **DTEPM**. So a proper M should be selected to get a balanced size of $\mathbf{CL}_4$. Here the completeness refers to the number of the optimal expansion lines covered by the candidate set $\mathbf{CL}$. The optimal expansion plan can be achieved by solving the **DTEPM** with all possible candidate lines. After *Stage 4*, the candidate set becomes:

$$\mathbf{CL} = \mathbf{CL}_1 \bigcup \mathbf{CL}_2 \bigcup \mathbf{CL}_4 .$$

3.4.5 *Stage 5*-Checking Residual Possible Corridors

In *Stage 4*, new corridors are selected by considering the LMP difference and investment cost. However, it may not be sufficient to select new corridors only based on LMP difference and investment cost. It is possible that after *Stage 4*, some promising candidate lines are still excluded from **CL**. In order to cover promising candidate lines as many as possible, all residual corridors connected to each candidate bus are examined. For each candidate bus $i \in \mathbf{CB}$, the following steps are carried out.

For each $i \in \mathbf{CB}$

1. Generate the residual corridors connected to bus i to form a temporary set of lines, noted as $\mathbf{RC}_i$. The residual corridors are referred to those corridors which are not included in the existing lines (corridors) and the candidate set **CL** up to now.

$$\mathbf{RC}_i = \left\{ (i, j) \mid j \in \mathbf{B}, i \neq j, (i, j) \notin \mathbf{E}_0 \bigcup \mathbf{CL} \right\}$$

2. The **DTEPM** is solved with candidate lines $\mathbf{CL} \bigcup \mathbf{RC}_i$. To reduce the computation time, the N-k reliability criteria are not considered in this **DTEPM** calculation. Also, the binary decision x_e^t is relaxed as continuous variable varying from 0 to 1. So the **DTEPM** problem is relaxed as a LP problem, which can then be solved easily.

3. In the optimal result, if x_e^{NT} for some residual corridors are greater than the

---

threshold ξ, and then the corresponding corridors are added into $\mathbf{CL}_5^i$.

$$\mathbf{CL}_5^i = \left\{ e \in \mathbf{RC}_i \middle| x_e^{NT} \geq \xi \right\}.$$

4. Update $\mathbf{CL}$

$$\mathbf{CL} = \mathbf{CL} \bigcup \mathbf{CL}_5^i$$

After the above five stages, the final candidate set created by the selection method is:

$$\mathbf{CL} = \mathbf{CL}_1 \bigcup \mathbf{CL}_2 \bigcup \mathbf{CL}_4 \bigcup \mathbf{CL}_5^{i_1} \bigcup \mathbf{CL}_5^{i_2} \cdots \bigcup \mathbf{CL}_5^{i_h}$$

where h is the number of candidate buses in $\mathbf{CB}$.

3.5　Case Studies

Two test systems are applied to verify the performance of the proposed method and analysis is carried out with different parameter settings. The two test systems are the revised IEEE 24-bus test system and revised IEEE RTS-96. Only N-1 and N-2 reliability criteria are considered in the case studies. Results with and without considering reliability criteria are compared. In *Stage 4*, the first *M* candidate corridors are added into the candidate set. The impact of different number of *M* is analysed. Also, in *Stage 5*, the continuous relaxation technique is applied to reduce the computation time. Results by solving the original MILP are compared with results by implementing continuous relaxation. In the two test systems, it is noted that the optimal value of x_e^t in

the relaxed problem is either zero or larger than 0.1 in most cases. So ξ is set to be 0.1 in the following tests.

All case studies were coded with the YALMIP[115], which is a modelling language for advanced modelling. CPLEX 12.1.4 was utilised as the solver. The program was run on an Intel Core-i5 2.5-GHz personal computer with 4G memory.

3.5.1 Revised IEEE 24-Bus Test System

The detail data for IEEE 24-bus test system can be found in [116]. This test system is revised by adding three wind farms at bus 13, 17 and 22, respectively. The revised test system is shown in Figure 3-6. The TEP problem is a six-year plan, with annual 10% growth rate of load and generation capacity. Three wind farms at bus 13, 17 and 22 are installed in the 1st, 2nd and 4th year, with the capacity of 200MW, 200MW and 250 MW, respectively. There should be no loss-of-load under normal state and N-1 contingency, and 1% of total load can be shed during N-2 contingencies[114]. The wind utilisation level is set to be 0.8. Load penalty and wind spillage penalty are set to be 5 times of average generation cost. M is set to be 3, and ξ is set to be 0.1.

3.5.1.1 Results of IEEE 24-bus with Reliability Criteria

Firstly, the case with reliability criteria is considered. Candidate lines added into the candidate set in each stage are presented in Table 3-1. In total, it includes 54 candidate lines. To get the optimal expansion planning of this test system, the **DTEPM** is solved

with all possible 23*12=276 candidate lines. The results are shown in Table 3-2. Also, the **DTEPM** is solved with the created candidate set listed out in Table 3-2. The only difference is the line (4,5) is replaced by two lines (1,5) and (4,8). Buses 4 and 5 become isolated when two lines connected to them disconnected during N-2 contingencies. To ensure N-2 contingencies, the best solution is to link bus 4 and 5. However, this line is not included in the candidate set, so (1, 5) and (4, 8) are selected to meet the N-2 contingencies.
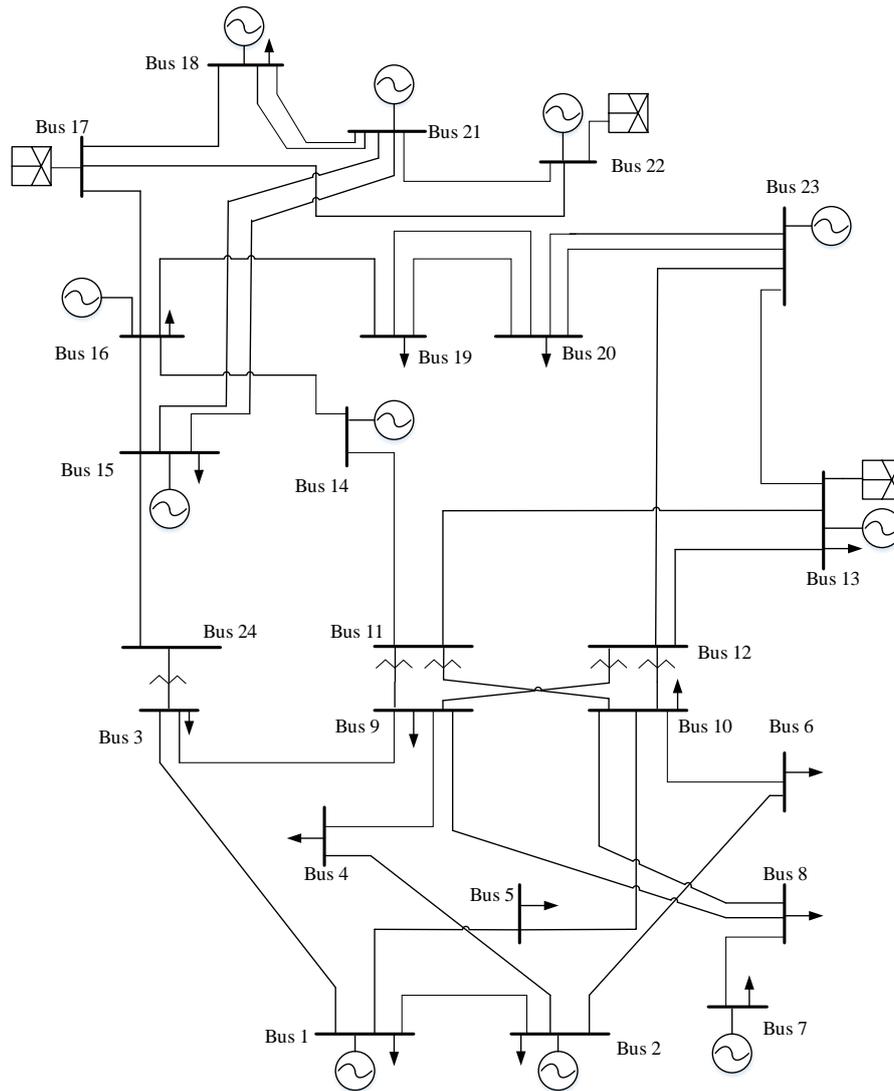
Figure 3-6 Revised IEEE 24-bus test system

The optimal cost (objective of **DTEPM** (3-1)) with created candidate set is only 0.8% higher than that with whole candidate lines. The reason is that if the expansion plan can select from the whole candidate lines, then it has more choices than from the limited candidate set. So the expansion plan selected from the whole set should be better than that selected from the given candidate set.

The total computation time for the whole procedure in Figure 3-2 and the required time

for selecting candidate lines (in bold fonts), is also shown in Table 3-2. With the created

candidate set, the total computation time is less than 1/5 of that for the procedure with

the whole set of candidate lines.

Table 3-1 Candidates For IEEE 24-Bus System With Reliability Criteria

Stages	New candidate lines	Number
Stage 1	(7,8) (14, 16), **(16,17)**, (8,9), (11,14), (3, 24), (14,16)	7
Stage 2	(2,6) (2,4), (4,9),(1,5),(5,10),(1,3),(15,24)	7
Stage 4	(3,7), (7,17), (7,18), (3,8), (8,17), (8,18), **(14,15)**, (14,19), (16,18), (14,17), (17,19), (3,9), (9,17), (9,18), (11,24), (11,15), (11,17), (3,10), (3,5), (14,24), (12,24), (2,3), (2,17), (2,18), (3,6), (6,17), (6,18), (3,4) (4,17), (4,18), (1,17), (1,18), (5,17), (5,18), (10,17) (10,18), (15,17)	37
Stage 5	(4,7), (4,8), **(6,9)**	3
Total		54

Table 3-2 Results Of **DTEPM** For IEEE 24-Bus System With Reliability Criteria

Approach	Lines to be built	Costs	Computation time (s)
DTEPM with whole candidate lines	(4, 5), (14, 15) (6, 9), (16, 17)	100%	2644 **(0)**
DTEPM with created candidate set	(14, 15), (6, 9), (16, 17), (1, 5), (4, 8)	100.8%	523 **(58)**

According to the proposed candidate selection method, the LMP is calculated before

carrying out selecting candidate lines. For IEEE 24-bus test system, LMP information

is shown in Table 3-3. Seen from Table 3-2, the best expansion planning is to build 4

lines, and corresponding LMPs are marked in grey in Table 3-3. The LMP differences

between 4 and 5, 6 and 9 are quite small. However, these two lines are included the

optimal expansion plan. The reason to build the line between 4 and 5 is for the

consideration of N-2 reliability criteria. If the LMP difference is considered as the only

factor to select candidate lines, then the line between 6 and 9 would not be selected. So

the LMP difference is not sufficient for the candidate selection, which in turn, shows

the importance of *Stage 5*.

Table 3-3 LMP FOR IEEE 24-BUS TEST SYSTEM

Bus No	LMP ($/MW)	Bus No	LMP ($/MW)	Bus No	LMP ($/MW)	Bus No	LMP ($/MW)
1	20.11	7	20.70	13	20.93	19	14.11
2	20.21	8	21.10	14	29.49	20	15.80
3	16.92	9	20.74	15	10.52	21	7.05
4	20.50	10	21.46	16	12.15	22	5.74
5	20.77	11	23.97	17	3.71	23	16.71
6	21.16	12	20.21	18	5.47	24	12.97

3.5.1.2   Results of IEEE 24-bus without Reliability Criteria

To analyse the impact of N-k reliability criteria to the TEP problem, scenarios without

considering N-k reliability criteria are also calculated. Results are shown in Table 3-4.

The total number of candidate lines is 33, which is largely reduced compared that with

reliability criteria. The optimal expansion planning is to build 3 lines, namely (16,17),

(14,15) and (4,8). All of them are include in the candidate set.

Table 3-4 CANDIDATES FOR IEEE 24-BUS SYSTEM WITHOUT RELIABILITY CRITERIA

Stages	New candidate lines	Number
Stage 1	(7,8) (14, 16), **(16,17)**, (8,9), (11,14), (3, 24), (14,16)	7
Stage 2	N/A	0
Stage 4	(3,7), (7,17), (7,18), (3,8), (8,17), (8,18), **(14,15)**, (14,19), (16,18), (14,17), (17,19), (3,9), (9,17), (9,18), (11,24), (11,15), (11,17), (3,10), (3,5), (14,24),	21
Stage 5	(4,7), **(4,8)**, (6,9) (6,8), (6,7)	5
Total		33

From Table 3-1 and Table 3-4, it can be seen that the optimal candidate lines are covered by the combination of proposed five stages. So each stage plays an important role in selecting the most promising candidate lines.

3.5.2 Revised IEEE RTS-96

This test system is revised by adding 9 wind farms to 9 different buses, which is shown in Figure 3-7. The detail data of this standard test system can refer to [117]. The other parameters are the same with those in the IEEE 24-bus test system, which include total planning years, annual increase rate of load and generation, wind utilisation level and reliability criteria.
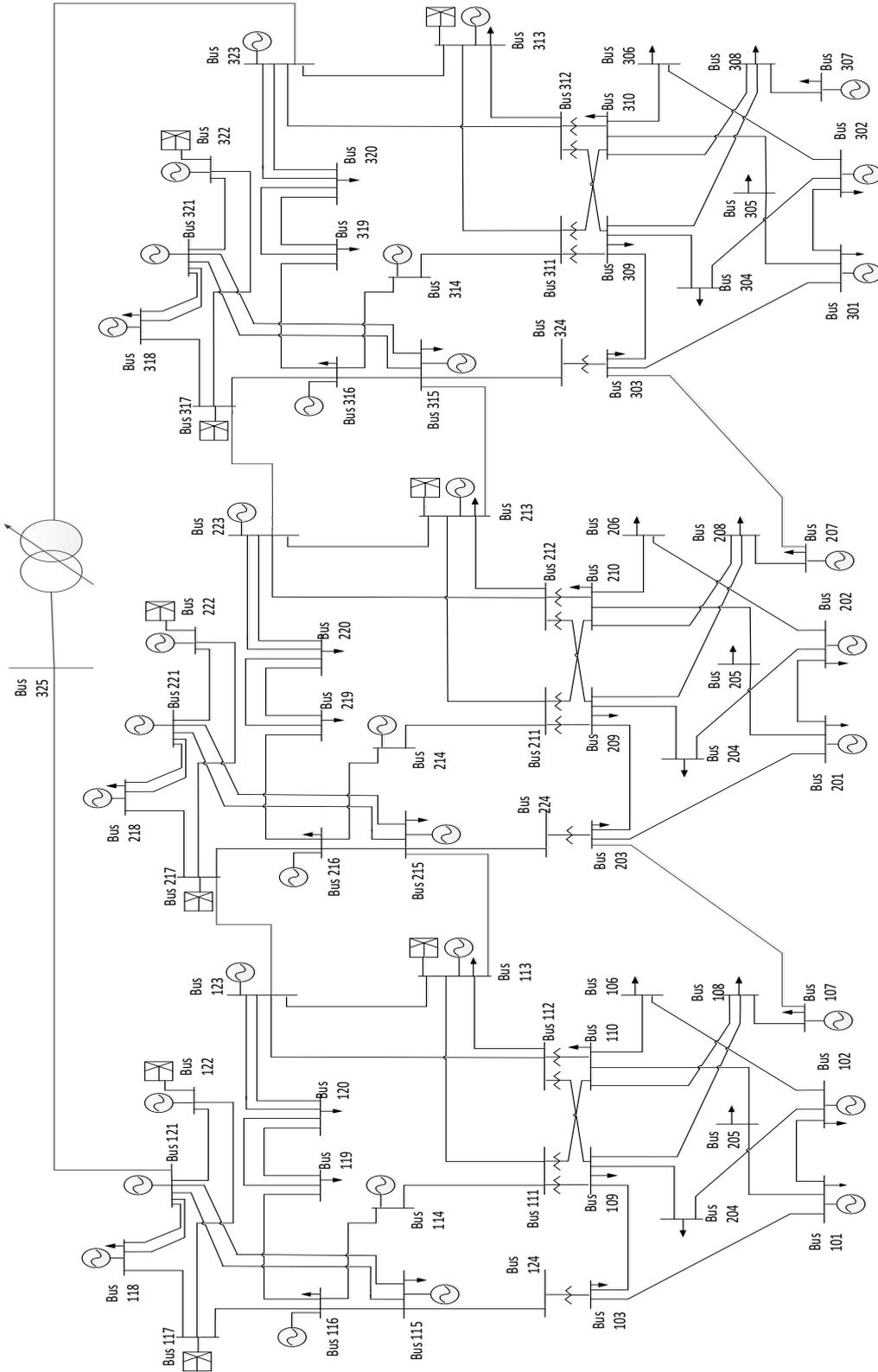
Figure 3-7 Revised IEEE RTS-96 [117]

Firstly, the candidate set is constructed with the reliability criteria. Results are shown in Table 3-5. The optimal expansion planning can be achieved by solving **DTEPM** with whole candidate lines. There are 73*36=2628 possible candidate lines for this test system. To save the computation time, candidate lines with high investment cost and long distance are excluded and only 437 candidate lines are taken into account into the **DTEPM**. Results of this **DTEPM** show that the best expansion planning is to build 23 lines and 17 out of 23 lines are included in the candidate set, just as the third column of Table 3-5 shows. It can be seen that about 74% of the optimal expansion plan is covered through the combination of four stages. Table VI shows the results with the whole candidate set (437 lines) and with created candidate set. The number of lines to be built in two plans is the same. The optimal cost (objective of **DTEPM** (3-1)) with created candidate set is only 1.13% higher than that with whole candidate lines. The total computation time with created set is only 28% of that for the procedure with the 437 candidate lines.

Table 3-5 CANDIDATES FOR IEEE RTS-96 WITH RELIABILITY CRITERIA

Stages	Number of candidate lines	Number of Optimal lines covered
Stage 1	23	2
Stage 2	2	0
Stage 4	83	9
Stage 5	12	6
Total	120	17

Table 3-6 RESULTS OF **DTEPM** FOR IEEE RTS-96 SYSTEM WITH Reliability CRITERIA

Approach	Number of lines to be built	Costs	Computation time (s)
DTEPM with whole candidate lines	23	100%	21603.6 **(0)**
DTEPM with created candidate set	23	101.13%	6053 **(452)**

Secondly, the candidate set is constructed without the reliability check. 116 lines are selected into the candidate set, with 23, 0, 82 and 11 lines in the four stages, respectively. Results of the **DTEPM** with the above mentioned 437 candidate lines show that the best expansion planning is to build 5 lines, and 4 of them are included in the candidate set. The optimal cost (objective of **DTEPM** (3-1)) with created candidate set is also only 0.3% higher than that with whole candidate lines.

3.5.3 Impact of Different *M* Values

According to the analysis above, the larger M is, the more candidate lines are selected. Although more candidate lines might increase the completeness of the candidate set, it increases the difficulty to solve the TEP problem. So a proper M value needs to be found to control the size of candidate set, as well as to ensure the completeness of the candidate set.

Table 3-7 and Table 3-8 show results for two test systems under different M values, considering the reliability criteria and implementing continuous relaxation. In these two tables, the second column shows the size of the candidate set by implementing

different M values; the third column is the increased ratio of optimal cost (objective of

DTEPM (3-1)) under given candidate set, compared with that with whole candidate

lines; the fourth column is the number of optimal lines (selected by using whole

candidate lines) that the candidate set can cover. According to results for IEEE 24-bus

test system shown in Table 3-7, different M values have no impact on the number of

optimal lines that the candidate set can cover. As to results for IEEE RTS-96 shown in

Table 3-8, the impact of different M values is small. Considering the size of the

candidate set and the completeness of the candidate set, M should be 3 for this

particular case, in accordance with Table 3-7and Table 3-8.

Table 3-7 RESULTS OF IEEE 24-BUS TEST SYSTEM UNDER DIFFERENT M VALUES

M value	Size of candidate set	Costs increased (%)	Number of Optimal lines covered
2	40	0.8	3
3	54	0.8	3
4	67	0.8	3

Table 3-8 RESULTS OF IEEE RTS-96 UNDER DIFFERENT M VALUES

M value	Size of candidate set	Costs increased (%)	Number of Optimal lines covered
2	92	1.19	16
3	120	1.13	17
4	148	0.96	18

3.5.4 Impact of Continuous Relaxation

In the final stage of the proposed selection method, the continuous relaxation is applied

to reduce the computation time. In the section, the impact of continuous relaxation is

evaluated. Candidate lines added in the *Stage 5* by solving the original MILP problem

and by solving the relaxed problem are shown in Table 3-9. Scenarios under different *M* values are compared from aspects of the number of optimal lines covered by *Stage 5*, and the increased ratio of optimal cost (objective of **DTEPM** (3-1)).

From Table 3-9, the number of candidate lines added in *Stage 5* by solving the MILP and relaxed model is 7 and 12, respectively. The number of optimal lines covered by *Stage 5* under two models is 3 and 6, respectively. In both models, different *M* values have no impact on the number of candidate lines added in *Stage 5* and the number of optimal lines covered by *Stage 5*. The fifth column shows the increased ratio of optimal cost (objective of **DTEPM** (3-1)) under the given candidate set. The sixth column is the computation time required to carry out candidate selection by implementing two models. According to the results shown in Table 3-9, the relaxed model can discover more optimal lines than MILP model, and the required computation time for the relaxed model is only 1/3 or even 1/4 of that for the MILP model.

Table 3-9 RESULTS OF IEEE RTS-96 BY SOLVING MILP AND RELAXED PROBLEMS

M value	Problem	candidate lines in *Stage 5*	Optimal lines in *Stage 5*	Costs increased (%)	Computation time(s)
M=2	MILP	7	3	2.04	1018.1
	Relaxed	12	6	1.19	371.2
M=3	MILP	7	3	1.93	1993.2
	Relaxed	12	6	1.13	452.4
M=4	MILP	7	3	1.82	2866.3
	Relaxed	12	6	0.96	406.1

3.6   Summary

The problem of selecting candidate lines for TEP is studied in this chapter. The research about the selection of the candidate lines is still in the preliminary stage. A method has been proposed to select candidate lines through an automatic process. The proposed method consists of five stages, which are the combination of enforcing existing lines and exploring new corridors. In the first two stages, existing corridors are enforced to ensure the utilisation of wind, reduce congestion and meet N-k reliability criteria. To replace the enforcement of existing lines, new corridors are explored in the latter three stages, by considering LMP difference and investment cost. The work to explore new corridors begins with collecting candidate buses in the third stage, which can reduce the scale of new corridors significantly. Moreover, to improve the completeness of candidate set, other possible corridors connected to the candidate buses are also examined by solving a linear relaxation TEP problem. Results have shown that the proposed algorithm can cover most of the optimal candidate lines. Each stage plays an important role in creating the candidate set. It has been demonstrated that selecting candidate lines according to LMP differences is neither sufficient nor necessary.

The selection method proposed in this chapter can provide a set of candidate lines for expert planners. However as the results of the case study shows, the selected candidate set can cover about 75% of the optimal expansion plan in the case of IEEE RTS-96. Thus, the selection method needs to be improved in the further research work.

CHAPTER 4 TWO-STAGE STOCHASTIC DUAL DYNAMIC PROGRAMMING FOR TRANSMISSION EXPANSION PLANNING WITH RENEWABLE ENERGY SOURCES

4.1   Introduction

As the development of wind, more and more attention has been paid to study the importance of considering uncertainties in TEP. There are two main uncertain sources, namely uncertain load demand and uncertain generation availability. The common approach to deal with load demand is to assume an annual increase ratio. As for generation availability, the uncertainty related to its availability is neglected in much published literature. However, as the penetration level of wind is increasing so quickly, wind generation is accounting for more and more percentage of the total generation. The intermittence nature of wind generation leads to the uncertain generation availability, which not only has considerable impact on system operations, but affects the planning strategy of TEP. It is quite often that wind-rich areas are always far away from load centres. As a consequence, the long distance transmission of wind power is required, through the means of high-voltage AC/DC technologies, or multi-regional interconnections, which all increase the difficulty of laying out TEP.

To deal with great uncertainties in the TEP problem, many methods have been investigated, including stochastic dual dynamic programming (SDDP), which is one of the most promising stochastic optimisation approaches. This method has been widely implemented in many areas of power system operations, such as generation expansion planning[118], TEP[111], hydro-thermal scheduling[119, 120]. In this chapter, the method to apply SDDP into a two-stage stochastic TEP problem is proposed.

The remainder of the chapter is organised as follows. Firstly, the two-stage stochastic formulation of TEP problem is presented. Secondly, the basic knowledge about SDDP is provided, as well as the overall procedure for the application of SDDP algorithm to the two-stage stochastic problem. Thirdly, the application of SDDP to the established two-stage stochastic TEP problem is introduced. Fourthly, the proposed algorithm is verified on two test systems. Finally, it presents the conclusion.

4.2　Two-stage Stochastic Formulation of Transmission Expansion Planning

In Section 3.2, it presents the deterministic TEP model. In this section, the general two-stage stochastic formulation of TEP is given out.

4.2.1 Nomenclature

The nomenclature used in the following model is the same or similar as that in Section 3.2. Several additional variables are required, which are listed as follows:

ξ Index of realisation of uncertain parameters.

Λ Specified set of realisations of uncertain parameters (indexed by ξ).

Ξ Set of all realisations of uncertain parameters (indexed by ξ).

$\mathbb{E}[\cdot]$ Expected value.

Variables associated with ξ represent the corresponding variables under different realisations of ξ. For example, $p_{g,d}^{t,s}(\xi)$ is the power generation of generator g in d^{th} interval of year t under contingency s under realisation ξ.

4.2.2 Two-Stage Stochastic Formulation of Transmission Expansion Planning

A two-stage stochastic formulation of TEP problem (noted as **STEPM**) is presented as follows, which is similar with that of the deterministic two-stage TEP problem (**DTEPM**).

$$\text{Min} \sum_{t=1}^{NT} 1/(1+r)^t \sum_{e \in \mathbf{E}} x_e^t C_e + \mathbb{E}\left[\sum_{t=1}^{NT} 1/(1+r)^t \sum_{d=1}^{ND} \Delta d \sum_{g \in \mathbf{G}_t} C_g\left(p_{g,d}^{t,0}(\xi)\right) \right] \quad (4\text{-}1)$$

s.t.

$$\sum_{g \in \mathbf{G}_{i,t}} p_{g,d}^{t,s}(\xi) + \sum_{e \in \mathbf{E}_{\cdot i}} f_{e,d}^{t,s}(\xi) - \sum_{e \in \mathbf{E}_{i \cdot}} f_{e,d}^{t,s}(\xi) + \sum_{w \in \mathbf{W}_{i,t}} p_{w,d}^{t,s}(\xi) + q_{i,d}^{t,s}(\xi) = D_{i,d}^{t}(\xi)$$

$$\forall i, \forall d, \forall t, \forall s, \forall \xi \tag{4-2}$$

$$-B_e \left(\theta_{i_e,d}^{t,s}(\xi) - \theta_{j_e,d}^{t,s}(\xi) \right) \leq -f_{e,d}^{t,s}(\xi) + M_e(1 - x_e^t + \tilde{h}_e^s) \quad \forall e, \forall d, \forall t, \forall s, \forall \xi \tag{4-3}$$

$$B_e \left(\theta_{i_e,d}^{t,s}(\xi) - \theta_{j_e,d}^{t,s}(\xi) \right) \leq f_{e,d}^{t,s}(\xi) + M_e(1 - x_e^t + \tilde{h}_e^s) \quad \forall e, \forall d, \forall t, \forall s, \forall \xi \tag{4-4}$$

$$-\overline{f}_e^s x_e^t (1 - \tilde{h}_e^s) \leq f_{e,d}^{t,s}(\xi) \leq \overline{f}_e^s x_e^t (1 - \tilde{h}_e^s) \quad \forall e, \forall d, \forall t, \forall s, \forall \xi \tag{4-5}$$

$$0 \leq p_{g,d}^{t,s}(\xi) \leq \overline{p}_g^t \quad \forall g, \forall d, \forall t, \forall s, \forall \xi \tag{4-6}$$

$$\sigma \, \overline{p}_{w,d}^t(\xi) \leq p_{w,d}^{t,s}(\xi) \leq \overline{p}_{w,d}^t(\xi) \quad \forall w, \forall d, \forall t, s \in \mathbf{S}_0, \forall \xi \in \mathbf{\Lambda} \tag{4-7}$$

$$0 \leq p_{w,d}^{t,s}(\xi) \leq \overline{p}_{w,d}^t(\xi) \quad \forall w, \forall d, \forall t, \forall s \in \mathbf{S} \backslash \mathbf{S}_0, \forall \xi \tag{4-8}$$

$$0 \leq q_{i,d}^{t,s}(\xi) \leq D_{i,d}^t(\xi) \quad \forall i, \forall d, \forall t, \forall s, \forall \xi \tag{4-9}$$

$$\sum_{i \in \mathbf{B}} q_{i,d}^{t,s}(\xi) \leq \varepsilon_{|s|} D_d^t(\xi) \quad \forall s, \forall d, \forall t, \forall \xi \in \mathbf{\Lambda} \tag{4-10}$$

$$x_e^t = 1 \quad \forall e \in \mathbf{E}_0, \forall t \tag{4-11}$$

$$x_e^{t-1} \leq x_e^t, x_e^t \in \{0,1\} \quad \forall e \in \mathbf{E} \backslash \mathbf{E}_0, \forall t \tag{4-12}$$

Similar with the objective function (3-1) for **DTEPM**, the objective function (4-1) for **STEPM** also represents the overall cost of investment for new lines and expected

operation cost for generators under various realisations. For **DTEPM**, the operation cost is calculated only under one deterministic realisation.

STEPM needs to meet constraints (4-2)-(4-12), most of which remain the same or similar meanings as those in **DTEPM**. However, each constraint needs to be satisfied under all possible realisations of ξ. The meaning of each constraint is introduced as follows.

The power balance at each bus under any possible contingencies $\forall s \in \mathbf{S}$ should be fulfilled, which is represented by (4-2). The Kirchhoff's voltage law for each line is represented by (4-3) and (4-4). Three assumption are applied: 1) the susceptance is larger relative to the conductance; 2) the phase angle difference is small enough to ensure $\sin(\theta_m - \theta_n) \approx \theta_m - \theta_n$; 3) the voltage magnitudes are close to 1.0 and does not vary significantly. The Big-M method is applied to represent the power flow no matter whether the line is available or not. The maximum power flow on each line is limited by (4-5). The power generation of each generation unit needs to be within the installation capacity, shown by (4-6). In order to ensure the utilisation level of wind generation under normal state ($\forall s \in \mathbf{S}_0$), (4-7) represents the utilisation level of wind generation needs to be larger than a given ratio, under a given set of realisations $\forall \xi \in \mathbf{\Lambda}$. Ideally, (4-7) should be satisfied under any possible realisation $\forall \xi \in \mathbf{\Xi}$. However, the size of the problem would become so huge that it might become intractable even by the application of BD technique. So it comes up a trade-off solution, by reducing all

possible realisations $\forall \xi \in \Xi$ to some specific realisations $\forall \xi \in \Lambda$. The detail of the specific realisations is explained in the following paragraph. (4-7) only needs to be satisfied under $\forall \xi \in \Lambda$ rather than $\forall \xi \in \Xi$. When selecting realisations of the set Λ, the strategy is to select extreme realisations which are most possible to lead to wind spillage. For example, when power generation from wind is relatively large, but the load demand is in the period of low consumption, then it might happen wind spillage under this realisation. In this chapter, four realisations are selected, including: (1) large wind generation, large load demand; (2) large wind generation, low load demand; (3) low wind generation, large load demand; (4) low wind generation, low load demand. Under any contingency state $\forall s \in \mathbf{S} \backslash \mathbf{S}_0$, (4-7) is not required to be met, for the reason that the priority under contingency state is to keep the system secure, just as shown in (4-8). The loss-of-load at each bus must be smaller than the load demand at that bus, represented by (4-9). According to N-k reliability criteria, the total loss-of-load under a certain rank k of contingencies should be less than a specified ratio $\varepsilon_{|s|}$ of the total load demand, just as shown in (4-10). Similar with the reason for (4-7), the problem might become intractable, if (4-10) is required to be satisfied under any possible realisations $\forall \xi \in \Xi$ and any possible contingencies. So the same strategy is applied for (4-10), which is to reduce all possible realisations $\forall \xi \in \Xi$ to the set $\forall \xi \in \Lambda$, applied in (4-7). (4-11) represents existing lines have been built. (4-12) ensures that once the candidate line is selected to be built, it remains in place in the later years.

4.3 Stochastic Dual Dynamic Programming Overview

4.3.1 Two-Stage Stochastic Problem

In this section, a brief introduction of SDDP method applied to the two-stage stochastic programming problem is given out[121]. The general two-stage stochastic problem can be formulated as follows:

$$\min_{\mathbf{x} \in \chi} \mathbf{c}^{\mathrm{T}} \mathbf{x} + \mathcal{Q}(\mathbf{x}) \tag{4-13}$$

where $\chi := \left\{ \mathbf{x} \in \mathbb{R}^{n_1} : \mathbf{Ax} \leq \mathbf{b}, \mathbf{x} \geq 0 \right\}, \mathcal{Q}(\mathbf{x}) := \mathbb{E}\left[Q(\mathbf{x}, \xi) \right]$ and $Q(\mathbf{x}, \xi)$ is the optimal value of the second stage problem under the realisation of ξ.

$$Q(\mathbf{x}, \xi) = \min_{\mathbf{y} \in \mathbb{R}^{n_2}} \mathbf{q}^{\mathrm{T}} \mathbf{y} \tag{4-14}$$

$$s.t. \quad \mathbf{Tx} + \mathbf{Wy} \geq \mathbf{h} \tag{4-15}$$

$$\mathbf{y} \geq 0 \tag{4-16}$$

It is assumed that some/all elements of $\mathbf{q}$, $\mathbf{T}$, $\mathbf{W}$ and $\mathbf{h}$ are random. The dual of the subproblem can be expressed as follows:

$$Q(\mathbf{x}, \xi) = \max_{\lambda} \lambda^{\mathrm{T}} (\mathbf{h} - \mathbf{Tx}) \tag{4-17}$$

$$s.t. \quad \mathbf{W}^{\mathrm{T}} \lambda \leq \mathbf{q} \tag{4-18}$$

$$\lambda \geq 0 \tag{4-19}$$

A random sample $\tilde{\xi}^1, \tilde{\xi}^2, \cdots, \tilde{\xi}^N$ of N realisations is created according to the distribution of the random vector ξ. The probability of each realisation is the same with each other, $1/N$ to be specific. By doing this, the original problem (4-13) can be replaced by the so-called SAA problem.

$$\min_{\mathbf{x} \in \chi} \mathbf{c}^{\mathrm{T}} \mathbf{x} + \tilde{\mathcal{Q}}(\mathbf{x}) \tag{4-20}$$

where $\tilde{\mathcal{Q}}(\mathbf{x}) = \mathbb{E}_N \left[Q(\mathbf{x}, \xi) \right] = N^{-1} \sum_{j=1}^{N} Q(\mathbf{x}, \tilde{\xi}^j)$ and we use the notation $\mathfrak{S}_N = \left[\tilde{\xi}^1, \tilde{\xi}^2, \cdots, \tilde{\xi}^N \right]$ to represent the random sample.

Now the SDDP algorithm is implemented to the SAA problem rather than to the original problem. At the kth iteration of the SDDP algorithm, it carries out the procedure, called as *backward pass*. Let $\tilde{\mathbf{x}}_k \in \mathcal{X}$ be the current first stage solution and $\mathfrak{Q}_k(\mathbf{x})$ be the approximation of $\tilde{\mathcal{Q}}(\mathbf{x})$. $\mathfrak{Q}_k(\mathbf{x})$ can be updated by the supporting planes obtained in each iteration. Suppose $\mathbf{g}_k \in \partial \tilde{\mathcal{Q}}(\tilde{\mathbf{x}}_k)$ is a subgradient of $\tilde{\mathcal{Q}}(\tilde{\mathbf{x}}_k)$, then the new supporting plane can be obtained:

$$\ell_k(\mathbf{x}) = \tilde{\mathcal{Q}}(\tilde{\mathbf{x}}_k) + \mathbf{g}_k^{\mathrm{T}}(\mathbf{x} - \tilde{\mathbf{x}}_k) \tag{4-21}$$

The approximation of the SAA problem can be updated with the new supporting plane: $\mathfrak{Q}_{k+1}(\mathbf{x}) = \max \left\{ \mathfrak{Q}_k(\mathbf{x}), \ell_k(\mathbf{x}) \right\}$. With the new approximation, $\tilde{\mathbf{x}}_k$ can be updated with the new optimal problem:

$$\min_{\mathbf{x} \in \chi} \mathbf{c}^{\mathrm{T}} \mathbf{x} + \mathfrak{Q}_{k+1}(\mathbf{x}) \tag{4-22}$$

Since each supporting plane $\ell_k(\mathbf{x})$ is less than or equal to $\tilde{\mathcal{Q}}(\mathbf{x})$, we can get:

$$\tilde{\mathcal{Q}}(\mathbf{x}) \geq \mathfrak{Q}_k(\mathbf{x}) \quad k = 1, 2, \cdots \tag{4-23}$$

So the optimal value of the problem (4-22) is less than or equal to the problem (4-20).

Let:

$$\underline{\mathcal{G}}_k = \inf \left\{ \mathbf{c}^{\mathrm{T}} \mathbf{x} + \mathfrak{Q}_k(\mathbf{x}) \right\} \quad k = 1, 2, \cdots \tag{4-24}$$

$\underline{\mathcal{G}}_k$ establishes the lower bound of the SAA problem in each iteration. To carry out the above mentioned *backward pass*, we need to calculate the second stage problem for $\mathbf{x} = \tilde{\mathbf{x}}_k$ and each realisation $\tilde{\boldsymbol{\xi}}^j = \left(\tilde{\mathbf{h}}_j, \tilde{\mathbf{T}}_j, \tilde{\mathbf{W}}_j, \tilde{\mathbf{q}}_j \right), j = 1, 2, \cdots, N$. Let $\mathbf{y}_{kj}$ be the optimal solution of the second stage problem (4-14)-(4-16), and $\boldsymbol{\lambda}_{kj}$ be the optimal dual solution for $\tilde{\boldsymbol{\xi}}^j$, then we can get:

$$\tilde{\mathcal{Q}}(\tilde{\mathbf{x}}_k) = N^{-1} \sum_{j=1}^{N} \tilde{\mathbf{q}}_j^{\mathrm{T}} \mathbf{y}_{kj} \text{ and } \mathbf{g}_k = -N^{-1} \sum_{j=1}^{N} \tilde{\mathbf{T}}_j^{\mathrm{T}} \boldsymbol{\lambda}_{kj} \tag{4-25}$$

Next, let us discuss the so-called *forward pass* of the SDDP algorithm. A subsample $\mathfrak{S}_M = \left[\tilde{\boldsymbol{\xi}}^1, \tilde{\boldsymbol{\xi}}^2, \cdots, \tilde{\boldsymbol{\xi}}^M \right]$ is generated from the $\mathfrak{S}_N = \left[\tilde{\boldsymbol{\xi}}^1, \tilde{\boldsymbol{\xi}}^2, \cdots, \tilde{\boldsymbol{\xi}}^N \right]$. Let $\mathcal{G}_{kj} = \tilde{\mathbf{q}}_j^{\mathrm{T}} \mathbf{y}_{kj}$ be the optimal objective of the corresponding second stage problem, with $\mathbf{x} = \tilde{\mathbf{x}}_k$ and $\tilde{\boldsymbol{\xi}} = \tilde{\boldsymbol{\xi}}^j$.

Let

$$\bar{\vartheta} = \frac{1}{M}\sum_{j=1}^{M}\vartheta_{kj} \text{ and } \hat{\sigma}_{\vartheta}^{2} = \frac{1}{M-1}\sum_{j=1}^{M}\left(\vartheta_{kj} - \bar{\vartheta}\right)^{2} \qquad (4\text{-}26)$$

be the corresponding average and variance of the optimal value ϑ_{kj}. $\bar{\vartheta}$ is an unbiased estimate of $\tilde{\mathcal{Q}}(\mathbf{x})$ and

$$\left[\bar{\vartheta} - \gamma_{\alpha/2}\hat{\sigma}_{\vartheta}/\sqrt{M}, \bar{\vartheta} + \gamma_{\alpha/2}\hat{\sigma}_{\vartheta}/\sqrt{M}\right] \qquad (4\text{-}27)$$

gives the $100(1-\alpha)\%$ confidence level for $\tilde{\mathcal{Q}}(\mathbf{x})$, where γ_{α} represents the $(1-\alpha)$-quantile of the standard normal distribution.

4.3.2 Overall Procedure of SDDP Algorithm

Steps to carry out SDDP algorithm are explained as follows and shown in Figure 4-1:

Step 1) Initialisation

➢ initialise the counter $k=0$; initialise the approximation of second stage objective $\mathfrak{Q}_{k}(\mathbf{x}) = 0$;

Step 2) Sampling

➢ Sample N realisations based on probability distribution functions $\mathfrak{S}_{N} = \left[\tilde{\boldsymbol{\xi}}^{1}, \tilde{\boldsymbol{\xi}}^{2}, \cdots, \tilde{\boldsymbol{\xi}}^{N}\right]$;

Step 3) Update $\mathbf{x}_{k}$

➢ Increase the counter $k=k+1$;

➢ Solve the following problem and update $\mathbf{x}_{k}$:

$$z = \min_{\mathbf{x} \in \chi} \mathbf{c}^{\mathrm{T}}\mathbf{x} + \mathfrak{Q}_{k-1}(\mathbf{x})$$

➢ Get the lower bound: $z_k = z$;

Step 4) Forward Pass

➢ Get a subsample $\mathfrak{S}_M = \left[\tilde{\xi}^1, \tilde{\xi}^2, \cdots, \tilde{\xi}^M\right]$ from $\mathfrak{S}_N = \left[\tilde{\xi}^1, \tilde{\xi}^2, \cdots, \tilde{\xi}^N\right]$;

➢ Solve the second stage problem (4-14)-(4-16) with the current solution

$\mathbf{x} = \tilde{\mathbf{x}}_k$, for each $\tilde{\xi} = \tilde{\xi}^j$, $j = 1, 2, \cdots, M$, and let $\vartheta_{kj} = \tilde{\mathbf{q}}_j^{\mathrm{T}} \mathbf{y}_{kj}$

➢ Calculate the unbiased estimate $z_u = \mathbf{c}^{\mathrm{T}}\mathbf{x}_k + \dfrac{1}{M}\sum_{j=1}^{M}\vartheta_{kj}$ of the second stage

problem with $\mathbf{x} = \tilde{\mathbf{x}}_k$, and the corresponding variance

$$\hat{\sigma}_\vartheta = \sqrt{\frac{1}{M-1}\sum_{j=1}^{M}\left(\vartheta_{kj} - \bar{\vartheta}\right)^2}$$

where $\bar{\vartheta} = \dfrac{1}{M}\sum_{j=1}^{M}\vartheta_{kj}$

➢ Stop if

$$z_u - \frac{\gamma_{\alpha/2}}{\sqrt{M}}\hat{\sigma}_\vartheta < z_l < z_u + \frac{\gamma_{\alpha/2}}{\sqrt{M}}\hat{\sigma}_\vartheta$$

➢ Else go to **Step 5)**.

Step 5) Backward pass

➢ For the current solution $\mathbf{x} = \tilde{\mathbf{x}}_k$, the problem (4-14)-(4-16) is solved

with each $\tilde{\xi} = \tilde{\xi}^j$, $j = 1, 2, \cdots, N$;

➢ Let $\tilde{\mathcal{Q}}(\tilde{\mathbf{x}}_k) = N^{-1}\sum_{j=1}^{N}\tilde{\mathbf{q}}_j^{\mathrm{T}}\mathbf{y}_{kj}$ and $\mathbf{g}_k = -N^{-1}\sum_{j=1}^{N}\tilde{\mathbf{T}}_j^{\mathrm{T}}\lambda_{kj}$;

➢ Let $\ell_k(\mathbf{x}) = \tilde{\mathcal{Q}}(\tilde{\mathbf{x}}_k) + \mathbf{g}_k^{\mathrm{T}}(\mathbf{x} - \tilde{\mathbf{x}}_k)$ and $\mathfrak{Q}_k(\mathbf{x}) = \max\left\{\mathfrak{Q}_{k-1}(\mathbf{x}), \ell_k(\mathbf{x})\right\}$;

➢ Go to **Step 3)**.

Step 1) Set $k=0$; $\mathfrak{Q}_k(x)=0$

Step 2) Sample N realizations $\mathfrak{S}_N = \left[\tilde{\xi}^1, \tilde{\xi}^2, \cdots, \tilde{\xi}^N\right]$

Step 3) Increase the counter $k=k+1$;

Solve the following problem and update $\mathbf{x}_k$:
$$z = \min_{\mathbf{x} \in \chi} \mathbf{c}^T \mathbf{x} + \mathfrak{Q}_{k-1}(\mathbf{x})$$

Get the lower bound: $z_k = z$;

Step 4) Get a subsample $\mathfrak{S}_M = \left[\tilde{\xi}^1, \tilde{\xi}^2, \cdots, \tilde{\xi}^M\right]$ from $\mathfrak{S}_N$

Solve the second stage problem (4-14)-(4-16) with the current solution $\mathbf{x}_k$, for each $\tilde{\xi} = \tilde{\xi}^j$, $j = 1, 2, \cdots, M$
Let $\vartheta_{kj} = \tilde{\mathbf{q}}_j^T \mathbf{y}_{kj}$

Calculate the unbiased estimate of the second stage problem
$$z_u = \mathbf{c}^T \mathbf{x}_k + \frac{1}{M} \sum_{j=1}^{M} \vartheta_{kj}$$
The variance
$$\hat{\sigma}_\vartheta = \sqrt{\frac{1}{M-1} \sum_{j=1}^{M} \left(\vartheta_{kj} - \bar{\vartheta}\right)^2} \qquad \bar{\vartheta} = \frac{1}{M} \sum_{j=1}^{M} \vartheta_{kj}$$

No

End

$$z_u - \frac{\gamma_{\alpha/2}}{\sqrt{M}} \hat{\sigma}_\vartheta < z_l < z_u + \frac{\gamma_{\alpha/2}}{\sqrt{M}} \hat{\sigma}_\vartheta$$

Yes

Step 5) Solve the second stage problem (4-14)-(4-16) with the current solution $\mathbf{x}_k$, for each $\tilde{\xi} = \tilde{\xi}^j$, $j = 1, 2, \cdots, N$
Let
$$\tilde{\mathcal{Q}}(\tilde{\mathbf{x}}_k) = N^{-1} \sum_{j=1}^{N} \tilde{\mathbf{q}}_j^T \mathbf{y}_{kj} \quad \mathbf{g}_k = -N^{-1} \sum_{j=1}^{N} \tilde{\mathbf{T}}_j^T \boldsymbol{\lambda}_{kj}$$
$$\ell_k(\mathbf{x}) = \tilde{\mathcal{Q}}(\tilde{\mathbf{x}}_k) + \mathbf{g}_k^T (\mathbf{x} - \tilde{\mathbf{x}}_k) \quad \mathfrak{Q}_k(\mathbf{x}) = \max\left\{\mathfrak{Q}_{k-1}(\mathbf{x}), \ell_k(\mathbf{x})\right\}$$

Figure 4-1 Steps for SDDP algorithm

4.4   Application of SDDP for Two-Stage Stochastic TEP problem

Similar with the decomposition approach for the deterministic two-stage TEP model (**DTEPM**, (3-1)-(3-10)), the stochastic two-stage TEP model (**STEPM**, (4-1)-(4-12)) can also be decomposed into a master problem and subproblems. The master problem for **STEPM** is the same as that for **DTEPM**, just as (3-25)-(3-26) show. The subproblem for **STEPM** is the operational problem, which is similar as that in **DTEPM**. The difference is that the subproblem for **STEPM** is to calculate the expected operation cost under all possible realisations, while the subproblem for **DTEPM** is to calculate the expected operation cost only under a specific realisation. Because the uncertainty is considered in **STEPM** in the form of calculating expected operation cost, the difficulty to solve **STEPM** is much larger than that to solve **DTEMP**.

The subproblem for **STEPM** can be formulated as follows:

$$\text{Min } \mathbb{E}\left[\sum_{t=1}^{NT} 1/(1+r)^t \sum_{d=1}^{ND} \Delta d \sum_{g \in \mathbf{G}_t} C_g\left(p_{g,d}^{t,0}(\xi) \right) \right] \tag{4-28}$$

s.t. (4-2)-(4-10)

As seen from (4-28), the operation cost is the sum of operation cost over the planning horizon. For each time interval, the operation cost only relies on constraints in that time interval, so it can be calculated independently. According to this principle, the

subproblem (4-28) can be divided into subproblems for different intervals, which are noted as **SP**(t,d) and expressed as follows:

$$\text{Min } \mathbb{E}\left[\Delta d \sum_{g \in \mathbf{G}_t} C_g\left(p_{g,d}^{t,0}(\xi)\right)\right] \tag{4-29}$$

$s.t.$ (4-2)-(4-10)

For the subproblem shown in (4-29) specified for each t and d, the size of the problem is greatly reduced, which is very helpful to make the problem tractable.

After solving the master problem, it can get the expansion plan $\tilde{\mathbf{x}}$. However, under the obtained $\tilde{\mathbf{x}}$, the subproblem **SP**(t,d) might not be feasible. For example, there might be loss-of-load under normal state or the amount of loss-of-load under contingencies exceeds the specified ratio, so constraint (4-10) is violate. Moreover, the utilisation level of wind generation cannot reach the specified ratio, so constraint (4-7) is violated. If the subproblem **SP**(t,d) is not feasible, corresponding feasibility cuts are generated and added into **MP** problem.

To solve the subproblem **SP**(t,d), it needs to make the subproblem itself feasible, which can be realised by three steps:

(1)   The constraint (4-10) needs to be satisfied under normal state ($s \in \mathbf{S}_0$), which means there is no load shedding.

(2)   The constraint (4-7) needs to be satisfied under normal state ($s \in \mathbf{S}_0$), which

means the utilisation level of wind should be no less than the specific level.

(3)   The constraint (4-10) needs to be satisfied under contingency states

   ($\forall s \in \mathbf{S} \backslash \mathbf{S}_0$), which means that the ratio of load shedding under a given rank of

   contingency k should be no larger than ε_k.

If the above three requirements cannot be met, then the corresponding feasibility cuts

are generated and added into the **MP** problem.

When the above three constraints can be satisfied, the subproblem is feasible. After

that, the subproblem shown in (4-29) can be optimised to get the optimal operation

cost, under the given expansion plan $\tilde{\mathbf{x}}$. In this chapter, N-k reliability criteria only

include N-1 and N-2 reliability criteria, so $\mathbf{S} = \mathbf{S}_0 \bigcup \mathbf{S}_1 \bigcup \mathbf{S}_2$. The approach to consider

N-k reliability criteria has been introduced in Section 3.3.2.

Figure 4-2 shows the overall steps to conduct the proposed algorithm. The original

complicated problem is decomposed into the **MP** problem and subproblems, based on

the implementation of BD approach. Steps to ensure the feasibility of subproblems are

carried out before solving subproblems to get the optimal operation cost. The N-k

reliability criteria can be fully considered by the proposed algorithm. The SDDP

method is applied to calculate the expected operation cost under uncertainties of load

demand and wind generation. Because of the independency of subproblems for each

time interval, the overall expectation of operation cost can be obtained by summing up

the operation cost of each interval. The $\mathfrak{Q}_k(\mathbf{x})$ represents the approximation of operation cost under a given expansion plan $\mathbf{x}$, which is calculated based on the subproblem $\mathbf{SP}(t,d)$ for each time interval.
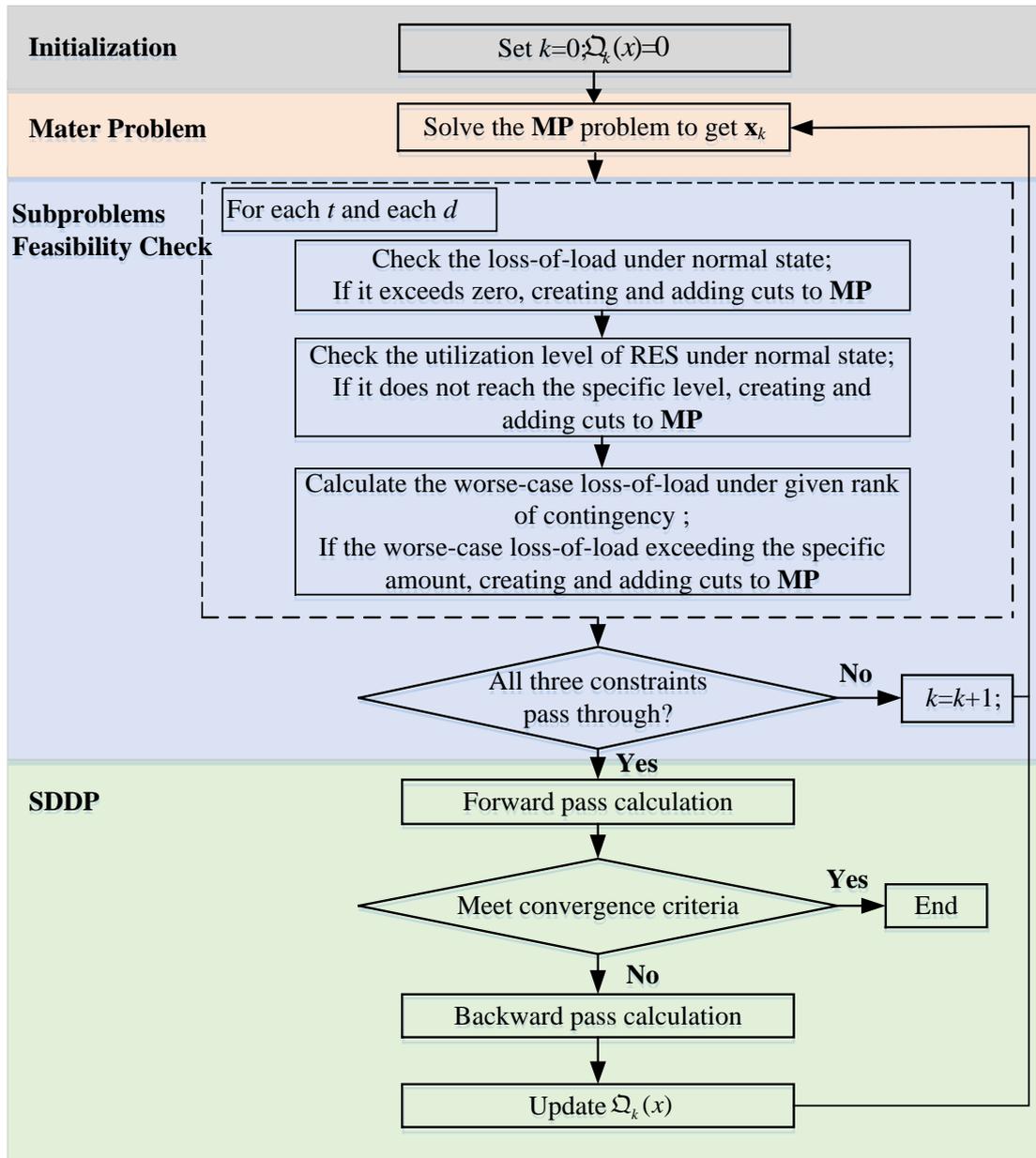
Figure 4-2 Overall Steps of proposed algorithm

4.5 Case Studies

To verify the performance of the proposed algorithm in this chapter, case studies are carried out on two test systems, which are similar as those applied in Chapter 3, namely revised IEEE 24-bus test system and revised IEEE RTS-96.

Since N-k reliability criteria are the most important and difficult factors in the TEP problem, expansion plans with and without considering N-k reliability criteria are compared. Without losing generality, only N-1 and N-2 reliability criteria are considered in the following case studies. N-k ($k \geq 3$) reliability criteria can also be integrated into the proposed algorithm, if required. It needs to check the feasibility of the solution in the stage of subproblem feasibility check, by checking the N-k ($k \geq 3$) reliability criteria, together with N-1 and N-2 criteria. The requirements for N-k reliability criteria are listed as follows: 1) loss-of-load should not happen under normal state and N-1 contingency; 2) the loss-of-load percentage should be no larger than 1% under N-2 contingencies.

To illustrate the impact of considering uncertainties in TEP, expansion plans with and without considering uncertainties are also compared. In other words, the difference between stochastic planning and deterministic planning is analysed.

As for the utilisation level of wind, it is assumed that the utilisation level should be no less than 80% of the available wind generation under normal state. As for parameters

in the SDDP approach, they can be summarised as follows: 1) the size of samples for backward pass is 200; 2) 50 samples are selected from the obtained 200 samples during the forward pass; 3) normal distributions are applied when generating random samples for loads and wind generation, with the standard deviation to be 20% of the expected value. For example, the probability distribution function for wind generation is $N(P_w, 0.2 \cdot P_w)$, where P_w is the expected wind generation.

The sets of candidate lines for these two test systems are selected according to the method proposed in Chapter 3. All case studies were coded with the YALMIP[115], which is a toolbox in Matlab. The commercial solver, CPLEX 12.1.4, was taken as the solver for MILP problem. All programs were run on an Intel Core-i5 2.5-GHz personal computer with 4G memory.

4.5.1   Revised IEEE 24-Bus Test System

The revised IEEE 24-bus test system is the same as that applied in Section 3.5.1, where details about this test system can be found.

Firstly, N-k reliability criteria are not considered in this test system. New lines need to be built in each year under two approaches, namely SDDP approach and deterministic approach, are shown in Table 4-1. It can be seen that these two approaches get the same expansion plan, with three new lines to be built over the planning horizon. In average, one line needs to be built in every two years.

The deterministic approach refers to the scenario that load demand and wind generation only have one realisation, which is the expectation of load demand and wind generation. It can be seen that these two approaches get the same expansion plan, with three new lines to be built over the planning horizon.

Table 4-1 EXPANSION PLAN FOR IEEE 24-BUS SYSTEM WITHOUT RELIABILITY CRITERIA

Years	New lines by SDDP	New lines by deterministic approach
1	N/A	N/A
2	N/A	N/A
3	N/A	N/A
4	(16,17),(14,15)	(16,17),(14,15)
5	(4,8)	(4,8)
6	N/A	N/A
Total lines	3	3

Secondly, N-k reliability criteria are considered in this test system. From Table 4-2, it can be seen that five new lines are selected to be built in both two approaches. Compared with the expansion plan without N-k reliability criteria, two more lines are built with the consideration of N-k reliability criteria, which illustrates the necessity of considering N-k reliability criteria in TEP problem. Although uncertainties of load demand and wind generation have no influence on expansion plans of two approaches in this test system, the impact of uncertainties is revealed by the next test system.

Table 4-2 EXPANSION PLAN FOR IEEE 24-BUS SYSTEM WITH RELIABILITY CRITERIA

Years	New lines by SDDP	New lines by deterministic approach
1	(14,15), (1,5), (4,8), (6,9)	(14,15), (1,5), (4,8), (6,9)
2	N/A	N/A
3	N/A	N/A
4	N/A	N/A
5	(16,17)	(16,17)
6	N/A	N/A
Total lines	5	5

4.5.2 Revised IEEE RTS-96 Test System

The revised IEEE RTS-96 test system is the same as that applied in Section 3.5.2. So details about this test system are not introduced here.

Firstly, N-k reliability criteria are not considered in this test system. Expansion plans under SDDP approach and deterministic approach are shown in Table 4-3. It can be seen that, four lines are selected to be built in the deterministic approach, while nine lines are built in the SDDP approach. So uncertainties of load demands and wind generation do make a difference to the expansion plan. The four lines obtained in the deterministic approach are also covered by the SDDP approach. However, the sequence to build those four lines in the deterministic approach is different from that in the SDDP approach. For instance, in the deterministic approach, the line $(23, 41)$ is built in the fourth year, while that line is built in the third year in the SDDP approach.

Table 4-3 EXPANSION PLAN FOR IEEE RTS-96 WITHOUT RELIABILITY CRITERIA

Years	New lines by SDDP	New lines by deterministic approach
1	N/A	N/A
2	N/A	N/A
3	**(23,41)**	N/A
4	**(13,38)**, (7,26)	**(23,41)**
5	**(14,15)**, (62,63), (52,56)	**(16,17)**
6	**(16,17)**, (28,32), (9,27)	**(14,15)**, **(13,38)**
Total lines	9	4

Two expansion plans are obtained from SDDP approach and deterministic approach, respectively. The question is which plan can have a better performance under the real operation with uncertainties of load demand and wind generation. For example, 1000 samples are generated by the Monte-Carlo simulation technique, according to the probability distribution functions of uncertain parameters (load demand and wind generation), then the expected operation cost (the objective of the second stage problem, which is the latter part of (4-1)) can be calculated. The expected operation cost under two plans is shown in Table 4-4. From the table, it can be seen that investment cost for SDDP approach is about 1.203 (M$) larger than that for deterministic approach. However, SDDP approach has a lower operation cost, which is about 7.65 (M$) less than that for deterministic approach. As a consequence, the overall cost for SDDP approach is about 6.4467(M$) (or 2.72% in percentage) smaller than that for deterministic approach. The expansion plan obtained by SDDP approach has a

better performance than that obtained by deterministic approach. So it is worthwhile to consider uncertainties during the process of TEP.

Table 4-4 TOTAL COST UNDER TWO PLANS WITHOUT RELIABILITY CRITERIA

Approaches	Operation Cost (M$)	Investment Cost(M$)	Total Cost(M$)
SDDP	236.3	1.8	238.1
Deterministic	243.95	0.6972	244.65

Secondly, N-*k* reliability criteria are considered in this test system. Expansion plans under SDDP approach and deterministic approach are shown in Table 4-5. It can be seen that the number of new lines to be built under two expansion plans is the same, with the size of 23 in total. Compared with expansion plans without N-*k* reliability criteria, the required number of lines to be built with N-*k* reliability criteria is greatly increased from 9 to 23 (SDDP approach), and 4 to 23 (deterministic approach), respectively. So N-*k* reliability criteria greatly affect the expansion plan.

Although the total number is the same, the detail expansion plans are not the same. There are fifteen same lines in two expansion plans, which are shown in the bold font. However, the consequence to build those fifteen lines is not the same. For instance, in the expansion plan under SDDP approach, the line (10,27) is planned to be built in the second year, while in the expansion plan under deterministic approach, that line is to be built in the fifth year.

Also, to compare the performance of two plans under the real operation with uncertainties, Monte-Carlo simulation is utilised to generate 1000 samples to calculate the expected operation cost. Results are shown in Table 4-6. Although the expansion plan obtained by SDDP approach has a larger investment cost than that for deterministic approach (increased by 0.473 (M$)), the operation cost under SDDP approach is about 4.43(M$) smaller than that under deterministic approach. In total, the cost under SDDP approach is about 3.957 (M$) (or 1.53% in percentage) less than that under deterministic approach. Again, SDDP approach can obtain a better expansion plan that under deterministic approach.

Compared with the total cost without N-k reliability criteria (in Table 4-4), the total cost with N-k reliability criteria (in Table 4-6) is increased by 7.65% (under SDDP approach) and 6.34% (under deterministic approach), respectively. So when considering N-k reliability criteria in TEP, not only more lines need to be built, but the overall cost is increased.

Table 4-5 EXPANSION PLAN FOR IEEE RTS-96 WITH RELIABILITY CRITERIA

Years	New lines by SDDP	New lines by deterministic approach
1	**(14,15), (13,38), (62,63), (4,8), (5,8), (51,53), (28,32), (52,56),(6,27), (30,33)**, (54,57)	(54,58), **(14,15), (13,38), (62,63)**, (4,8), **(5,8), (51,53)**, (6,29), **(28,32), (52,56)**
2	**(6,29), (10,27)**, (6,9), (6,10)	**(30,33)**
3	(7,26)	N/A
4	**(23,41)**	**(23,41)**
5	(3,29), **(9,27)**	(3,7), (11,48), **(6,27),(9,27), (10,27)**
6	(16,17), **(7,27)**, (7,8), (6,7)	**(7,27)**, (38,48), (35,48), (6,33), (6,34), (7,32)
Total lines	23	23

Table 4-6 TOTAL COSTS UNDER TWO PLANS WITH RELIABILITY CRITERIA

Approaches	Operation Costs (M$)	Investment Costs(M$)	Total Costs(M$)
SDDP	245	11.218	256.22
Deterministic	249.43	10.745	260.18

4.5.3 Convergence Analysis and Computation Time

The performance of convergence is a very important aspect of an algorithm. In this section, the convergence analysis is carried out, and results are shown in Table 4-7. The required number of iteration and computation time with and without N-k reliability criteria are presented in this table. It is obvious that N-k reliability criteria greatly increase the difficulty of TEP. In IEEE 24-bus test system, the required computation time without N-k reliability criteria is 43.1 seconds, while it is 523.2 seconds for that with N-k reliability criteria. In IEEE RTS-96 test system, the required computation time with and without N-k reliability criteria is 105.8 seconds and 6053.5 seconds, respectively. In two test systems, the required computation time without N-k

reliability criteria is only a twelfth and a fifty-seventh of that with N-k reliability criteria, respectively. The number of iteration required in two test systems is smaller than 30, which is acceptable for practical application.

Table 4-7 COMPUTATION PERFORMANCE

Test system	Reliability criteria	Number of Iteration	Computation time (s)
IEEE 24-bus	×	5	43.1
	√	13	523.2
IEEE RTS-96	×	17	105.8
	√	23	6053.5

4.6   Summary

The problem of TEP with uncertainties of load demand and wind generation is investigated in this chapter. A two-stage stochastic formulation of TEP is presented, with the objective to minimise investment cost and the expected operation cost under different realisations of uncertain parameters. To solve the established model, BD approach is applied to decompose the original complicated problem into a **MP** problem and subproblems. SDDP is applied to get the expansion plan under uncertainties. The method to apply SDDP to a two-stage stochastic problem is presented, as well as the overall procedure. Moreover, the application of SDDP for two-stage stochastic TEP problem is explained. To verify the performance of the proposed algorithm, two test systems, IEEE 24-bus test system and IEEE RTS-96, are utilised. Results with and without uncertainties, with and without N-k reliability criteria are all compared. Monte-Carlo simulation is applied to get the expected

operation cost of a given expansion plan. Results show that the expansion plan obtained by SDDP approach has a better performance than that obtained by deterministic approach. Results also show that the proposed algorithm can converge within an acceptable number of iterations.

According to the results from the case studies of IEEE 24-bus system and IEEE RTS-96, it can be seen that the uncertainties of load demand and wind generation do affect the optimal expansion plan. So in the future TEP, the impact of uncertainties should not be neglected. The approach proposed in this chapter can be applied in the practical TEP, considering the acceptable computation time and convergence performance.

CHAPTER 5   CHANCE- CONSTRAINED TWO-STAGE PROGRAM FOR UNIT COMMITMENT WITH RENEWABLE ENERGY SOURCES

5.1   Introduction

The UC problem is to get an optimal schedule and the production level of generation units over a specified horizon of time. It needs to satisfy various constraints, such as physical constraints for generators, system-wide constraints and reliability constraints. As the development of wind generation, it has been bringing great challenges to the system operation. On one hand, wind generation is environment-friendly and sustainable, which has been considered as the priority alternative for traditional energy source. On another hand, the intermittence nature of wind generation also increases the difficulty to determine the optimal schedule for each unit. The fluctuation of wind generation needs to be compensated by sufficient amount of spinning reserve. However, to get enough spinning reserve, the scheme of demand response has been widely investigated to reduce reliance on conventional generators to provide spinning reserve [122]. If the spinning reserve cannot support the variation of wind generation, then it might need to shed load or curtail wind generation to ensure the secure operation of the system [123]. However, for consideration of the long-term

113

development, the penetration level of wind generation should be increased to relieve energy crisis and carbon emission. Hence, it has been becoming a critical problem to maximise the utilisation of wind generation, while keeping the reliability of the system.

The most common objective for a stochastic UC problem is to minimise the overall operation cost [85, 124, 125]. To ensure the utilisation level of wind generation, constraints to restrict the minimum utilisation level of wind generation are included into the model. The policy to absorb wind generation might vary in different countries. For example, in some countries like Germany[126], wind generation is given the priority to be utilised. To achieve this task, it requires advanced schedule techniques and sufficient spinning reserve capacity to accommodate the fluctuation of wind generation. In some extreme scenarios of wind generation and load demand, it is possible that the scheduled reserve amount from thermal and other generation technologies cannot cover the power shortage. It might not be economical to schedule excessive reserve only to deal with some extreme scenarios with very low probability. It needs cost to request reserve service from providers, no matter thermal generation or demand response scheme. So it might be more reasonable to permit loss-of-load or wind spillage in some scenarios but with very small probability, which can be realised by the application of CCP.

In this chapter, the chance-constrained two-stage stochastic program for UC problem is proposed. Three chance constraints are established, namely LOLP, LOWP and TLOP.

114

Here, LOWP represents the probability that wind power utilisation level is less than a specified level. A new approach to convert chance constraints into equivalent deterministic constraints is proposed through a sequence of approximation and verification.

This chapter is organised as follows. Firstly, it describes uncertainties of loads and wind power, presents the background of chance-constrained optimisation, formulates the chance-constrained two-stage stochastic UC problem. Secondly, the method to convert chance constraints into equivalent deterministic constraints is presented. Thirdly, it presents the methodology to solve the proposed problem. Fourthly, numerical results are presented and analysed. Finally, it presents the conclusion.

5.2 Chance-Constrained Two-Stage Stochastic Unit Commitment Formulation

5.2.1 Nomenclature

Sets and indices

b Index of bus

B Set of all buses

i Index of thermal units

j Index of wind farms

k Index of loads

t	Index of time period
NG	Number of thermal units
NL	Number of loads
NT	Number of time periods
NW	Number of wind farms
NE	Number of scenarios to calculate the expected second-stage costs
N_v	Number of scenarios to verify chance constraints
N_{op}	Number of iterations to optimise the z values
Ω_b	Set of wind farms connected to bus b
Ξ_b	Set of thermal units connected to bus b
Ψ_b	Set of loads connected to bus b
$\mathbf{R}$	Correlation matrix of random variables
$\boldsymbol{\rho}_{ww}$	Correlation matrix of wind power at different buses
$\boldsymbol{\rho}_{lw}$	Correlation matrix of loads and wind power at different buses
$\boldsymbol{\rho}_{ll}$	Correlation matrix of loads at different buses
Δ_L	Set of all transmission lines linking bus pairs
c_i^f / c_i^l	Fixed/linear cost for thermal unit i ($\$/MW$)
c_i^{up} / c_i^{dw}	Up/down spinning reserve costs unit i ($\$/MW$)
c_{lsd}	Penalty costs of load shedding ($\$/MW$)
c_{wsp}	Penalty costs of wind spillage ($\$/MW$)
G_i, H_i	Minimum on/off time for thermal unit i($\$$)

$k_{m,n}^{b}$ Line flow distribution factor for transmission line linking bus m and bus n due to the net injection at bus b

$L_{k,t}^{0}$ Forecast demand of load k, at time t (MW)

$\underline{q}_i^{g}, \overline{q}_i^{g}$ Minimum/maximum generation of thermal units i (MW)

RU_i, RD_i Ramp-up/ramp-down rate limit for thermal unit i (MW/h)

$\overline{r}_i^{up}, \overline{r}_i^{dw}$ Maximum up/down spinning reserve from thermal unit i (MW)

$\overline{r}_t^{up}, \overline{r}_t^{dw}$ Maximum up/down spinning reserve from all thermal units at time t(MW)

$\underline{r}_t^{up}, \underline{r}_t^{dw}$ Minimum up/down spinning reserve from all units at time t(MW)

$\overline{P}_{m,n}$ Power limits on transmission line which links bus m and bus n(MW)

$W_{j,t}^{0}$ Forecast power of wind farm j at time t(MW)

ε_{LOLP} Probability limit for loss of load

ε_{LOWP} Probability limit for wind utilisation not meeting the specified level

ε_{TLOP} Probability limit for transmission line overloading

μ_i Start up cost for thermal unit i($)

β_w Specified wind utilisation level

σ Tolerance of chance constraints

κ Tolerance of transmission line overloading ratio

$\sigma_{k,t}^{l}$ Standard deviation of load k at time t(MW)

$\sigma_{j,t}^{w}$ Standard deviation of wind farm j at time t(MW)

$\lambda_{1-\varepsilon}$ $100(1-\varepsilon)$th percentile for the standard normal distribution

Variables

$o_{i,t}$ Binary variable to indicate if unit i is on at time t

$u_{i,t}$ Binary variable to indicate if thermal unit i is started up at time t

$r_{i,t}^{up}$, $r_{i,t}^{dw}$ Up/down spinning reserve provided by thermal unit i at time t (MW)

$p_{m,n}^{t,0}$ Day-ahead power in transmission line connected bus m and bus n at time t

        (MW)

$q_{i,t}^{g}$ Power generation of thermal unit i, at time t (MW)

$q_{j,t}^{w,0}$ Day-ahead power from wind farm j at time t (MW)

$\mathbf{z}_{d}$ Vector of $\mathbf{z}$ value in the dth iteration

$\varepsilon_{d,t}^{l}$ LOLP in the dth iteration at time t

$\varepsilon_{d,t}^{w}$ LOWP in the dth iteration at time t

$\varepsilon_{d,t}^{m,n}$ TLOP of line connecting bus m and bus n in the dth iteration at time t

$C_{i}^{g}(\cdot)$ Cost function for thermal units

$C_{i,t}^{r}(\cdot,\cdot)$ Cost function for providing reserve service

$C_{t}^{lsd}(\cdot)$ Cost function for load shedding

$C_{t}^{wsp}(\cdot)$ Cost function for wind spillage

$TN(\cdot,\cdot)$ Truncated normal distribution function

$N(\cdot,\cdot)$ Normal distribution function

$\Pr\{\cdot\}$ Probability measure

$\mathbb{E}[\cdot]$ Expectation of random variable

Random Variables

$l_{k,t}(\tau)$ Demand of load *k*, at time *t* (MW)

$l_{k,t}^{lsd}(\tau)$ Load shedding of load *k* at time *t*(MW*)*

$p_{m,n}^{t}(\tau)$ Line power connecting bus *m* and *n* at time *t* (MW)

$q_{j,t}^{w}(\tau)$ Power of wind farm *j*, at time *t*(MW)

$q_{j,t}^{w,sp}(\tau)$ Wind spillage of wind farm *j* at time *t* (MW)

$q_{j,t}^{w,real}(\tau)$ Power utilisation of wind farm *j* at time *t* (MW)

$r_{i,t}^{up,real}(\tau)$ Up reserve provided by thermal unit *i* at time *t* (MW)

$r_{i,t}^{dw,real}(\tau)$ Down reserve provided by thermal unit *i* at time *t* (MW)

5.2.2   Uncertainties of Loads and Wind Power

Various probability distribution functions (PDF) have been studied to represent the forecast of load demand, such as normal distribution function[83, 104], hyperbolic distribution function[127] and truncated normal distribution function[106, 128]. In this chapter, the truncated normal distribution is applied to represent the forecast of load demand, which is shown by (5-1). Compared with the other two distributions, the truncated normal distribution is more reasonable considering the fact that the forecast should be within a specified level [129]. The application of truncated normal distribution for the forecast of load demand and wind power is verified in[129], and it showed that truncated normal distribution can represent the forecast of load and wind power properly.

$$l_{k,t}(\tau) \sim TN(L_{k,t}^{0}, \sigma_{k,t}^{l}{}^{2}) \quad \forall k, \forall t \qquad (5\text{-}1)$$

Similarly, the forecast of wind power can also be represented by various PDFs [130, 131]. In this chapter, the uncertainty of wind power is also represented by the truncated normal distribution, represented by (5-2).

$$q_{j,t}^{w}(\tau) \sim TN(W_{j,t}^{0}, \sigma_{j,t}^{w\,2}) \quad \forall j, \forall t \qquad (5\text{-}2)$$

Monte Carlo simulation is utilised to create multiple realisations of uncertain parameters, based on given PDFs. The probability of each realisation is equal with each other, which is one divided by the total number of realisations. For example, if 200 realisations are generated according to the PDF, then the probability for each realisation is set to be 0.005.

5.2.3 Chance-Constrained Two-Stage Stochastic Unit Commitment Formulation

In this section, a chance-constrained two-stage stochastic mathematical model for the UC problem is presented, considering uncertainties of load demand and wind power. The whole problem can be divided into two stages. In the first stage, it determines the optimal day-ahead schedule for each unit, including 1) the status and power output of each generation unit, 2) the up/down spinning reserve capacity provided by each generation unit, 3) the wind power to be utilised. The objective of the first-stage problem is to minimise the total energy dispatch cost, which includes fuel cost for generation, startup cost and up/down spinning reserve cost. The second stage problem is to dispatch the reserve capacity and to reschedule the wind power, after knowing

the real realisation of load demand and wind power. The objective of the second stage problem is to minimise the penalty of load shedding and wind spillage. The penalty of load shedding is widely considered in literatures related to the UC problem. In this chapter, the penalty of wind spillage is also included into the objective, to emphasise the utilisation of wind power or to avoid excessive wind spillage. The formulation of first stage problem and second stage problem is presented as follows, which can refer to [104, 105].

5.2.3.1 First Stage Problem

$$\min \sum_{i=1}^{NG} \sum_{t=1}^{NT} \left\{ C_i^g(q_{i,t}^g) + \mu_i u_{i,t} + C_{i,t}^r(r_{i,t}^{up}, r_{i,t}^{dw}) \right\} \tag{5-3}$$

$$s.t. \qquad \sum_{i=1}^{NG} q_{i,t}^g + \sum_{j=1}^{NW} q_{j,t}^{w,0} = \sum_{k=1}^{NL} L_{k,t}^0 \quad \forall t \tag{5-4}$$

$$\underline{q}_i^g o_{i,t} \leq q_{i,t}^g \leq \overline{q}_i^g o_{i,t} \quad \forall i, \forall t \tag{5-5}$$

$$-o_{i,t-1} + o_{i,t} - o_{i,k} \leq 0 \quad 1 \leq k - (t-1) \leq G_i, \forall i, \forall t \tag{5-6}$$

$$o_{i,t-1} - o_{i,t} + o_{i,k} \leq 1 \quad 1 \leq k - (t-1) \leq H_i, \forall i, \forall t \tag{5-7}$$

$$-o_{i,t-1} + o_{i,t} - u_{i,t} \leq 0 \quad \forall i, \forall t \tag{5-8}$$

$$q_{i,t}^g - q_{i,t-1}^g \leq (2 - o_{i,t-1} - o_{i,t})\underline{q}_i^g + (1 + o_{i,t-1} - o_{i,t})RU_i \quad \forall i, \forall t \tag{5-9}$$

$$q_{i,t-1}^g - q_{i,t}^g \leq (2 - o_{i,t-1} - o_{i,t})\underline{q}_i^g + (1 - o_{i,t-1} + o_{i,t})RD_i \quad \forall i, \forall t \tag{5-10}$$

$$q_{i,t}^g + r_{i,t}^{up} \leq \overline{q}_i^g o_{i,t} \quad \forall i, \forall t \tag{5-11}$$

$$q_{i,t}^g - r_{i,t}^{dw} \geq \underline{q}_i^g o_{i,t} \quad \forall i, \forall t \tag{5-12}$$

$$r_{i,t}^{up} \leq \overline{r}_i^{up} o_{i,t} \quad \forall i, \forall t \tag{5-13}$$

$$r_{i,t}^{dw} \leq \overline{r}_i^{dw} o_{i,t} \quad \forall i, \forall t \tag{5-14}$$

$$\underline{r}_t^{up} \leq \sum_{i=1}^{NG} r_{i,t}^{up} \leq \overline{r}_t^{up} \quad \forall i, \forall t \tag{5-15}$$

$$\underline{r}_t^{dw} \leq \sum_{i=1}^{NG} r_{i,t}^{dw} \leq \overline{r}_t^{dw} \quad \forall i, \forall t \tag{5-16}$$

$$q_{i,t}^g - q_{i,t-1}^g + r_{i,t}^{up} \leq (2 - o_{i,t-1} - o_{i,t})\underline{q}_i^g + (1 + o_{i,t-1} - o_{i,t})RU_i \quad \forall i, \forall t \tag{5-17}$$

$$q_{i,t-1}^g - q_{i,t}^g - r_{i,t}^{dw} \leq (2 - o_{i,t-1} - o_{i,t})\underline{q}_i^g + (1 - o_{i,t-1} + o_{i,t})RD_i \quad \forall i, \forall t \tag{5-18}$$

$$q_{j,t}^{w,0} \leq W_{j,t}^0 \quad \forall j, \forall t \tag{5-19}$$

$$p_{m,n}^{t,0} = \sum_{b \in B} k_{m,n}^b \left(\sum_{j \in \Omega_b} q_{j,t}^{w,0} + \sum_{i \in \Xi_b} q_{i,t}^g - \sum_{k \in \Psi_b} L_{k,t}^0 \right) \quad \forall (m,n) \in \Delta_L, \forall t \tag{5-20}$$

$$-\overline{p}_{m,n} \leq p_{m,n}^{t,0} \leq \overline{p}_{m,n} \quad \forall (m,n) \in \Delta_L, \forall t \tag{5-21}$$

$$\Pr\{\sum_{k=1}^{NL} l_{k,t}(\tau) \leq \sum_{i=1}^{NG} q_{i,t}^g + \sum_{i=1}^{NG} r_{i,t}^{up} + \sum_{j=1}^{NW} q_{j,t}^w(\tau)\} \geq 1 - \varepsilon_{LOLP} \quad \forall t \tag{5-22}$$

$$\Pr\{\sum_{k=1}^{NL} l_{k,t}(\tau) \geq \beta_w \cdot \sum_{j=1}^{NW} q_{j,t}^w(\tau) + \sum_{i=1}^{NG} q_{i,t}^g - \sum_{i=1}^{NG} r_{i,t}^{dw}\} \geq 1 - \varepsilon_{LOWP} \quad \forall t \tag{5-23}$$

$$\Pr\{|p_{m,n}^t(\tau)| \leq \overline{p}_{m,n}\} \geq 1 - \varepsilon_{TLOP} \quad \forall (m,n) \in \Delta_L, \forall t \tag{5-24}$$

$$r_{i,t}^{up}, r_{i,t}^{dw}, q_{j,t}^w \geq 0, u_{i,t}, o_{i,t} \in \{0,1\} \quad \forall i, \forall t \tag{5-25}$$

Equation (5-3) represents the first stage objective, which includes fuel cost for generation, startup cost and up/down spinning reserve. The cost function for the thermal generator is simplified as a linear function: $C_i^g(q_{i,t}^g) = c_i^f \cdot o_{i,t} + c_i^l \cdot q_{i,t}^g$; $C_{i,t}^r(r_{i,t}^{up} + r_{i,t}^{dw}) = c_i^{up} \cdot r_{i,t}^{up} + c_i^{dw} \cdot r_{i,t}^{dw}$.

The meanings of constraints (5-4)-(5-25) are introduced as follows. Constraint (5-4) represents the active power balance, which means the load demand should be equal to

the power generation from thermal units and wind power. Constraint (5-5) represents the power output of each generator must be within the maximum capacity. Constraint (5-6) ensures that the minimum on time of the thermal unit. For example, if $o_{i,t-1} = 0$ and $o_{i,t} = 1$, it represents the unit is turned on at time period t, then $o_{i,k}$ should be 1 in the following G_i time periods. So the minimum on time limit can be satisfied by (5-6). Also, the thermal unit needs to keep the off status for a minimum time period once it is shut down. Constraint (5-7) can fulfil this limitation, which is similar as (5-6). Constraint (5-8) indicates the time period, in which the unit is started up. Constraints (5-9) and (5-10) represent ramp up/down limits of thermal units. Constraints (5-11) and (5-12) ensure the power output of the thermal unit is still within its feasible range after dispatching up/down spinning reserve. Constraints (5-13) and (5-14) restrict the maximum amount of up/down spinning reserve that each thermal unit can provide. To ensure the reliability of the system, the amount of down/up spinning reserve should be no less than the minimum level, which is defined by constraint (5-15). Also, the available amount of up/down spinning reserve in a system is limited and should be less than a certain maximum level, which is defined by constraint (5-16). Constraints (5-17) and (5-18) ensure the thermal unit can dispatch the scheduled up/down spinning reserve, considering the status of the unit, ramping up/down limit and minimum/maximum power output. Constraint (5-19) restricts that in the day-ahead schedule, the committed wind power should be less than or equal to its forecast power. Constraint (5-20) uses the line flow distribution factor to calculate the power flow on each transmission line. Constraint (5-21) restricts that in day-ahead schedule the power flow on each line should be less than or equal to its maximum capacity. Three chance constraints for

LOLP, LOWP and TLOP are represented by constraints (5-22), (5-23) and (5-24) respectively. How to convert chance constraints into deterministic constraints are explained in the next section. The rest of ancillary constraints are listed out in (5-25).

5.2.3.2 Second Stage Problem

$$\min \sum_{t=1}^{NT} \left(\sum_{k=1}^{NL} C_t^{lsd} \left(l_{k,t}^{lsd}(\tau) \right) + \sum_{j=1}^{NW} C_t^{wsp} \left(q_{j,t}^{w,sp}(\tau) \right) \right) \tag{5-26}$$

$$\sum_{i=1}^{NG} q_{i,t}^g + \sum_{j=1}^{NW} q_{j,t}^{w,real}(\tau) + \sum_{i=1}^{NG} r_{i,t}^{up,real}(\tau) + \sum_{i=1}^{NG} r_{i,t}^{dw,real}(\tau) = \sum_{k=1}^{NL} l_{k,t}(\tau) - l_{k,t}^{lsd}(\tau) \quad \forall t, \forall \tau \tag{5-27}$$

$$q_{j,t}^{w,sp}(\tau) = q_{j,t}^{w}(\tau) - q_{j,t}^{w,real}(\tau) \quad \forall t, \forall \tau \tag{5-28}$$

$$p_{m,n}^t(\tau) = \sum_{b \in B}(k_{m,n}^b \cdot \sum_{i \in \Xi_b} q_{i,t}^g) + \sum_{b \in B}(k_{m,n}^b \cdot \sum_{j \in \Omega_b} (q_{j,t}^w(\tau) - q_{j,t}^{w,sp}(\tau)))$$
$$+ \sum_{b \in B}(k_{m,n}^b \cdot \sum_{i \in \Xi_b} r_{i,t}^{up,real}(\tau)) - \sum_{b \in B}(k_{m,n}^b \cdot \sum_{i \in \Xi_b} r_{i,t}^{dw,real}(\tau)) \tag{5-29}$$
$$- \sum_{b \in B}(k_{m,n}^b \cdot \sum_{k \in \Psi_b} (l_{k,t}(\tau) - l_{k,t}^{lsd}(\tau))) \quad \forall(m,n) \in \Delta_L, \forall t$$

$$\left| p_{m,n}^t(\tau) \right| \le \overline{p}_{m,n} \cdot \kappa \quad \forall(m,n) \in \Delta_L, \forall t \tag{5-30}$$

$$0 \le r_{i,t}^{up,real}(\tau) \le r_{i,t}^{up} \quad \forall i, \forall t, \forall \tau \tag{5-31}$$

$$0 \le r_{i,t}^{dw,real}(\tau) \le r_{i,t}^{dw} \quad \forall i, \forall t, \forall \tau \tag{5-32}$$

$$l_{k,t}^{lsd}(\tau) \ge 0, q_{j,t}^{w,sp}(\tau) \ge 0 \quad \forall k, \forall j, \forall t, \forall \tau \tag{5-33}$$

The second stage problem is defined under each realisation of uncertain parameters, including the load demand and wind power. The objective of the second stage problem, shown by (5-26), is to minimise the penalty of load shedding and wind spillage, by means of dispatching up/down spinning reserve and rescheduling wind power. The day-ahead schedule, referring to the three first stage decision variables $q_{i,t}^g$, $r_{i,t}^{up}$ and $r_{i,t}^{dw}$, is included into the second stage problem. For the sake of simplicity, the

penalty of load shedding and wind spillage is defined as a linear function:

$$C_t^{lsd}(l_{k,t}^{lsd}(\tau)) = c_{lsd} \cdot l_{k,t}^{lsd}(\tau), C_t^{wsp}(q_{j,t}^{w,sp}(\tau)) = c_{wsp} \cdot q_{j,t}^{w,sp}(\tau).$$

Constraints for the second stage problem are listed by (5-27)-(5-33). Constraint (5-27) represents the power balance under the specified realisation. Constraint (5-28) represents the amount of wind power which is wasted under the realisation. Constraint (5-29) represents the power flow of each transmission line under the specified realisation. Constraint (5-30) represents the overloading of the line should be within the limit.

After defining the first stage problem and second stage problem, the overall problem can be formulated as a two-stage stochastic problem. The objective of the overall problem is shown in (5-34). It has two parts: the former part is the objective of the first stage problem and the latter part is the expectation of the second stage problem under a number of realisations. Constraints for the overall problem include first stage constraints (5-4)-(5-25) and second stage constraints (5-27)-(5-33) under each realisation. It can be seen that the overall problem can be formulated as a MILP problem, which can be solved by state-of-the-art solvers (CPLEX, Gurobi, and so on).

$$\min \sum_{i=1}^{NG} \sum_{t=1}^{NT} \left\{ C_i^g(q_{i,t}^g) + \mu_i u_{i,t} + C_{i,t}^r(r_{i,t}^{up}, r_{i,t}^{dw}) \right\}$$
$$+ \mathbb{E}\left[\sum_{t=1}^{NT} \left(\sum_{k=1}^{NL} C_t^{lsd}\left(l_{k,t}^{lsd}(\tau)\right) + \sum_{j=1}^{NW} C_t^{wsp}\left(q_{j,t}^{w,sp}(\tau)\right) \right) \right]$$

(5-34)

5.3 Convert Chance Constraints into Equivalent Deterministic Constraints

As mentioned above, chance constraints (5-22), (5-23) and (5-24) cannot be solved directly. In this section, a method to convert those three chance constraints into equivalent deterministic ones is proposed.

5.3.1 Loss of Load Probability

Firstly, the method to convert the chance constraint (5-22) into an equivalent deterministic one is presented in this section. The reason for load shedding is that the load demand under one realisation exceeds the available power output from thermal units, wind power and up spinning reserve, as shown in Figure 5-1. So constraint (5-22) can be reformulated as follows:

$$\Pr\{\sum_{k=1}^{NL} l_{k,t}(\tau) - \sum_{j=1}^{NW} q_{j,t}^{w}(\tau) \le \sum_{i=1}^{NG} q_{i,t}^{g} + \sum_{i=1}^{NG} r_{i,t}^{up}\} \ge 1 - \varepsilon_{LOLP} \ \forall t \tag{5-35}$$

Figure 5-1 Load shedding and wind spillage

Load demands at different buses may have some certain correlations, rather than are totally independent from each other. However, the correlation of load demand has been neglected in most literatures related to UC. Also, the wind power at different buses may have some correlations. Moreover, load demands and wind power might also correlate with each other to some degree. Here, the correlation matrix of load demands $l_{k,t}(\tau)$ and wind power $q_{j,t}^w(\tau)$ is denoted by **R**:

$$\mathbf{R} = \begin{bmatrix} \boldsymbol{\rho}_{ww} & \boldsymbol{\rho}_{wl} \\ \boldsymbol{\rho}_{lw} & \boldsymbol{\rho}_{ll} \end{bmatrix}$$

$\boldsymbol{\rho}_{ww}$ is a submatrix to represent correlations among wind generation at different buses. $\boldsymbol{\rho}_{ll}$ is a submatrix to represent correlations among load demands at different buses. $\boldsymbol{\rho}_{lw}$ and $\boldsymbol{\rho}_{wl}$ are two submatrices to represent correlations among load demands and wind generation. $\boldsymbol{\rho}_{wl}$ is the transposition of $\boldsymbol{\rho}_{lw}$. The wind generation and load demands might be correlated in the long run (e.g. seasons). However, such correlations can be neglected in a short run (e.g. a day). So in this chapter, correlations among load demands and wind generation are set to be 0, which means $\boldsymbol{\rho}_{wl}$ and $\boldsymbol{\rho}_{lw}$ are zero matrix. Even if correlations among load demands and wind generation do exist in a short run, correlations can also be considered in the proposed method.

To convert (5-35) into the deterministic constraint, we need to know the exact PDF of $\sum_{k=1}^{NL} l_{k,t}(\tau) - \sum_{j=1}^{NW} q_{j,t}^w(\tau)$. However, it has two obstacles: 1) $l_{k,t}(\tau)$ and $q_{j,t}^w(\tau)$ follow

truncated normal distributions 2) $l_{k,t}(\tau)$ and $q_{j,t}^w(\tau)$ have certain correlations. So it is very difficult to get the PDF of $\sum_{k=1}^{NL} l_{k,t}(\tau) - \sum_{j=1}^{NW} q_{j,t}^w(\tau)$, considering it combines multiple truncated normal distributions and the correlation matrix. To make it possible, two assumptions are applied to deal with these two obstacles, and a sequence of approximation and verification is carried out to get the optimal deterministic constraint.

The two assumptions are explained as follows:

(1) To deal with the first obstacle, which is caused by the truncated normal distribution, here we assume $l_{k,t}(\tau)$ and $q_{j,t}^w(\tau)$ follow the normal distribution:

$$l_{k,t}(\tau) \sim N(L_{k,t}^0, \sigma_{k,t}^{l\,2}) \quad \forall k, \forall t \tag{5-36}$$

$$q_{j,t}^w(\tau) \sim N(W_{j,t}^0, \sigma_{j,t}^{w\,2}) \quad \forall j, \forall t \tag{5-37}$$

(2) To deal with the second obstacle, which is caused by correlations among $l_{k,t}(\tau)$ and $q_{j,t}^w(\tau)$, here we assume the load demand and wind power are independent from each other.

By applying above two assumptions, the PDF of $\sum_{k=1}^{NL} l_{k,t}(\tau) - \sum_{j=1}^{NW} q_{j,t}^w(\tau)$ can be obtained easily:

$$\sum_{k=1}^{NL} l_{k,t}(\tau) - \sum_{j=1}^{NW} q_{j,t}^w(\tau) \sim N(L_{k,t}^0 - W_{j,t}^0, \sum_{k=1}^{NL} \sigma_{k,t}^{l\,2} + \sum_{j=1}^{NW} \sigma_{j,t}^{w\,2}) \, \forall t \tag{5-38}$$

After knowing the PDF of $\sum_{k=1}^{NL} l_{k,t}(\tau) - \sum_{j=1}^{NW} q_{j,t}^w(\tau)$, the chance constraint (5-35) can be approximately converted into the following equivalent deterministic one:

$$\sum_{i=1}^{NG} q_{i,t}^g + \sum_{i=1}^{NG} r_{i,t}^{up} \geq L_{k,t}^0 - W_{j,t}^0 + z_t^l \cdot \lambda_{1-\varepsilon_{LOLP}} \cdot (\sum_{k=1}^{NL} \sigma_{k,t}^{l\ 2} + \sum_{j=1}^{NW} \sigma_{j,t}^{w\ 2})^{1/2} \ \forall t \qquad (5\text{-}39)$$

It is worthwhile to mention that there is a parameter z_t^l in the constraint (5-39), which is caused by the application of two assumptions. How to get the optimal z_t^l becomes a new challenge, since z_t^l cannot be calculated directly. According to (5-39), it can find that the right hand side of (5-39) increases together with the increase of z_t^l. That is to say, if z_t^l is increased, the left hand of (5-39) also needs to be increased to meet the inequality, which results in the increase of up spinning reserve. Based on the analysis of load shedding, if the up spinning reserve is increased, then the probability to happen load shedding should be reduced. As seen from Figure 5-1, the probability of load shedding, also called as LOLP, is the area covered by oblique lines in the right side of the figure. As the increase of up spinning reserve, the area representing LOLP is reduced. So the value of z_t^l has a direct impact on LOLP. The choice of z_t^l is the most important factor to convert the chance constraint into the deterministic constraint. The method to get the optimal z_t^l is introduced in the next section.

Although the method to convert chance constraints into deterministic ones had been studied in[106], two simplifications were applied. On one hand, the wind generation

was not considered when converting the chance constraint for LOLP. However, as the development of wind generation, the penetration level of wind generation is increasing, and the wind generation should not be neglected in the power balance. On another hand, the second obstacle mentioned above was neglected. That is to say, the load demand and wind generation were assumed to be independent from each other.

5.3.2   Loss of Wind Probability

When the load demand is low but the scheduled power from thermal units is high, then the down spinning reserve is dispatched to reduce the power generation from thermal units. However, if even after the full dispatch of down spinning reserve, the available generation from thermal units and wind generation is still larger than the load demand, then the wind generation is required to be curtailed.

Under a given realisation of wind generation, the minimum available power generation can be calculated as $\beta_w \cdot \sum_{j=1}^{NW} q_{j,t}^w(\tau) + \sum_{i=1}^{NG} q_{i,t}^g - \sum_{i=1}^{NG} r_{i,t}^{dw}$, which is the sum of power from thermal units and wind power, subtracted by down spinning reserve. β_w is the minimum utilisation level of wind generation. So under the given realisation, if the load demand is less than $\beta_w \cdot \sum_{j=1}^{NW} q_{j,t}^w(\tau) + \sum_{i=1}^{NG} q_{i,t}^g - \sum_{i=1}^{NG} r_{i,t}^{dw}$, then the minimum utilisation of wind generation cannot be fulfilled. The chance constraint for LOWP is represented by (5-23), which can be converted into the deterministic constraint by the similar

method to convert the chance constraint (5-22). By applying two assumptions mentioned above, the chance constraint (5-23) can be converted into the following equivalent deterministic constraint, shown as follows:

$$\sum_{i=1}^{NG} q_{i,t}^g - \sum_{i=1}^{NG} r_{i,t}^{dw} \leq L_{k,t}^0 - \beta_w \cdot W_{j,t}^0 + z_t^w \cdot \lambda_{\varepsilon_{LOWP}} \cdot (\sum_{k=1}^{NL} \sigma_{k,t}^{l\ 2} + \sum_{j=1}^{NW} (\beta_w \cdot \sigma_{j,t}^w)^2)^{1/2} \ \forall t \quad (5\text{-}40)$$

Also, there is a new parameter z_t^w in the deterministic constraint (5-40). As the increase of z_t^w, the right hand side of (5-40) decreases, leading to the left hand side to be smaller. As a result, the down spinning reserve needs to be increased to make the left hand side smaller. As seen from Figure 5-1, LOWP is covered by oblique lines in the left side of the figure. As the increase of down spinning reserve, the area of representing LOWP is reduced. So the value of z_t^w has a direct impact on LOWP. As for how to choose z_t^w, the method will be discussed in the next section.

5.3.3   Transmission Line Overloading Probability

The chance constraint of transmission line overloading is represented by (5-24). To convert chance constraint (5-24) into the deterministic constraint, one more assumption is required. As we all know, the power flow on the transmission line might be in two directions: the positive direction or the negative direction. So the transmission line overloading might happen in two directions. However, we assume that during one

interval, the probability to happen overloading in both directions can be neglected. The assumption can be further explained by the following equations:

$$\Pr\{p_{m,n}^{t}(\tau) > \overline{p}_{m,n}\}=\varepsilon_1, \ \Pr\{p_{m,n}^{t}(\tau) < -\overline{p}_{m,n}\} = \varepsilon_2,$$

$$\varepsilon_1 + \varepsilon_2 > \varepsilon_{TLOP}$$

For example, transmission line overloading happens in two directions in the same interval: 1) ε_1 is the probability of overloading in the positive direction; 2) ε_2 is the probability of overloading in the negative direction. The sum of ε_1 and ε_2 is larger than the specified limit of overloading ε_{TLOP}. That is to say, the chance constraint (5-24) for the TLOP cannot be satisfied under this situation. However, in the practical operation, the probability of happening overloading in both directions is rather small and can be neglected. Based on this assumption, the chance constraint (5-24) only needs to be satisfied in two directions, which are shown by the following two constraints:

$$\Pr\{p_{m,n}^{t}(\tau) \le \overline{p}_{m,n}\} \ge 1-\varepsilon_{TLOP} \quad \forall(m,n) \in \Delta_L, \forall t \qquad (5\text{-}41)$$

$$\Pr\{-\overline{p}_{m,n} \le p_{m,n}^{t}(\tau)\} \ge 1-\varepsilon_{TLOP} \quad \forall(m,n) \in \Delta_L, \forall t \qquad (5\text{-}42)$$

According to the expression of $p_{m,n}^{t}(\tau)$, shown by (5-29), the constraint (5-41) can be expressed as follows:

$$\left(\begin{array}{l} \sum_{b \in B}(k^b_{m,n} \cdot \sum_{i \in \Xi_b} q^g_{i,t}) + \sum_{b \in B}(k^b_{m,n} \cdot \sum_{j \in \Omega_b} (q^w_{j,t}(\tau) - q^{w,sp}_{j,t}(\tau))) + \\ \sum_{b \in B}(k^b_{m,n} \cdot \sum_{i \in \Xi_b} r^{up,real}_{i,t}(\tau)) - \sum_{b \in B}(k^b_{m,n} \cdot \sum_{i \in \Xi_b} r^{dw,real}_{i,t}(\tau)) \\ - \sum_{b \in B}(k^b_{m,n} \cdot \sum_{k \in \Psi_b} (l_{k,t}(\tau) - l^{lsd}_{k,t}(\tau))) \end{array}\right) \le \overline{p}_{m,n} \qquad (5\text{-}43)$$

It can be seen that there are $l^{lsd}_{k,t}(\tau)$ and $q^{w,sp}_{j,t}(\tau)$ on the left hand side of (5-43). To simplify the expression of (5-43), $l^{lsd}_{k,t}(\tau)$ can be omitted for two reasons: 1) the probability of happening load shedding is quite small; 2) during the event of load shedding, the loss-of-load is also only a small percentage of the overall load demand. According to (5-31) and (5-32), the constraint (5-43) can be simplified as follows:

$$\sum_{b \in B}(k^b_{m,n} \cdot \varpi \sum_{j \in \Omega_b} q^w_{j,t}(\tau)) - \sum_{b \in B}(k^b_{m,n} \cdot \sum_{k \in \Psi_b} l_{k,t}(\tau)) \le \overline{p}_{m,n} - \sum_{b \in B}(k^b_{m,n} \cdot \sum_{i \in \Xi_b} q^g_{i,t})$$
$$- \sum_{b \in B} k^{b'}_{m,n} \cdot \sum_{i \in \Xi_b} r^{up}_{i,t} + \sum_{b \in B} k^{b''}_{m,n} \cdot \sum_{i \in \Xi_b} r^{dw}_{i,t} \qquad (5\text{-}44)$$

where

$$k^{b'}_{m,n} = \begin{cases} 0 & k^b_{m,n} > 0 \\ k^b_{m,n} & k^b_{m,n} \le 0 \end{cases} \qquad k^{b''}_{m,n} = \begin{cases} k^b_{m,n} & k^b_{m,n} > 0 \\ 0 & k^b_{m,n} \le 0 \end{cases}$$

$$\varpi = \begin{cases} \varpi_{\min} & k^b_{m,n} > 0 \\ 1 & k^b_{m,n} \le 0 \end{cases}$$

In the constraint (5-44), a new parameter ϖ is introduced. The function of ϖ is explained as follows:

(1) If $k^b_{m,n} > 0$, then $\varpi = \varpi_{\min}$. In this case, $q^w_{j,t}(\tau) - q^{w,sp}_{j,t}(\tau)$ is simplified as $\varpi_{\min} \cdot q^w_{j,t}(\tau)$. $\varpi_{\min}$ is recommended to be equal to β_w, considering the fact that

$q_{j,t}^{w}(\tau) - q_{j,t}^{w,sp}(\tau)$ is larger than $\beta_w \cdot q_{j,t}^{w}(\tau)$ with a very large probability $1 - \varepsilon_{LOWP}$.

(2) If $k_{m,n}^{b} \leq 0$, then $\varpi = 1$. In that case, $q_{j,t}^{w}(\tau) - q_{j,t}^{w,sp}(\tau)$ is simplified as $q_{j,t}^{w}(\tau)$.

Because of $k_{m,n}^{b} \leq 0$, then $k_{m,n}^{b} \cdot \left(q_{j,t}^{w}(\tau) - q_{j,t}^{w,sp}(\tau) \right)$ is reduced to $k_{m,n}^{b} \cdot q_{j,t}^{w}(\tau)$.

Based on the above analysis, constraint (5-43) is simplified as constraint (5-44). The impact of different $\varpi_{\min}$ choices is analysed in case studies.

Similarly, equation $-\bar{p}_{m,n} \leq p_{m,n}^{t}(\tau)$ can be expressed as:

$$\sum_{b \in B}(k_{m,n}^{b} \cdot \varpi \sum_{j \in \Omega_b} q_{j,t}^{w}(\tau)) - \sum_{b \in B}(k_{m,n}^{b} \cdot \sum_{k \in \Psi_b} l_{k,t}(\tau)) \geq -\bar{p}_{m,n} - \sum_{b \in B}(k_{m,n}^{b} \cdot \sum_{i \in \Xi_b} q_{i,t}^{g})$$
$$- \sum_{b \in B} k_{m,n}^{b"} \cdot \sum_{i \in \Xi_b} r_{i,t}^{up} + \sum_{b \in B} k_{m,n}^{b'} \cdot \sum_{i \in \Xi_b} r_{i,t}^{dw} \quad (5\text{-}45)$$

where

$$\varpi = \begin{cases} 1 & k_{m,n}^{b} > 0 \\ \varpi_{\min} & k_{m,n}^{b} \leq 0 \end{cases}$$

Also, by applying the assumptions of (5-36) and (5-37), as well as the assumption of independence from each other, it can get:

$$\sum_{b \in B}(k_{m,n}^{b} \cdot \varpi \sum_{j \in \Omega_b} q_{j,t}^{w}(\tau)) - \sum_{b \in B}(k_{m,n}^{b} \cdot \sum_{k \in \Psi_b} l_{k,t}(\tau))$$
$$\sim N \left(\sum_{b \in B}(k_{m,n}^{b} \cdot \varpi \sum_{j \in \Omega_b} W_{j,t}^{0}) - \sum_{b \in B}(k_{m,n}^{b} \cdot \sum_{k \in \Psi_b} L_{k,t}^{0}), \quad (5\text{-}46) \right.$$
$$\left. \sum_{b \in B}(\sum_{j \in \Omega_b}(k_{m,n}^{b} \cdot \varpi \cdot \sigma_{j,t}^{w})^2) + \sum_{b \in B}(\sum_{k \in \Psi_b}(k_{m,n}^{b} \cdot \sigma_{k,t}^{l})^2) \right)$$

According to (5-44) and (5-46), the chance constraint (5-41) can be converted into the following equivalent deterministic constraint:

$$\overline{p}_{m,n} - \sum_{b \in B}(k_{m,n}^{b} \cdot \sum_{i \in \Xi_{b}} q_{i,t}^{g}) - \sum_{b \in B} k_{m,n}^{b'} \cdot \sum_{i \in \Xi_{b}} r_{i,t}^{up} + \sum_{b \in B} k_{m,n}^{b''} \cdot \sum_{i \in \Xi_{b}} r_{i,t}^{dw}$$

$$\geq \sum_{b \in B}(k_{m,n}^{b} \cdot \varpi \sum_{j \in \Omega_{b}} W_{j,t}^{0}) - \sum_{b \in B}(k_{m,n}^{b} \cdot \sum_{k \in \Psi_{b}} L_{k,t}^{0}) + z_{m,n}^{t+} \cdot \lambda_{1-\varepsilon_{TLOP}} \quad (5\text{-}47)$$

$$\cdot \left\{ \sum_{b \in B}(\sum_{j \in \Omega_{b}}(k_{m,n}^{b} \cdot \varpi \cdot \sigma_{j,t}^{w})^{2}) + \sum_{b \in B}(\sum_{k \in \Psi_{b}}(k_{m,n}^{b} \cdot \sigma_{k,t}^{l})^{2}) \right\}^{1/2}$$

Similarly, the chance constraint (5-42) can be converted into the following constraint:

$$-\overline{p}_{m,n} - \sum_{b \in B}(k_{m,n}^{b} \cdot \sum_{i \in \Xi_{b}} q_{i,t}^{g}) - \sum_{b \in B} k_{m,n}^{b''} \cdot \sum_{i \in \Xi_{b}} r_{i,t}^{up} + \sum_{b \in B} k_{m,n}^{b'} \cdot \sum_{i \in \Xi_{b}} r_{i,t}^{dw}$$

$$\leq \sum_{b \in B}(k_{m,n}^{b} \cdot \varpi \sum_{j \in \Omega_{b}} W_{j,t}^{0}) - \sum_{b \in B}(k_{m,n}^{b} \cdot \sum_{k \in \Psi_{b}} L_{k,t}^{0}) + z_{m,n}^{t-} \cdot \lambda_{\varepsilon_{TLOP}} \cdot \quad (5\text{-}48)$$

$$\left\{ \sum_{b \in B}(\sum_{j \in \Omega_{b}}(k_{m,n}^{b} \cdot \varpi \cdot \sigma_{j,t}^{w})^{2}) + \sum_{b \in B}(\sum_{k \in \Psi_{b}}(k_{m,n}^{b} \cdot \sigma_{k,t}^{l})^{2}) \right\}^{1/2}$$

According to constraint (5-47), the right hand side of the constraint increases together with the increase of $z_{m,n}^{t+}$. As a result, the left hand side of the constraint also needs to be increased, which can be achieved through three options: 1) decreasing $\sum_{b \in B}(k_{m,n}^{b} \cdot \sum_{i \in \Xi_{b}} q_{i,t}^{g})$, or 2) increasing up spinning reserve with negative $k_{m,n}^{b}$, or 3) increasing down spinning reserve with positive $k_{m,n}^{b}$. Based on the expression of power flow, shown by (5-29), all these three options can reduce the power flow in the positive direction, which can decrease the probability of happening $p_{m,n}^{t}(\tau) > \overline{p}_{m,n}$. So $z_{m,n}^{t+}$ directly affects the probability of overloading with the power flow in the positive direction.

Similarly, the probability of overloading with the power flow in the negative direction is directly affected by $z_{m,n}^{t-}$. According to (5-48), the right hand side of (5-48) would

decrease as the increase of $z_{m,n}^{t-}$. In order to meet the inequality, the left hand of (5-48) needs to be reduced, which can be realised by three options: 1) increasing $\sum_{b \in B}(k_{m,n}^{b} \cdot \sum_{i \in \Xi_b} q_{i,t}^{g})$, or 2) increasing up spinning reserve with positive $k_{m,n}^{b}$, or 3) increasing down spinning reserve with negative $k_{m,n}^{b}$.

So chance constraints (5-22), (5-23) and (5-24) are converted into four deterministic constraints (5-39), (5-40), (5-47) and (5-48) with new parameters z_t^l, z_t^w, $z_{m,n}^{t+}$ and $z_{m,n}^{t-}$. In the overall problem (5-34), three chance constrains (5-22), (5-23) and (5-24) are replaced by these four deterministic constraints (5-39), (5-40), (5-47) and (5-48).

5.4   New Solving Algorithm for the Proposed Formulation

In the last section, it has been pointed that chance constraints for LOLP, LOWP and TLOP are directly affected by the choice of z_t^l, z_t^w, $z_{m,n}^{t+}$ and $z_{m,n}^{t-}$. In this section, how to select optimal values for these parameters are presented in this section. According to the analysis carried out in the last section, if values of z_t^l, z_t^w, $z_{m,n}^{t+}$ and $z_{m,n}^{t-}$ are increased, the corresponding LOLP, LOWP and TLOP are decreased. So a feasible strategy is to set up small values for z_t^l, z_t^w, $z_{m,n}^{t+}$ and $z_{m,n}^{t-}$ at first, and the UC problem (5-34) is solved with obtained deterministic constraints with the given values. When solving the problem (5-34), it can get the day-ahead schedule for thermal units, the capacity of up/down spinning reserve and wind power to be utilised. After obtaining the day-ahead schedule, Monte Carlo technique can be applied to get values of LOLP,

LOWP and TLOP. If some LOLP, LOWP and TLOP are not met, corresponding parameters of z_t^l, z_t^w, $z_{m,n}^{t+}$ and $z_{m,n}^{t-}$ should be increased and updated. The UC problem (5-34) needs to be solved again with new values of z_t^l, z_t^w, $z_{m,n}^{t+}$ and $z_{m,n}^{t-}$. To simplify the description, we denote z_t^l, z_t^w, $z_{m,n}^{t+}$ and $z_{m,n}^{t-}$ as a vector $\mathbf{z}_d = \{ z_1^{d,l}, \cdots, z_{NT}^{d,l}, z_1^{d,w}, \cdots, z_{NT}^{d,w}, z_{m,n}^{d,1+}, \cdots, z_{m,n}^{d,NT+}, z_{m,n}^{d,1-}, \cdots, z_{m,n}^{d,NT-} \}$, where d is the counter for the iteration and $\mathbf{z}_d$ is the value of $\mathbf{z}$ at the dth iteration. To get the optimal $\mathbf{z}$ values, it needs to go through the following steps:

Step 1): Create a number of N_E realisations of load demand and wind generation, which are applied to calculated the expectation of the second stage problem.

Step 2): Create a number of N_v realisations, which are applied to calculate LOLP, LOWP and TLOP after solving the UC problem (5-34).

Step 3): Set the lower bound $\mathbf{z}_{\text{lower}}$ and upper bound $\mathbf{z}_{\text{upper}}$ for $\mathbf{z}$, where

$\mathbf{z}_{\text{lower}} = \{ z_1^{l,lower}, \cdots, z_{NT}^{l,lower}, z_1^{w,lower}, \cdots, z_{NT}^{w,lower}, z_{m,n}^{1+,lower}, \cdots, z_{m,n}^{NT+,lower}, z_{m,n}^{1-,lower}, \cdots, z_{m,n}^{NT-,lower} \}$,

$\mathbf{z}_{\text{upper}} = \{ z_1^{l,upper}, \cdots, z_{NT}^{l,upper}, z_1^{w,upper}, \cdots, z_{NT}^{w,upper}, z_{m,n}^{1+,upper}, \cdots, z_{m,n}^{NT+,upper}, z_{m,n}^{1-,upper}, \cdots, z_{m,n}^{NT-,upper} \}$.

Step 4): initialise $\mathbf{z}_1$

      4.1): set $\mathbf{z}_1 = (\mathbf{z}_{\text{lower}} + \mathbf{z}_{\text{upper}})/2$;

      4.2): replace chance constraints (5-22), (5-23) and (5-24) with (5-39), (5-40), (5-47) and (5-48);

      4.2): solve the problem (5-34) to get values of LOLP, LOWP and TLOP, which are represented by $\varepsilon_{1,t}^l$, $\varepsilon_{1,t}^w$, $\varepsilon_{1,t}^{m,n}$.

Step 5): optimise $\mathbf{z}$ values

5.1): $d=d+1$;

5.2): update $\mathbf{z}_d$ according to $\varepsilon_{d-1,t}^l$, $\varepsilon_{d-1,t}^w$ and $\varepsilon_{d-1,t}^{m,n}$ in the $(d\text{-}1)^{\text{th}}$ iteration;

5.3): solve the problem (5-34) with constraints (5-39), (5-40), (5-47) and (5-48) and new values of $\mathbf{z}_d$;

5.4): calculate $\varepsilon_{d,t}^l$, $\varepsilon_{d,t}^w$ and $\varepsilon_{d,t}^{m,n}$ with the new schedule obtained in Step 5.3);

5.5): *if* chance constraints (5-22), (5-23) and (5-24) are met, and $d<=N_{op}$, go to Step 6);

else if there are violations of chance constraints and $d>N_{op}$, go to Step 7);

else go to Step 5.1).

Step 6): Successfully solve the two-stage stochastic UC problem (5-34).

Step 7): Fail to solve the problem (5-34) and quit.

In Step 3.1), the lower and upper bounds for $\mathbf{z}$ can be given based on several rounds of numerical tests. The strategy is quite direct, and can be summarised as two rules: 1) when $\mathbf{z}$ equals to $\mathbf{z}_{\text{lower}}$, LOLP, LOWP and TLOP should be greater than the specified levels; 2) when $\mathbf{z}$ equals to $\mathbf{z}_{\text{upper}}$, LOLP, LOWP and TLOP should be less than the specified levels,

In Step 5.2), $\mathbf{z}_d$ are updated in each iteration, according to values of LOLP, LOWP and TLOP in the $(d\text{-}1)^{\text{th}}$ iteration. The task of Step 5) is to optimise $\mathbf{z}$ values to provide a day-ahead schedule, so that LOLP, LOWP and TLOP can be met. To achieve this task,

the following method to update $\mathbf{z}$ values are applied. Take the method to update $z_{d,t}^{l}$ as the example, the strategy is explained as follows:

If $\varepsilon_{d-1,t}^{l} > \varepsilon_{LOLP} \cdot (1+\sigma)$

    Then $z_{t}^{l,lower} = z_{d-1.t}^{l}$, $z_{t}^{l,upper} = z_{t}^{l,upper}$;

$$z_{d,t}^{l} = (z_{t}^{l,lower} + z_{t}^{l,upper})/2 ;$$

Else if $\varepsilon_{d-1,t}^{l} < \varepsilon_{LOLP} \cdot (1-\sigma)$

    Then $z_{t}^{l,upper} = z_{d-1.t}^{l}$, $z_{t}^{l,lower} = z_{t}^{l,lower}$;

$$z_{d,t}^{l} = (z_{t}^{l,lower} + z_{t}^{l,upper})/2 ;$$

Else $z_{d,t}^{l} = z_{d-1,t}^{l}$;

End

The same method is applied to update $z_{d,t}^{w}$, $z_{m,n}^{d,t+}$ and $z_{m,n}^{d,t-}$. By applying the above strategy, the gap between the lower bound and upper bound is reduced. As the decrease of gap, the optimal $\mathbf{z}$ values can be achieved through a number of iterations. Based on numerical experiments, the required number of iterations to reach optimal $\mathbf{z}$ values is mostly less than 10. The lower and upper bounds can be set to be 0 and 5, respectively.

5.5   Case Studies

To evaluate the performance of the new algorithm for the chance-constrained two-stage stochastic UC problem, two test systems are applied, namely the 6-bus test system and the IEEE 118-bus test system with several wind farms added into the system. Case studies are carried out in the following aspects:

(1) Different levels of LOLP are simulated to reveal the relationship between LOLP and the required up spinning reserve.

(2) Different levels of LOWP are simulated to reveal the relationship between LOWP and the required down spinning reserve.

(3) Different correlation matrices are simulated to analyze the impact of correlations among the load demand and wind generation.

(4) Different values of ϖ_{min} are simulated to analyze the impact of ϖ_{min} to the required up/down spinning reserve capacity.

A number of 200 realisations are applied to calculate the expectation of the second stage cost, and a number of 1000 realisations are applied to calculate LOLP, LOWP and TLOP under the given day-ahead schedule. The maximum number of iterations to get the optimal $\mathbf{z}$ values is 20. To check whether chance constraints are met, the tolerance is set to be $\sigma=0.1$. The time interval is set to be 1 hour, and there are 24 time intervals in total, considering it is a day-ahead schedule problem.

All case studies were coded with the YALMIP[115], which is a toolbox in Matlab. The commercial solver, CPLEX 12.1.4, was taken as the solver for the MILP problem. All programs were run on an Intel Core-i5 2.5-GHz personal computer with 4G memory.

5.5.1 Case A: 6-Bus System

This test system was applied in [105], and detail data can be found in that paper. In this test system, there are three generators, two wind farms and three loads, which are all shown in Figure 5-2. From Table 5-1 to Table 5-4, the detail information about this test system (including physical constraints for generators, generation costs, transmission lines, loads and wind farms) is all listed. As for the uncertainties of loads and wind generation, the forecast errors are set to be 10% and 30%, respectively. In practice, the cost caused by loss-of-load is much larger than that caused by wind spillage. So in the section, we set $\phi_{lsd} = 100$ and $\phi_{wsp} = 5.3$. The limits of LOLP, LOWP and TLOP are set to be 0.01, 0.05 and 0.01, respectively. The ratio of overloading κ needs to be less than 1.1. The required utilisation level of wind generation β_w is set to be 0.8, and ϖ_{min} is set to be equal with β_w.

The impact of correlation is not studied in the section 5.5.1 and 5.5.2. That is to say, the load demand and wind generation are assumed to be independent from each other. In the latter section, the importance of correlation is studied in the section 5.5.3.
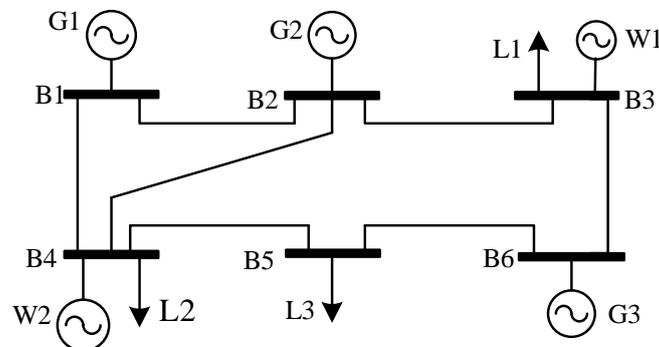
Figure 5-2 Layout of the 6-bus system

Table 5-1 GENERATORS

Unit	$\underline{q}_i^g$	$\overline{q}_i^g$	G_i	H_i	RU_i / RD_i	$\overline{r}_i^{up} / \overline{r}_i^{dw}$
G1	100	300	4	2	50	60
G2	80	200	3	3	40	40
G3	150	350	2	3	15	70

Table 5-2 COSTS

Unit	c_i^f	c_i^l	μ_i	c_i^{up} / c_i^{dw}
G1	50	6	100	1.2
G2	40	5.5	300	1.1
G3	60	4.5	0	0.9

Table 5-3 WIND FARMS AND LOADS

Loads	Capacity(MW)	Wind Farms	Capacity(MW)
L1	320	W1	50
L2	320	W2	50
L3	160		

Table 5-4 LINE INFORMATION

Line Number	From	To	Reactance(p.u.)	Capacity(MW)
1	1	2	0.17	200
2	1	4	0.15	200
3	2	4	0.197	200
4	5	6	0.16	180
5	3	6	0.14	180
6	2	3	0.258	300
7	4	5	0.15	200

Results for this test system are shown in Table 5-5. It takes 6 iterations before getting

the optimal **z** values. Information about LOLP, LOWP, TLOP, up spinning reserve,

down spinning reserve, total costs and computation time is all listed out. Also, the

change of $z_{d,t}^l$ and $z_{d,t}^w$ for the 10th time interval over the optimisation process is

present.

The 8th and 9th columns represent the ratio of scheduled up/down spinning reserve capacity to the forecast load at the 10th time period. Obviously, when $z_{d,10}^l$ and $z_{d,10}^w$ increases, the corresponding up and down spinning reserve capacity also increases, which leads to the decrease of LOLP and LOWP. This finding can approve the analysis of constraints (5-39) and (5-40).

Table 5-5 RESULTS FOR CASE A

Iteration Count	$z_{d,10}^l$	$z_{d,10}^w$	$z_{3,6}^{15-}$	LOLP	LOWP	TLOP	Up (%)	Down (%)	Total Costs($)	Computation Time(s)
1	0	0	0	0.113	0.97	0.0825	4.62	3.47	85386	10.0
2	0.6	0.6	2	0.005	0.008	0	8.81	8.86	86515	10.1
3	0.3	0.3	1	0.113	0.081	0.0025	4.62	3.85	85682	10.1
4	0.45	0.45	0.5	0.027	0.073	0.0075	6.65	5.67	85663	10.2
5	0.375	0.525	0.25	0.008	0.052	0.017	7.68	7.28	85852	10.2
6	0.375	0.525	0.375	0.008	0.052	0.012	7.72	7.29	85845	10.2

The power flow on line 5 (connecting bus 3 and bus 6) is overloaded in the negative power direction during the 15th time interval. So the change of $z_{3,6}^{15-}$ over the optimisation process is presented in the 4th column of Table 5-5. It can be seen that as the increase of $z_{3,6}^{15-}$, TLOP is reduced correspondingly, which is accordant with the analysis of constraint (5-48).

Table 5-6 TLOP INFORMATION FOR CASE A

	Without TLOP				With TLOP			
	G1	G2	G3	Total	G1	G2	G3	Total
$k_{3,6}^b$	0.0781	0	-0.4796		0.0781	0	-0.4796	
$q_{i,15}^g$	134.8	188.6	*342.8*	666.2	134.8	195.9	*335.5*	666.2
$r_{i,15}^{up}$	40.0	11.4	7.2	58.6	40.0	4.1	14.5	58.6
$r_{i,15}^{dw}$	34.7	0	*0*	34.7	22.1	0	*15.0*	37.1

To show the effect of TLOP, scenarios with and without considering TLOP are all illustrated in Table 5-6. As mentioned above, there is overloading in the line 5 from bus 6 to bus 3, which is in the negative power direction. According to results in Table 5-6, the total generation, up spinning reserve capacity and down spinning reserve capacity dispatched by three generators are the same or almost the same under two scenarios. However, the dispatched power and reserve capacity from each generator are not the same. To reduce TLOP, the following operations are applied:

(1) Generation from G3 is reduced to cut down $\sum_{b \in B} (k_{m,n}^b \cdot \sum_{i \in \Xi_b} q_{i,t}^g)$. To calculate the line

flow distribution factor $k_{m,n}^b$, bus 2 is taken as the slack bus. G3 is connected to bus 6, and $k_{3,6}^6$ has a negative value. So it can reduce the power flow on line 5 if the power output from G3 is decreased, while the power output from G2 is increased. According to generation costs in Table 5-2, generation from G2 is more expensive than G3. However, G2 is scheduled with more power to reduce the line power in line 5.

(2) According to the analysis of constraint (5-48), the down spinning reserve with negative $k_{m,n}^b$ should be increased to reduce the power flow. So the down spinning reserve at G3 is increased, since $k_{3,6}^6$ is negative.

(3) As for the option to increase up spinning reserve with positive $k_{m,n}^b$, the up spinning reserve from G1 can reduce the power flow on line 5. However, G1 only has a small very positive $k_{m,n}^b$, which is not an effective option, compared with

144

the other two options.

To investigate the impact of LOLP to the required up spinning reserve and the total cost, different levels of LOLP are simulated. The level of LOWP and TLOP keeps the same, 0.05 and 0.01, respectively. Results are presented in Table 5-7. The 2nd column shows the total cost under different levels of LOLP. The 3rd and 4th columns represent the average ratio of up and down spinning reserve to the corresponding load demand over the whole time periods. From Table 5-7, it clearly shows that as the increase of LOLP, the total cost and required up spinning reserve capacity is decreased. The variation of LOLP has little effect to the required down spinning reserve.

Table 5-7 DIFFERENT LEVELS OF LOLP IN CASE A

LOLP	Total Costs($)	Up (%)	Down (%)
0.001	86215	9.46	7.61
0.005	85968	8.33	7.46
0.01	85845	7.72	7.29
0.02	85781	7.48	7.27
0.05	85775	7.33	7.37

Similarly, different levels of LOWP are simulated to investigate the impact of LOWP to the required down spinning reserve capacity. Results are shown in Table 5-8. It can be seen that as the increase of LOWP, the total cost and required down spinning reserve capacity are reduced, while the required up spinning reserve almost keeps the same level.

Table 5-8 DIFFERENT LEVELS OF LOWP IN CASE A

LOWP	Total Costs($)	Up (%)	Down (%)
0.01	86121	7.72	9.13
0.02	85956	7.67	8.29
0.05	85845	7.72	7.29
0.08	85755	7.70	6.94
0.10	85716	7.76	6.74

5.5.2 Case B: Modified IEEE 118-Bus System

This system is revised according to the IEEE 118-bus test system, presented in [132]. A number of 14 wind farms are added into this test system, to replace the original thermal generation units. The overall penetration level of wind generation reaches 20%. Results of this test system are shown in Table 5-9.

It can be seen that it takes seven iterations before reaching the optimal **z** values. Taking results in the 8th time interval as the example, information about $z_{d,8}^l$, $z_{d,8}^w$, LOLP, LOWP, up spinning reserve amount, down spinning reserve amount, total cost and computation time is all listed out in that table. The same findings are obtained as that in the first test system. Also, there is overloading in the line (connecting bus 82 and bus 83) in the negative power direction (from bus 83 to bus 82) during the 19th time interval. Detail results about the change of $z_{82,83}^{d,t-}$ and TLOP are shown in Table 5-9.

Table 5-9 DETAILS FOR CASE B

Iteration Count	$z_{d,8}^{l}$	$z_{d,8}^{w}$	$z_{82,83}^{d,19-}$	LOLP	LOWP	TLOP	Up (%)	Down (%)	Total Costs($)	Computation Time(s)
1	0	0	0	0.117	0.092	0.11	2.38	1.78	1.0916E06	61.1
2	3	4	6	0	0	0	10.36	8.61	1.2767E06	61.4
3	1.5	2	3	0	0.018	0.005	6.36	5.42	1.1371E06	61.7
4	0.75	1	1.5	0.034	0.086	0.055	3.01	2.08	1.0963E06	61.7
5	1.125	1.5	2.25	0.002	0.041	0.025	4.93	3.27	1.1112E06	62.1
6	0.9375	1.25	2.6250	0.012	0.069	0.018	4.25	2.17	1.1043E06	62.2
7	0.9375	1.375	2.4375	0.012	0.051	0.012	4.24	2.52	1.1044E06	62.4

To prove the relationship between LOLP and the required up spinning reserve amount, as well as the relationship between LOWP and the required down spinning reserve, different levels of LOLP and LOWP are simulated, just as the work done in Case A. The results relating to different levels of LOLP and up spinning reserve capacity are shown in Table 5-10. The results relating to different levels of LOWP and down spinning reserve capacity are shown in Table 5-11. The same finding is obtained as that in Case A. It can be seen that the larger LOLP and LOWP are, the less required up/down spinning reserve capacity would be.

Table 5-10 DIFFERENT LEVELS OF LOLP IN CASE B

LOLP	Total Costs($)	Up (%)	Down (%)
0.001	1.1083E06	5.68	2.53
0.005	1.1057E06	4.87	2.56
0.01	1.1044E06	4.24	2.52
0.02	1.1041E06	4.12	2.54
0.05	1.1028E06	3.75	2.52

Table 5-11 DIFFERENT LEVELS OF LOWP IN CASE B

LOWP	Total Costs($)	Up (%)	Down (%)
0.01	1.1058E06	4.33	3.45
0.02	1.1053E06	4.28	3.09
0.05	1.1044E06	4.24	2.52
0.08	1.1041E06	4.26	2.14
0.10	1.1032E06	4.27	1.98

5.5.3   Impact of Correlation

To study of the impact of correlations, different correlation matrices $\mathbf{R}$ are simulated in this section. Here, LOLP and LOWP are set to be 0.01 and 0.05 respectively. The whole correlation matrix R is composed by four submatrices, namely $\boldsymbol{\rho}_{ww}$, $\boldsymbol{\rho}_{ll}$ $\boldsymbol{\rho}_{wl}$ and $\boldsymbol{\rho}_{lw}$. In this section, $\boldsymbol{\rho}_{wl}$ and $\boldsymbol{\rho}_{lw}$ are set to be 0, just as explained in Section 5.3.1. Different $\boldsymbol{\rho}_{ww}$ and $\boldsymbol{\rho}_{ll}$ are simulated in this section. For example, $\boldsymbol{\rho}_{ll}=0.3$ represents that the diagonal of $\boldsymbol{\rho}_{ll}$ is filled with one, and the rest elements are set to be 0.3. That is to say, the correlations between different loads are set to be 0.3. Although the correlation matrices used in this section might be too ideal or simple, it can prove the proposed algorithm can consider the correlations of the load demand and wind generation.

Simulations are carried out in both test systems. Results for these two test systems with different $\boldsymbol{\rho}_{ww}$ and $\boldsymbol{\rho}_{ll}$ are shown in Table 5-12 and Table 5-13. In Case A, the correlations of the load demand and the wind generation have no obvious impact on the results of total cost, up and down spinning reserve capacity. However in Case B, the correlations do affect the day-ahead schedule. As $\boldsymbol{\rho}_{ww}$ or $\boldsymbol{\rho}_{ll}$ increases from 0 to 0.5,

the total costs, up and down spinning reserve capacity also increase. As seen from the table, up and down spinning reserve capacity are greatly affected by the correlations.

Table 5-12 DIFFERENT CORRELATIONS IN CASE A

Correlation Level	Total Costs($)	Up (%)	Down (%)
$\rho_{ww}=0, \rho_{ll}=0$	85845	7.72	7.29
$\rho_{ww}=0, \rho_{ll}=0.1$	86052	8.13	7.38
$\rho_{ww}=0, \rho_{ll}=0.3$	86531	8.68	7.98
$\rho_{ww}=0, \rho_{ll}=0.5$	86709	9.49	7.32
$\rho_{ww}=0.1, \rho_{ll}=0$	85782	7.75	7.28
$\rho_{ww}=0.3, \rho_{ll}=0$	85957	8.01	7.26
$\rho_{ww}=0.5, \rho_{ll}=0$	85916	7.95	7.31

Table 5-13 DIFFERENT CORRELATIONS IN CASE B

Correlation Level	Total Costs($)	Up (%)	Down (%)
$\rho_{ww}=0, \rho_{ll}=0$	1.1044E06	4.24	2.52
$\rho_{ww}=0, \rho_{ll}=0.1$	1.1321E06	6.92	3.71
$\rho_{ww}=0, \rho_{ll}=0.3$	1.1789 E06	10.16	6.01
$\rho_{ww}=0, \rho_{ll}=0.5$	1.2023E06	12.81	8.13
$\rho_{ww}=0.1, \rho_{ll}=0$	1.1129E06	5.11	3.12
$\rho_{ww}=0.3, \rho_{ll}=0$	1.1302E06	6.81	4.23
$\rho_{ww}=0.5, \rho_{ll}=0$	1.1412E06	8.43	4.93

5.5.4 Impact of Different ϖ_{min}

To analyse the importance of ϖ_{min} to the optimal day-ahead schedule, different choices of ϖ_{min} are studied in this section. Simulations are carried out in both test systems, and results are shown in Table 5-14 and Table 5-15. Although different ϖ_{min} is applied, the total costs, up spinning reserve capacity and down spinning reserve capacity are most unchanged. The difference is that the optimal **z** values are changed.

The reason is that the algorithm can find the best **z** values to adapt different $\varpi_{\min}$, while keeping the left hand side of (5-47) and (5-48) unchanged. So the choice of $\varpi_{\min}$ only has very little effect to the optimal schedule. So $\varpi_{\min}$ can be equal to the utilisation level of wind generation.

Table 5-14 DIFFERENT $\varpi_{\min}$ IN CASE A

$\varpi_{\min}$	Total Costs($)	Up (%)	Down (%)	$z_{3,6}^{15-}$
$\varpi_{\min} = 0.3$	85862	7.75	7.31	0.6250
$\varpi_{\min} = 0.5$	85821	7.67	7.26	0.6875
$\varpi_{\min} = 0.8$	85845	7.72	7.29	0.375

Table 5-15 DIFFERENT $\varpi_{\min}$ IN CASE B

$\varpi_{\min}$	Total Costs($)	Up (%)	Down (%)	$z_{82,83}^{d,19-}$
$\varpi_{\min} = 0.3$	1.1054E06	4.31	2.55	3.0625
$\varpi_{\min} = 0.5$	1.1031E06	4.18	2.48	1.5156
$\varpi_{\min} = 0.8$	1.1044E06	4.24	2.52	2.4375

5.5.5 Discussion of the Proposed Approach

In this chapter, a new method to convert chance constraints into equivalent deterministic constraints is proposed, based on two assumptions. A sequence of approximation and verification is carried out to get the optimal deterministic formulations. According to results obtained from two test systems, the proposed method can achieve the optimal schedule within 10 iterations.

Although the proposed method has been only testified under the condition that the load demand and wind generation obey truncated normal distributions, the proposed method

can be apply to other PDFs, as long as knowing the expectation and deviation of the corresponding PDFs.

5.6   Summary

The chance-constrained two-stage stochastic program for UC is studied in this chapter. The first stage problem is the day-ahead optimal dispatch problem, with the objective to minimise the total energy dispatch cost, including generation cost, startup cost and up/down spinning reserve cost. The second stage problem is to dispatch the reserve capacity and to reschedule the wind power, after knowing the real realisation of load demand and wind power. The objective of the second stage problem is to minimise the penalty of load shedding and wind spillage.

Three chance constraints are considered, namely, LOLP, LOWP and TLOP. To solve the proposed chance-constrained formulation, a new method to convert chance constraints into equivalent deterministic constraints is proposed. Two main assumptions are applied during the conversion, and a sequence of approximation and verification is carried out to get the optimal deterministic formulation.

The proposed method is testified on two test systems, namely a 6-bus test system and a modified IEEE 118-bus test system. Case studies show that 1) the level of LOLP affects the required up spinning reserve capacity; 2) the level of LOWP affects the required down spinning reserve capacity; 3) the correlations of the load demand and

wind generation also affect the required up/down spinning reserve capacity; 4) the choice of $\varpi_{\min}$ has no great impact on the final day-ahead schedule.

CHAPTER 6   CONCLUSION AND FUTURE RESEARCH WORK

6.1   Conclusions

To deal with energy crisis and environmental problems, wind generation (mainly wind and solar generation) has been considered as the most favourite choice to replace traditional fossil energy. Compared with fossil energy, wind generation is environmentally friendly, and can reduce the greenhouse gas emissions. However, the intermittence of wind generation raises many great challenges to every aspect of power system operations, such as TEP and UC problems, which are two main research focuses of this thesis. For the TEP problem, researches are carried out from two aspects: the selection of candidate lines and TEP under uncertainties. For the UC problem, a chance-constrained two-stage stochastic programming for UC with wind is studied. Conclusions for each research point are summarised as follows.

Firstly, the selection of candidate lines is one of the most important prerequisites for the TEP problem, especially when the size of the system is relatively large. The size and completeness of candidate lines have a direct impact on the optimal expansion plan. Currently, the selection of candidate lines is mainly carried out manually by system operation planners. There are several shortcomings of the manual selection. For one hand, it takes great efforts to get the set of candidate lines. For another, the

obtained candidate set might be suboptimal, because of the limitation of planner's experience. However, the existing research about candidate lines selection is insufficient. The research about the selection of candidate lines is still in its preliminary stage and much more research work can be done. Hence the selection of candidate lines becomes the first research focus of this thesis. An automatic selection method for candidate lines is proposed in Chapter 3. There are five stages in the proposed method, which consists of enforcing existing corridors at the first two stages and exploring new corridors at the latter three stages. Each stage proposed in the method plays an important role in the process of selecting candidate lines. New corridors can be efficiently identified through the identification of candidate buses. The technique of LP can not only reduce the required computation time, but can also improve the completeness of the created candidate lines. Results of two case studies show that the LMP difference between two buses cannot be the only index to select new corridors. Some corridors with small LMP difference can also become part of the optimal expansion plan.

As the case studies show, the LMP difference is neither sufficient nor necessary condition for the candidate lines. The selection method in Chapter 3 is proposed according to the practical needs of TEP, such as reducing the congestion, satisfying N-k reliability criteria, LMP difference.

Secondly, the main task of TEP is to determine the optimal plan to upgrade the transmission network to meet the increasing load demands and generation. As the development of wind generation, the penetration level of wind generation is increasing so quickly that uncertainties brought by wind generation play an important role in the TEP problem. There are three main constraints within the TEP problem: 1) loss-of-load should not occur under any possible scenarios under the normal state, or LOLP should be less than a given probability; 2) although wind generation has the characteristic of intermittence, the utilisation level of wind generation should be ensured; 3) N-k reliability check should be satisfied under any possible scenarios, or be satisfied with a large probability. All these constraints make the TEP problem complicated. To deal with this dilemma, a two-stage stochastic dual dynamic programming for the TEP problem is proposed, with the overall objective to minimise the sum of investment costs and expected operation costs, considering uncertainties of loads and wind generation. SDDP algorithm is applied to get the optimal expansion plan under uncertainties of load demands and wind generation. Through the implementation of BD approach, the original intractable problem can be decomposed into the master problem and many simple operation subproblems. Results of two case studies show that expansion plan obtained from SDDP approach has a better performance than the expansion plan obtained from the deterministic approach. As the case study results show, it is quite important to consider the uncertainties of load

demand and wind generation during the process of TEP. The method presented in Chapter 4 provides an approach to include the uncertainties into the TEP as well as considering the N-k reliability criteria. The required computation time is within a reasonable limit for a practical application.

Thirdly, the UC problem is to determine the optimal schedule of generation units over a given operation period, while meeting relative constraints, including physical constraints, system-wide constraints and reliability constraints. The UC problem can be modelled as a MILP problem, which is NP-hard. However, the large-scale integration of wind increases the difficulty of the UC problem. Three constraints might be violated because of the intermittence of wind generation. (1) There might be load shedding, because insufficient ramping capability is provided to tackle the fluctuation brought by wind generation. (2) The utilisation level of wind generation might be violated under some realisations of wind generation. (3) The power flow on transmission lines might exceed corresponding transmission capacity under some realisations. To deal with this problem, the chance-constrained two-stage stochastic program for UC problem is proposed, including chance constraints for LOLP, LOWP and TLOP. An approach based on a sequence of approximation and verification is proposed to convert chance constraints into equivalent deterministic constraints. Correlation between loads at different buses and correlation between wind power outputs at different buses are also considered in the proposed approach. Results of two

case studies demonstrate the proposed method can solve the chance-constrained two-stage UC problem efficiently. It is reasonable to allow violations under some extreme scenarios but with very small probability, otherwise the UC might be too conservative with the costs of wind spillage or much up/down spinning reserve. The solving approach proposed in Chapter 5 enables the UC commitment with chance constraints, and the approach is also applicable if the uncertain parameters follow different PDFs.

6.2   Future Research Work

Based on the research work presented in this thesis, future studies can be continued in the following aspects:

Firstly, in Chapter 3, a method to select candidate lines is proposed. Further studies can be carried out in several aspects. (1) The proposed method should be verified on larger test systems. Currently, the method was only tested on the IEEE RTS-96 with 73 buses. However, the bus number for a practical transmission network might be even larger. The performance of the proposed method on the practical system needs to be verified. However, it is not available data for the practical system, especially the detail geographical information. (2) How to improve the completeness of the proposed method, as well as to control the size of the candidate lines, are also worthwhile to be studied. In the case study of the IEEE RTS-96, the completeness of

the proposed selection method is about 74%. How to improve the completeness of the selection method based on some other indices rather than the LMP difference is worthwhile to be studied.

Secondly, in Chapter 4, SDDP is proposed to solve a two-stage stochastic TEP problem. The technique of BD is applied to solve the overall problem. How to select the proper M value for the Big-M approach and to ensure the convergence performance of the algorithm needs to be further studied. The N-k reliability criteria are checked under four specified realizations of uncertainties. However, it cannot ensure that the N-k reliability criteria can be satisfied under any realizations of uncertainties. So how to realize the robust TEP to meet N-k reliability criteria will be studied in the further research.

Thirdly, in Chapter 5, a new method is proposed to convert chance constraints into equivalent deterministic constraints by a sequence of approximation and verification. The method needs to be further verified when the penetration level of wind generation becomes larger (e.g. 40% of the overall generation comes from wind generation). The chance-constrained UC problem can also be solved by the approach of BD. The comparison of the BD approach and the approach proposed in Chapter 5 can be carried out.

LIST OF PUBLICATIONS & OUTCOMES

Journal Papers

[1] **Zhi Wu**, Pingliang Zeng, Xiao-Ping Zhang and Qinyong Zhou, "A Solution to the Chance-Constrained Two-Stage Stochastic Program for Unit Commitment With Wind Energy Integration," *IEEE Transactions on Power Systems*. (Online available, DOI: 10.1109/TPWRS.2015.2513395)

[2] **Zhi Wu**, Suyang Zhou, Jianing Li and Xiao-Ping Zhang, "Real-Time Scheduling of Residential Appliances via Conditional Risk-at-Value," *IEEE Transactions on Smart Grid*, vol. 5, no, 3, pp. 1282-1291, 2014.

[3] **Zhi Wu**, Pingliang Zeng, Hao Fu, "Two-Stage Stochastic Dual Dynamic Programming for Transmission Expansion Planning with Significant Renewable Generation and N-*k* Criterion," *CSEE Journal of Power and Energy Systems*. (In Press)

[4] Suyang Zhou, **Zhi Wu**, Jianing Li and Xiao-Ping Zhang, "Real-time Energy Control Approach for Smart Home Energy Management System," *Electric Power Components and Systems,* vol. 43, no. 3-4, pp. 315-326, 2014.

[5] Jianing Li, **Zhi Wu**, Suyang Zhou, Hao Fu and Xiao-Ping Zhang, "A Novel Aggregator Service for Residential Apartment Buildings with PV and Battery Energy Storage Systems," *CSEE Journal of Power and Energy Systems*. (In Press)

[6] **Zhi Wu**, Xiao-Ping Zhang, Pingliang Zeng, "Automatic Selection Method for Candidate Lines in Transmission Expansion Planning," *IEEE Transactions on Power Systems*. (Submitted)

Conference papers

[1] **Zhi Wu**, Pingliang Zeng, Xiao-Ping Zhang, etc. "A fast and automatic candidate lines selection approach for transmission expansion planning", *IET Resilience of Transmission and Distribution Networks*, Sept. 2015.

[2] **Zhi Wu**, Pingliang Zeng, Xiao-Ping Zhang, etc. "Two-stage stochastic dual dynamic programming for transmission expansion planning with significant renewable generation", *IET Resilience of Transmission and Distribution Networks*, Sept. 2015.

[3] **Pingliang** Zeng, **Zhi Wu**, Xiao-Ping Zhang, etc. "Model predictive control for energy storage systems in a network with high penetration of renewable energy and limited export capacity", *Power Systems Computation Conference*, Aug. 2014.

REFERENCE

[1]   "2014 key world energy statistics," International Energy Agency, 2014.

[2]   "World energy outlook 2014 factsheet," International Energy Agency.

[3]   Huang Can, Li Fangxing, and Jin Zhiqiang, "Maximum power point tracking strategy for large-scale wind generation systems considering wind turbine dynamics," *IEEE Transactions on Industrial Electronics,* vol. 62, no. 4, pp. 2530-2539, 2015.

[4]   Huang Can, Li Fangxing, Ding Tao, Jin Zhiqiang, and Ma Xiao, "Second-order cone programming-based optimal control strategy for wind energy conversion systems over complete operating regions," *IEEE Transactions on Sustainable Energy,* vol. 6, no. 1, pp. 263-271, 2015.

[5]   International Energy Agency, "Renewable energy mdium-term market report to 2020," 2015.

[6]   National Renewable Energy Laboratory, "Bulk electric power systems: Operations and transmission planning," 2012.

[7]   Eu on track to meeting 20% renewable energy target [Online]. Available: https://ec.europa.eu/energy/en/news/eu-track-meeting-20-renewable-energy-target

[8]   European Commission, "Eu energy, transport and ghg emissions trends to 2050," 2013.

[9]   World Resources Institute, "Renewable energy in china: An overview," 2015.

[10]   Solar Energy Industries Association, "Solar energy facts: 2014 year in review," 2014.

[11]   Solar installation capacity [Online]. Available: http://www.pv-tech.org/news/global-solar-installations-hit-59gw-in-2015-gtm

[12]   Electric power system operation decision support by expert system built with paraconsistent annotated logic [Online]. Available: http://www.intechopen.com/books/howtoreference/advances-in-expert-systems/electric-power-system-operation-decision-support-by-expert-system-built-with-paraconsistent-annotate

[13]   Typical   demand   patterns   [Online].   Available:
         http://www.pennenergy.com/blogs/the-black-swan-blog/2013/12/why_renewa
         bles_haven.html

[14]   The European Wind Energy Association. Ewea position paper on priority
         dispatch   of   wind   power   [Online].   Available:
         http://www.ewea.org/fileadmin/files/library/publications/position-papers/EWE
         A_position_on_priority_dispatch.pdf

[15]   Emmanuel   Brutin.   European   connections   [Online].   Available:
         http://www.nationalgridconnecting.com/european-connections/

[16]   S. Lumbreras, A. Ramos, and P. Sanchez, "Automatic selection of candidate
         investments for transmission expansion planning," *International Journal of
         Electrical Power & Energy Systems,* vol. 59, pp. 130-140, Jul 2014.

[17]   Yifan Li and James D. McCalley, "Design of a high capacity inter-regional
         transmission overlay for the u.S," *IEEE Transactions on Power Systems,* vol. 30,
         no. 1, pp. 513-521, Jan 2015.

[18]   "A dynamic programming decomposition method for making overbooking
         decisions over an airline network," *INFORMS Journal on Computing,* vol. 22,
         no. 3, pp. 443-456, 2010.

[19]   Sumit Kunnumkal and Huseyin Topaloglu, "A new dynamic programming
         decomposition method for the network revenue management problem with
         customer choice behavior," *Production and Operations Management,* vol. 19,
         no. 5, pp. 575-590, 2010.

[20]   Rabih A. Jabr, "Optimization of ac transmission system planning," *IEEE
         Transactions on Power Systems,* vol. 28, no. 3, pp. 2779-2787, Aug 2013.

[21]   R. L. Y. Chen, A. Cohn, Fan Neng, and A. Pinar, "Contingency-risk informed
         power system design," *IEEE Transactions on Power Systems,* vol. 29, no. 5, pp.
         2087-2096, 2014.

[22]   Hui Zhang, Vijay Vittal, Gerald Thomas Heydt, and Jaime Quintero, "A
         mixed-integer   linear   programming   approach   for   multi-stage
         security-constrained transmission expansion planning," *IEEE Transactions on
         Power Systems,* vol. 27, no. 2, pp. 1125-1133, May 2012.

[23]   Fang Zhang, Zechun Hu, and Yonghua Song, "Mixed-integer linear model for
         transmission expansion planning with line losses and energy storage systems,"

IET Generation Transmission & Distribution, vol. 7, no. 8, pp. 919-928, Aug 2013.

[24] Reza Hemmati, Rahmat-Allah Hooshmand, and Amin Khodabakhshian, "State-of-the-art of transmission expansion planning: Comprehensive review," *Renewable and Sustainable Energy Reviews,* vol. 23, no. 0, pp. 312-319, 2013.

[25] Ahmad Rouhani, Seyyed Hadi Hosseini, and Mahdi Raoofat, "Composite generation and transmission expansion planning considering distributed generation," *International Journal of Electrical Power & Energy Systems,* vol. 62, pp. 792-805, Nov 2014.

[26] Masoud Jenabi, Seyyed Mohammad Taghi Fatemi Ghomi, and Yves Smeers, "Bi-level game approaches for coordination of generation and transmission expansion planning within a market environment," *IEEE Transactions on Power Systems,* vol. 28, no. 3, pp. 2639-2650, Aug 2013.

[27] Hyoungtae Kim and Wook Kim, "Integrated optimization of combined generation and transmission expansion planning considering bus voltage limits," *Journal of Electrical Engineering & Technology,* vol. 9, no. 4, pp. 1202-1209, Jul 2014.

[28] Hani Mavalizadeh and Abdollah Ahmadi, "Hybrid expansion planning considering security and emission by augmented epsilon-constraint method," *International Journal of Electrical Power & Energy Systems,* vol. 61, pp. 90-100, Oct 2014.

[29] David Pozo, Enzoe E. Sauma, and Javier Contreras, "A three-level static milp model for generation and transmission expansion planning," *IEEE Transactions on Power Systems,* vol. 28, no. 1, pp. 202-210, Feb 2013.

[30] Eric Maskin, "Commentary: Nash equilibrium and mechanism design," *Games and Economic Behavior,* vol. 71, no. 1, pp. 9-11, 1// 2011.

[31] N. Alguacil, A. L. Motto, and A. J. Conejo, "Transmission expansion planning: A mixed-integer lp approach," *IEEE Transactions on Power Systems,* vol. 18, no. 3, pp. 1070-1077, 2003.

[32] Rong-Ceng Leou, "A multi-year transmission planning under a deregulated market," *International Journal of Electrical Power & Energy Systems,* vol. 33, no. 3, pp. 708-714, Mar 2011.

[33]   Tohid Akbari and Mohammad Tavakoli Bina, "A linearized formulation of ac multi-year transmission expansion planning: A mixed-integer linear programming approach," *Electric Power Systems Research,* vol. 114, pp. 93-100, Sep 2014.

[34]   Somphop Asadamongkol and Bundhit Eua-arporn, "Transmission expansion planning with ac model based on generalized benders decomposition," *International Journal of Electrical Power & Energy Systems,* vol. 47, pp. 402-407, May 2013.

[35]   S. Binato, M. V. F. Pereira, and S. Granville, "A new benders decomposition approach to solve power transmission network design problems," *IEEE Transactions on Power Systems,* vol. 16, no. 2, pp. 235-240, 2001.

[36]   G. A. Orfanos, P. S. Georgilakis, and N. D. Hatziargyriou, "Transmission expansion planning of systems with increasing wind power integration," *IEEE Transactions on Power Systems,* vol. 28, no. 2, pp. 1355-1362, 2013.

[37]   Heejung Park, Ross Baldick, and David P. Morton, "A stochastic transmission planning model with dependent load and wind forecasts," *IEEE Transactions on Power Systems,* vol. 30, no. 6, pp. 3003-3011, Nov 2015.

[38]   M. J. Rider, A. V. Garcia, and R. Romero, "Transmission system expansion planning by a branch-and-bound algorithm," *IET Generation Transmission & Distribution,* vol. 2, no. 1, pp. 90-99, Jan 2008.

[39]   R. Romero, E. N. Asada, E. Carreno, and C. Rocha, "Constructive heuristic algorithm in branch-and-bound structure applied to transmission network expansion planning," *IET Generation Transmission & Distribution,* vol. 1, no. 2, pp. 318-323, Mar 2007.

[40]   Soheil Sarhadi and Turaj Amraee, "Robust dynamic network expansion planning considering load uncertainty," *International Journal of Electrical Power & Energy Systems,* vol. 71, pp. 140-150, Oct 2015.

[41]   Enrique B. Cedeno and Sant Arora, "Convexification method for bilinear transmission expansion problem," *International Transactions on Electrical Energy Systems,* vol. 24, no. 5, pp. 638-652, May 2014.

[42]   Isabela Miranda de Mendonca, Ivo Chaves Silva Junior, and Andre L. M. Marcato, "Static planning of the expansion of electrical energy transmission systems using particle swarm optimization," *International Journal of Electrical Power & Energy Systems,* vol. 60, pp. 234-244, Sep 2014.

[43]   Mohsen Rahmani, Ruben Romero, and Marcos J. Rider, "Strategies to reduce the number of variables and the combinatorial search space of the multistage transmission expansion planning problem," *IEEE Transactions on Power Systems,* vol. 28, no. 3, pp. 2164-2173, Aug 2013.

[44]   Kakuta Hiroki and Hiroyuki Mori, "An efficient multi-objective meta-heuristic method for probabilistic transmission network planning," in *Complex adaptive systems.* vol. 36, C. H. Dagli, Ed., ed, 2014, pp. 446-453.

[45]   A. Arabali, M. Ghofrani, M. Etezadi-Amoli, M. S. Fadali, and M. Moeini-Aghtaie, "A multi-objective transmission expansion planning framework in deregulated power systems with wind generation," *IEEE Transactions on Power Systems,* vol. 29, no. 6, pp. 3003-3011, Nov 2014.

[46]   Aleksa B. Babic, Andrija T. Saric, and Aleksandar Rankovic, "Transmission expansion planning based on locational marginal prices and ellipsoidal approximation of uncertainties," *International Journal of Electrical Power & Energy Systems,* vol. 53, pp. 175-183, Dec 2013.

[47]   Ibrahim Alhamrouni, Azhar Khairuddin, Ali Khorasani Ferdavani, and Mohamed Salem, "Transmission expansion planning using ac-based differential evolution algorithm," *IET Generation Transmission & Distribution,* vol. 8, no. 10, pp. 1637-1644, Oct 2014.

[48]   P. Murugan, "Modified particle swarm optimisation with a novel initialisation for finding optimal solution to the transmission expansion planning problem," *IET Generation Transmission & Distribution,* vol. 6, no. 11, pp. 1132-1142, Nov 2012.

[49]   A. Sadegheih, "New formulation and analysis of the system planning expansion model," *European Transactions on Electrical Power,* vol. 19, no. 2, pp. 240-257, Mar 2009.

[50]   Rongrit Chatthaworn and Surachai Chaitusaney, "Improving method of robust transmission network expansion planning considering intermittent renewable energy generation and loads," *IET Generation Transmission & Distribution,* vol. 9, no. 13, pp. 1621-1627, Oct 1 2015.

[51]   A. Sadegheih and P. R. Drake, "System network planning expansion using mathematical programming, genetic algorithms and tabu search," *Energy Conversion and Management,* vol. 49, no. 6, pp. 1557-1566, Jun 2008.

[52] Mojtaba Shivaie and Mohammad T. Ameli, "An implementation of improved harmony search algorithm for scenario-based transmission expansion planning," *Soft Computing,* vol. 18, no. 8, pp. 1615-1630, Aug 2014.

[53] Abdollah Rastgou and Jamal Moshtagh, "Improved harmony search algorithm for transmission expansion planning with adequacy-security considerations in the deregulated power system," *International Journal of Electrical Power & Energy Systems,* vol. 60, pp. 153-164, Sep 2014.

[54] Chandrakant Rathore and Ranjit Roy, "A novel modified gbmo algorithm based static transmission network expansion planning," *International Journal of Electrical Power & Energy Systems,* vol. 62, pp. 519-531, Nov 2014.

[55] Mit study on the future of the electric grid-chapter 4 transmission planning [Online]. Available: https://mitei.mit.edu/system/files/Electric_Grid_4_Transmission_Expansion.pdf

[56] Choi Jaeseok, T. D. Mount, and R. J. Thomas, "Transmission expansion planning using contingency criteria," *IEEE Transactions on Power Systems,* vol. 22, no. 4, pp. 2249-2261, 2007.

[57] Choi Jaeseok, Tran TrungTinh, A. A. El-Keib, R. Thomas, Oh HyungSeon, and R. Billinton, "A method for transmission system expansion planning considering probabilistic reliability criteria," *IEEE Transactions on Power Systems,* vol. 20, no. 3, pp. 1606-1615, 2005.

[58] Rahmat-Allah Hooshmand, Reza Hemmati, and Moein Parastegari, "Combination of ac transmission expansion planning and reactive power planning in the restructured power system," *Energy Conversion and Management,* vol. 55, pp. 26-35, 3// 2012.

[59] Zhao Jun Hua, Dong Zhao Yang, P. Lindsay, and Wong Kit Po, "Flexible transmission expansion planning with uncertainties in an electricity market," *IEEE Transactions on Power Systems,* vol. 24, no. 1, pp. 479-488, 2009.

[60] A. Moreira, A. Street, and J. M. Arroyo, "An adjustable robust optimization approach for contingency-constrained transmission expansion planning," *IEEE Transactions on Power Systems,* vol. 30, no. 4, pp. 2013-2022, 2014.

[61] Ebrahim Karimi and Akbar Ebrahimi, "Inclusion of blackouts risk in probabilistic transmission expansion planning by a multi-objective framework," *IEEE Transactions on Power Systems,* vol. 30, no. 5, pp. 2810-2817, Sep 2015.

[62]   R. Moreno, D. Pudjianto, and G. Strbac, "Transmission network investment with probabilistic security and corrective control," *IEEE Transactions on Power Systems,* vol. 28, no. 4, pp. 3935-3944, 2013.

[63]   I. Konstantelos and G. Strbac, "Valuation of flexible transmission investment options under uncertainty," *IEEE Transactions on Power Systems,* vol. 30, no. 2, pp. 1047-1055, 2015.

[64]   Jing Zheng, Fushuan Wen, Gerard Ledwich, and Jiansheng Huang, "Risk control in transmission system expansion planning with wind generators," *International Transactions on Electrical Energy Systems,* vol. 24, no. 2, pp. 227-245, Feb 2014.

[65]   Francisco D. Munoz, Benjamin F. Hobbs, Jonathan L. Ho, and Saamrat Kasina, "An engineering-economic approach to transmission planning under market and regulatory uncertainties: Wecc case study," *IEEE Transactions on Power Systems,* vol. 29, no. 1, pp. 307-317, Jan 2014.

[66]   Jonas Christoffer Villumsen, Geir Bronmo, and Andy B. Philpott, "Line capacity expansion and transmission switching in power systems with large-scale wind power," *IEEE Transactions on Power Systems,* vol. 28, no. 2, pp. 731-739, May 2013.

[67]   Heejung Park and Ross Baldick, "Transmission planning under uncertainties of wind and load: Sequential approximation approach," *IEEE Transactions on Power Systems,* vol. 28, no. 3, pp. 2395-2402, Aug 2013.

[68]   Lu Liu, Hao-zhong Cheng, Liang-zhong Yao, Ze-liang Ma, and Masoud Bazargan, "Multi-objective multi-stage transmission network expansion planning considering life cycle cost and risk value under uncertainties," *International Transactions on Electrical Energy Systems,* vol. 23, no. 3, pp. 438-450, Apr 2013.

[69]   C. Ruiz and A. J. Conejo, "Robust transmission expansion planning," *European Journal of Operational Research,* vol. 242, no. 2, pp. 390-401, 2015.

[70]   Shahab Dehghan, Ahad Kazemi, and Nima Amjady, "Multi-objective robust transmission expansion planning using information-gap decision theory and augmented e-constraint method," *IET Generation Transmission & Distribution,* vol. 8, no. 5, pp. 828-840, May 2014.

[71]   Behnam Alizadeh and Shahram Jadid, "Uncertainty handling in power system expansion planning under a robust multi-objective framework," *IET*

Generation Transmission & Distribution, vol. 8, no. 12, pp. 2012-2026, Dec 2014.

[72]   R. A. Jabr, "Robust transmission network expansion planning with uncertain renewable generation and loads," *IEEE Transactions on Power Systems,* vol. 28, no. 4, pp. 4558-4567, 2013.

[73]   Behnam Alizadeh, Shahab Dehghan, Nima Amjady, Shahram Jadid, and Ahad Kazemi, "Robust transmission system expansion considering planning uncertainties," *IET Generation Transmission & Distribution,* vol. 7, no. 11, pp. 1318-1331, Nov 2013.

[74]   Han Yu, C. Y. Chung, and K. P. Wong, "Robust transmission network expansion planning method with taguchi's orthogonal array testing," *IEEE Transactions on Power Systems,* vol. 26, no. 3, pp. 1573-1580, Aug 2011.

[75]   P. A. Ruiz, C. R. Philbrick, E. Zak, K. W. Cheung, and P. W. Sauer, "Uncertainty management in the unit commitment problem," *IEEE Transactions on Power Systems,* vol. 24, no. 2, pp. 642-651, 2009.

[76]   Qipeng P. Zheng, Jianhui Wang, and Andrew L. Liu, "Stochastic optimization for unit commitment-a review," *IEEE Transactions on Power Systems,* vol. 30, no. 4, pp. 1913-1924, Jul 2015.

[77]   R. Baldick, "The generalized unit commitment problem," *IEEE Transactions on Power Systems,* vol. 10, no. 1, pp. 465-475, 1995.

[78]   C. Zhao and Y. Guan, "Data-driven stochastic unit commitment for integrating wind generation," *IEEE Transactions on Power Systems,* vol. PP, no. 99, pp. 1-10, 2015.

[79]   Wu Lei, M. Shahidehpour, and Li Tao, "Cost of reliability analysis based on stochastic unit commitment," *IEEE Transactions on Power Systems,* vol. 23, no. 3, pp. 1364-1374, 2008.

[80]   S. Takriti, J. R. Birge, and E. Long, "A stochastic model for the unit commitment problem," *IEEE Transactions on Power Systems,* vol. 11, no. 3, pp. 1497-1508, 1996.

[81]   Wu Lei, M. Shahidehpour, and Li Tao, "Stochastic security-constrained unit commitment," *IEEE Transactions on Power Systems,* vol. 22, no. 2, pp. 800-811, 2007.

[82]   Qipeng P. Zheng, Jianhui Wang, Panos M. Pardalos, and Yongpei Guan, "A decomposition approach to the two-stage stochastic unit commitment problem," *Annals of Operations Research,* vol. 210, no. 1, pp. 387-410, 2012.

[83]   J. M. Morales, A. J. Conejo, and J. Perez-Ruiz, "Economic valuation of reserves in power systems with high penetration of wind power," *IEEE Transactions on Power Systems,* vol. 24, no. 2, pp. 900-910, 2009.

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

[85]   Wang Jianhui, M. Shahidehpour, and Li Zuyi, "Security-constrained unit commitment with volatile wind power generation," *IEEE Transactions on Power Systems,* vol. 23, no. 3, pp. 1319-1327, 2008.

[86]   Hengyong Tang and Yufang Zhao, "L-shaped algorithm for two stage problems of stochastic convex programming," *Journal of Applied Mathematics and Computing,* vol. 13, no. 1, pp. 261-275.

[87]   Gilbert Laporte and François V. Louveaux, "The integer l-shaped method for stochastic integer programs with complete recourse," *Operations Research Letters,* vol. 13, no. 3, pp. 133-142, 1993/04/01 1993.

[88]   Lewis Ntaimo and Matthew W. Tanner, "Computations with disjunctive cuts for two-stage stochastic mixed 0-1 integer programs," *Journal of Global Optimization,* vol. 41, no. 3, pp. 365-384, 2007.

[89]   D. Hanif Sherali and Xiaomei Zhu, "On solving discrete two-stage stochastic programs having mixed-integer first- and second-stage variables," *Mathematical Programming,* vol. 108, no. 2, pp. 597-616, 2006.

[90]   Anthony Papavasiliou and Shmuel S. Oren, "Multiarea stochastic unit commitment for high wind penetration in a transmission constrained network," *Operations Research,* vol. 61, no. 3, pp. 578-592, 2013.

[91]   Matthias P. Nowak, Rüdiger Schultz, and Markus Westphalen, "A stochastic integer programming model for incorporating day-ahead trading of electricity into hydro-thermal unit commitment," *Optimization and Engineering,* vol. 6, no. 2, pp. 163-176.

[92]   F. Bouffard and F. D. Galiana, "An electricity market with a probabilistic spinning reserve criterion," *IEEE Transactions on Power Systems,* vol. 19, no. 1, pp. 300-307, 2004.

[93]   A. Ahmadi-Khatir, M. Bozorg, and R. Cherkaoui, "Probabilistic spinning reserve provision model in multi-control zone power system," *IEEE Transactions on Power Systems,* vol. 28, no. 3, pp. 2819-2829, 2013.

[94]   A. J. Conejo, F. J. Nogales, J. M. Arroyo, and R. Garcia-Bertrand, "Risk-constrained self-scheduling of a thermal power producer," *IEEE Transactions on Power Systems,* vol. 19, no. 3, pp. 1569-1574, 2004.

[95]   M. Asensio and J. Contreras, "Stochastic unit commitment in isolated systems with renewable penetration under cvar assessment," *Smart Grid, IEEE Transactions on,* vol. PP, no. 99, pp. 1-1, 2015.

[96]   Sheena Yau, Roy H. Kwon, J. Scott Rogers, and Desheng Wu, "Financial and operational decisions in the electricity sector: Contract portfolio optimization with the conditional value-at-risk criterion," *International Journal of Production Economics,* vol. 134, no. 1, pp. 67-77, Nov 2011.

[97]   Qin Zhang and Xifan Wang, "Hedge contract characterization and risk-constrained electricity procurement," *IEEE Transactions on Power Systems,* vol. 24, no. 3, pp. 1547-1558, Aug 2009.

[98]   Yuping Huang, Qipeng P. Zheng, and Jianhui Wang, "Two-stage stochastic unit commitment model including non-generation resources with conditional value-at-risk constraints," *Electric Power Systems Research,* vol. 116, pp. 427-438, Nov 2014.

[99]   Jiang Ruiwei, Wang Jianhui, and Guan Yongpei, "Robust unit commitment with wind power and pumped storage hydro," *IEEE Transactions on Power Systems,* vol. 27, no. 2, pp. 800-810, 2012.

[100]   D. Bertsimas, E. Litvinov, X. A. Sun, Zhao Jinye, and Zheng Tongxin, "Adaptive robust optimization for the security constrained unit commitment problem," *IEEE Transactions on Power Systems,* vol. 28, no. 1, pp. 52-63, 2013.

[101]   Wang Qianfan, J. P. Watson, and Guan Yongpei, "Two-stage robust optimization for n-k contingency-constrained unit commitment," *IEEE Transactions on Power Systems,* vol. 28, no. 3, pp. 2366-2375, 2013.

[102] A. Street, F. Oliveira, and J. M. Arroyo, "Contingency-constrained unit commitment with n-k security criterion: A robust optimization approach," *IEEE Transactions on Power Systems,* vol. 26, no. 3, pp. 1581-1590, 2011.

[103] U. A. Ozturk, M. Mazumdar, and B. A. Norman, "A solution to the stochastic unit commitment problem using chance constrained programming," *IEEE Transactions on Power Systems,* vol. 19, no. 3, pp. 1589-1598, 2004.

[104] D. Pozo and J. Contreras, "A chance-constrained unit commitment with an n-k security criterion and significant wind generation," *IEEE Transactions on Power Systems,* vol. 28, no. 3, pp. 2842-2851, 2013.

[105] Wang Qianfan, Guan Yongpei, and Wang Jianhui, "A chance-constrained two-stage stochastic program for unit commitment with uncertain wind power output," *IEEE Transactions on Power Systems,* vol. 27, no. 1, pp. 206-215, 2012.

[106] H. Wu, M. Shahidehpour, Z. Li, and W. Tian, "Chance-constrained day-ahead scheduling in stochastic power system operation," *IEEE Transactions on Power Systems,* vol. 29, no. 4, pp. 1583-1591, 2014.

[107] Qiu Feng and Wang Jianhui, "Chance-constrained transmission switching with guaranteed wind power utilization," *IEEE Transactions on Power Systems,* vol. 30, no. 3, pp. 1270-1278, 2015.

[108] Feng Qiu and Jianhui Wang, "Chance-constrained transmission switching with guaranteed wind power utilization," *IEEE Transactions on Power Systems,* vol. 30, no. 3, pp. 1270-1278, May 2015.

[109] Zhao Chaoyue, Wang Qianfan, Wang Jianhui, and Guan Yongpei, "Expected value and chance constrained stochastic unit commitment ensuring wind power utilization," *IEEE Transactions on Power Systems,* vol. 29, no. 6, pp. 2696-2705, 2014.

[110] Wang Qianfan, Wang Jianhui, and Guan Yongpei, "Stochastic unit commitment with uncertain demand response," *IEEE Transactions on Power Systems,* vol. 28, no. 1, pp. 562-563, 2013.

[111] Newham Nikki, "Power system investment planning using stochastic dual dynamic programming," Doctor of Philosophy, Electrical and Computer Engineering, University of Canterbury, 2008.

[112] Cplex optimizer [Online]. Available: http://www-01.ibm.com/software/commerce/optimization/cplex-optimizer/index.html

[113] Gurobi [Online]. Available: http://www.gurobi.com/

[114] North Amer. Electric Reliability Corp. (NERC). *Transmission system planning performance requirements*. Available: http://www.nerc.com/pa/Stand/Reliability%20Standards/TPL-001-4.pdf

[115] J. Löfberg. (1 April 2016). *Yalmip*. Available: http://users.isy.liu.se/johanl/yalmip/pmwiki.php?n=Main.HomePage

[116] P. M. Subcommittee, "Ieee reliability test system," *IEEE Transactions on Power Apparatus and Systems,* vol. PAS-98, no. 6, pp. 2047-2054, 1979.

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

[118] Steffen Rebennack, "Generation expansion planning under uncertainty with emissions quotas," *Electric Power Systems Research,* vol. 114, no. 0, pp. 78-85, 9 2014.

[119] Tito Homem-de-Mello, VitorL de Matos, and ErlonC Finardi, "Sampling strategies and stopping criteria for stochastic dual dynamic programming: A case study in long-term hydrothermal scheduling," *Energy Systems,* vol. 2, no. 1, pp. 1-31, 2011.

[120] S. Rebennack, B. Flach, M. V. F. Pereira, and P. M. Pardalos, "Stochastic hydro-thermal scheduling under co2 emissions constraints," *IEEE Transactions on Power Systems,* vol. 27, no. 1, pp. 58-68, 2012.

[121] Alexander Shapiro, "Analysis of stochastic dual dynamic programming method," *European Journal of Operational Research,* vol. 209, no. 1, pp. 63-72, 2011.

[122] K. Dietrich, J. M. Latorre, L. Olmos, and A. Ramos, "Demand response in an isolated system with high wind integration," *IEEE Transactions on Power Systems,* vol. 27, no. 1, pp. 20-29, 2012.

[123] Hong Ying-Yi and Wei Shih-Fan, "Multiobjective underfrequency load shedding in an autonomous system using hierarchical genetic algorithms," *Power Delivery, IEEE Transactions on,* vol. 25, no. 3, pp. 1355-1362, 2010.

[124] D. Q. Hung, N. Mithulananthan, and K. Y. Lee, "Determining pv penetration for distribution systems with time-varying load models," *IEEE Transactions on Power Systems,* vol. 29, no. 6, pp. 3048-3057, Nov 2014.

[125] Han Daolan, Jian Jinbao, and Yang Linfeng, "Outer approximation and outer-inner approximation approaches for unit commitment problem," *IEEE Transactions on Power Systems,* vol. 29, no. 2, pp. 505-513, 2014.

[126] C. Mudd S. Fink, K. Porter, and B. Morgenstern, "Wind power curtailment case studies," 2009.

[127] B. M. Hodge, D. Lew, and M. Milligan, "Short-term load forecast error distributions and implications for renewable integration studies," in *Green Technologies Conference, 2013 IEEE*, 2013, pp. 435-442.

[128] M. E. Khodayar, M. Shahidehpour, and Wu Lei, "Enhancing the dispatchability of variable wind generation by coordination with pumped-storage hydro units in stochastic power systems," *IEEE Transactions on Power Systems,* vol. 28, no. 3, pp. 2808-2818, 2013.

[129] Integration of renewable resources: Technical appendices for california iso renewable integration studies [Online]. Available: http://www.caiso.com/1ca5/1ca5a7a026270.pdf

[130] Xiaochen Wang, Peng Guo, and Xiaobin Huang, "A review of wind power forecasting models," *Energy Procedia,* vol. 12, no. 0, pp. 770-778, 2011.

[131] T. B. M. J. Ouarda, C. Charron, J. Y. Shin, P. R. Marpu, A. H. Al-Mandoos, M. H. Al-Tamimi, H. Ghedira, and T. N. Al Hosary, "Probability distributions of wind speed in the uae," *Energy Conversion and Management,* vol. 93, pp. 414-434, 3/15/ 2015.

[132] Julio Usaola, "Probabilistic load flow with correlated wind power injections," *Electric Power Systems Research,* vol. 80, no. 5, pp. 528-536, 2010.