Modeling the Diversification Benefit of Transmission Investments in the Presence of Uncorrelated Generation Sources

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MODELING THE DIVERSIFICATION BENEFIT OF TRANSMISSION INVESTMENTS IN THE PRESENCE OF UNCORRELATED GENERATION SOURCES

by

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Abstract

It is well known that transmission investment yields two major benefits: (a) it allows cheaper remote generation to substitute for more expensive local generation, (the efficiency benefit) and (b) by increasing the diversification of uncorrelated generation sources, allows a reduction in the volume of balancing services required (the diversification benefit). Conventional transmission planning processes tend to focus exclusively on the efficiency benefit.

It is well known that increasing wind penetration increases the need for balancing services. Even where the market is able to provide the signals to generators as to when and how much to produce, increasing wind penetration increases the need for higher-flexibility plant (such as OCGT or very fast start hydro plant) which typically has a higher long-run cost.

The purpose of this study is to develop a mathematical model for quantifying the diversification benefit for transmission investment.

To do this two-step economic dispatch of the day-ahead energy market and the real-time balancing market are mathematically formulated in a single optimization problem which calculates the results of day-ahead market dispatch and real-time market dispatch in one optimization problem. The new formulation is a linear programming problem which calculates the dispatch cost and the economic deviation
from the dispatch cost.

Firstly, this single optimization problem is used for quantifying the diversification benefit of the additional transmission capacity.

Then, a stochastic optimization model for modeling the diversification benefit of additional transmission capacity in the transmission planning process is formulated. Uncertainty of system parameters are modeled using scenarios. ARIMA models and a scenario reduction technique based on Kantorovich distance are used for generating the scenarios.

To explain the diversification benefit, two example systems are studied. Firstly, to evaluate the impact of additional transmission capacity on the dispatch cost of the day-ahead energy market and the real-time balancing market, IEEE thirty-node example system is studied. The diversification benefit is calculated and the conclusions are extracted. Then, a transmission planning approach, which considers the diversification benefit along with the efficiency benefit, is proposed. The proposed and conventional transmission planning approaches are applied to modified IEEE 24-node example system. Conventional transmission planning approach (which models only efficiency benefit in its formulation) is used as a benchmark in this study.

The numerical results show that the proposed approach can effectively quantify the diversification benefit of additional transmission capacity.
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List of Tables

5.1 Generation and demand data of the modified IEEE thirty-node example system ........................................ 44
5.2 The marginal cost of energy, up-regulation, and down-regulation for different generating units in the modified IEEE thirty-node example system ........................................ 46
5.3 Transmission network data of the modified IEEE thirty-node example system ........................................ 48
5.4 The marginal cost of energy, up-regulation, and down-regulation for different generating units in the modified IEEE 24-node example system 54
5.5 Parameters of designed ARIMA model for forecasted demand ........ 56
5.6 Parameters of designed ARIMA model for wind speed ................. 59
5.7 Optimal transmission planning schedule approved in conventional approach ........................................ 62
5.8 Optimal transmission planning schedule approved in proposed approach 63
## List of Figures

2.1 Price and traded quantity for a certain hour in day-ahead energy market[1] .......................... 11
2.2 The interaction between day-ahead market and real-time market ... 13
2.3 Supply curve of day-ahead energy market .............................................. 16
2.4 Supply curve of real-time balancing market .......................................... 16
2.5 Supply curve of both day-ahead energy market and real-time balancing market ................................. 17

3.1 Decomposition algorithm ................................................................. 21
3.2 Generation operating costs of the energy market and balancing market over several dispatch interval ................................. 23

4.1 A scenario fan example ................................................................. 30
4.2 Scenario-generation algorithm ....................................................... 33
4.3 Scenario-reduction algorithm ......................................................... 36

5.1 The single line diagram of the modified IEEE thirty-node example system 44
5.2 Decomposition total benefit of augmentation into efficiency benefit and diversification benefit (Case study of the IEEE thirty-node example system) ................................. 51
5.3 The single line diagram of the modified 24-node example system . . . 53
5.4 Comparison of time series of demand generated by the ARIMA model
with original time series . . . . . . . . . . . . . . . . . . . . . . . . . . . . 57
5.5 Comparison of time series generated by the ARIMA model for wind
speed at node 103 with original time series . . . . . . . . . . . . . . . . 59
5.6 Comparison of time series generated by the ARIMA model for wind
speed at node 106 with original time series . . . . . . . . . . . . . . . . 60
5.7 The single line diagram of the modified IEEE 24-node example system
after transmission planning . . . . . . . . . . . . . . . . . . . . . . . . . 64
5.8 Impact of transmission planning on the dispatch of balancing services
(period $t = 35$ and scenario $\omega = 22$) . . . . . . . . . . . . . . . . . . . 65
5.9 Decomposition total benefit of augmentation into efficiency benefit and
diversification benefit (Case study of the IEEE 24-node example sys-
tem), TB: total benefit, EB: efficiency benefit, DB: diversification benefit 66
# Contents

Abstract i

Acknowledgments iii

List of Tables iv

List of Figures v

Contents vii

Nomenclature 1

Chapter 1: Introduction 3

1.1 Background 3

1.2 Motivation of the Project 7

1.3 Objectives 8

1.4 Resources/Tools used with that purpose 8

1.5 Overview of the Report 9

Chapter 2: Mathematical Formulation of the Electricity Market 10

2.1 Introduction 10
2.2 Two-step Model of Day-Ahead Energy Market and Real-Time Balancing Market ........................................... 11
  2.2.1 Day-Ahead Energy Market ......................................................... 11
  2.2.2 Real-Time Balancing Market ..................................................... 13
2.3 Integrated Model of Day-Ahead Energy Market and Real-Time Balancing Market ..................................................... 15

Chapter 3: The Diversification Benefit of Additional Transmission Capacity
  3.1 Introduction ............................................................................... 20
  3.2 Quantifying the Diversification Benefit ........................................... 21
  3.3 Transmission Planning with Explicit Modeling of Diversification Benefit 22
  3.4 Conventional Transmission Planning Approach ................................. 25

Chapter 4: Stochastic Programming
  4.1 Introduction ............................................................................... 27
  4.2 Expected Value of a Random Variable ............................................. 27
  4.3 Two-Stage Stochastic Programming Problems with Recourse ............... 28
  4.4 Scenario Generation ..................................................................... 29
    4.4.1 Example: Scenario Generation ..................................................... 32
  4.5 Scenario Reduction ....................................................................... 35
    4.5.1 Example: Scenario Reduction ..................................................... 38

Chapter 5: Case Studies
  5.1 Introduction ............................................................................... 43
  5.2 IEEE Thirty-Node Example System ............................................... 43
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.2.1</td>
<td>System Parameters</td>
<td>43</td>
</tr>
<tr>
<td>5.2.2</td>
<td>Results and Discussions</td>
<td>51</td>
</tr>
<tr>
<td>5.3</td>
<td>IEEE Twenty-Four Node Example System</td>
<td>52</td>
</tr>
<tr>
<td>5.3.1</td>
<td>System Parameters</td>
<td>52</td>
</tr>
<tr>
<td>5.3.2</td>
<td>Results and Discussions</td>
<td>62</td>
</tr>
</tbody>
</table>

**Chapter 6: Conclusions and Future Work**

6.1 Conclusion

6.2 Future Work

Bibliography
Nomenclature

Indexes

\[
\begin{align*}
  i & \quad \text{Node of the network} \\
  l & \quad \text{Transmission line of the system} \\
  \omega & \quad \text{Random scenario} \\
  t & \quad \text{Dispatch period} \\
  y & \quad \text{Year} \\
  N & \quad \text{Set of the nodes in the system} \\
  L & \quad \text{Set of transmission line in the system} \\
  \Omega & \quad \text{Set of random scenarios} \\
  T & \quad \text{Set of dispatch periods} \\
  Y & \quad \text{Set of years}
\end{align*}
\]

Parameters

\[
\begin{align*}
  c_i & \quad \text{Variable cost of generator at node } i \ (\$/\text{MW}) \\
  c_{i}^{up} & \quad \text{Up-regulation cost at node } i \ (\$/\text{MW}) \\
  c_{i}^{dn} & \quad \text{Down-regulation cost at node } i \ (\$/\text{MW}) \\
  \pi_{i,\omega} & \quad \text{Probability of occurrence of scenario } \omega \\
  \pi_{\omega}^{\Delta D} & \quad \text{Probability of occurrence of forecast error scenario } \omega \\
  c_{l}^{\text{ine}} & \quad \text{Construction cost of new line } l \ (\$/\text{line})
\end{align*}
\]
$D_{i,t,\omega,y}$ Forecasted demand in period $t$ at node $i$ in scenario $\omega$ and year $y$ (MW)

$\Delta D_{i,t,y}$ Forecast error in period $t$ at node $i$ and in year $y$ (MW)

$G_{i,t}^E$ Bid generation capacity for energy market by generator at node $i$ in period $t$ (MW)

$G_{i,t}^B$ Bid generation capacity for balancing market by generator at node $i$ in period $t$ (MW)

$F_l$ Minimum capacity of power line $l$ (MW)

$\overline{F}_l$ Maximum capacity of power line $l$ (MW)

$H_{l,i}$ Power Transfer Distribution Factor for line $l$ and net power injection at node $i$

$\overline{n}_l$ Maximum number of new transmission lines for link $l$

$r$ Interest rate

**Variables**

$F_{l,t,\omega,y}^E$ Power flow after day-ahead market dispatch in period $t$ in line $l$ in scenario $\omega$ and year $y$

$F_{l,t,\omega,y}^B$ Power flow after real-time market dispatch in period $t$ in line $l$ in scenario $\omega$ and year $y$

$G_{i,t,\omega,y}$ Power produced by generator $i$ in period $t$ in scenario $\omega$ and year $y$ (MW)

$\Delta G_{i,t,\omega,y}^{up}$ Up-regulation provided by generator $i$ in period $t$ in scenario $\omega$ and year $y$ (MW)

$\Delta G_{i,t,\omega,y}^{dn}$ Down-regulation provided by generator $i$ in period $t$ in scenario $\omega$ and year $y$ (MW)

$n_l$ Number of new transmission lines for link $l$
Chapter 1

Introduction

1.1 Background

Historically, electricity sector was organized as state-owned vertically-integrated monopolies. The essential principle of traditional transmission planning was to do it in a least cost approach which focuses to minimize the investment cost of planned expansion scheme while satisfying the reliability requirements [2]. Over the last three decades, this paradigm has changed. In today’s power industry, generation and transmission is unbundled. The transmission planning processes also changed from the least cost approach to a market-based economic benefit approach. This market-based approach aims to obtain the optimum expansion planning scheme not only to upgrade the system in a least-cost manner but also to maximize economic benefits for the system [3]. In literature, these two approaches are commonly discussed and different mathematical methods for modeling the expansion problem are proposed. In [4], a multi objective optimization problem for transmission upgrade planning is formulated. To minimize the investment cost and cost of unserved demand at the same time fulfilling the stability constraints is the main purpose of this model. In
1.1. BACKGROUND

[5], transmission expansion planning problem which is modeled using AC model of transmission network aims to minimize the investment cost of line construction. Reference [6] uses chaos particle swarm optimization to solve the expansion planning problem. Reference [7] proposed an elasticity model for the same problem and solved it by transforming the elastic variables to deterministic variables related to an elasticity factor. Reference [8],[9],[10],[11] discusses the transmission upgrade planning in a market-based approach which aims to minimize construction cost of new lines and operating cost of generating units. In [8], transmission planning problem takes into account the transmission losses is modeled as mixed-integer linear programming problem. Load curtailment cost is also taken into account in [9] in a multi objective transmission expansion model. Reference [10], models the planning problem in multiple year range. Reference [11] proposes a transmission expansion planning schedule which considers the demand uncertainties in the system.

Transmission planning schedules improve the efficiency of the transmission network by allowing remote lower-cost generation to be substituted by the local high-cost generation. The literature on the market-based transmission planning is mainly focused on this type of benefit of additional transmission capacity, [12].

Balancing services become more of an issue since large amount of wind power generation penetrates into the electricity industry and brings fluctuating generation that increases the uncertainty in power system. This varying net load (i.e. the difference between generation and load), increase the demand for short-term services for balancing the supply and demand of electricity.

Formulating real-time balancing market and designing different methods to reduce the cost of ancillary services are popular topics in both engineering and economics
1.1. BACKGROUND

literature. References [13], [14] and [15], model the real-time balancing market apart from day-ahead energy market. In [13], the dispatch problem of the balancing market considers both the regulation cost and the opportunity cost of generators which provides reserves for the system. In [14], demand response is also considered with regulation cost and opportunity cost in modeling the dispatch problem. In [15], the dispatch problem is formulated for both deterministic and elastic constraints. Penalty cost is introduced to relax the deterministic constraints. In [16], energy and balancing market is cleared in an integrated market which takes into account the environmental effects by adding external constraints to optimization problem. Reference [17] aims to study the effect of the demand response in reserve market. Energy and reserve market is cleared simultaneously in a probabilistic model which penalizes the loss of load. In [18], energy and ancillary services, which is characterized by deployment time as primary, secondary and tertiary reserves, are modeled in deterministic and probabilistic approach which clears both markets in a simultaneous model. In [19], day-ahead and real-time market, which is formed from six different commodities, are modeled in a hybrid market model. This model includes both sequential and simultaneous approaches of market clearing in four steps. Firstly solely the energy market dispatch is done. In the next three steps energy and various balancing market commodities are cleared simultaneously. In [20], energy and balancing market are modeled as bi-level optimization problem. Upper level does the energy market dispatch and scheduling of reserve capacity while in lower level formulates the balancing market dispatch. In [21] authors show the impact of the preventive actions on the corrective ones and also the benefits of the dispatch interval under the system physical limits (e.g. short dispatch interval).
1.1. BACKGROUND

This study focuses on the impact of such a large volume of intermittent generation on the expansion planning of the transmission network. The link between the volume of intermittent generation in the market and the expansion planning of the transmission network arises from the way that balancing services are dispatched and delivered. In the Nordic electricity market, the system operator manually activates the upward and downward regulation bids in a merit order dispatch ignoring the transmission constraints. In case, the activated bids cannot be delivered because of transmission constraints, higher cost regulating bids in the merit order list will be activated, [22]. This imposes a real economic cost in the form of higher levels of balancing market dispatch cost resulting from transmission congestion. This economic impact of intermittent generation technology on the transmission network could be reduced by moving to a transmission planning approach under which the impact of additional transmission capacity on reducing the dispatch cost of the balancing market is considered.

Additional transmission capacities can increase the diversification of uncorrelated generation sources, allow a reduction in the volume of balancing services required. The reduction in the cost of balancing services required resulted from additional transmission capacity is termed “diversification benefit”. References [23] and [24] study the interaction of the reserve market and energy market in a network-constrained electricity market. These studies only consider the operating capability of the transmission network and they do not discuss the impact of planning capability on balancing market.
1.2. MOTIVATION OF THE PROJECT

When the literature is reviewed, variety of models for real-time balancing market and different aspects of the transmission expansion planning problem are studied. However, none of these studies mentioned about the diversification benefit and considered the transmission planning policies as a solution for increasing balancing costs. The purpose of this study is to propose a methodology to model and quantify the diversification benefit of additional capacity and suggest a transmission planning process which takes into account both the efficiency benefit and the diversification benefit.

1.2 Motivation of the Project

Many countries set up environmental targets due to climate changes. European Union (EU) aims to achieve 20-20-20 targets by 2020. The EU environmental policy intends to (a) a reduction in EU greenhouse gas emissions of at least 20% below from 1990 levels, (b) 20% of EU energy consumption to come from renewable resources, (c) a 20% reduction in primary energy use compared to projected levels, to be achieved by improving energy efficiency [25]. Wind power has significant role to reach these targets. This policy has driven large amount of wind power penetration in the electricity, and this trend will continue for the following years. Increased share of wind power in the electricity generation mix brings fluctuating generation and increases the uncertainty in power system. To handle this varying net load (i.e. the difference between generation and load), the need for balancing services increases. It can be said that reducing the cost of balancing services becomes one of the major challenges in the following years for the electricity market. The idea of this project is to prove that additional transmission capacities can increase the alternatives for procurement
of the balancing services by substituting the remote cheap balancing services with the local expensive ones. Transmission planning processes which considers this type of benefit of transmission investments, the diversification benefit, can help to reduce the cost of the procurement of ancillary services.

1.3 Objectives

In order to achieve this goal, reducing the cost of balancing services, the traditional two-step economic dispatch of the energy market and balancing market is formulated as one-shot optimization problem which calculates the results of energy market dispatch and real-time balancing market dispatch in one optimization problem. This two-step economic dispatch is used for quantifying the diversification benefit of the additional transmission capacity. A decomposition approach is proposed to decompose the total benefit of additional transmission capacity into the efficiency benefit and the diversification benefit. Finally, a transmission planning process which takes into account the diversification benefit along with the efficiency benefit is constituted to find the optimum level of transmission augmentation in the transmission system.

1.4 Resources/Tools used with that purpose

The optimization problems are solved by CPLEX solver in General Algebraic Modeling System (GAMS) platform [26]. The ARIMA coefficients are estimated by ”R” software [27]. Then Matlab software is used to implement the scenario generation and reduction. The codes are run on a computer with quad-core Intel Xeon E5345 CPU with a 2.33 GHz clocking frequency and 16 GB of RAM.
1.5 Overview of the Report

In Chapter 2, mathematical formulation of electricity market is given in separated and integrated framework. Chapter 3 presents an algorithm to quantify the diversification benefit of additional transmission capacity and the formulation of the proposed transmission planning approach which considers the diversification benefit is given. Chapter 4 introduces the stochastic programming and scenario generation and reduction processes used in this study. Chapter 5 discusses simulation results. Finally, Chapter 6 is a summary of the thesis, conclusions based on the study carried out and gives a proposal for future work in this area.
Chapter 2

Mathematical Formulation of the Electricity Market

2.1 Introduction

In this study, we assume an electricity market design with two sequential markets: day-ahead energy market and the real-time balancing market. For the sake of simplicity, some assumptions are made. It is considered that only one generator and one inelastic load exist in a bus. Start-up cost and ramp rate limit of generators are neglected. A DC-power flow model with power transfer distribution factors (PTDF) which is expressed as sensitivities between power flows on lines and nodal injections is used. Further information about DC power flow model can be found in [28]. In this chapter, two-step and integrated model of electricity market are described.
2.2 Two-step Model of Day-Ahead Energy Market and Real-Time Balancing Market

2.2.1 Day-Ahead Energy Market

The day-ahead energy market where participants can trade energy for different dispatch intervals of the next day is organized as a public auction. Examples of the day-ahead energy market are EEX [29], Nordpool Elspot [30] and Omel [31]. The players in the electricity market put their demand or sell offers to the energy market. A demand offer shows the maximum price that the player is willing to pay for a certain amount of energy during a certain dispatch interval. A sell offer shows the minimum price that the player is willing to sell for a certain amount of electricity during a certain dispatch interval [32].

![Figure 2.1: Price and traded quantity for a certain hour in day-ahead energy market][1]

The system operator forecasts the day-ahead demand and runs a security-constrained economic dispatch based on submitted offers to clear the day-ahead energy market.
2.2. TWO-STEP MODEL OF DAY-AHEAD ENERGY MARKET AND REAL-TIME BALANCING MARKET

He calculates the optimum level of each generating units to meet the market demand. The demand and sell offers are matched in aggregated curves and power price and the quantity of power that will be delivered are set. This process is illustrated in figure 2.1.

The optimization problem related to day-ahead energy market is presented in (2.1).

\[
\text{Minimize } \quad \text{OC} = \sum_{i=1}^{N} c_i G_i \tag{2.1a}
\]

Subject to

\[
\sum_{i=1}^{N} (G_i - D_i) = 0 \tag{2.1b}
\]

\[
F_l \leq F_{lEM} \leq \overline{F}_l, \quad \forall l \in L \tag{2.1c}
\]

\[
0 \leq G_i \leq G_{iEM}, \quad \forall i \in N \tag{2.1d}
\]

\[G_i \geq 0\]

Where

\[
F_{lEM} = \sum_{i=1}^{N} H_{l,i}(G_i - D_i)
\]

Here equation (2.1a) is the generation operating cost in the day-ahead energy market, equation (2.1b) is the energy balance constraint, equation (2.1c) represents capacity constraint on transmission lines. Finally, equation (2.1d) represents the capacity constraint on generating units related to day-ahead energy market.
2.2. TWO-STEP MODEL OF DAY-AHEAD ENERGY MARKET AND REAL-TIME BALANCING MARKET

2.2.2 Real-Time Balancing Market

The real-time balancing market, where participants have the possibility to trade power with the system operator, is designed to deal with the deviations of the market players from their dispatch schedules. Examples of this market are the real-time balancing market in PJM [33], regulating market in the Nordic power system, [30], and frequency ancillary service market in Australia [34]. The participants submit their regulating offers to real-time balancing market. In the real-time market an up-regulation bid shows maximum amount of power in minimum price the player is willing to sell to the grid by increasing its generation or decreasing its consumption. Similarly, down-regulation bid shows minimum amount of power in maximum price the player is willing to buy from the grid by decreasing its generation or increasing its consumption. In the real-time market, the system operator uses the output of the day-ahead energy market dispatch and the real demand (which of course might have some deviations from the forecasted demand). Then he runs an optimization problem similar to the day-ahead market one to determine how much each generator should increase or decrease their output from the energy market levels to compensate the deviations in the forecasted demand. This process is illustrated in figure 2.2.

![Figure 2.2: The interaction between day-ahead market and real-time market](image_url)
2.2. TWO-STEP MODEL OF DAY-AHEAD ENERGY MARKET AND REAL-TIME BALANCING MARKET

Let’s define the change in the operation cost as in (2.2):

$$\Delta OC = \sum_{i=1}^{N} c_i^{up} \Delta G_i^{up} + \sum_{i=1}^{N} c_i^{dn} \Delta G_i^{dn}$$ (2.2)

Using this definition the optimization problem concerning real-time balancing market can be formulated as in (2.3).

Minimize \[ \Delta OC = \sum_{i=1}^{N} c_i^{up} \Delta G_i^{up} + \sum_{i=1}^{N} c_i^{dn} \Delta G_i^{dn} \] (2.3a)

Subject to

$$\sum_{i=1}^{N} (G_i + \Delta G_i^{up} + \Delta G_i^{dn} - (D_i + \Delta D_i)) = 0,$$ (2.3b)

$$F_l \leq F_i^{BM} \leq F_l, \forall l \in L$$ (2.3c)

$$0 \leq G_i + \Delta G_i^{up} + \Delta G_i^{dn} \leq G_i^{EM} + G_i^{BM}, \forall i \in N$$ (2.3d)

$$|\Delta G_i^{up} + \Delta G_i^{dn}| \leq G_i^{BM}$$ (2.3e)

$$\Delta G_i^{up} \geq 0, \Delta G_i^{dn} \leq 0$$

Where

$$F_i^{BM} = \sum_{i=1}^{N} H_{l,i} (G_i + \Delta G_i^{up} + \Delta G_i^{dn} - (D_i + \Delta D_i))$$

The constraints of the real-time market are very similar to the day-ahead market but only difference here, the decision variables are \( \Delta G_i^{up} \) and \( \Delta G_i^{dn} \) instead of \( G_i \), which is fixed by the day-ahead market. Here equation (2.3a) is the generation operating cost in the real-time balancing market, equation (2.3b) is the energy balance constraint, equation (2.3c) represents capacity constraint on transmission lines, equation (2.3d) represents the capacity constraint on generating units related to real-time balancing market. Finally, equation (2.3e) is the reserve capacity constraint.
Optimization problem (2.3) is run after (2.1). The only interaction between these two linear optimization problems is through the optimal solution of the problem (2.1), $G$, which is fixed in the optimization problem (2.3).

2.3 Integrated Model of Day-Ahead Energy Market and Real-Time Balancing Market

This two-step economic dispatch can be formulated as a one-shot optimization problem by introducing expected total dispatch cost, $E[TDC]$, of the system in the objective function. This one-shot optimization problem is used to derive an integrated model for calculating the diversification benefit of additional transmission capacity.

To explain the integrated optimization problem for both day-ahead market and real-time market, a simple example is used. Suppose an electricity industry with three generating units and no transmission constraints and an inelastic demand. These three generators submit their bids to both day-ahead market and real-time market. They bid 100 MW, 200 MW and 300 MW at 1, 2, 3 $/MW respectively. They also offer 10, 20 and 30 MW to real-time balancing market. For simplicity also assume that up-regulation costs of generators are identical with their variable costs. Demand is forecasted at 500 MW. The graphical presentation of optimization problem in (2.1) is illustrated in figure 2.3.

The system operator runs the optimization problem (2.1) and dispatches the first, second, and third generating units at 100 MW, 200 MW, and 200 MW respectively to supply the 500 MW of the forecasted demand.

In the real-time balancing market there is a 50 MW deviation from the forecasted demand and it needs to be covered by the up-regulating generating units. This
2.3. INTEGRATED MODEL OF DAY-AHEAD ENERGY MARKET AND REAL-TIME BALANCING MARKET

leads the system operator to run the optimization problem in (2.3) and find the economic level that each generating unit needs to increase its output. The dispatches of up-regulation generation are 10 MW supplied by generator 1, 20 MW supplied by generator 2 and 20 MW supplied by generator 3 as shown in figure 2.4.
The supply curve for both energy market and balancing market is illustrated in figure 2.5.

Figure 2.5: Supply curve of both day-ahead energy market and real-time balancing market

Figure 2.5 shows that this two-step sequential optimization problem can be formulated in one optimization problem. The objective function of this integrated optimization problem is minimizing the expected total dispatch cost in the system.

Let’s assume that with probability $p$, a disturbance to the system such as deviations of demand level can be occurred and this disturbance will be corrected in the real-time balancing market. These disturbances are referred as contingency in this study.

The expected total dispatch cost, $E[TDC]$, of the system is given in (2.4).

$$E[TDC] = \frac{1}{T} \sum_{t=1}^{T} OC_t + \frac{p}{T} \sum_{t=1}^{T} \Delta OC_t$$  \hspace{1cm} (2.4)

Here $p$ is the probability of occurrence of a contingency in the system. In this
study, it is assumed that \( p = 0.01 \). The expected total dispatch cost is the weighted sum of the generation operating costs in the day-ahead energy market and real-time balancing market over the period, \( T \).

The optimization problem which models the day-ahead energy market and real-time balancing market in an integrated framework is presented in (2.5)

\[
\begin{align*}
\text{Minimize} & \quad G_{i,t}^{up, i, t}, \Delta G_{i,t}^{up, i, t}, \Delta G_{i,t}^{dn, i, t} \\
\text{Subject to} & \quad E[TDC] = \frac{1}{T} \sum_{t=1}^{T} OC_t + \frac{p}{T} \Delta OC_t \\
& \quad \sum_{i=1}^{N} (G_{i,t} - D_{i,t}) = 0, \quad \forall t \in T \quad (2.5a) \\
& \quad \sum_{i=1}^{N} (G_{i,t} + \Delta G_{i,t}^{up} + \Delta G_{i,t}^{dn} - (D_{i,t} + \Delta D_{i,t})) = 0, \quad \forall t \in T \quad (2.5b) \\
& \quad F_{l,t}^{EM} \leq F_{l,t} \leq F_{l,t}^{BM}, \quad \forall t \in T, \forall l \in L \quad (2.5c) \\
& \quad F_{l,t}^{BM} \leq F_{l,t} \leq F_{l,t}^{EM}, \quad \forall t \in T, \forall l \in L \quad (2.5d) \\
& \quad 0 \leq G_{i,t} \leq G_{i,t}^{EM}, \quad \forall i \in N, \forall t \in T \quad (2.5e) \\
& \quad 0 \leq G_{i,t} + \Delta G_{i,t}^{up} + \Delta G_{i,t}^{dn} \leq G_{i,t}^{EM} + G_{i,t}^{BM}, \quad \forall i \in N, \forall t \in T \quad (2.5f) \\
& \quad |\Delta G_{i,t}^{up} + \Delta G_{i,t}^{dn}| \leq G_{i,t}^{BM}, \quad \forall t \in T \quad (2.5g) \\
& \quad G_{i,t} \geq 0, \quad \Delta G_{i,t}^{up} \geq 0, \quad \Delta G_{i,t}^{dn} \leq 0 \\
\end{align*}
\]

Where

\[
\begin{align*}
F_{l,t}^{EM} &= \sum_{i=1}^{N} H_{l,i}(G_{i,t} - D_{i,t}) \\
F_{l,t}^{BM} &= \sum_{i=1}^{N} H_{l,i} (G_{i,t} + \Delta G_{i,t}^{up} + \Delta G_{i,t}^{dn} - (D_{i,t} + \Delta D_{i,t}))
\end{align*}
\]

Here Equations (2.5a) and (2.5b) are the energy balance constraints, equations
(2.5c) and (2.5d) represent capacity constraints on transmission lines, equation (2.5e) and (2.5f) represent the capacity constraints on generating units related to day-ahead energy market and real-time balancing market, respectively. Finally equation (2.5g) is the reserve capacity constraint.

The optimization problem (2.5) operates in a way that first it dispatches the generators available in the day-ahead energy market and then it dispatches the generators in the real-time balancing market taking the dispatched quantities of the day-ahead energy market $G_{i,t}$ as constant. This process is formulated through introducing the parameter $p$ which is defined as the probability of a contingency within the dispatch interval, (it is assumed that only one contingency happens in a dispatch interval). In the optimization problem (2.5) index $t$ models different dispatch periods of the power system.
Chapter 3

The Diversification Benefit of Additional Transmission Capacity

3.1 Introduction

Additional transmission capacity has two major benefits; first it increases the diversification of uncorrelated generation sources and allows cheaper remote balancing services to substitute for more expensive local ones. This is called the 'Diversification Benefit'. Second it helps to remote cheap generating units to be dispatched more compared to the local expensive ones. This improves the productive efficiency of the electricity market. This is called the 'Efficiency Benefit'. In this chapter, the methodology of quantifying these benefits of additional transmission capacity and mathematical formulation of the proposed transmission planning which models explicitly the diversification benefit is described. In addition, conventional transmission planning formulation is reviewed.
3.2 Quantifying the Diversification Benefit

To quantify the efficiency benefit and the diversification benefit, a decomposition algorithm is presented in figure 3.1.

First we introduce a few definitions:

- **C1**: The generation operating cost of the system in the balancing market given the existing transmission system
- **C2**: The generation operating cost of the system in the balancing market given the expanded transmission system
- **C3**: The generation operating cost of the system in the energy market given the existing transmission system
- **C4**: The generation operating cost of the system in the energy market given the expanded transmission system
- **C5**: The generation operating cost of the system in the energy market given the existing transmission system
- **C6**: The generation operating cost of the system in the energy market given the expanded transmission system

Figure 3.1: Decomposition algorithm
3.3 Transmission Planning with Explicit Modeling of Diversification Benefit

- C5: The generation operating cost of the system in the both energy market and balancing market given the existing transmission system
- C6: The generation operating cost of the system in the both energy market and balancing market given the expanded transmission system

Using the definitions above for a particular transmission planning schedule:

- Diversification benefit = $C_1 - C_2$
- Efficiency benefit = $C_3 - C_4$
- Total benefit = $C_5 - C_6$ (=Diversification benefit + Efficiency benefit)

The developed decomposition algorithm can provide valuable information when we compare different transmission planning decisions. This will be discussed more in section 5 of this thesis.

3.3 Transmission Planning with Explicit Modeling of Diversification Benefit

In this thesis, after justifying that transmission planning schedules have positive diversification benefit, a transmission expansion approach which takes into account the diversification benefit along with the efficiency benefit is formulated to find the optimum level of transmission augmentation in the transmission system.

To do this, transmission investment cost, $TIC$, is added to objective function of the optimization problem given in (2.5). Let’s define the transmission investment cost as in (3.1).

$$TIC = \sum_{l \in L} c_{line}^{l} n_l$$  \hspace{1cm} (3.1)
Here $n_l$ is the number of new transmission lines for link $l$.

In the optimization problem (2.5) index $t$ models different planning periods of the transmission planning problem. Each period is subject to uncertainties in system parameters. These uncertainties at each planning period are modeled using several scenarios which represent the possible system condition. These scenarios are generated using the ARIMA models and the Kantorovich distance measure which will be discussed more in chapter 4. Using the scenarios generated for each planning period $t$, the optimization problem (2.5) can be formulated as a stochastic optimization problem.

The transmission planner evaluates the impact of its planning decisions on economic efficiency of both energy market and balancing market. The economic efficiency is measured by calculating the total generation operating costs in these two markets for each period. The transmission planner then selects the transmission planning decision which has the highest economic efficiency. This is illustrated in figure 3.2.

![Figure 3.2: Generation operating costs of the energy market and balancing market over several dispatch interval](image)

The optimization problem of the transmission planner is set out in (3.2).
3.3. TRANSMISSION PLANNING WITH EXPLICIT MODELING OF DIVERSIFICATION BENEFIT

Minimize
\[ \Delta G_{i,t,\omega,y}^{up}, \Delta G_{i,t,\omega,y}^{dn}, G_{i,t,\omega,y}, n_l \]
\[ \sum_{y=1}^{Y} \sum_{l=1}^{L} c_l^{line} n_l + \sum_{y=1}^{Y} \left( \frac{1}{1 + r} \right)^{y-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{\omega=1}^{\Omega} \pi_{i,\omega}^{D} c_i G_{i,t,\omega,y} \]
\[ + p \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{\omega=1}^{\Omega} \pi_{i,\omega}^{D} \left[ c_i^{up} \Delta G_{i,t,\omega,y}^{up} + c_i^{dn} \Delta G_{i,t,\omega,y}^{dn} \right] \] \hspace{1cm} (3.2a)

Subject to
\[ \sum_{i=1}^{N} (G_{i,t,\omega,y} - D_{i,t,\omega,y}) = 0, \forall t \in T, \forall \omega \in \Omega, \forall y \in Y \] \hspace{1cm} (3.2c)
\[ \sum_{i=1}^{N} (G_{i,t,\omega,y} + \Delta G_{i,t,\omega,y}^{up} + \Delta G_{i,t,\omega,y}^{dn} - (D_{i,t,\omega,y} + \Delta D_{i,t,y})) = 0, \forall t \in T, \forall \omega \in \Omega, \forall y \in Y \] \hspace{1cm} (3.2d)
\[ F_{l,t,\omega,y} \leq F_{l,t,\omega,y}^{EM}, \forall t \in T, \forall l \in L, \forall \omega \in \Omega, \forall y \in Y \] \hspace{1cm} (3.2e)
\[ F_{l,t,\omega,y} \leq F_{l,t,\omega,y}^{BM}, \forall t \in T, \forall l \in L, \forall \omega \in \Omega, \forall y \in Y \] \hspace{1cm} (3.2f)
\[ 0 \leq G_{i,t,\omega,y} \leq \overline{G}_{i,t,\omega,y}^{EM}, \forall t \in T, \forall i \in N, \forall \omega \in \Omega, \forall y \in Y \] \hspace{1cm} (3.2g)
\[ 0 \leq G_{i,t,\omega,y} + \Delta G_{i,t,\omega,y}^{up} + \Delta G_{i,t,\omega,y}^{dn} \leq \overline{G}_{i,t,\omega,y}^{EM} + \overline{G}_{i,t,\omega,y}^{BM}, \forall t \in T, \forall i \in N, \forall \omega \in \Omega, \forall y \in Y \] \hspace{1cm} (3.2h)
\[ \left| \Delta G_{i,t,\omega,y}^{up} + \Delta G_{i,t,\omega,y}^{dn} \right| \leq \overline{G}_{i,t,\omega,y}^{BM}, \forall t \in T, \forall i \in N, \forall \omega \in \Omega, \forall y \in Y \] \hspace{1cm} (3.2i)
\[ 1 \leq n_l \leq \overline{n}_l, \forall l \in L \] \hspace{1cm} (3.2j)
\[ \Delta G_{i,t,\omega,y}^{up} \geq 0, G_{i,t,\omega,y} \geq 0, \Delta G_{i,t,\omega,y}^{dn} \leq 0, n_l \text{ integer} \]

Where
\[ F_{l,t,\omega,y}^{EM} = \sum_{i=1}^{N} H_{i,i} (G_{i,t,\omega,y} - D_{t,i,\omega,y}) \]
\[ F_{l,t,\omega,y}^{BM} = \sum_{i=1}^{N} H_{i,i} (G_{i,t,\omega,y} + \Delta G_{i,t,\omega,y}^{up} + \Delta G_{i,t,\omega,y}^{dn} - (D_{i,t,\omega,y} + \Delta D_{i,t,y})) \]
3.4. CONVENTIONAL TRANSMISSION PLANNING APPROACH

Here equation (3.2a) is transmission investment cost, equation (3.2b) is the total dispatch cost of the system, equations (3.2c) and (3.2d) are the energy balance constraints, equations (3.2e) and (3.2f) represent capacity constraints on transmission lines, equations (3.2g) and (3.2h) represent the capacity constraints on generating units related to day-ahead market and real-time market, respectively. Equation (3.2i) represents the reserve capacity constraint. Equation (3.2j) is the transmission expansion constraint. Here index \( y \) models different planning years of the transmission planning problem.

3.4 Conventional Transmission Planning Approach

The conventional transmission planning approach is used as a benchmark in this study. As it was mentioned earlier, this approach mainly focuses on the efficiency benefit of the additional transmission capacity. This approach is mathematically modeled in optimization problem (3.3).

\[
\begin{align*}
\text{Minimize} & \quad \sum_{y=1}^{Y} \sum_{l}^{L} c_{\text{line}}^{l} + \left( \sum_{y=1}^{Y} \left( \frac{1}{1+r} \right)^{y-1} \left( \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{\omega=1}^{\Omega} \pi_{D_{i,\omega}}^{c_{i}} G_{i,t,\omega,y} \right) \right) \\
\text{Subject to} & \quad \sum_{i=1}^{N} (G_{i,t,\omega,y} - D_{i,t,\omega,y}) = 0, \quad \forall t \in T, \forall \omega \in \Omega, \forall y \in Y \quad (3.3c) \\
& \quad F_{l} \leq F^{EM}_{l,t,\omega,y} \leq \bar{F}_{l}, \quad \forall t \in T, \forall l \in L, \forall \omega \in \Omega, \forall y \in Y \quad (3.3d) \\
& \quad 0 \leq G_{i,t,\omega,y} \leq G^{EM}_{i,t,\omega}, \quad \forall t \in T, \forall i \in N, \forall \omega \in \Omega, \forall y \in Y \quad (3.3e)
\end{align*}
\]
1 ≤ n_l ≤  m_l, ∀ l ∈ L \tag{3.3f}

G_{i,t,\omega,y} \geq 0, \text{ } n_l \text{ integer}

Where

\[ F_{EM}^{l,t,\omega,y} = \sum_{i=1}^{N} H_{i,t}(G_{i,t,\omega,y} - D_{t,i,\omega,y}) \]

The definition of equations and constraints in optimization problem (3.3) are similar to those in optimization problem (3.2). Equation (3.3a) is transmission investment cost, equation (3.3b) is the generation operating cost in the day-ahead energy market, equation (3.3c) is the energy balance constraint, equation (3.3d) represents capacity constraint on transmission lines, equation (3.3e) represents the capacity constraints on generating units related to day-ahead market. Equation (3.3f) is the transmission expansion constraint.
Chapter 4

Stochastic Programming

4.1 Introduction

In deterministic programming all parameters are certainly known. However, in the real world, perfect information does not exist. Stochastic programming is a useful tool to deal with situations where some of the data adjoined in objective function or constraints is uncertain [35]. In this chapter, fundamentals of stochastic programming is briefly described and the methodology followed for scenario tree construction in this study is explained.

4.2 Expected Value of a Random Variable

Uncertainty in the parameters can be distinguished by certain probability distributions. To transform its deterministic equivalent is the way of solving a stochastic optimization problem. For this transformation every possible state of nature is characterized by scenarios and a certain probability of the realization of this scenarios. An appropriate linear program is formulated for each scenario and expected values of all random variables for whole scenario set are calculated by multiplication of value
4.3. TWO-STAGE STOCHASTIC PROGRAMMING PROBLEMS WITH RE COURSE

of the parameter in the scenario and the probability of that scenario.

For instance, suppose that $y$ is a random variable which can be expressed by $y_\omega$. It shows possible realizations of the random variable $y$ where $\omega$ is random scenario and each of these realizations has a certain probability, $\pi_\omega$. The expected value of random variable $y$ can be calculated as given in (4.1).

$$E[y_\omega] = \sum_{\omega=1}^{\Omega} \pi_\omega \times y_\omega, \forall \omega \in \Omega \quad (4.1)$$

The random variables are replaced by their expected values. Then the obtained optimization problem is solved.

4.3 Two-Stage Stochastic Programming Problems with Recourse

A standard form for a two-stage stochastic programming problem is given in the following [36], [37] and [38]:

Minimize $z = c^T x + E[Q(\omega)]$ \hspace{1cm} (4.2)

Subject to $A x = b$

$x \geq 0$

Where

$$Q(x, \omega) = \text{Minimize} \quad q^T y \hspace{1cm} (4.3)$$

Subject to \[ W y = h - T x, \]

$y \geq 0$

Where $c, q, W, h, T$ are known vectors and matrices. $x$ represents the first-stage or here-and-now decisions which are made before the realization of the random variable
and \( y \) represents the second-stage or wait-and-see decisions which are made after observing the actual values of the random variable. Note that if random variables are represented by set of scenarios, a second stage decision variable is defined for each scenario.

The deterministic equivalent of the two-stage stochastic programming problem in (4.2) is given in (4.4)

\[
\begin{align*}
\text{Minimize} \quad & \quad z = c^T x + \sum_{\omega} \pi_\omega q^T_\omega y_\omega \\
\text{Subject to} \quad & \quad A x = b \\
& \quad W_\omega y_\omega + T_\omega x = h_\omega \\
& \quad x \geq 0, \ y_\omega \geq 0, \ \forall \omega \in \Omega
\end{align*}
\]

The scenarios which models the uncertain parameters are disposed as a scenario-tree. In engineering literature, several methodologies are proposed to build scenario tree. In this study, to constitute the scenario tree, firstly large set of scenarios are generated by a path-based method, ARIMA models, then a scenario-reduction technique based on Kantorovich distance is used to obtain sufficient number of scenarios.

4.4 Scenario Generation

Path-based models generate scenarios via time series models. Hence, the scenario sets acquired by time series models indicate scenario fan instead of scenario tree. An example of scenario fan is given in figure 4.1. To transform scenario fan to scenario tree, scenarios have to be bundled together [39].

The time series belongs to electricity prices shows certain characteristics which are
Figure 4.1: A scenario fan example

(a) non-constant mean and variance, (b) multi-seasonality (daily and weekly seasonality), (c) calendar effect on weekends. Differencing (subtracting \( Y_{t-1} \) from \( Y_t \), where \( Y \) is the value of a variable at time \( t-1 \) and \( t \), respectively) the original series with the formula \((1 - B)\) where \( B \) is the backshift operator eases the non-constant mean feature. Taking logarithm and seasonal differencing eases the non-constant variance and multi-seasonal aspect of time series. For handling the calendar effect, some ad-hocs can be used [40]. It can be said that these characteristics of the price series and the methods to tackle them are also valid for electricity demand series.

Autoregressive Integrated Moving Average (ARIMA) model is linear model that is able to represent time series. The general form of ARIMA model, which has the general expression \((p, d, q)\) is given as:

\[
\left(1 - \sum_{i=1}^{p} \varphi_i B^i\right)\left(1 - B\right)^d y_t = c + \left(1 - \sum_{j=1}^{q} \theta_j B^j\right) a_t
\]

where \(\varphi_i\) are the coefficients of autoregressive (AR) polynomial and \(p\) is the order of this polynomial; \(\theta_j\) are the coefficients of moving average (MA) polynomial and \(q\)
is the order of this polynomial; $a_t$ is the white noise with zero mean and standard deviation $\sigma$. $c$ is a constant which represents the deterministic trend of the series and $(1 - B)^d$ is the differencing term where $d$ gives the order of differencing.

ARIMA models should be improved to represent a time series which shows seasonal characteristic appropriately. The general form of the seasonal ARIMA models which has the general expression $(p, d, q) \times (P, D, Q)_S$ are given as:

\[
(1 - \sum_{i=1}^{p} \varphi_i B^i) \left(1 - \sum_{i=1}^{P} \Phi_i B^{iS}\right) (1 - B)^d (1 - B^S)^D y_t = c + \left(1 - \sum_{j=1}^{q} \theta_j B^j\right) \left(1 - \sum_{j=1}^{Q} \Theta_j B^{jS}\right) a_t
\]

(4.6)

where $\Phi_i$ are the coefficients of seasonal autoregressive (SAR) polynomial and $P$ is the order of this polynomial; $\Theta_j$ are the coefficients of seasonal moving average (SMA) polynomial and $Q$ is the order of this polynomial; $(1 - B^S)^D$ is the seasonal differencing term where $D$ and $S$ give the order of seasonal differencing and the order of seasonality, respectively.

The methodology for constituting the ARIMA models is an iterative process;

- An initial model is chosen based on observation of time series itself, autocorrelation (ACF) and partial autocorrelation (PACF) functions of time series.

- ARIMA coefficients with respect to selected ARIMA model are obtained by an appropriate computer software.

- Time series is generated by using ARIMA coefficients belong to selected ARIMA model.

- The generated time series is compared with original time series to check if it
4.4. SCENARIO GENERATION

accurately represents the data.

- If the generated series is not convincing, the procedure is repeated until one is developed.

- Once a satisfactory ARIMA model is found, this model can be used.

This study does not focus on ARIMA model building, further information about it can be found in [41]. The scope of using ARIMA models in this study, is to generate scenarios which has similar characteristic with historical data. An efficient scenario generation methodology is proposed in [35]. According to this methodology, after appropriate ARIMA model has specified and ARIMA coefficients are obtained, ARIMA process in time t, \( y_t \), can be expressed in (4.7).

\[
y_t = c + \varphi(y_{t-1}, y_{t-2}, \ldots, y_{t-p}) + \Phi(y_{t-s}, y_{t-s-1}, \ldots, y_{t-s-p}) \\
+ \theta(a_{t-1}, a_{t-2}, \ldots, a_{t-q}) + \Theta(a_{t-s}, a_{t-s-1}, \ldots, a_{t-s-q}) \\
\tag{4.7}
\]

The scenario-generation algorithm using ARIMA model is illustrated in figure 4.2 [35]:

where \( N_\Omega \) and \( N_T \) are the number of generated scenarios and periods, respectively and \( y_{tw} \) is the ARIMA process in the period t, in the scenario \( \omega \).

An example is illustrated in the following to clarify the scenario generation using ARIMA models.

4.4.1 Example: Scenario Generation

Let a random variable \( y_t \) is represented by the ARIMA(1,0,1) model. The ARIMA parameters are \( \phi_1 = 0.98 \), \( \theta_1 = 0.17 \) and \( \sigma = 0.0153 \). The historical value of the
variable, $y_0$, is 8.274 and $a_0$ is $-0.0255$. According to given data, let’s generate four scenarios for a two-period horizon.

Primarily, let’s obtain the formula of ARIMA process using equation (4.5);

\[(1 - \phi_1 B) y_t = (1 - \theta_1 B) a_t\]

The ARIMA process $y_t$ can be written as;

\[y_t = \phi_1 y_{t-1} + a_t - \theta_1 a_{t-1}\] (4.8)

In the next step the scenarios are generated using (4.8), to do that random values for error terms are generated for each scenario. Since the time horizon contains two periods, two random values, which are normally distributed ($N(0, \sigma)$), are generated for each scenario. The value of the error terms generated for the first scenario are
4.4. SCENARIO GENERATION

$a_{11} = 0.0019$ and $a_{21} = 0.0044$. The first scenario, $\omega = 1$, of $y_{t\omega}$ is obtained in the following:

\[
y_{11} = \phi_1 y_0 + a_{11} - \theta_1 a_0
\]

\[
y_{11} = 0.98 \times 8.274 + 0.0019 - 0.17 \times (-0.0255) = 8.1148
\]

\[
y_{21} = \phi_1 y_{11} + a_{21} - \theta_1 a_{11}
\]

\[
y_{21} = 0.98 \times 8.1148 + 0.0044 - 0.17 \times 0.0019 = 7.9566
\]

The value of the error terms generated for the second scenario are $a_{12} = -0.0175$ and $a_{22} = 0.0182$. The second scenario, $\omega = 2$, of $y_{t\omega}$ is obtained in the following:

\[
y_{12} = \phi_1 y_0 + a_{12} - \theta_1 a_0
\]

\[
y_{12} = 0.98 \times 8.274 - 0.0175 - 0.17 \times (-0.0255) = 8.0954
\]

\[
y_{22} = \phi_1 y_{12} + a_{22} - \theta_1 a_{12}
\]

\[
y_{22} = 0.98 \times 8.0954 + 0.0182 - 0.17 \times (-0.0175) = 7.9547
\]

The value of the error terms generated for the third scenario are $a_{13} = 0.0050$ and $a_{23} = 0.0027$. The third scenario, $\omega = 3$, of $y_{t\omega}$ is obtained in the following:

\[
y_{13} = \phi_1 y_0 + a_{13} - \theta_1 a_0
\]

\[
y_{13} = 0.98 \times 8.274 + 0.0050 - 0.17 \times (-0.0255) = 8.1179
\]

\[
y_{23} = \phi_1 y_{13} + a_{23} - \theta_1 a_{13}
\]

\[
y_{23} = 0.98 \times 8.1179 + 0.0027 - 0.17 \times 0.0050 = 7.9574
\]

The value of error terms generated for forth scenario are $a_{14} = -0.0015$ and $a_{24} = -0.0127$. The forth scenario, $\omega = 4$, of $y_{t\omega}$ is obtained in the following:
4.5. Scenario Reduction

To represent the uncertainty in a decision making process, large number of scenarios are needed. This makes computation of the problem intractable. Therefore a mathematical technique for reducing the number of scenarios is required. A reduced scenario tree which is close to original one can be obtained if the closeness is measured by probability distance. In stochastic optimization problems, one of the most common used probability distance is the Kantorovich distance which is defined between two probability distributions $Q$ and $Q'$. It is obtained by assigning the probabilities of non-selected scenarios $\omega \in \Omega \setminus \Omega_S$ to the closest scenario $\omega'$ in the selected scenario set $\Omega_S$ can be expressed as [42],[43]:

$$D_K(Q, Q') = \sum_{\omega \in \Omega \setminus \Omega_S} \pi(\omega) \min(||y(\omega) - y(\omega')||)$$

(4.9)

where $\omega$ and $\omega'$ are the scenarios, $Q$ and $Q'$ are the probability distributions in initial scenarios set $\Omega$ and selected scenarios set $\Omega_S$, respectively. Further details about Kantorovich distance can be found in [35] and [44].

In [44], two different scenario-reduction algorithms based on Kantorovich distance are proposed. In this study, fast forward selection algorithm is used for diminishing the number of scenarios. Primarily the multi-period problem is clustered to single one

\begin{align*}
y_{14} &= \phi_1 y_0 + a_{14} - \theta_1 a_0 \\
y_{14} &= 0.98 \times 8.274 - 0.0015 - 0.17 \times (-0.0255) = 8.1114 \\
y_{24} &= \phi_1 y_{14} + a_{24} - \theta_1 a_{14} \\
y_{24} &= 0.98 \times 8.1114 - 0.0127 - 0.17 \times (-0.0015) = 7.9367
\end{align*}
4.5. SCENARIO REDUCTION

to apply this technique. This technique is an iterative process. It starts with empty scenario tree and each iteration, one by one, the scenario that minimizes Kantorovich distance between selected and initial set is selected. It ends when the specified number of selected scenarios is reached. Then the probabilities of each non-selected scenarios is transferred to its closest selected scenario. In the end, a reduced scenario tree with associated probabilities is obtained. Flow-chart of forward selection algorithm is presented in figure 4.3 [35].

Step-by-step explanation of the algorithm, [35], is also given in the following.

Figure 4.3: Scenario-reduction algorithm
4.5. SCENARIO REDUCTION

- Step 0:
  Compute $c^{[1]}(\omega, \omega') = \sum_{t=1}^{N_T} \| y(\omega_t) - y(\omega'_t) \|$, $\forall \omega \in \Omega$

- Step 1:
  Compute $d_\omega = \sum_{w=1}^{N_\Omega} \pi_\omega c^{[1]}(\omega, \omega')$
  Choose $\omega_1 \in \arg\min_{\omega \in \Omega} d_\omega$
  Update the set $\Omega_f \leftarrow \Omega \setminus \omega_1$

- Step n:
  Compute $c^{[n]}(\omega, \omega')$ where
  $c^{[n]}(\omega, \omega') = \min c^{[n-1]}(\omega, \omega'), c^{[n-1]}(\omega, \omega_{n-1})$ $\forall \omega, \omega' \in \Omega^{[n-1]}_f$
  $d^{[n]}_\omega = \sum_{\omega \in \Omega^{[n-1]}_f \setminus \omega} \pi_\omega c^{[n-1]}(\omega', \omega)$, $\forall \omega \in \Omega^{[n-1]}_f$
  Choose $\omega_n \in \arg\min_{\omega \in \Omega} d^{[n]}_\omega$
  Update the set $\Omega^{[n]}_f \leftarrow \Omega^{[n-1]}_f \setminus \omega_n$

- Step $N_{\Omega_S} + 1$:
  $\Omega^*_S = \Omega^{N_{\Omega_S}}_f$
  $\Omega^*_S = \Omega \setminus \Omega^*_S$
  $\pi^*_\omega = \pi_\omega + \sum_{\omega' \in J(\omega)} \pi_{\omega'}$ where
  $J(\omega) = \omega' \in \Omega^*_f | \omega = j(\omega')$, such that
  $j(\omega') \in \arg\min_{\omega'' \in \Omega^*_S} c(\omega'', \omega')$

where $N_T$ and $N_\Omega$ are the number of the periods and scenarios in the initial set, respectively. $\Omega^*_f$ is the final set of deleted scenarios and $\Omega^*_S$ is the set of selected scenarios after the scenario-reduction process. Further details about the algorithm can be found in [35] and [45].

An example can be found in [35] to clarify the scenario reduction process. However that example focuses only the scenario reduction not the bundling, that’s why this
example is constructed. The whole process (scenario reduction with bundling) is applied to a small case with five scenarios.

4.5.1 Example: Scenario Reduction

Suppose that the speed of wind in a certain wind farm is represented by a set of five equally-probable wind speed scenarios for two-period horizon.

<table>
<thead>
<tr>
<th>Scenario#</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>wind speed (m/s) for $t = 1$</td>
<td>3.2</td>
<td>3.8</td>
<td>4.7</td>
<td>5.9</td>
<td>7.5</td>
</tr>
<tr>
<td>wind speed (m/s) for $t = 2$</td>
<td>3.7</td>
<td>4.3</td>
<td>5.5</td>
<td>6.6</td>
<td>8</td>
</tr>
</tbody>
</table>

The goal of this example is to reduce the number of the scenarios to two using the approach explained above:

Firstly, the distances between scenario pairs are calculated for each period $\| y(\omega_i) - y(\omega'_i) \|$. Then by taking the summation of the distances, the cost function $c(\omega, \omega') = \sum_{i=1}^{N_T} \| y(\omega_i) - y(\omega'_i) \|$ is computed.

$$
c = \begin{pmatrix}
0 & 0.6 & 1.5 & 2.7 & 4.3 \\
0.6 & 0 & 0.9 & 2.1 & 3.7 \\
1.5 & 0.9 & 0 & 1.2 & 2.8 \\
2.7 & 2.1 & 1.2 & 0 & 1.6 \\
4.3 & 3.7 & 2.8 & 1.6 & 0
\end{pmatrix}
+ \begin{pmatrix}
0 & 0.6 & 1.8 & 2.9 & 4.3 \\
0.6 & 0 & 1.2 & 2.3 & 3.7 \\
1.8 & 1.2 & 0 & 1.1 & 2.5 \\
2.9 & 2.3 & 1.1 & 0 & 1.4 \\
4.3 & 3.7 & 2.5 & 1.4 & 0
\end{pmatrix}
$$
4.5. SCENARIO REDUCTION

\[
c = \begin{pmatrix}
0 & 1.2 & 3.3 & 5.6 & 8.6 \\
1.2 & 0 & 2.1 & 4.4 & 7.4 \\
3.3 & 2.1 & 0 & 2.3 & 5.3 \\
5.6 & 4.4 & 2.3 & 0 & 3.0 \\
8.6 & 7.4 & 5.3 & 3.0 & 0 \\
\end{pmatrix}
\]

Secondly, Kantorovich distances between scenario pairs are calculated. The scenario with the minimum distance is chosen. Since the scenarios are equally-probable, the probability of occurrence of each scenario is \(1/5 = 0.2\).

\[
d_1 = \pi_1 \cdot c(1, 1) + \pi_2 \cdot c(1, 2) + \pi_3 \cdot c(1, 3) + \pi_4 \cdot c(1, 4) + \pi_5 \cdot c(1, 5)
\]

\[
= 3.74
\]

\[
d_2 = \pi_1 \cdot c(2, 1) + \pi_2 \cdot c(2, 2) + \pi_3 \cdot c(2, 3) + \pi_4 \cdot c(2, 4) + \pi_5 \cdot c(2, 5)
\]

\[
= 3.02
\]

\[
d_3 = \pi_1 \cdot c(3, 1) + \pi_2 \cdot c(3, 2) + \pi_3 \cdot c(3, 3) + \pi_4 \cdot c(3, 4) + \pi_5 \cdot c(3, 5)
\]

\[
= 2.6
\]

\[
d_4 = \pi_1 \cdot c(4, 1) + \pi_2 \cdot c(4, 2) + \pi_3 \cdot c(4, 3) + \pi_4 \cdot c(4, 4) + \pi_5 \cdot c(4, 5)
\]

\[
= 3.06
\]

\[
d_5 = \pi_1 \cdot c(5, 1) + \pi_2 \cdot c(5, 2) + \pi_3 \cdot c(5, 3) + \pi_4 \cdot c(5, 4) + \pi_5 \cdot c(5, 5)
\]

\[
= 4.86
\]
4.5. **SCENARIO REDUCTION**

Hence,

\[ \Omega^{[1]}_S = \{3\}, \]
\[ \Omega^{[1]}_J = \{1, 2, 4, 5\}. \]

In the next step, the cost matrix needs to be updated

\[ c^{[2]}(1, 2) = \min(c(1, 3), c(1, 2)) = 1.2 \]
\[ c^{[2]}(1, 4) = \min(c(1, 3), c(1, 4)) = 3.3 \]
\[ c^{[2]}(1, 5) = \min(c(1, 3), c(1, 5)) = 3.3 \]
\[ c^{[2]}(2, 1) = \min(c(2, 3), c(2, 1)) = 1.2 \]
\[ c^{[2]}(2, 4) = \min(c(2, 3), c(2, 4)) = 2.1 \]
\[ c^{[2]}(2, 5) = \min(c(2, 3), c(2, 5)) = 2.1 \]
\[ c^{[2]}(4, 1) = \min(c(4, 3), c(4, 1)) = 2.3 \]
\[ c^{[2]}(4, 2) = \min(c(4, 3), c(4, 2)) = 2.3 \]
\[ c^{[2]}(4, 5) = \min(c(4, 3), c(4, 5)) = 2.3 \]
\[ c^{[2]}(5, 1) = \min(c(5, 3), c(5, 1)) = 5.3 \]
\[ c^{[2]}(5, 2) = \min(c(5, 3), c(5, 2)) = 5.3 \]
\[ c^{[2]}(5, 4) = \min(c(5, 3), c(5, 4)) = 3.0 \]
For choosing the second scenario, the Kantorovich distance should be calculated again using the updated cost function.

\[
d_{1}^{[2]} = \pi_{2} \cdot c(1, 2) + \pi_{4} \cdot c(1, 4) + \pi_{5} \cdot c(1, 5)
\]
\[
= 1.56
\]
\[
d_{2}^{[2]} = \pi_{1} \cdot c(2, 1) + \pi_{4} \cdot c(2, 4) + \pi_{5} \cdot c(2, 5)
\]
\[
= 1.08
\]
\[
d_{4}^{[2]} = \pi_{1} \cdot c(4, 1) + \pi_{2} \cdot c(4, 2) + \pi_{5} \cdot c(4, 5)
\]
\[
= 1.38
\]
\[
d_{5}^{[2]} = \pi_{1} \cdot c(5, 1) + \pi_{2} \cdot c(5, 2) + \pi_{4} \cdot c(5, 4)
\]
\[
= 2.72
\]

Hence,

\[
\Omega_{S}^{[1]} = \{2, 3\},
\]
\[
\Omega_{J}^{[1]} = \{1, 4, 5\}.
\]
4.5. SCENARIO REDUCTION

Since the desired number of selected scenarios are obtained, the algorithm ends with the transfer of probability from non-selected scenarios, \( \Omega_J^* \) to selected scenarios, \( \Omega_S^* \).

To find the closest scenario in the selected scenarios set to scenario 1, comparison of the related matrix elements in the initial cost matrix is made. \( c(1, 2) \) is 1.2 while \( c(1, 3) \) is 3.3. Since \( c(1, 2) \) is less than \( c(1, 3) \), it can be seen that scenario 2 is the closest scenario to scenario 1.

To find the closest scenario in the selected scenarios set to scenario 4, comparison of the related elements in cost matrix is made. \( c(4, 2) \) is 4.4 while \( c(4, 3) \) is 2.3. Since \( c(4, 3) \) is less than \( c(4, 2) \), it can be seen that scenario 3 is the closest scenario to scenario 4.

To find the closest scenario in the selected scenarios set to scenario 5, comparison of the related elements in cost matrix is made. \( c(5, 2) \) is 7.4 while \( c(5, 3) \) is 5.3. Since \( c(5, 3) \) is less than \( c(5, 2) \), it can be seen that scenario 3 is the closest scenario to scenario 5.

At last, the associated probabilities are in the following:

\[
\pi_2^* = \pi_2 + \pi_1 = 0.4
\]

\[
\pi_3^* = \pi_3 + \pi_4 + \pi_5 = 0.6
\]

To sum up, using the scenario reduction algorithm described above, a discarded set \( \Omega_S^* = \{2, 3\} \) with associated probabilities \( \pi_2^* = 0.4 \) and \( \pi_3^* = 0.6 \) is obtained.
Chapter 5

Case Studies

5.1 Introduction

In this chapter two example systems are studied. Primarily, modified IEEE thirty-node example system is used to show how the diversification benefit is calculated. Then, the proposed transmission planning approach which considers the diversification benefit of additional transmission capacity and the conventional approach are applied to the modified version of the IEEE twenty-four node example system.

5.2 IEEE Thirty-Node Example System

To explain the integrated optimization problem and the diversification benefit of the transmission planning schedules, the IEEE 30-node example system is studied.

5.2.1 System Parameters

This example system, given in figure 5.1, has thirty nodes and forty-one power lines. Some features from original IEEE 30-node example system have been changed to make it more useful for this study. The parameters of this system are presented in
5.2. IEEE THIRTY-NODE EXAMPLE SYSTEM

Figure 5.1: The single line diagram of the modified IEEE thirty-node example system

Table 5.1: Generation and demand data of the modified IEEE thirty-node example system

<table>
<thead>
<tr>
<th>Gen#</th>
<th>$G_i^{EM}$ (MW)</th>
<th>$G_i^{BM}$ (MW)</th>
<th>$D_i$(MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus 1</td>
<td>200</td>
<td>20</td>
<td>100</td>
</tr>
<tr>
<td>Bus 2</td>
<td>200</td>
<td>20</td>
<td>0</td>
</tr>
</tbody>
</table>

Continued on next page
### Table 5.1 – continued from previous page

<table>
<thead>
<tr>
<th>Gen#</th>
<th>$G_i^{EM}$ (MW)</th>
<th>$G_i^{BM}$ (MW)</th>
<th>$D_i$ (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus 3</td>
<td>100</td>
<td>10</td>
<td>60</td>
</tr>
<tr>
<td>Bus 4</td>
<td>0</td>
<td>0</td>
<td>90</td>
</tr>
<tr>
<td>Bus 5</td>
<td>250</td>
<td>25</td>
<td>55</td>
</tr>
<tr>
<td>Bus 6</td>
<td>400</td>
<td>40</td>
<td>150</td>
</tr>
<tr>
<td>Bus 7</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 8</td>
<td>500</td>
<td>50</td>
<td>380</td>
</tr>
<tr>
<td>Bus 9</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 10</td>
<td>500</td>
<td>50</td>
<td>250</td>
</tr>
<tr>
<td>Bus 11</td>
<td>120</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Bus 12</td>
<td>150</td>
<td>15</td>
<td>100</td>
</tr>
<tr>
<td>Bus 13</td>
<td>120</td>
<td>12</td>
<td>30</td>
</tr>
<tr>
<td>Bus 14</td>
<td>160</td>
<td>16</td>
<td>80</td>
</tr>
<tr>
<td>Bus 15</td>
<td>350</td>
<td>35</td>
<td>210</td>
</tr>
<tr>
<td>Bus 16</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 17</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 18</td>
<td>100</td>
<td>10</td>
<td>80</td>
</tr>
<tr>
<td>Bus 19</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 20</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 21</td>
<td>200</td>
<td>20</td>
<td>40</td>
</tr>
<tr>
<td>Bus 22</td>
<td>110</td>
<td>11</td>
<td>100</td>
</tr>
</tbody>
</table>

Continued on next page
### Table 5.1 – continued from previous page

<table>
<thead>
<tr>
<th>Gen#</th>
<th>$G_i^{EM}$ (MW)</th>
<th>$G_i^{BM}$ (MW)</th>
<th>$D_i$ (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus 23</td>
<td>150</td>
<td>15</td>
<td>85</td>
</tr>
<tr>
<td>Bus 24</td>
<td>280</td>
<td>28</td>
<td>100</td>
</tr>
<tr>
<td>Bus 25</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 26</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 27</td>
<td>500</td>
<td>50</td>
<td>270</td>
</tr>
<tr>
<td>Bus 28</td>
<td>300</td>
<td>30</td>
<td>0</td>
</tr>
<tr>
<td>Bus 29</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 30</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

### Table 5.2: The marginal cost of energy, up-regulation, and down-regulation for different generating units in the modified IEEE thirty-node example system

<table>
<thead>
<tr>
<th>Gen#</th>
<th>$c_i$ ($/MW$)</th>
<th>$c_i^{up}$ ($/MW$)</th>
<th>$c_i^{dn}$ ($/MW$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus 1</td>
<td>12</td>
<td>16</td>
<td>9</td>
</tr>
<tr>
<td>Bus 2</td>
<td>14</td>
<td>17</td>
<td>11</td>
</tr>
<tr>
<td>Bus 3</td>
<td>20</td>
<td>27</td>
<td>16</td>
</tr>
<tr>
<td>Bus 4</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 5</td>
<td>29</td>
<td>30</td>
<td>20</td>
</tr>
<tr>
<td>Bus 6</td>
<td>32</td>
<td>34</td>
<td>29</td>
</tr>
<tr>
<td>Bus 7</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 8</td>
<td>35</td>
<td>39</td>
<td>29</td>
</tr>
</tbody>
</table>

Continued on next page
Table 5.2 – continued from previous page

<table>
<thead>
<tr>
<th>Gen#</th>
<th>$c_i$/($/MW$)</th>
<th>$c_{i}^{up}$/($/MW$)</th>
<th>$c_{i}^{dn}$/($/MW$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus 9</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 10</td>
<td>33</td>
<td>40</td>
<td>30</td>
</tr>
<tr>
<td>Bus 11</td>
<td>10</td>
<td>21</td>
<td>8</td>
</tr>
<tr>
<td>Bus 12</td>
<td>24</td>
<td>26</td>
<td>21</td>
</tr>
<tr>
<td>Bus 13</td>
<td>9</td>
<td>11</td>
<td>7</td>
</tr>
<tr>
<td>Bus 14</td>
<td>18</td>
<td>22</td>
<td>13</td>
</tr>
<tr>
<td>Bus 15</td>
<td>11</td>
<td>13</td>
<td>9</td>
</tr>
<tr>
<td>Bus 16</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 17</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 18</td>
<td>10</td>
<td>13</td>
<td>11</td>
</tr>
<tr>
<td>Bus 19</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 20</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 21</td>
<td>26</td>
<td>26</td>
<td>22</td>
</tr>
<tr>
<td>Bus 22</td>
<td>15</td>
<td>19</td>
<td>12</td>
</tr>
<tr>
<td>Bus 23</td>
<td>24</td>
<td>29</td>
<td>19</td>
</tr>
<tr>
<td>Bus 24</td>
<td>31</td>
<td>36</td>
<td>23</td>
</tr>
<tr>
<td>Bus 25</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 26</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 27</td>
<td>35</td>
<td>39</td>
<td>32</td>
</tr>
<tr>
<td>Bus 28</td>
<td>20</td>
<td>23</td>
<td>16</td>
</tr>
</tbody>
</table>

Continued on next page
### Table 5.2 – continued from previous page

<table>
<thead>
<tr>
<th>Gen#</th>
<th>$c_i($/MW)$</th>
<th>$c_i^{up}($/MW)$</th>
<th>$c_i^{dn}($/MW)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus 29</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bus 30</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

### Table 5.3: Transmission network data of the modified IEEE thirty-node example system

<table>
<thead>
<tr>
<th>Line#</th>
<th>From</th>
<th>To</th>
<th>Transmission Capacity (MW)</th>
<th>Expanded Capacity (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>Bus 1</td>
<td>Bus 2</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L2</td>
<td>Bus 1</td>
<td>Bus 3</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L3</td>
<td>Bus 2</td>
<td>Bus 4</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L4</td>
<td>Bus 3</td>
<td>Bus 4</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L5</td>
<td>Bus 2</td>
<td>Bus 5</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L6</td>
<td>Bus 2</td>
<td>Bus 6</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L7</td>
<td>Bus 4</td>
<td>Bus 6</td>
<td>130</td>
<td>3</td>
</tr>
<tr>
<td>L8</td>
<td>Bus 5</td>
<td>Bus 7</td>
<td>65</td>
<td>1</td>
</tr>
<tr>
<td>L9</td>
<td>Bus 6</td>
<td>Bus 7</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L10</td>
<td>Bus 6</td>
<td>Bus 8</td>
<td>130</td>
<td>3</td>
</tr>
<tr>
<td>L11</td>
<td>Bus 6</td>
<td>Bus 9</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L12</td>
<td>Bus 6</td>
<td>Bus 10</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L13</td>
<td>Bus 9</td>
<td>Bus 11</td>
<td>65</td>
<td>2</td>
</tr>
</tbody>
</table>

Continued on next page
<table>
<thead>
<tr>
<th>Line#</th>
<th>From</th>
<th>To</th>
<th>Transmission Capacity (MW)</th>
<th>Expanded Capacity (n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>L14</td>
<td>Bus 9</td>
<td>Bus 10</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L15</td>
<td>Bus 4</td>
<td>Bus 12</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L16</td>
<td>Bus 12</td>
<td>Bus 13</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L17</td>
<td>Bus 12</td>
<td>Bus 14</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L18</td>
<td>Bus 12</td>
<td>Bus 15</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L19</td>
<td>Bus 12</td>
<td>Bus 16</td>
<td>32</td>
<td>3</td>
</tr>
<tr>
<td>L20</td>
<td>Bus 14</td>
<td>Bus 15</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L21</td>
<td>Bus 16</td>
<td>Bus 17</td>
<td>65</td>
<td>2</td>
</tr>
<tr>
<td>L22</td>
<td>Bus 15</td>
<td>Bus 18</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L23</td>
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<td>2</td>
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<tr>
<td>L26</td>
<td>Bus 10</td>
<td>Bus 17</td>
<td>65</td>
<td>2</td>
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<tr>
<td>L27</td>
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<td>Bus 21</td>
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</tr>
<tr>
<td>L29</td>
<td>Bus 21</td>
<td>Bus 22</td>
<td>32</td>
<td>1</td>
</tr>
<tr>
<td>L30</td>
<td>Bus 15</td>
<td>Bus 23</td>
<td>65</td>
<td>2</td>
</tr>
<tr>
<td>L31</td>
<td>Bus 22</td>
<td>Bus 24</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>L32</td>
<td>Bus 23</td>
<td>Bus 24</td>
<td>130</td>
<td>2</td>
</tr>
<tr>
<td>L33</td>
<td>Bus 24</td>
<td>Bus 25</td>
<td>130</td>
<td>1</td>
</tr>
</tbody>
</table>

Continued on next page
Forecasted demand and forecast error at each node at each period are modeled as a random variable with normal distribution. The mean value is set as equal to demand level in table 5.1. The deviations are calculated as below:

$$\Delta D_{i,t} = U_t(-0.15, 0.15)D_i, \quad t = 1, 100$$

$$D_{i,t} = U_t(0.9, 1.1)D_i, \quad t = 1, 100$$

Where $U_t(-0.15, 0.15)$ and $U_t(0.9, 1.1)$ are random numbers from uniform distribution over the interval $[-0.15, 0.15]$ and $[0.9, 1.1]$ respectively.
5.2. IEEE THIRTY-NODE EXAMPLE SYSTEM

5.2.2 Results and Discussions

The proposed integrated optimization problem, given in 2.5, is run for two scenarios. The first scenario is the base scenario which shows status que of the transmission system. The second scenario has a transmission planning schedule as given in table 5.3. Results from calculating the diversification benefit of the transmission planning schedule is given in figure 5.2.

![Diagram of transmission planning](image)

Figure 5.2: Decomposition total benefit of augmentation into efficiency benefit and diversification benefit (Case study of the IEEE thirty-node example system)

As it can be seen that the proposed transmission augmentation has both the efficiency benefit and diversification benefit. The diversification benefit is an element which hidden from the eyes of a transmission planner which only expand the transmission system based on its efficiency benefit. However, the proposed approach can be seen as an approach for calculating the diversification benefit of transmission planning
5.3 IEEE Twenty-Four Node Example System

To clarify the proposed transmission augmentation approach which is described in section 3.3, the IEEE twenty-four node example system [46] is modified and used. The conventional transmission approach is used as a benchmark in this study. Both proposed transmission planning approach and conventional transmission planning approach are applied to the modified IEEE 24-node example system. In this example system hourly demand, wind generation and the forecast errors are modeled as random variables. Section 5.3.1 explains how different pieces of data are prepared for this study. Section 5.3.2 presents and discusses the results.

5.3.1 System Parameters

This example system, has twenty-four nodes and thirty-four power lines, is shown in figure 5.3. Some features from original IEEE 24-node example system have been changed to make it more useful for this study.

- The multi lines between same nodes are modeled as one line with double capacity.
- The capacities of all the transmission lines in the system are 15% decreased.
- The cost of line construction, $c_{\text{line}}$, is set to 100$/\text{line}$ for all transmission lines.
- The generators connected to same node are modeled as one generator.
- Installed capacities of the generators are increased by 25%.
• In addition to existing generating units in the example system two wind farms, each has 250 MW installed capacity, are connected to node 103 and node 106.

• All generating units bid 80% of their installed capacities to the day-ahead energy market and 20% of the capacities to the real-time balancing market.
The generation and corrective actions cost of this system are presented in table 5.4.

Table 5.4: The marginal cost of energy, up-regulation, and down-regulation for different generating units in the modified IEEE 24-node example system

<table>
<thead>
<tr>
<th>Generator#</th>
<th>$c_i^{up}$ ($/MW$)</th>
<th>$c_i^{dn}$ ($/MW$)</th>
<th>$c_i$ ($/MW$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bus 101</td>
<td>42</td>
<td>36</td>
<td>40</td>
</tr>
<tr>
<td>Bus 102</td>
<td>42</td>
<td>36</td>
<td>40</td>
</tr>
<tr>
<td>Bus 103</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Bus 106</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Bus 107</td>
<td>40</td>
<td>34</td>
<td>37</td>
</tr>
<tr>
<td>Bus 113</td>
<td>37</td>
<td>29</td>
<td>32</td>
</tr>
<tr>
<td>Bus 115</td>
<td>39</td>
<td>32</td>
<td>35</td>
</tr>
<tr>
<td>Bus 116</td>
<td>32</td>
<td>25</td>
<td>28</td>
</tr>
<tr>
<td>Bus 118</td>
<td>28</td>
<td>21</td>
<td>24</td>
</tr>
<tr>
<td>Bus 121</td>
<td>26</td>
<td>21</td>
<td>24</td>
</tr>
<tr>
<td>Bus 122</td>
<td>25</td>
<td>20</td>
<td>21</td>
</tr>
<tr>
<td>Bus 123</td>
<td>30</td>
<td>25</td>
<td>28</td>
</tr>
</tbody>
</table>

**Uncertainty in Forecasted Demand**

To characterize the stochasticity of the forecasted demand and wind production, scenario-based modeling is used. Seasonal ARIMA models are used to generate the demand scenarios. The hourly demand data of weekdays of a year in IEEE 24-node example system are used to train ARIMA model. To eliminate the calendar effect on weekends, only hours of weekdays ($24 \times 5 \times 52 = 6240$ hours) are taken into account. Logarithmic transformation is applied to historical data for dealing with daily and weekly seasonal effects. In iterative model selection phase, different ARIMA models are fitted to this data and the model parameters are obtained by
a statistical computing software, "R". After comparison with original data and the
data generated by different ARIMA models, the selected ARIMA model is designed
with the following settings $(p, d, q) \times (P, D, Q)_S = (1, 0, 1) \times (1, 1, 2)_{120}$.

The selected model can be expressed according to general form in (4.4) in the
following:

$$(1 - \varphi_1 B) \left(1 - \Phi_1 B^{120}\right) \left(1 - B^{120}\right) \log(y_t) = (1 - \theta_1 B) \left(1 - \Theta_1 B^{120} - \Theta_2 B^{240}\right) a_t$$

(5.1)

Note that the historical data does not have any deterministic trend, so the deter-
mindistic term $c$ in (4.5) is equal to zero. The ARIMA process for the selected model
can be formulated as given below:

$$
\log(y_t) = a_t - \theta_1 a_{t-1} - a_{t-120} - \Theta_1 a_{t-120} - \theta_1 \Theta_1 a_{t-121} - \Theta_2 a_{t-240} \\
+ \theta_1 \Theta_2 a_{t-242} - [\varphi_1 y_{t-1} - y_{t-120} - \Phi_1 y_{t-120} + \varphi_1 y_{t-121} \\
+ \varphi_1 \Phi_1 y_{t-121} \varphi_1 \Phi_1 y_{t-121} + \Phi_1 y_{t-240} - \varphi_1 \Phi_1 y_{t-241}]$$

(5.2)

Since the proposed transmission planning approach is computationally intensive
and to have the results in a reasonable running time, 480 periods ($T = 480$) are
modeled for the modified IEEE 24-node example system. Using scenario generation
algorithm explained in section 4.4 and ARIMA process in equation (5.2), at each
period 100 demand scenarios are generated in each demand node ($\omega = 100$). Total
generated data from ARIMA process is $480 \times 100 \times 17 = 816000$ ( in the regarded
example system seventeen nodes contain load). Each scenario is obtained by randomly
generated 242-element vector of white noise, $a_t$, with zero mean and $\sigma_D$ standard
deviation. Parameters of designed ARIMA model is given in table 5.5.
Table 5.5: Parameters of designed ARIMA model for forecasted demand

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varphi_1$</td>
<td>0.9652</td>
</tr>
<tr>
<td>$\Phi_1$</td>
<td>-0.4981</td>
</tr>
<tr>
<td>$\theta_1$</td>
<td>0.0614</td>
</tr>
<tr>
<td>$\Theta_1$</td>
<td>0.2546</td>
</tr>
<tr>
<td>$\Theta_2$</td>
<td>0.0029</td>
</tr>
<tr>
<td>$\sigma_{\hat{D}}^2$</td>
<td>0.0002287</td>
</tr>
</tbody>
</table>

In figure 5.4, original time series and the one of the scenarios produced by ARIMA model for demand at node 101 is given. Note that the time axes of the figure starts from January 1 at 00:00.

It can be said that, ARIMA process performs very well for the hours belongs to winter and summer, two plots fits very well for these hours. However, the behavior of the time series for the hours in spring and autumn is not reflected as successful as in prior ones because of multi-seasonal characteristic of the original data. But still it can be said that time series generated by trained ARIMA model represents the general aspects of original time series adequately. The hourly demand data is calculated by multiplication of annual peak load which has different value for each node and hourly peak load in percent of annual peak which has same value for each node. Since the characteristic of the hourly demand data for each node is identical, the success of ARIMA model representing the original data at node 101 can be generalized for every demand node.

The amount of the scenarios makes the process intractable. For regaining the tractability, the fast forward selection algorithm is used to reduce the number of scenarios while conserving the main aspects of the original scenario tree. After scenario
5.3. IEEE TWENTY-FOUR NODE EXAMPLE SYSTEM

Figure 5.4: Comparison of time series of demand generated by the ARIMA model with original time series

reduction process, 25 demand scenarios for each hour are acquired.

Uncertainty in Wind Generation

Apart from forecasted demand, uncertain nature of wind generation is also modeled by scenarios. However, unlike the demand, wind generation has a non-gaussian characteristic, [47]. Since the output of a wind generator is equal to zero when the wind speed is above and under a certain value. As a result, the ARIMA models are not useful to directly represent varying wind generation. Instead, in this study wind generation scenarios are created by transforming the wind speed scenarios through the power curve of the wind turbine model in the wind farm. It is assumed that every
wind turbine in the wind farm is exposed to same amount of the wind so the total generation of the wind farm can be calculated by multiplication of output of one of the wind turbine and the number of the wind turbines.

ARIMA models are used to characterize the uncertain nature of wind speed. The hourly wind speed data of a year is obtained from publicly available website of Alaska Energy Authority [48]. It is assumed that node 103 and node 106 has the same wind speed characteristics as Adak and Ambler in the reference [48], respectively. To keep consistency with the demand scenarios, only working days are taken into account for generating wind speed scenarios. Logarithm of historical wind speed data is taken for eliminating the effects of extreme maximum and minimum values in the data. In iterative model selection phase, different ARIMA models are fitted and the model parameters are also obtained by "R" software. After comparison with original data and the data generated by different ARIMA models, The designed ARIMA model has the following settings \((p, d, q) = (1, 0, 0)\). Same ARIMA model is selected for both areas. ARIMA process can be expressed according to general formula in (5.3) in the following:

\[
\log(x_t) = c + \varphi_1 x_{t-1} + a_t
\]  

(5.3)

Using scenario generation algorithm explained above and ARIMA process in equation (5.3), 100 wind speed scenarios are generated at each period for two wind turbines located at nodes 103 and 106. Total generated wind speed data from ARIMA process is \(480 \times 100 \times 2 = 96000\). Each scenario is obtained by randomly generated one-element vector of white noise, \(a_t\), with a mean value equals to zero and standard deviation \(\sigma_{WS}\). Parameters of selected ARIMA model for wind speed scenario
5.3. IEEE TWENTY-FOUR NODE EXAMPLE SYSTEM

generation are given in table 5.6.

Table 5.6: Parameters of designed ARIMA model for wind speed

<table>
<thead>
<tr>
<th>Parameters</th>
<th>node 103</th>
<th>node 106</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varphi_1$</td>
<td>0.8113</td>
<td>0.8102</td>
</tr>
<tr>
<td>$c$</td>
<td>0.1044</td>
<td>0.0555</td>
</tr>
<tr>
<td>$\sigma_{WS}^2$</td>
<td>0.1319</td>
<td>0.1119</td>
</tr>
</tbody>
</table>

In figures 5.5 and 5.6, original time series and the ones produced by ARIMA models is given.

Figure 5.5: Comparison of time series generated by the ARIMA model for wind speed at node 103 with original time series

It can be seen that for both cases time series generated by trained ARIMA models represent the general aspects of original time series adequately.
For regaining the tractability, the fast forward selection algorithm is used to reduce the number of scenarios. After scenario reduction process, 25 wind speed scenarios at each period are acquired. The installed capacity of each wind farm is 250MW. The power curve of NEG Micon 2000/72 turbine model is used to transform wind speeds to wind generations, [49]. The power curve which is used to transform wind speeds to wind generations is provided from [49]. The maximum output of wind farms are variable due to wind speed. The expected value of wind generation at each period is the maximum output provided by wind farms is determined as in equation (5.4).

\[
E \left[ WG_t \right] = \pi_{(i, \omega)}^{WG} \times WG_{(t, i, \omega)}, \quad t = 1, 480
\] (5.4)
Where $\pi_{(i,\omega)}^{WG}$ is the associated probability of wind speed scenarios and $WG_{(i,t,\omega)}$ is the wind generation at node $i$ in period $t$ and scenario $\omega$. The wind generation scenarios which are obtained from transformation of wind speed scenarios through the power curve belongs to the wind turbine. The difference between wind farms and other generators is that the other generators bid 80% of their installed capacity to energy market and 20% of their installed capacity to real-time balancing market. However, the wind farms bid 80% of the expected value of their wind generation to day-ahead energy market and 20% of the expected value to real-time balancing market.

Uncertainty in Forecast Errors

The deviations from forecasted demand which is cleared in the real-time balancing market are modeled as a random variable with normal distribution over the interval $[a,b]$. The deviation is calculated as below:

$$\Delta D_{i,t} = a + (b - a)U_t(0,1), \quad t = 1, 480$$ (5.5)

Where $U_t(0,1)$ is a random variable from uniform distribution over interval $[-30, 30]$. For each demand node, one load deviation value is generated at each period. To be consistent with the production level of generators, $G_{i,t,\omega,y}$, which is scenario-based modeled, up-regulation and down-regulation provided by generators, $\Delta G_{i,t,\omega,y}^{up}$ and $\Delta G_{i,t,\omega,y}^{dn}$, are also scenario-based modeled. In the balancing market the same amount of forecast error is cleared (because one error value is generated at each period) so the scenarios are equally-probable and the probability $\pi^D_\omega$, is equal to $1/25 = 0.04$. 


Three scenarios are studied. The first scenario is the existing transmission system without any expansion. The second scenario has a transmission planning schedule which is obtained from the conventional transmission planning approach. The third scenario has a transmission expansion plan which is obtained from the proposed transmission planning approach.

The results of transmission planning for the second and the third scenarios are presented in tables 5.7 and 5.8. In table 5.7, the lines belong to the optimal solution in the conventional transmission planning approach and in table 5.8, the lines belong to optimal solution found by the proposed transmission planning approach.

Table 5.7: Optimal transmission planning schedule approved in conventional approach

<table>
<thead>
<tr>
<th>Line#</th>
<th>From</th>
<th>To</th>
<th>$n_l$</th>
<th>Expanded Capacity (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Node 106</td>
<td>Node 110</td>
<td>2</td>
<td>148.75</td>
</tr>
<tr>
<td>2</td>
<td>Node 107</td>
<td>Node 108</td>
<td>2</td>
<td>148.75</td>
</tr>
<tr>
<td>3</td>
<td>Node 108</td>
<td>Node 109</td>
<td>2</td>
<td>148.75</td>
</tr>
<tr>
<td>4</td>
<td>Node 108</td>
<td>Node 110</td>
<td>2</td>
<td>148.75</td>
</tr>
<tr>
<td>5</td>
<td>Node 116</td>
<td>Node 117</td>
<td>2</td>
<td>425</td>
</tr>
</tbody>
</table>

As in tables 5.7 and 5.8, the proposed approach for transmission planning approves lines Node103-Node124, Node104-Node109 and Node114-Node116 in addition to those approved in the conventional approach. The single line diagram of the expanded system is illustrated in figure 5.7. Here the green lines are those which approved in the conventional approach and the green and the red lines are approved in the proposed approach.
Table 5.8: Optimal transmission planning schedule approved in proposed approach

<table>
<thead>
<tr>
<th>Line#</th>
<th>From</th>
<th>To</th>
<th>n_t</th>
<th>Expanded Capacity (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Node 103</td>
<td>Node 124</td>
<td>2</td>
<td>340</td>
</tr>
<tr>
<td>2</td>
<td>Node 104</td>
<td>Node 109</td>
<td>2</td>
<td>148.75</td>
</tr>
<tr>
<td>3</td>
<td>Node 106</td>
<td>Node 110</td>
<td>2</td>
<td>148.75</td>
</tr>
<tr>
<td>4</td>
<td>Node 107</td>
<td>Node 108</td>
<td>2</td>
<td>148.75</td>
</tr>
<tr>
<td>5</td>
<td>Node 108</td>
<td>Node 109</td>
<td>2</td>
<td>148.75</td>
</tr>
<tr>
<td>6</td>
<td>Node 108</td>
<td>Node 110</td>
<td>2</td>
<td>148.75</td>
</tr>
<tr>
<td>7</td>
<td>Node 114</td>
<td>Node 116</td>
<td>2</td>
<td>425</td>
</tr>
<tr>
<td>8</td>
<td>Node 116</td>
<td>Node 117</td>
<td>2</td>
<td>425</td>
</tr>
</tbody>
</table>

Figure 5.8 illustrates the impact of transmission planning on the dispatch of balancing services. In this figure (A) represents the status quo transmission system, (B) the case where the transmission system is expanded using the conventional transmission planning approach, and (C) the case where the transmission system is expanded using the proposed transmission planning approach. All pie charts refer to period \( t = 35 \) and scenario \( \omega = 22 \). As in this figure, in case (A), expensive generators 101 and 102 have overall 49% share in the balancing market. This is while the less-expensive generator 121 has only 6% share in the balancing market. This situation is improved in case (B). In this case the overall share of expensive generators 101 and 102 is reduced to 17% and the difference is taken over by less-expensive generator 121. The best situation happens in case (C) when the transmission planner explicitly models the diversification benefit in its transmission planning process. In this case, the system operator can provide balancing services using the cheapest generators. Expensive generators 101 and 102 are not dispatched anymore and they are substituted by less-expensive generator 121. The generation operating cost of the balancing
5.3. IEEE TWENTY-FOUR NODE EXAMPLE SYSTEM

Figure 5.7: The single line diagram of the modified IEEE 24-node example system after transmission planning

market in case (A), (B), and (C) are $5640, $4772, and $4309. This means for the specified period and scenario, the conventional transmission planning schedule has a diversification benefit of $868 and the proposed transmission planning schedule has a diversification benefit of $1331 (an increase of 53% as compared to the conventional approach).

The efficiency benefit and diversification benefit of the optimal transmission planning schedule found by conventional approach and proposed approach are calculated
Figure 5.8: Impact of transmission planning on the dispatch of balancing services (period $t = 35$ and scenario $\omega = 22$)

using the decomposition algorithm. Figure 5.9 shows these benefits in a diagram.

As in figure 5.9, the diversification benefit and efficiency benefit of the optimal planning solution by the proposed approach are $80,436$ and $17,104$, respectively. These values for the conventional approach are $78,419$ and $17,103$. The efficiency benefit of the optimal transmission planning schedules by the proposed and conventional approaches are slightly different. But the diversification benefit is improved by $2,017$. It is interesting to see that the extra lines approved by the proposed
Figure 5.9: Decomposition total benefit of augmentation into efficiency benefit and diversification benefit (Case study of the IEEE 24-node example system), TB: total benefit, EB: efficiency benefit, DB: diversification benefit

transmission planning approach compared to conventional approach (red lines in figure. 5.7 ) are mainly for increasing the diversification of uncorrelated generation sources. This is a benefit of additional transmission capacity which is usually ignored by transmission planner.
Chapter 6

Conclusions and Future Work

6.1 Conclusion

Transmission planning schedules improve the efficiency of the transmission network by allowing remote lower-cost generation to be substituted by the local high-cost generation. This benefit of augmenting the transmission network is referred to as the efficiency benefit. The conventional transmission planning approaches are centered around calculating this type of additional transmission capacities.

Increased level of the intermittent generating units raises the demand for balancing services. These balancing services need to be transferred through the transmission network. This means that additional transmission capacities can help to remote cheap balancing services be substituted by the local expensive ones. This type of benefit of investment in additional transmission capacity is termed as the diversification benefit.

This master thesis proposes an integrated optimization problem which can determine the economically-efficient transmission expansion plan and quantify the diversification benefit of additional transmission capacity. Uncertainties in power system, such as forecasted demand, deviations in forecasted demand and wind generation are
taken into account in this study by scenario-based modeling. The ARIMA models are used for generating different scenarios. A scenario reduction technique based on Kantorovich distance is used for reducing the number of the scenarios. An algorithm is proposed for decomposition of the total benefit of transmission augmentation into the efficiency benefit and diversification benefit.

The case studies show that the proposed approach can be used for modeling the diversification benefit of transmission planning schedules and using it in transmission planning processes. This suggests that transmission planner and electricity market regulator can consider the diversification benefit in their process of transmission planning.

6.2 Future Work

This is the first step to model the diversification benefit of transmission investments. Suggestions for future research are provided below:

- Start-up cost and ramp rate of the generating units and system losses may be considered.

- Proposed methodology may be applied to a national grid or a electricity market like the NORDEL market.

- Balancing services may be modeled according to the deployment time like primary, secondary and tertiary reserves.

- More accurate cost function for generating units may be used.

- Transmission investment is modeled in a simple way, it may be improved. For
instances, line construction cost was assumed the same for each line, in a complex approach, length of line can be taken into account.
Bibliography


