Market Design for the Future Electricity Grid: Modeling Tools and Investment Case Studies

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Chin Yen Tee
B.A., Engineering and Economics, Smith College
M.S., Engineering and Public Policy, Carnegie Mellon University

Carnegie Mellon University
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Abstract

The future electricity grid is likely to be increasingly complex and uncertain due to the introduction of new technologies in the grid, the increased use of control and communication infrastructure, and the uncertain political climate. In recent years, the transactive energy market framework has emerged as the key framework for future electricity market design in the electricity grid. However, most of the work done in this area has focused on developing retail level transactive energy markets. There seems to be an underlying assumption that wholesale electricity markets are ready to support any retail market design.

In this dissertation, we focus on designing wholesale electricity markets that can better support transactive retail market. On the highest level, this dissertation contributes towards developing tools and models for future electricity market designs. A particular focus is placed on the relationship between wholesale markets and investment planning.

Part I of this dissertation uses relatively simple models and case studies to evaluate key impediments to flexible transmission operation. In doing so, we identify several potential areas of concern in wholesale market designs:

1. There is a lack of consideration of demand flexibility both in the long-run and in the short-run
2. There is a disconnect between operational practices and investment planning
3. There is a need to rethink forward markets to better manage resource adequacy under long-term uncertainties
4. There is a need for more robust modeling tools for wholesale market design

In Part II and Part III of this dissertation, we make use of mathematical decomposition and agent-based simulations to tackle these concerns.

Part II of this dissertation uses Benders Decomposition and Lagrangian Decomposition to spatially and temporally decompose a power system and operation problem

with active participation of flexible loads. In doing so, we are able to not only improve the computational efficiency of the problem, but also gain various insights on market structure and pricing. In particular, the decomposition suggests the need for a coordinated investment market and forward energy market to bridge the disconnect between operational practices and investment planning.

Part III of this dissertation combines agent-based modeling with state-machine based modeling to test various spot, forward, and investment market designs, including the coordinated investment market and forward energy market proposed in Part II of this dissertation. In addition, we test a forward energy market design where 75% of load is required to be purchased in a 2-year-ahead forward market and various transmission cost recovery strategies. We demonstrate how the different market designs result in different investment decisions, winners, and losers. The market insights lead to further policy recommendations and open questions.

Overall, this dissertation takes initial steps towards demonstrating how mathematical decomposition and agent-based simulations can be used as part of a larger market design toolbox to gain insights into different market designs and rules for the future electricity grid. In addition, this dissertation identifies market design ideas for further studies, particularly in the design of forward markets and investment cost recovery mechanisms.

Acknowledgments

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Chapter 1

Introduction

With rapid technological advances and increasing concerns over environmental and climate issues, the electricity industry is poised to undergo significant changes in the coming decades. On the generation-side, advances in non-fossil fuel generation and storage technologies, along with new environmental regulations, have resulted in a strong push towards increasing the penetration of renewable energy in the United States. In 2015, wind and solar energy made up approximately 67% of all new generation capacity addition in the United States [3]. With the United States agreement to the Paris Climate Agreement, this trend of increasing renewable energy penetration is likely to continue [4]. On the demand-side, electricity consumers are given increasing control over how they would like to purchase and use electricity. New consumer technologies such as electric vehicles and smart appliances have the potential to change consumer electricity demand patterns. In addition, the proliferation of residential renewable generation, such as residential rooftop solar, allows consumers to be both a net consumer and a net producer of electricity.

One key impact of this changing electricity industry landscape is the increasing level of operational, investment, and institutional uncertainties faced by power system industry stakeholders [5]. System operators are faced with the challenge of ensuring the reliability and efficiency of the power system in the face of increasing level of variability and uncertainty from both electricity generation and demand. Similarly, system planners and investors are challenged with making economically efficient investment decisions under uncertain long-term energy demand and supply outlook and regulatory decisions. The jobs of system operators, planners, regulators, and asset owners are made even more difficult by the uncertain political landscape that inevitably affects energy and electricity policies.

These changes happening in the electricity grid have significantly increased the level of complexity in the grid. While significant amount of research and development has been done to attempt to understand the technical implications of this increasing grid complexity, the economic and regulatory implications of this increasing grid complexity are not well understood. The availability of new power system technologies is both a bane and a boon in the context of electricity market and regulation. On one hand, the current electricity market and regulation framework is not equipped to deal with the level of complexity that these technologies could bring to power system operations and planning. On the other hand, advances in control, communication, and sensing technologies provide a level of flexibility to the grid that could be harnessed to give market designers and regulators the ability to design robust market systems and regulation to better manage the future electricity grid.

This dissertation was at first motivated by the need to develop market and regulatory tools to manage flexibility brought about by new transmission technologies as will be discussed in Part I of this dissertation. However, it became apparent that there is a lack of modeling tools to handle the level of complexity brought about by these technologies and that there is an urgent need to develop market design tools that could handle the level of complexity. Therefore, Part II and Part III of this dissertation contribute to the development of tools for electricity market design for the future, with a particular focus on the relationship between operational markets and investment planning and on the design of wholesale electricity markets that better support transactive energy.

1.1 Future Electric Transmission System [1]

Most of the recent work on grid modernization in the context of the future electric grid or “Smart Grids" focuses on the distribution system instead of on the transmission system. While increased distribution automation will be a key aspect of the future electricity grid, the need to update the

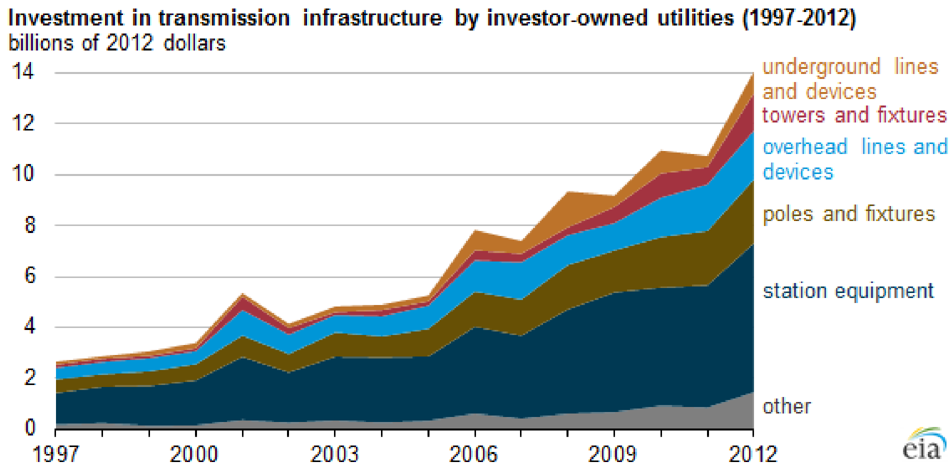

Figure 1.1: Investment in Transmission Infrastructure by Investor-owned Utilities Taken from [2]

transmission system should not be neglected. Investment in transmission infrastructure has been steadily increasing over the years (Fig. 1.1) and is expected to continue increasing due to aging infrastructure, changes in demand patterns, and renewable energy integration [6]. Therefore, it is important that we consider opportunities to modernize the electric transmission system.

Transmission flexibility has not been a major consideration in the traditional operation and design of the transmission system [1]. Transmission needs are typically met by building additional transmission capacity, with little consideration for alternatives solutions and technologies. This is unfortunate as advances in fast power electronics have resulted in the availability of various control and sensing technologies that could provide a greater level of flexibility in the transmission grids, and in some cases, reduce the need for new transmission lines [1]. With the challenges faced by investors looking to build new transmission lines, such as right-of-way issues and regulatory uncertainties, transmission investors should be encouraged to consider alternative solutions that could reduce the need for new line capacity.

In order to encourage investors to consider alternative investment options, there is a need to design operational and market frameworks that support and appropriately value such technologies. The conventional transmission planning process was designed with transmission line investments in mind, and generally does not consider the unique characteristics of disruptive transmission technologies, such as flexible line flow control and switching devices [1]. The value of flexible transmission technologies is often hidden under overly restrictive operational and regulatory rules. Therefore, a thorough reconsideration of power system operational practices and market design is needed to accommodate a greater variety of transmission investment options, and to provide incentives for system operators and transmission owners to consider alternatives to transmission line investments. Part I of this dissertation evaluates some of the key impediments to flexibility in the transmission sector using a small test system and provides some preliminary policy recommendations that could provide better incentives for investments in both flexible and conventional transmission technologies.

1.2 Transactive Energy Markets for Flexible Power System Operation and Planning

In the power system industry, generation, transmission, distribution, and loads are highly interdependent and hence designing appropriate incentives for transmission investment inevitably requires rethinking electricity markets at all levels. The design of electricity markets is a highly challenging task due to the complex interactions among the physical, economic, and information constraints of the system. These physical constraints come about due to physical laws governing energy conversion and energy flow through the system and are highly technology dependent. The economic constraints come about due to pricing and compensation structures that are defined by regulatory and market rules. Finally, information constraints come about due to private and public information held by different stakeholders and are strongly influenced by institutional and market structures.

In recent years, "transactive energy" markets have emerged as a framework for future electricity market designs. It is intended to support distributed decision-making in order to better manage complexity in the power system and to promote risk-sharing among stakeholders [7, 8]. In the United States, research on transactive energy markets is led by the Gridwise Architecture Council (GWAC) formed by the Department of Energy. The GWAC describes transactive energy markets as "techniques for managing the generation, consumption or flow of electric power within an electric power system through the use of economic or market based constructs while considering grid reliability constraints [9]". The design of transactive energy markets involves the design of appropriate price signals and market structures to enable distributed decision-making and to provide incentives for stakeholders to make private decisions that align with public objectives. This is not a straightforward endeavor as it requires joint considerations of both the physical and economic constraints in the system, as well as the coordination of a diverse group of stakeholders with frequently misaligned objectives.

Though the design of transactive energy market is still in its early stages, some theoretically promising market models have been proposed, such as the TeMIX [8] framework proposed by Ed Cazalet, which is a power exchange-based framework [10], and the Pacific Northwest GridWise Olympic Peninsula Project, which uses a double auction market. However, there are still many open research questions that need to be answered as we consider these proposed market designs. Some of these questions include:

1. How should the market structure be designed? How do we assign different decision-making responsibilities to different stakeholders?
2. What kind of information needs to be exchanged among stakeholders? What kind of price signals is needed?
3. What are some potential unexpected consequences of the different market designs? Who would be the winners/losers? Are there any negative externalities?

In order to better understand some of these questions, we need to develop tools to evaluate different market structures and market rules and to allow us to compare different proposed market designs. Part II and Part III of this dissertation contribute to developing and demonstrating such tools that could help us better understand different transactive energy market designs.

1.3 Tools for Transactive Energy Market Design

There are several approaches that economists have traditionally used to analyze and design market structures and market rules. One approach uses mathematical and economic theories, such as partial equilibrium theory, optimization theory, and game theory, to model and study market structures and behaviors [11]. Models using these techniques are frequently mathematically and theoretically elegant and are useful in describing market behavior under idealized conditions. However, they are driven by assumptions that are not reflective of real world conditions. A second approach uses econometric studies of empirical market data to study market behavior [11]. This approach is challenging in the context of transactive energy market because of the lack of data on actual transactive energy market implementation. Yet another approach uses experimental studies with human participants (e.g. [12]). The one big downside of this approach is that it is often difficult and costly to scale up such experimental studies to accurately reflect the behavior of large-scale transactive energy markets.

In order to provide additional tools that could help policy makers and researchers better study transactive energy markets, various research groups have developed modeling framework that provides the flexibility required to model the complex interactions present in transactive energy markets. Such efforts include the Dynamic Monitoring and Decision Systems(DYMONDS) framework developed at Carnegie Mellon University [13] and the prosumer-based smart grid modeling framework developed at Georgia Institute of Technology[14]. All these tools provide frameworks that enable distributed decision-making by intelligent agents interacting under a specified set of rules. The key design question in applying these frameworks is how to define the decision-making problem of individual agents. There are two key approaches that can be used to design the decision problems for the distributed decision makers: the bottom-up approach and the top-down approach. Both these approaches have their own strengths and weaknesses which will be discussed below.

1.3.1 Top-Down Approach: Mathematical Decomposition for Market Design

Mathematical optimization and economic theory were closely linked in the early days of optimization theory, but have drifted further and further apart in recent years [15][1]. In [15], Herbert Scarf argues that "it may be fruitful to view economic institutions as highly specialized computational procedures, and to view numerical algorithms as the analogs of economic activity engaged in by individual firm". In this dissertation, we explore this relationship between mathematical optimization and economic theory further by demonstrating how mathematical decomposition can be used to provide insights into market design.

In this approach, we start with an overall centralized problem and use mathematical decomposition techniques to decompose the centralized optimization problem into individual stakeholders' subproblems, as demonstrated in [16–18]. The two key strengths of this approach are: (1) It provides a systematic approach to derive market structure, and (2) It frequently results in distributed decision-making models that are provably optimal under certain conditions.

In Part II of this dissertation, we demonstrate how mathematical decomposition can be used to not only improve the computational efficiency of complex power system operation and planning problem, but also to provide insights into market structure and pricing.

1.3.2 Bottom-Up Approach: Simulation for Market Design

In the bottom-up approach, we start by considering each stakeholders' individual objectives and constraints and design the appropriate price signals that are needed to provide the necessary system-wide coordination. The resulting models are then tested through simulations. This bottom-up modeling approach is used in [19, 20] and agent-based electricity market modeling literature such as [21, 22]. The strength of this approach is that it is highly scalable and flexible, which allows researchers to easily experiment with different market models under different market assumptions. However, this flexibility can be a weakness as the complexity of the resulting models can make it difficult to evaluate any emergent behaviors shown through simulations. Nevertheless,

[1] See [15] for an interesting discussion on the relationship between mathematical programming and economic theory

we believe that this approach complements other more theoretical market design approaches and is particularly useful for testing different market structures under different experimental conditions. In Part III of this dissertation, we demonstrate how this approach can be useful in testing different electricity market rules and structures for power system operation and planning.

1.4 Wholesale Electricity Market Design In Support of Transactive Retail Markets

In this dissertation, we focus on wholesale electricity market design. The reason for this is that in the foreseeable future, a majority of electricity transactions will still happen on the wholesale level. Most work in the area of transactive energy markets focus on retail level transactive energy design and there seems to be an implicit assumption that current wholesale electricity market design is sufficient to support retail level transactive energy markets. We believe that this implicit assumption is not true, and that inefficiencies and disincentives in current wholesale market design will impede the development of retail level transactive energy markets. In Chapter 4 (Part I) of this dissertation, we highlight several aspects of wholesale electricity market design that need to be updated to better support retail level transactive energy markets.

1.5 Dissertation Outline

As indicated in the discussion above, the rest of this dissertation is divided into three parts. Part I uses simple models and case studies to highlight impediments to flexibility in the transmission sector and makes several initial recommendations on wholesale market designs that better support transactive energy. In Part I, it quickly becomes apparent that new tools need to be developed to allow us to evaluate different market structures and market rules, and to test some of the policy recommendations. Therefore, Part II and Part III focus on tools for transactive energy market design that allow for more complex case studies. Part II uses a top-down mathematical decomposition approach to provide insights into wholesale market design for a power system operation and planning problem, while Part III adopts a bottom-up simulation approach to test various multi-timescale wholesale market designs for power system operation and planning. In the concluding chapter, we discuss the role of the tools presented in this dissertation in the broader context of an overall market design framework and highlight the key contributions of this dissertation.

Part I

Analytical Evaluation of Flexibility in Electric Transmission System

The content in Chapter 2 and Chapter 3 (and part of Chapter 4) of this dissertation is a restructured version of Chapter 8: “Towards Valuing Flexibility in Transmission Planning" in “Equilibrium of Electricity Market Efficiency and Power System Operation Risk" (2016), edited by Chen, Hong and published by IEEE-Wiley. It is reproduced with permission by the publisher. The following copyright notice is valid only for Part I of this dissertation.

Chapter 2

Models for Transmission Investment Decisions

As discussed in the introduction, the current institutional framework supporting the electricity industry generally does not support flexibility in the transmission sector. One of the key reasons for this is the decoupling between power system operations and planning. Infrastructure planning in the power system industry is traditionally done for the worst case scenarios, without considerations of how real time operational flexibility can be used to manage these worst case scenarios during actual system operation. Large infrastructure investments are often made to handle scenarios that rarely occur, resulting in infrastructures that are underused most of the time. This is likely to worsen with increasing level of renewable energy penetration as the transmission lines used to support renewables are typically sized based on the maximum generating capacity of the renewable [23], even though the capacity factors for intermittent energy sources such as wind and solar energy are typically only 20% to 40% of rated capacity [24]. Such large transmission infrastructure investments could be avoided if we make transmission investment and sizing decision at value and consider potential options for operational flexibility, such as demand response and storage technologies. However, the current institutional framework does not typically support such considerations.

In addition to the decoupling of operations and planning, there is also a disconnect between power markets and power system operation and planning. Mismatches between the constraints considered in electricity markets and the actual physical constraints during real-time operations have resulted in a need for significant uplift payments in the energy market [25]. In markets for financial transmission rights (FTR), mismatches between FTR capacity and real-time operational transmission capacity have caused revenue inadequacy in the system [26]. These inconsistencies between market prices and actual values make it difficult for stakeholders to effectively manage risk both in the short-run and long-run. In addition, they provide inaccurate and inefficient signals for investments in both conventional and flexible technologies.

The goal of Part I of this dissertation is to highlight how the disconnect among power markets, power system operations, and power system planning not only impedes improvements in flexibility in the transmission sector, but also affects the performance of electricity markets. Using a two-bus test system, we demonstrate flaws in the current power system operations and planning framework, and suggest potential solutions to provide better incentives for flexibility. In this chapter, we begin by considering how flexible technologies could potentially change the scale economies of the transmission sector and benefit the electricity grid. Next, we develop two models that can be used to support optimal investment decision-making in conventional transmission line and flexible reactance device.

Chapters 2 and 3 (and part of chapter 4) of this dissertation are based on [1] and is reproduced with permission by the publisher.

2.1 Scale Economies of Transmission Technologies

The well-recognized argument for the heavy regulation of the transmission sector is that the electric transmission grid represents a natural monopoly due to the economies of scale and lumpiness of transmission infrastructure. However, similar to how technological developments have reduced economies of scale in the generation sector, the introduction of new, flexible technologies in the transmission sector has the potential of changing the scale economies of the transmission sector.

For example, line power flow control devices, such as slow mechanically-switched phase angle regulators (PAR) and very fast power electronically-switched Thyristor-Controlled Series Capacitors (TCSC), can be used to adjust the electrical parameters of the system, especially when there exists significant unused transmission line capacity in the system. These technologies allow for incremental investments in line flow control technologies to be made. To illustrate this, we consider a technology that controls line power flow by changing the line reactance. Such flexible reactance can be modeled as a controllable capacitor placed in series with the transmission line (Fig. 2.1). The controllable capacitor changes the admittance matrix of the transmission network, which, in turn, alters the pattern of line power flow in the system. For a single line with flexible reactance, the line impedance can be written as:

$$Z_{line} = R_{line} + j(X_{line} - X_{Flex}) \tag{2.1}$$

where j is the imaginary unit defined to be $\sqrt{-1}$, R_{line} and X_{line} are the resistance and reactance of the line, and X_{Flex} is the controllable reactance of the series capacitor.

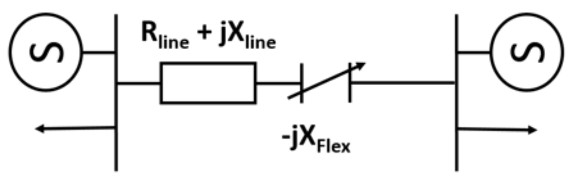

Figure 2.1: Model of Line with Device Providing Flexible Reactance

Changes in the reactance of a line in the system affect the line power flow distribution in the system according to Kirchhoff's Current Law (KCL) and Kirchhoff's Voltage Law (KVL). The effects of variable reactance on line flows in the grid can be illustrated using a small two-node electric power system comprising two parallel lines whose reactances are X_A and X_B respectively. It can be shown that under the "DC" power flow formulation, KCL causes real power flow in the two lines to split in inverse proportion to the proportion of reactance in each branch [27]. Mathematically, the real power line flows (F_A and F_B) through two parallel lines carrying a combined power of P are:

$$F_A = \frac{X_B}{X_A + X_B} P \tag{2.2}$$

$$F_B = \frac{X_A}{X_A + X_B} P \tag{2.3}$$

The potential of flexible reactance devices in providing more flexibility in making transmission investment decision can be illustrated via a simple example. In the two bus base case system shown in Fig. 2.2, two nodes are connected via two transmission lines with equal reactance but different thermal capacity limit. The cheaper generation is connected to the node on the left. To simplify the exposition, we assume that the generator limits are not binding constraints in this system.

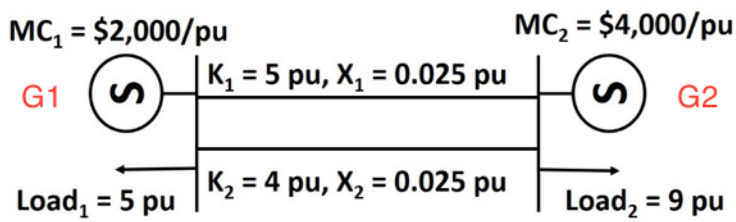

Figure 2.2: Base Case System for Example to Show Investment Effects of Flexible Reactance

In such a system, the most economically efficient power dispatch is to try to transfer as much power as possible from the less expensive generator (G1) to the load where the more expensive generator (G2) is located. In the base case, the maximum power that can be transferred from G1 to the load where G2 is located is 8 pu if we consider only the thermal capacity limit. Even though line 1 has a thermal limit of 5 pu, the maximum power that can flow through line 1 is still 4 pu (i.e. the thermal limit of line 2) due to KCL.

Now, consider the following question: What do we need to do to increase the power delivered from G1 to the load located at node 2 to 9 pu? First, we consider potential investment in new transmission line (Fig. 2.3).

Assuming that the reactance of the new line will be the same as the reactance of the original lines, the minimum new line investment of 3 pu is needed to increase the transfer capacity to 9 pu. With a new line investment of 3 pu, the maximum power flow in each of the three lines will be 3

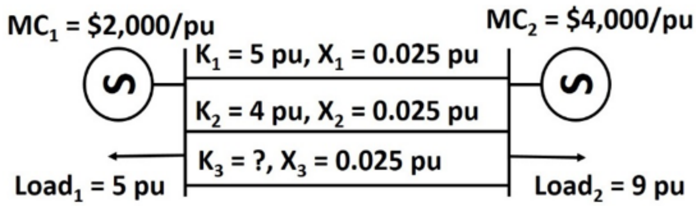

Figure 2.3: Transmission Line Capacity Needed to Increase Transfer Capacity to 9 pu

pu. Given that transmission line investment is lumpy, it is likely that a line whose thermal capacity is higher than 3 pu will have to be installed to provide the increase in transmission capacity. The lumpy nature of transmission investment and the economies of scale of such investment are often cited as reasons why merchant transmission investments are inefficient [28].

Now, we consider potential investment in devices that provide flexible reactance to reach the same goal. In this case, such devices can be used to lower the reactance of line 1 to enable more of its line capacity to be used:

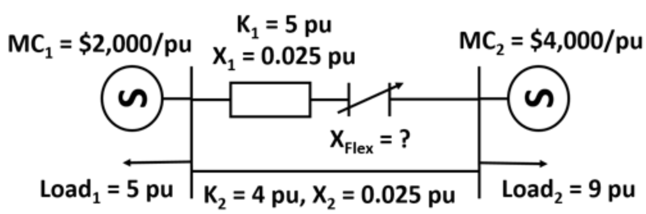

Figure 2.4: Flexible Reactance Investment Needed to Increase Transfer Capacity to 9 pu

In this case, a device that provides 0.005 pu of flexible reactance will lower the reactance of line 1 to 0.02 pu. Using equations (2.2) and (2.3), it follows that this will increase the maximum flow in line 1 to its thermal limit of 5 pu, while the maximum flow in line 2 remains at 4 pu.

The key difference between investment in flexible reactance device and investment in new transmission line is that investment in flexible reactance device is not lumpy, which allows us to make marginal expansion in transmission capacity. In addition, investment in flexible reactance device allows us to avoid right-of-way cost that often plagues transmission line deployment. To further demonstrate the changing scale economies of transmission investment, we estimate the cost of the two investment options presented in the example above.

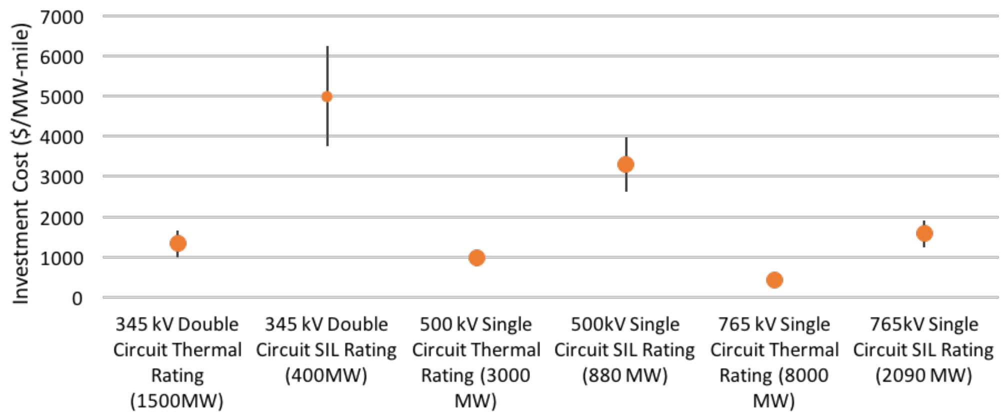

Figure 2.5: Typical cost ranges for new transmission line investments

The cost of new transmission investment is dependent on the voltage rating, the number of circuits, and the length of the transmission line. The limiting factor for the operational capacity of transmission line is dependent on the voltage rating and length of the line. Lines with higher voltage ratings tend to have higher capacity. Shorter lines (< 50 miles) tend to be limited by the thermal capacity limit of the line, whereas longer lines (> 50 miles) tend to be limited by the surge impedance loading limits [29]. Figure 8.5 shows some typical cost for new transmission line investments using data taken from [29] and [30], which include the cost of obtaining right of way. Information about the cost of Flexible AC Transmission System (FACTS) devices is difficult to obtain. For devices that provide flexible reactance, a cost of $135000/MVar has been cited in literature [31]. The MVar operating range of the flexible reactance is given by the following equation [31]:

$$s = X_c \frac{K_{line}^2}{S_{base}} \tag{2.4}$$

where X_c is the maximum series capacitor reactance in pu, K_{line} is the thermal line limit of the transmission line, and S_{base} is the MVA base power (100MVA in this examples shown in this chapter).

The cost of investments for the two options presented in the example above is estimated for different assumptions of length and voltage rating of transmission lines. In the graph in Fig. 2.6,

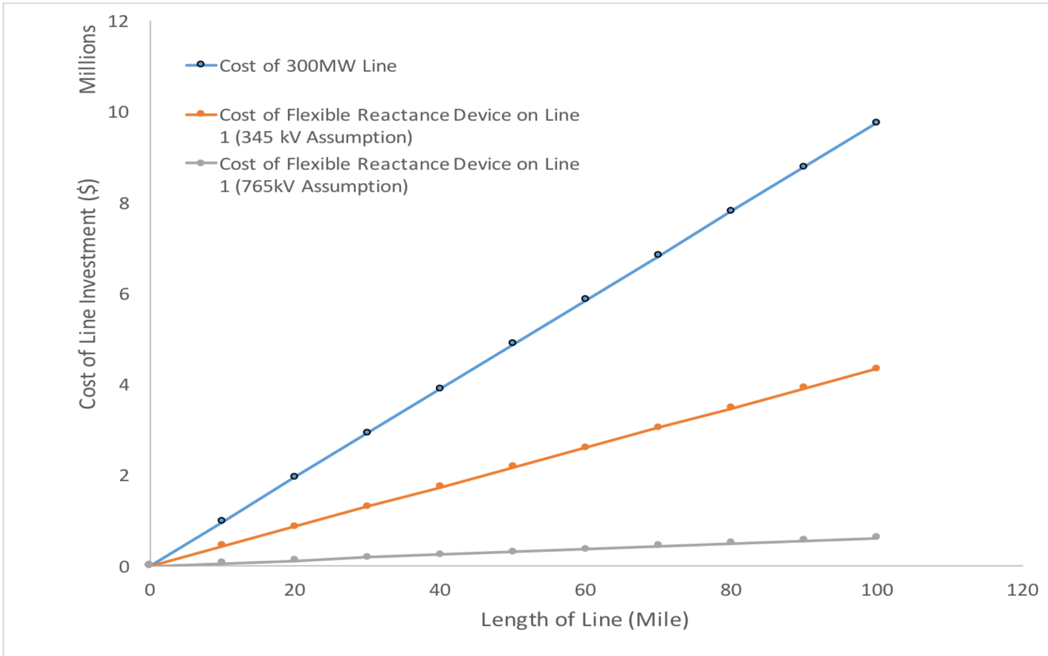

Figure 2.6: Comparison of cost of new line investment and cost of investment in flexible reactance device

the cost of building the 300 MW new line in the example is presented for lines of different length, using the lowest $/MW-mile line investment cost shown in Fig. 2.5. The cost of installing the flexible reactance device in line 1 is also calculated based on per mile line reactance for 345kV and 765kV transmission lines given in [32]. Based on the graph, it can be seen that for transmission line of all lengths, the flexible reactance is the lower cost option for achieving the same increase in transmission capacity. If we assume the higher $/MW-mile line investment cost shown in Fig. 2.5, the results would favor the flexible reactance device even more.

The relative cost of investing in new transmission lines and investing in flexible devices to achieve the same increase in capacity is dependent on the current configuration in the system. Flexible devices are useful in systems with low utilization of existing lines. New transmission lines are useful when larger capacity expansion is needed. A comprehensive cost analysis of the different investment options needs to be done on a case by case basis. In closing, new technologies have changed the economics of transmission investment. Changes in scale economies in the generation sector have allowed for greater competition and market-based solutions in the generation

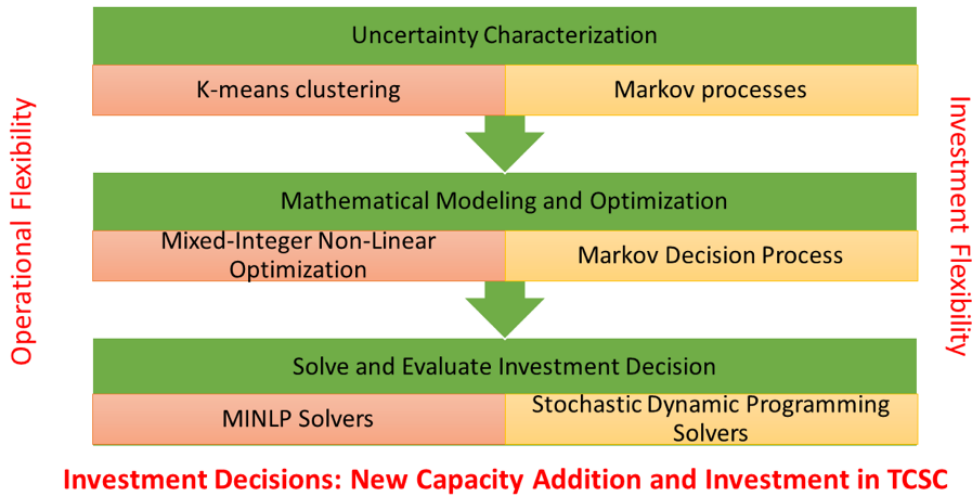

Figure 2.7: Flowchart of Transmission Investment Decision Making Framework

sector, suggesting that market-based solutions could play a greater role in the transmission sector, especially if the appropriate institutional framework exists to support such solutions.

2.2 Models for Optimal Transmission Investment Decision Making Under Uncertainty

In order to further evaluate the potential and challenges of integrating flexible technologies in the grid, we develop two models to evaluate the optimal investment decision in conventional transmission line and flexible reactance device. The first model accounts for the value of operational flexibility, while the second model extends the first model to account for the value of investment flexibility. Here, operational flexibility is the ability of the system to effectively react to short-run uncertainties and system conditions, whereas investment flexibility is the ability of the investment plan to react to long-run uncertainties and changes in system conditions. A three-step transmission investment decision making framework is used for the models and summarized in Fig. 2.7.

The first step of the framework is to characterize the uncertainties being considered. In order to select an appropriate method to characterize uncertainty, a sound understanding of the uncertainty being characterized and the information available is important. The investment decision is strongly influenced by which uncertainties are characterized and how they are characterized. In addition, it is also strongly affected by the institutional structure of the electricity industry. Factors such as who is making the investment decision and what information are shared among stakeholders have a strong effect on the resulting investment decision.

The second step of the framework is to develop a mathematical model of the decision-making problem. The objective function and constraints in the mathematical models are dependent on how uncertainties are characterized and the operational framework that is being modeled. In addition, the decision-making problem can be modeled as either a static decision-making process or a dynamic decision-making process. In a static decision-making process, a single optimal decision plan is found. In a dynamic decision-making process, the optimal decision plan will be dependent on information that is received over time.

The final step of the framework is to solve the mathematical model developed in order to evaluate the investment decision. The optimal investment decision-making problem can be difficult to solve for realistic problem size. New algorithms and heuristics will need to be developed for the large scale decision-making problem. Since the goal of this part of the dissertation is not to design new algorithms, the models are implemented for small case studies that can be solved using readily available optimization software and packages. The development of algorithms to handle more complex case studies will be deferred to the next part of this dissertation.

2.2.1 Model 1: Valuing Short-term Operational Flexibility for Transmission Investment Decisions

In this first model, the goal is to evaluate how the optimal investment decision-making is affected by short-run operational uncertainties under different operational frameworks. Short-run uncertainties considered here include uncertainties in renewable energy generation and power demand and also potential outages in transmission elements.

Step 1: Uncertainty Characterization Using K-means Clustering

For the purpose of this problem, we are interested in the influence of short-run fluctuations in wind and loads, and transmission line outages on investment decision. Uncertainty in transmission line outages is captured by the probability that the given element will fail. This probability can be obtained from historical outage data for similar line types or engineering knowledge. More effort was taken to properly characterize wind and load uncertainty.

Transmission line flow is affected not only by the level of wind and load at each bus, but also by the relative level of wind and load located at different buses. Therefore, we select an uncertainty characterization method that not only allows us to capture uncertainty in the wind and load level at a given bus, but also allows us to capture the correlation among wind generation and load of different buses. The K-means clustering algorithm was selected as it allows us to create a set of representative wind and load scenarios that accurately capture the wind and load profile at each bus as well as the correlation among wind generation and load in the system. K-means clustering was used in [33] to create wind generation and load scenarios for wind generation investment decisions.

K-means clustering is an iterative algorithm that clusters data into similar groups. In this case, the dataset are historical wind generation and power demand data for the entire system. Each data point is multi-dimensional and consists of the wind generation and load data at all nodes for a given point of time. The K-means clustering algorithm is used to group the data set into a representative set of clusters. The centroid of each cluster will give us the wind and load level for one scenario, and the number of observations in each cluster will give us the probability that the scenario happens. A general outline of the K-means algorithm is shown below [33]:

1. Select the appropriate number of clusters (N). One method of selecting the number of cluster is by testing out different number of clusters and plotting out the graph of percentage of variance explained by the clusters vs number of clusters. The appropriate number of clusters is selected such that any additional increase in number of clusters does not produce any substantial increase in model performance.

2. Randomly select N points from the data set to be used as initial centroids for the N clusters.

3. The squared Euclidean distances between each original data point and the centroids are calculated. Each original data point is assigned to the cluster that it is closest to based on the Euclidean distances calculated.

4. Calculate the mean of each cluster to get the set of new centroids.

5. Repeat steps 3-5 until there are no changes in cluster composition between iterations and store the clusters and the total sum of distance of the resulting clusters.

6. In order to reduce the possibility of landing in a local minimum, repeat steps 2 to 5 for a user-selected number of times.

7. Select the result with the minimum total sum of distance as the final clusters.

Step 2: Mathematical Modeling and Optimization for Optimal Investment

In this step, a mathematical model of the optimal investment problem is developed. The objective of the problem is to minimize the overall expected operational and investment cost of the system, subjected to operational and investment constraints. The exact forms of the objective function and constraints are dependent on the operational rules being modeled. The general form of the mathematical optimization problem can be written as:

$$\min_{x,y} \sum_{s=1}^{N_S} Ct(s) C_{opt}(x,s) + C_{invt}(y) \tag{2.5}$$

$$s.t. \quad g_{op}(x,y,s) = 0 \tag{2.6}$$

$$h_{op}(x,y,s) \leq 0 \tag{2.7}$$

$$g_{invt}(y,s) = 0 \tag{2.8}$$

$$h_{invt}(y,s) \leq 0 \tag{2.9}$$

$$x_{min} \leq x \leq x_{max} \tag{2.10}$$

$$y_{min} \leq y \leq y_{max} \tag{2.11}$$

where x represents the operational decision variables, y represents the investment decision variables, C_{opt} represents the hourly operational cost, C_{invt} represents the annualized investment cost, N_S represents the number of scenarios, and $Ct(s)$ is the number of hours scenario s happens in a year. Equations (2.6) and (2.7) represent the equality and inequality operational constraints respectively, while equations (2.8) and (2.9) represent the equality and inequality investment constraints respectively. Equations (2.10) and (2.11) represent the variable limits for the operational and investment decision variables. The investment decision variables y include investment capacity for both new transmission lines and devices that provide flexible reactance.

Optimal investment decision models using the following four different types of operational dispatch approaches are developed in this chapter:

- Economic dispatch with economic considerations only
- Preventive (N-1) security constrained economic dispatch
- Corrective (N-1) security constrained economic dispatch with inelastic load
- Corrective (N-1) security constrained economic dispatch with elastic load

The four different models are outlined next.

Economic Dispatch with Economic Considerations Only: The first case uses the standard economic dispatch where the only operational objective is to minimize generation cost. The objective function here is the minimization of the expected generation cost and transmission investment cost:

$$\min_{\substack{P_g^s, x_{Flex,t}^s, \theta_n^s, f_{line,l/\bar{l}}^s \\ b_{line,\bar{l}}, K_{line,\bar{l}}, K_{Flex,t}}} \sum_{s=1}^{N_S} Ct(s) \sum_{g=1}^{N_G} c_g(P_g^s) + \sum_{\bar{l}=1}^{N_{\bar{l}}} c_{invt,\bar{l}}(K_{line,\bar{l}}) + \sum_{t=1}^{N_T} c_{invt,t}(K_{Flex,t}) \tag{2.12}$$

where $N_S, N_G, N_{\bar{l}}, N_T$ represent the number of scenarios, number of generators, number of new lines, and number of flexible devices respectively, $c_g, c_{invt,\bar{l}}, c_{invt,t}$ represent the generation cost, new line investment cost, and new flexible reactance cost respectively, P_g^s is the power generation,

$x^s_{Flex,t}$ is the operational setting of the flexible reactance device in terms of change in reactance, θ^s_n represents the nodal angles, $f^s_{line,l/\bar{l}}$ represents the line flows, $K_{line,\bar{l}}$, $K_{Flex,t}$ represent new transmission line and flexible reactance capacity respectively, and $b_{line,\bar{l}}$ is a binary variable indicating whether the new line is built.

The operational constraints are:

$$\mathbf{GP^s_g} + \mathbf{Sf^s_{line}} - \mathbf{D^s} = 0 \quad \forall\, s \in N_s \tag{2.13}$$

$$P^{min}_g \leq P^s_g \leq P^{max}_g \quad \forall\, s \in N_s, g \in N_G \tag{2.14}$$

$$f^s_{line,l} = \frac{\theta^s_{l,to} - \theta^s_{l,from}}{x_l - x^s_{Flex,t\rightsquigarrow l}} \quad \forall\, s \in N_s, l \in N_l \tag{2.15}$$

$$-K_{line,l} \leq f^s_{line,l} \leq K_{line,l} \quad \forall\, s \in N_s, l \in N_l \tag{2.16}$$

$$-M(1 - b_{line,\bar{l}}) \leq f^s_{line,\bar{l}} - \frac{\theta^s_{\bar{l},to} - \theta^s_{\bar{l},from}}{x_{\bar{l}} - x^s_{Flex,t\rightsquigarrow\hat{l}}} \leq M(1 - b_{line,\bar{l}}) \quad \forall\, s \in N_s, \bar{l} \in N_{\bar{l}} \tag{2.17}$$

$$-K_{line,\bar{l}} \leq f^s_{line,\bar{l}} \leq K_{line,\bar{l}} \quad \forall\, s \in N_s, \bar{l} \in N_{\bar{l}} \tag{2.18}$$

$$0 \leq x^s_{Flex,t} \leq K_{Flex,t} \quad \forall\, s \in N_s, t \in N_T \tag{2.19}$$

where N_l is the number of existing lines and the rest are as defined earlier. The symbols in bold represent matrices or vectors. Equation (2.13) is the nodal power balance, where $\mathbf{G}$ is a binary matrix indicating the nodal location of the generators, $\mathbf{S}$ is a matrix that is -1 for a transmission line exiting a node, and +1 for a transmission line entering a node, and $\mathbf{P^s_g}$, $\mathbf{f^s_{line}}$, $\mathbf{D^s}$ are vectors of power generation, transmission line flow, and nodal power demand respectively. Equation (2.14) represents the generation limit, where P^{min}_g and P^{max}_g are the maximum and minimum generation capacity respectively. Equation (2.15) and (2.16) are the line flow constraints for existing transmission lines, where $\theta^s_{l,to}$, $\theta^s_{l,from}$ are the nodal power angles at the two nodes connected by the transmission line, x_l represents the transmission line reactance, $K_{line,l}$ is the existing transmission line capacity, $x^s_{Flex,t\rightsquigarrow l}$ is the flexible reactance setting for the flexible reactance device t that is on line l, and the remaining variables are as defined earlier. Equation (2.17) and (2.18) are the line flow constraints for new transmission lines. Equation (2.17) is a big-M constraint, which uses a large penalty term M to enforce the line flow constraint only when the line is actually built. Finally, equation (2.19) is the operational limits of the flexible reactance device.

The investment constraints are:

$$0 \leq K_{line,\bar{l}} \leq K^{max}_{line,\bar{l}} b_{line,\bar{l}} \quad \forall\, \bar{l} \in N_{\bar{l}} \tag{2.20}$$

$$0 \leq K_{Flex,t} \leq 0.5 x_l \quad \forall\, l \in N_l \tag{2.21}$$

Equation (2.20) and (2.21) are the investment limits of new transmission lines and flexible reactance device, where $K^{max}_{line,\bar{l}}$ is the maximum line investment capacity. In this chapter, we assume that the maximum capacity of flexible reactance device that can be installed in a line is 50% of the base reactance of the line.

Preventive (N-1) Security Constrained Economic Dispatch: In the first case, we assume that power is dispatched by minimizing the generation cost only. In actual system operation, power is often dispatched more conservatively due to security constraints to maintain the reliability of the grid. In this second case, we assume that the power system is operated under (N-1) security. This means that power is dispatched such that the system will remain within the operating limits defined by constraints (2.13) - (2.18) even if any single system element fails. Under preventive (N-1) security, the system should remain within the specified operating limits without any corrections in power dispatch or control settings in the system. This dispatch approach is commonly used in current system operation. The key drawback of this approach is that it leads to highly conservative and economically-inefficient dispatch.

Note that in actual system operation, the acceptable operating limits under normal condition and emergency operating conditions are different. For instance, the emergency (short-term) line flow limits for transmission lines are higher than the line flow limits during normal operating condition. For the purpose of this chapter, we do not account for the differences in emergency and normal line flow limits. In addition, we only consider failures in transmission elements (i.e. transmission line or flexible reactance device).

The preventive (N-1) security constrained economic dispatch is similar to the basic economic dispatch problem presented in the last section. The only difference is that there is an increase in the number of operational constraints. The base case set of operational constraints shown earlier is replicated with one transmission element removed at a time. Therefore, the final number of operational constraints is equal to (1 + the total number of transmission elements) times the number of operational constraints in the base case set of operational constraints shown earlier. For each scenario, the power dispatch and flexible reactance settings have to remain the same for all (N-1) line failures, however, the line flows and nodal power angles will be different and governed by Kirchhoff's Laws.

Corrective N-1 Security Constrained Economic Dispatch with Inelastic Load: Preventive (N-1) operation results in conservative operation of the system that is often highly inefficient. In recent years, "smart grid" proponents have proposed the use of a corrective (N-1) operational strategy to minimize the inefficiency in the system [34]. In corrective (N-1) operation, corrective dispatch and control changes can be made to the system when outages happen as long as it can be done within a certain time to avoid dynamic instabilities. In this case, we assume that the potential corrective actions that can be taken are changing the power dispatch and changing the flexible reactance control setting. This is the operational approach that is frequently touted by smart grid proponents as it accounts for the value of corrective control technologies. The main arguments in support of corrective (N-1) security constrained economic dispatch is that the system can often remain operational for a short period of time after outages occur, which allows for fast corrective actions to be taken to bring the system within the acceptable operational limits [34].

As with the previous case, the number of operational constraints is equal to (1 + the total number of transmission elements) times the number of operational constraints in the base case operational constraints. However, in this case, the power dispatch and control settings of the flexible reactance are allowed to change in response to (N-1) contingencies. In addition, adjustment needs to be made to the objective function to account for the probability of each of the contingencies happening. The objective function for the corrective (N-1) security constrained economic dispatch is given by:

$$\min_{\substack{P_g^{s,c}, x_{Flex,t}^{s,c}, \theta_n^{s,c}, f_{line,l/\bar{l}}^{s,c} \\ b_{line,\bar{l}}, K_{line,\bar{l}}, K_{Flex,t}}} \sum_{c=1}^{N_c} p_c(c) \sum_{s=1}^{N_S} Ct(s) \sum_{g=1}^{N_G} c_g(P_g^{s,c}) + \sum_{\bar{l}=1}^{N_{\bar{l}}} c_{invt,\bar{l}}(K_{line,\bar{l}}) + \sum_{t=1}^{N_T} c_{invt,t}(K_{Flex,t}) \tag{2.22}$$

where p_c is the probability of each case c happening and N_c is the total number of cases. The cases include the base case with no contingencies and the cases representing all (N-1) contingencies. The other variables are as defined earlier.

Corrective N-1 Security Constrained Economic Dispatch with Elastic Load: In the previous case, we assume that the load is inelastic and non-dispatchable. In this case, we assume that part of the load is elastic and dispatchable. A "loss of load" price is assigned to each load. This loss of load price is the amount that needs to be compensated to the consumers if their load is shed at any point of time. The new operational objective is hence to minimize both expected generation and load cost:

$$\begin{aligned} \min_{\substack{P_g^{s,c}, x_{Flex,t}^{s,c}, \theta_n^{s,c}, f_{line,l/\bar{l}}^{s,c} \\ b_{line,\bar{l}}, K_{line,\bar{l}}, K_{Flex,t}, P_{loss,d}^{s,c}}} & \sum_{c=1}^{N_c} p_c(c) \sum_{s=1}^{N_S} Ct(s) \big[\sum_{g=1}^{N_G} c_g(P_g^{s,c}) + \sum_{d=1}^{N_D} c_D(P_{loss,d}^{s,c}) \big] \\ & + \sum_{\bar{l}=1}^{N_{\bar{l}}} c_{invt,\bar{l}}(K_{line,\bar{l}}) + \sum_{t=1}^{N_T} c_{invt,t}(K_{Flex,t}) \end{aligned} \tag{2.23}$$

where N_D is the number of dispatchable load, $P_{loss,d}^{s,c}$ is the amount of load being shed, c_D represents the price of loss load, and the remaining variables are as defined earlier. The power balance constraints shown earlier (Equation (2.13) needs to be altered to account for the potential of dispatching load:

$$\mathbf{G}\mathbf{P}_{\mathbf{g}}^{\mathbf{s,c}} + \mathbf{S}\mathbf{f}_{\mathbf{line}}^{\mathbf{s,c}} - \mathbf{D}^{\mathbf{s}} + \mathbf{P}_{\mathbf{loss,d}}^{\mathbf{s,c}} = 0 \quad \forall\, s \in N_s \tag{2.24}$$

In addition, an additional constraint representing the capacity limits for the dispatchable load needs to be added:

$$P_{loss,d}^{min} \leq P_{loss,d}^{s,c} \leq P_{loss,d}^{max} \quad \forall\, s \in N_s, d \in N_D \tag{2.25}$$

where $P_{loss,d}^{min}$ and $P_{loss,d}^{max}$ is the minimum and maximum capacity of dispatchable load respectively.

Step 3: Solve Optimization Problem to Evaluate Investment Decisions

The optimization problems presented above are mixed-integer non-linear programming problems (MINLP). MINLP are challenging problems to solve. Even though various optimization algorithms and heuristics have been developed in recent years to enable us to better solve such problems, large scale MINLP problems are still computationally challenging. As mentioned earlier, the goal of this part of the dissertation is not to design new algorithms and heuristics to solve the optimal transmission investment decision problem. Instead, the goal is to use simple case studies to generate insights into institutional and policy design for flexible transmission technologies. Therefore, the simple case studies used in this chapter are designed to be solvable using generic MINLP solvers such as BARON and SCIP that can be used with well-established optimization platforms. In this case, OptiToolbox for MATLAB is used to implement SCIP to solve the optimization problem [35].

2.2.2 Model 2: Valuing Long-term Investment Flexibility for Transmission Investment Decisions

In this second model, the goal is to evaluate how the optimal investment decision-making is affected by different levels of long-run uncertainties and with different level of load responsiveness. The long-run uncertainties that are considered here include long-run uncertainties in load growth and generation investment patterns.

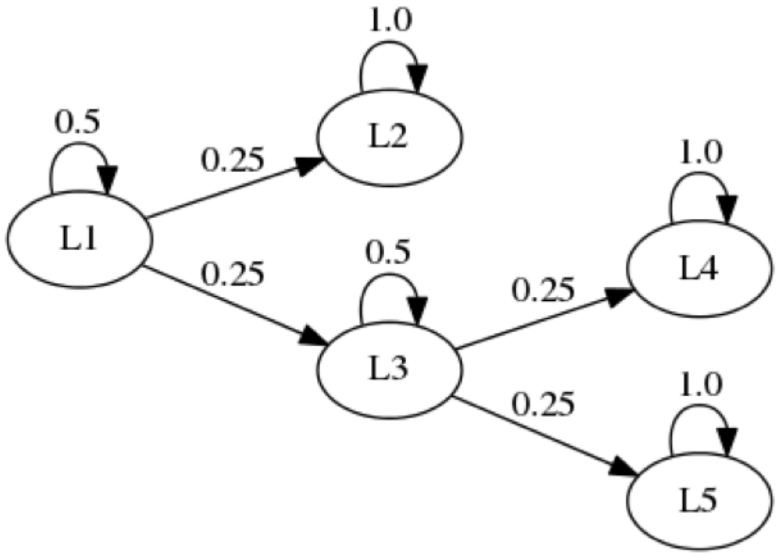

Figure 2.8: Graphical Illustration of a Hypothetical Markov Chain for Long-term Load Growth

Step 1: Uncertainty Characterization Using Markov Processes

In this model, the uncertain load growth and generation investment patterns are modeled using a discrete-time Markov process (also known as Markov chain). A Markov process is a memoryless process, which means that the next state of the process is only dependent on the current state and not on any previous state. Markov chains are described by discrete states and a state transition matrix. A graphical illustration of a hypothetical Markov chain for long-term load growth is shown in Figure 2.8.

In Figure 2.8, the nodes (L1, L2, L3, L4, L5) represent the five different states (i.e. load levels in this example). The numbers on the edges represent the state transition probabilities. The numbers on the self-loops tell us the probability that the state will stay the same in the next time period, while the numbers on the edges connecting two nodes tell us the probability of transitioning from one state to another. For instance, if the current load level is L1, there is a 50% chance that the next load level will be the same, a 25% chance that the next load level will be L2, and a 25% chance that the next load level will be L3.

The challenge of obtaining a Markov chain representation of uncertainty in generation and load growth lies in determining the appropriate state transition matrix. Historical system data and expert elicitation can be used to determine the appropriate states and state transition matrix.

Step 2: Mathematical Modeling and Optimization for Optimal Investments

A stochastic dynamic programming model is used to model this long-term optimal investment problem. More specifically, the optimal investment decision problem is modeled as a discrete-time Markov decision process (MDP). MDP provides an elegant framework to model decision-making under uncertainty under a set of modeling assumptions [36, 37]. These assumptions are:

- There is a finite number of states.
- There is a finite number of actions/decisions.
- The system state transition process has the Markov property. Future states are only influenced by the current state and not previous states.
- The cost/reward associated with each state-action pair can be computed.

The five key components of a MDP problem formulation are: (1) decision epoch, (2) state space, (3) action space, (4) transition probabilities, and (5) reward function [36]. The MDP problem formulation for the long-term optimal investment problem will be presented next.

Decision Epoch: The decision epoch in our problem formulation represents the time interval between investment decisions. This is dependent on the institutional framework governing investment decisions. An annual decision-making cycle would be a reasonable assumption to make here. However, to simplify computation, a four-year decision cycle is used in this part of the dissertation.

State Space(S) and Action Space(A): The states of the model is described by three types of state variables: Network Configuration (NC), Maximum Load Level (ML), Generation Capacity (GC). The action space is the set of transmission investment options.

State Transition Probabilities ($P(s'|s,a), P_a(s',s)$): The load level and generation capacity are modeled as Markov processes as described earlier. These are exogenous state variables and their state transition probabilities are assumed to not be affected by the actions taken (*i.e.* $P(s'|s,a) = P(s'|a)$). The network configuration represents the state of the transmission network, including both new lines and flexible reactance devices. This is an endogenous state variable where the state transition matrix is dependent on the decision being taken (*i.e.* $P(s'|s,a) \neq P(s'|s)$).

Reward Function($R_a(s',s)$): The reward function gives the value of transitioning from state s to state s' after taking action a. The reward function represents the savings in operational cost in state s' given the new network configuration. It can be calculated using the following formula:

$$R_a(s',s) = C_{Op}(\{NC_0, ML_{S'}, CG_{S'}\}) - C_{Op+invt}(\{NC_{S'}, ML_{S'}, CG_{S'}\}) \tag{2.26}$$

where $C_{Op}(\{.\})$ is the annual operational cost at the state defined by the state variables and $C_{Op+invt}(\{.\})$ is the annual operational cost and annualized investment cost at the state defined by the state variables. The first term of the formula represents the operational cost at the new load level and generation capacity assuming that base case configuration. The second term in the formula represents the operational cost and total annualized investment cost at the new load level and generation capacity at the new network configuration. The operational cost can be obtained by running the optimal power flow for the set of scenarios obtained using the K-means clustering technique discussed earlier adjusted based on the appropriate network configuration, load level and generation capacity.

Terminal Reward: Since the problem is modeled as a finite horizon Markov Decision Process, a terminal reward is defined for the problem. The terminal reward is defined to be the expected operational savings due to the investment minus the cost of investment over the remaining lifetime of the investment. It is assumed that the state remains at the final state for the rest of the lifetime of the investment. The terminal reward is calculated based on the following formula:

$$R_{term}(S) = \frac{1-(1+i)^{-N_p}}{i}[C_{Op}(\{NC_0, ML_S, CG_S\}) - C_{Op+invt}(\{NC_S, ML_S, CG_S\})] \tag{2.27}$$

where i is the interest rate and N_p is the number of remaining time periods in the lifetime of the investment. The first term in the equation above represents the annual operational cost at the final load and generation level if the network configuration remained at the base case (i.e. no investment is made). The second term represents the annual operational cost and annualized investment cost at the final load and generation level with the new network configuration.

Solution Objective: The goal of the MDP problem is to determine the best "policy". The policy function ($\pi_t(s)$) specifies the action that the decision maker will choose in state s at each time period t. At every time period the decision maker can choose to do nothing and wait for more information, invest in a flexible reactance device, or invest in new line. The goal is to choose a policy that maximizes the expected discounted sum of cumulative reward over the time horizon:

$$V_\pi = E_{\pi,S}\big\{\sum_{t=1}^{T}\gamma^t R_\pi(s', s)\big\} \tag{2.28}$$

where γ is the discount factor and R_π is the reward due to following the policy.

Step 3: Solve Optimization Problem to Evaluate Investment Decision

The Markov decision process can be solved using various dynamic programming algorithm such as policy iteration, value iteration, and various approximate dynamic programming techniques. For a large problem with a large state space, various heuristics and approximation techniques will be needed to fully solve the dynamic programing problem. However, for the purpose of this part of the dissertation, the basic backward induction technique is used to solve this finite-stage MDP. The backward induction algorithm is a recursive algorithm that does the follow [38]:

1. For the final period, T, let the value function be equal to the terminal reward:

$$v_T(s) = R_{term}(S) \tag{2.29}$$

2. Set counter $n = 1$

3. For $t = T - n$ and for all states s, calculate the follow:

$$v_t(s) = \max_{\alpha \in A} \big\{ \sum_{s' \in A} P_a(s', s)(R_a(s', s) + \gamma v_{t+1}(s')) \big\} \tag{2.30}$$

$$\pi_t(s) = arg \max_{\alpha \in A} \big\{ \sum_{s' \in A} P_a(s', s)(R_a(s', s) + \gamma v_{t+1}(s')) \big\} \tag{2.31}$$

4. Increase counter $n = n + 1$

5. If $n = T$, end algorithm. Otherwise, repeat 2 to 5.

The MDP Toolbox for MATLAB is used to solve the case studies presented in Part I of this dissertation [38].

Chapter 3

Case Studies and Policy Discussion

In this chapter, we use the models presented in the last chapter to illustrate how different operational approaches can have different impacts on investment decisions, and highlight the importance of considering the operational and market effects when making investment decisions. We also demonstrate the need for well-designed long-term markets to encourage information and risk sharing among stakeholders. In this part of the dissertation, the case studies are done using simple 2-bus systems for clearer exposition. More complex test systems will be used in later parts of this dissertation as appropriate tools are developed to handle more complex problems.

3.1 Impact of Operational and Market Practices on Investment Planning

The decoupling among operation, market, and planning is problematic as the value of different technologies depends on the supporting operational and market framework. In particular, rigid operational and market mechanisms, such as the use of preventive (N-1) security constrained dispatch and the treatment of load as inelastic, favor conventional technologies and hide the value of flexible technologies. In contrast, flexible operational and market mechanisms that enable operational flexibility incentivize flexible technologies.

A simple two-bus example is used to illustrate the impact of different operational and market practices on investment decision making. The four different operational approaches modeled in

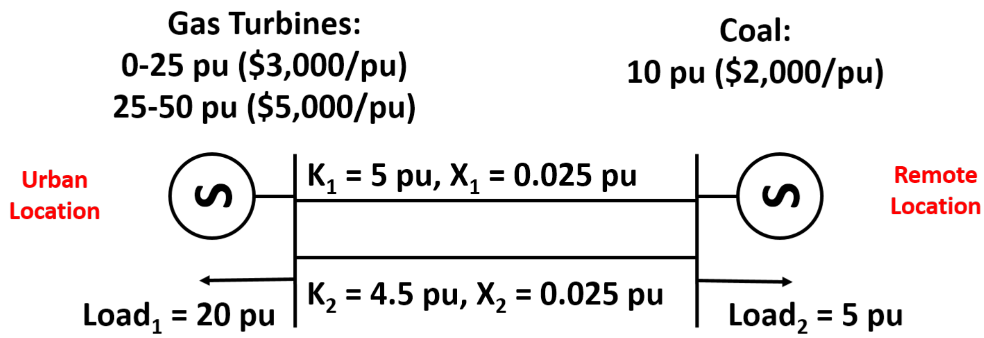

Figure 3.1: Base Case System for Case Study

Section 2.2.1 is considered.

3.1.1 Case Study A

In this case study, there is an urban location (Node 1) and a remote location (Node 2) connected via two transmission lines (Figure 3.1). The urban location has a higher maximum load of 2000 MW or 20 pu, while the remote location has a lower maximum load of 500 MW or 5 pu. In addition, the urban location has two types of gas turbines (a 2500MW, $30/MWh gas turbine and a 2500MW, $50/MWh gas turbine), while the remote location has a coal power plant (500MW, $20/MWh).

Now, assume that a new environmental regulation is being considered that will cause the coal plant to be shut down in the near future. In anticipation of the coal plant being closed, a wind power developer is considering building a new 2000 MW wind farm at the remote location. In addition, a tech company is considering building a large data center at the remote location, which would increase the load at the remote location to 1000 MW. This is illustrated in Figure 3.2.

The key question to be answered here is: What is the optimal level of transmission line and flexible reactance device investment in anticipation of these changes under different operational and market framework? Model 1 presented in the previous chapter will be used to answer this question.

As mentioned earlier, the first step to valuing investment decision is to characterize the uncer-

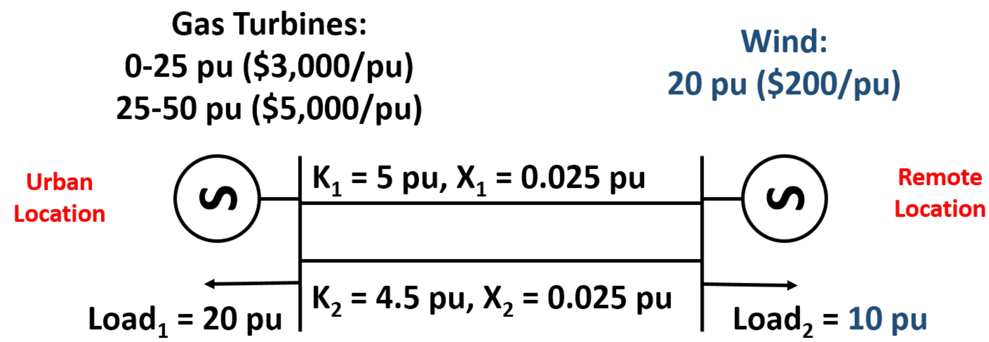

Figure 3.2: System with Anticipated Changes

tainties being considered. In this case study, short-run wind and load fluctuations and transmission element outages are considered. Each transmission element is assumed to have a 2% chance of failure. Historical hourly wind and load data from PJM for the year 2012 and 2013 were used to obtain wind and load fluctuation patterns for this case study [12]. The urban location uses load data from the PJM Mid-Atlantic region, while the remote location uses wind and load data from the PJM West region. The K-means clustering technique presented in Section 2.2.1 was used to produce 100 scenarios that together capture the wind and load fluctuations and correlation among the data.

In order to evaluate the performance of the K-means clustering algorithm in providing a reduced model of the dataset, the cumulative distribution function and correlation matrix of the 100 generated scenarios were compared to that of the complete dataset. The comparison of the cumulative distribution function for the wind generation, urban load, and remote load are shown in Figure 3.3.

The spearman correlation coefficient is used to compare the rank correlation among the generated scenarios and the complete dataset. The correlation matrix for the complete dataset and the correlation matrix for the generated scenarios are shown in Table 3.1. Both the comparison of the cumulative distribution function and correlation matrix confirm that the set of scenario generated via K-means clustering is a good representation of the original data.

Having generated the representative scenarios using K-means clustering, we implemented

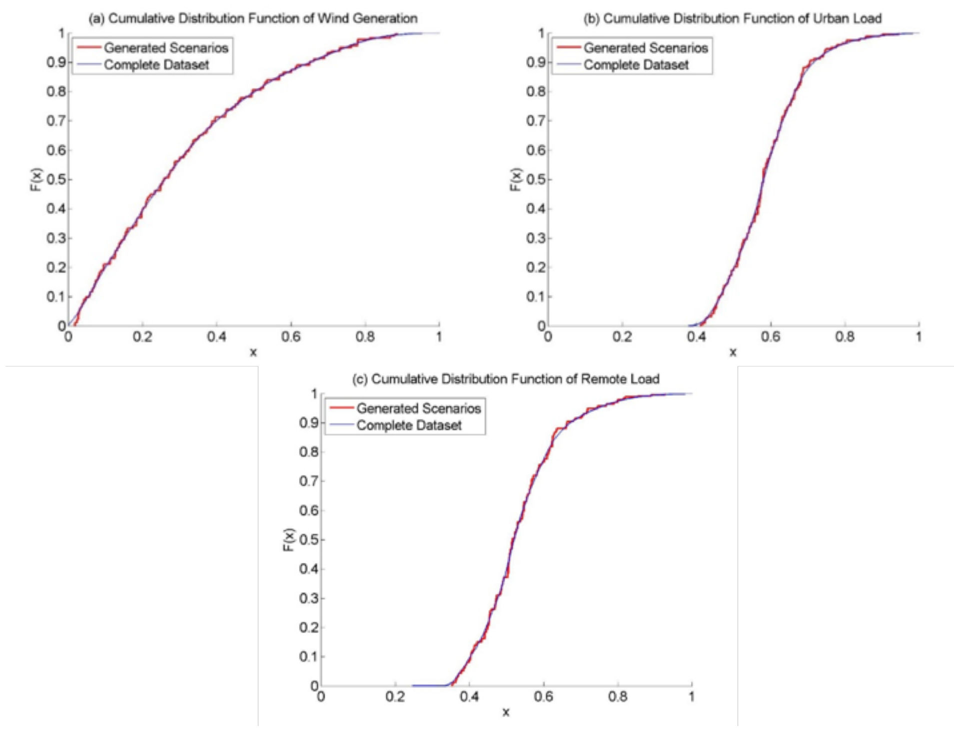

Figure 3.3: Comparison of Cumulative Distribution Function. (a) Wind Generation (b) Urban Load (c) Remote Load

Table 3.1: Comparison of Correlation Matrix of Complete Dataset and Generated Scenarios (Generated Scenarios Correlation in Parenthesis)

	Wind	Urban Load	Remote Load
Wind	1(1)	-0.09(-0.09)	-0.16(-0.16)
Urban Load	-0.09(0.09)	1(1)	0.92(0.96)
Remote Load	-0.16(-0.16)	0.92(0.96)	1(1)

Model 1 for the 4 different operational approaches presented in the previous chapter. The results of the simulations are summarized in Table 3.2.

In the first case, we do not consider the reliability needs of the system. Under this optimization approach, investments are only made if the cumulative value of the generation cost savings is greater than the cost of investment. The optimal investment option is to invest in 0.0025pu of flexible reactance in line 1, which allows for the full 500MW capacity of line 1 to be used. This entails a total operational and investment cost of $0.303 Billion/year.

In the second case, we consider the preventive N-1 security constrained economic dispatch.

Table 3.2: Results of Simulation for Optimal Investment Considering Short-Run Operational Flexibility (FRD stands for Flexible Reactance Device)

Operational Framework	Investment Decision	Operational and Annualized Investment Cost (B$)
Economic Dispatch	FRD Line 1 (0.0025pu)	0.303
Preventive N-1	Line(450MW)	0.314
Corrective N-1	Line(353MW), FRD Both Line (0.0053pu)	0.311
Corrective N-1 with Dispatchable Load	FRD Line 1 (0.0025pu)	0.307

In this case, the optimal investment decision is to invest in a new 450MW transmission line. This line is needed to maintain enough transmission capacity when any of the other two lines fail. As expected, this results in the most conservative and expensive option.

In the third case, we account for the ability of the system to take corrective actions to maintain the reliability of the system during contingencies. In this case, a transmission line with a smaller capacity is required. Flexible reactance devices are installed in both of the existing lines to ensure that the full capacity of those lines can be used when any of the other lines fail. This scenario cost slightly less than the second scenario.

Finally, in the fourth case, we account for the ability to shed load during contingencies. The "loss-of-load" price assigned to the urban load is $5000/MWh whereas the price assigned to the remote load is $1000/MWh. Due to the additional flexibility brought about by the ability to dispatch loads during contingencies, the optimal investment decision is identical to the investment decision for the purely economic case (i.e. invest in flexible reactance in line 1).

The results demonstrate the importance of accounting for the underlying operational and market framework when making investment decisions. In particular, the results demonstrate that rigid operational and market frameworks, such as preventive N-1 security constrained economic dispatch and the treatment of load as inelastic can result in inefficient line over-investment. As it stands, the value of many flexible technologies are hidden and lost under the current conservative and rigid operational framework, which deters investors from investing in such technologies. In order to provide appropriate incentives for investment in flexible technologies and transition towards a smart grid, it is critical that we not only adopt a more flexible operational and market framework, but also account for operational and market flexibility during investment planning.

3.2 Information and Risk Sharing in the Face of Uncertainties

Even if we account for operational and market flexibility in making investment planning, the ability to make efficient investment decision in the transmission sector is still limited due to the difficulty of making accurate long-term predictions in the electricity sector. Long-term load predictions done by system operators and transmission planners have been demonstrated to be highly inaccurate [39]. In addition, generation expansion plans have been known to change suddenly and unexpectedly. Historical data is insufficient in making accurate long-term predictions due to the rapidly changing technological landscape in the electricity industry. This uncertainty in generation and load patterns can result in inefficient overinvestment or underinvestment. Under a guaranteed rate-of-return regulatory framework, consumers bear the risk of inefficient investments and there are no true incentives or mechanisms for transmission planners to improve the way they deal with uncertainty in transmission planning.

We extend the case study presented earlier to illustrate the impact of long-term uncertainty on investment decisions.

3.2.1 Case Study B

Now, we extend the previous case study and consider the fact that policy changes and business plans are often uncertain. In this case, we assume that there is a possibility that the environmental policy does not get approved by Congress. If the environmental policy does not get approved by Congress, the coal plant remains open and the new wind farm is not built. In addition, the tech company is not sure how much energy will be needed by the new data center. The two uncertain state variables here are the generation capacity at the remote region (GC) and the maximum load

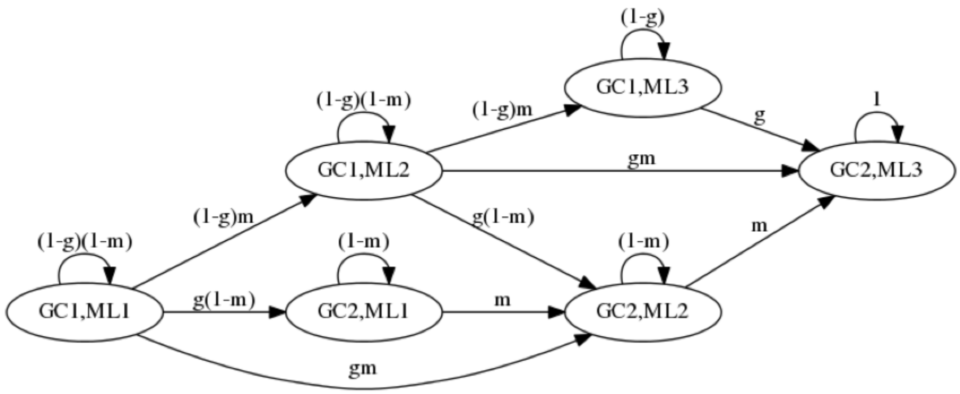

Figure 3.4: State Transition Matrix for Uncertain States

level at the remote region (ML). The potential states for these uncertain state variables are:

$$GC \in \begin{cases} \text{Coal Remains, No Wind (GC1,Base)} \\ \text{2000 MW Wind Generation (GC2)} \end{cases} \tag{3.1}$$

$$ML \in \begin{cases} \text{No Increase in Load (ML1,Base)} \\ \text{Load Level Increase to 1000MW (ML2)} \\ \text{Load Level Increase to 1500MW (ML3)} \end{cases} \tag{3.2}$$

The state transition matrix for the uncertain states are shown in Figure 8.10. In this figure, m represents the probability that the load level will increase from $ML1 \rightarrow ML2$ and from $ML2 \rightarrow ML3$, while g represents the probability that the wind farm will be built. Notice that the model could support different transitional probabilities from ML1 to ML2 and from ML2 to ML3.

A Markov decision process as described in Model 2 in the previous chapter is used to solve this long-term dynamic investment problem. A 10% per annum discount rate and interest rate is used. As mentioned earlier, we assume that investment decisions are made every 4 years and the lifetime of the investments is 20 years. The operational cost at each state was calculated using the same 100 wind and load scenarios found through K-means clustering. The wind and load levels for the different scenarios are scaled to correspond to the appropriate states. In the cases with inelastic load, the system is penalized heavily for not meeting the load, such that the system will always seek to meet the load. The investment decisions being considered are whether to invest in 0.0025 pu of flexible reactance in Line 1 and whether to invest in a new 450MW new transmission line. The results of three different cases are described next.

First, we consider the deterministic case, where g=1 and m=1. The operational approach considered here is the economic dispatch only approach. In this case, we know for sure that the demand will increase from 500 to 1000MW at the remote node between decision periods 1 (Year 1) and 2 (Year 5), and from 1000MW to 1500MW between decision periods 2 and 3 (Year 9). In addition, the wind farm will be built between decision periods 1 and 2. In this case, the optimal investment decision is to invest in 0.0025 pu of flexible reactance in line 1 during Year 1 and invest in the 450MW new line in Year 9.

For the second case, we consider a case similar to the first case. However, in this case g=0.5 and m=0.5. In this case, future evolution of demand and generation investment are uncertain. The optimal investment decision in Year 1 here is to build the 450 MW new line. The investment decision in Year 5 and Year 9 will be dependent on the actual realization of the demand and generation investment. The flexible reactance device will be built in Year 5 or Year 9 only if the demand increased from the base case. In this case, it can be observed that uncertainty in future demand growth and generation investment pattern resulted in more aggressive and expensive investment decision. One key reason for this conservative investment decision is due to the assumption that demand is inelastic.

In the final case, we use the same assumptions as the second case (g=0.5, m=0.5). However, load is considered to be elastic in this case. Similar to the earlier simulations, we assume that the "loss-of-load" price for the urban load is \$5000/MWh whereas the "loss-of-load" price for the remote load is \$1000/MWh. In this case, the optimal investment decision in Year 1 is to invest in the flexible reactance device. The new line will only be built in Year 5 or Year 9 if the load increased to 1500MW and the wind farm is built. This demonstrates how accounting for load elasticity gives us the flexibility to invest in smaller, flexible devices as an intermediate measure in face of long-term uncertainty. This enables us to delay the decision to invest in the more expensive transmission line until more information on future load and generation pattern can be obtained.

The results above highlight two key requirements for efficient transmission investment:

1. Load needs to participate in the market, both in the long-run and in the short-run. In current long-term transmission planning, transmission investment is made to fully accommodate all future load growth without considering how much customers are willing to pay for the delivery of the energy. This is despite the fact that loads are more elastic in the long-run as customers can take steps to reduce their load consumptions through energy efficiency programs or installation of private generators. The results demonstrate that if we demand that total load has to be met at all cost, transmission planner will tend to overinvest to account for the worst case load scenario. In addition, the potential of incremental expansion in transmission capacity using smaller, flexible devices is often ignored when the incentive is to over-design the system.

   Accounting for load elasticity allows more flexibility to transmission planners, by enabling them to make incremental, smaller transmission upgrades/investments while waiting for more information on future load and generation pattern to arrive. Technologies are available to allow for more fine grained dispatched of demand. However, in order to enable greater participation of load in electricity markets, some sort of market mechanism needs to exist for load to make their long-term willingness-to-pay function for electricity or willingness-to-accept-compensation function for load shedding be known. One way in which this can be done is to design electricity markets that are symmetric (i.e. load submit bids along with generation to reveal how much they are willing to pay for electricity). Another potential way in which this can be done is to put in place a menu of reliability insurance program where load can purchase different level of reliability and be compensated at different price level should load be shed. Regardless of how it is done, there need to be a way to allow load to participate and express their preference in electricity markets of all time-scales.

2. There need to be a mechanism for long-term information to be exchanged among stakeholders, such as the multi-timescale stratum energy market framework proposed in [40].

Long-term uncertainty has a significant impact on investment decisions. The key question to be answered here is: How can we empower transmission owners and planners with more accurate information about future load and generation uncertainties and allow for long-term risks to be shared among stakeholders?

These will be discussed further in the next chapter.

3.3 Challenges in Designing Financial Rights for Flexibility

Another open question and design challenge for transmission flexibility is how would we design financial transmission rights such that they not only encourage efficient operation of the system, but also incentivize economically efficient investment in both flexible and conventional transmission technologies? Can we design a system of short-term and long-term transmission rights that provide appropriate price signals for investments and potentially allow for greater participation of merchant transmission investments?

The inefficiency of current financial transmission rights implementation can be seen from the revenue shortfall that frequently occurs due to the mismatch between the system constraints considered during financial transmission rights auction and real time system condition. Currently, this revenue inadequacy is dealt with via an "uplift" payments to owners of financial transmission rights that are funded either through surplus revenue from periods of excess congestion rent or through transmission owners who pass the cost over to consumers via access charges [41]. In the cases where the "uplift" payments are funded by surplus revenue, holders of financial transmission rights are not guaranteed full payment. One main cause of this revenue inadequacy issue is the lack of considerations for both short-run and long-run uncertainties during financial transmission rights auctions and allocations, which are commonly implemented via deterministic approaches [26]. Even without flexible technologies, the electric transmission network is not static due to line de-ratings and outages. With the inclusion of flexible technologies that change the topology and electrical properties of the network, the revenue inadequacy problem brought about by current financial transmission rights implementation is likely to worsen. By neglecting the stochastic nature of the power system, financial transmission rights ignore the value of flexibility and do not provide efficient signals for optimal investments in both flexible and conventional technologies. A key open question for the design of financial rights for flexibility is to develop market mechanisms to manage the uncertainties inherent in electricity operations [42]. At the very minimum, we believe that this would involve the creation of multi-timescale reconfiguration markets for financial transmission rights that goes as close to real time as possible, to enable market participants to adjust their transmission rights portfolio as new information is available on the anticipated system configuration.

The theoretical development of financial transmission rights has traditionally focused on its use as a hedging mechanism for congestion cost. In recent years, there has been increased interest in the use of long-term financial transmission rights to encourage efficient investment decisions (e.g. [43] and [44]). [44] presents the results of several experiments on using long-term financial transmission rights for inducing efficient investment decision and finds that price signals from long-term financial transmission rights do not provide consistent and efficient signals for investment and much is left up to the discretion of the transmission planner to interpret the price signal. [43] combines concepts from long-term financial transmission rights literature with concepts from performance-based regulation literature to propose a combined merchant-regulatory framework for transmission. The proposed mechanism has the potential of being a highly flexible institutional framework for transmission investment as depending on the nature of the transmission investment, a merchant-based approach or performance based regulatory approach might be more suitable. Despite some interesting results that have been presented in current literature, there remain many open research questions as to how long-term financial transmission rights need to be designed to provide efficient price signals for investment. The design of well-functioning long-term financial rights mechanism is a second key challenge for the design of financial rights for flexibility.

3.4 Conclusions

In this part of the dissertation, we illustrate how flexible technologies have reduced the economies of scale of transmission sector. Models were developed to account for the value of operational flexibility and investment flexibility in making investment decisions. These models were used to demonstrate impediments to flexibility in the transmission sector and to make policy recommendation. Using simple case studies, we demonstrated the importance of not only adopting flexible operational and market framework, but also the importance of accounting for these flexibility in making investment decisions. In addition, we demonstrated the need for loads to participate more actively in electricity markets, both in short-term markets and long-term markets, and presented a preliminary framework for how a long-term market can be designed to provide more information for system planner and to enable long-term investment risk-sharing. Finally, we identified some challenges in designing financial rights for transmission flexibility.

Several initial policy recommendations were made throughout this part of the dissertation. In the next chapter, we discuss these recommendations in the context of wholesale electricity market design and highlight how we will tackle some of these issues in the rest of the dissertation.

3.5 Appendix 1: Investment Cost

Investment cost has a huge influence on the overall investment decision. The investment cost for new transmission capacity expansion and flexible reactance are calculated based on the following assumptions.

The transmission line cost was calculated using the following cost assumptions:

- Investment Cost: $1000 per MW-mile [29]
- Length of transmission line is 200 miles
- 10 % interest rate
- 20-year life-time of investment

There is a lack of detailed investment cost information for flexible reactance devices and hence we had to use the limited information we can find to make a best faith estimate. The flexible reactance device investment cost was calculated using the following cost assumptions for TCSC:

- Investment Cost: $135/kVAR[31]
- The MVar operating range of TCSC can be calculated using the following formula[31]:

$$\text{Operating Range} = X_C \frac{K^s_{line}}{S_{base}} \tag{3.3}$$

  where X_c is the maximum series capacitor reactance in pu, K_{line} is the thermal line limit of the transmission line, and S_{base} is the MVA base power (100 MVA in this case).

- 10% interest rate
- 20-year life-time of investment

The investment cost assumption for the transmission line used is the lower end of the cost given in the referenced source. The resulting investment costs used in this case study are:

Table 3.3: Annualized Investment Costs

	Annualized Investment Cost
New Line Investment	$ 23k/MW
Flexible Reactance Device in Line 1	$ 40M/pu flexible reactance
Flexible Reactance Device in Line 2	$ 32M/pu flexible reactance

Chapter 4

Implications for Wholesale Electricity Market Design

In the last two chapters, we used simple models and case studies to highlight potential impediments to flexibility in the transmission sector. Many of the policy recommendations made are not transmission specific, but involved changing the way the overall electricity markets are designed. In this chapter, we provide a broader discussion of the recommendations in the context of wholesale electricity market design. In particular, we focus on how these recommendations influence our modeling in the rest of this dissertation.

4.1 Need to Allow for Active Participation of Load in Wholesale Electricity Markets

Traditionally, electricity loads are considered to be inelastic and do not actively participate in wholesale electricity markets. This lack of load flexibility often results in large volatility in wholesale electricity prices and made it easier for generators to exercise market power [45]. In recent years, the use of demand response programs has become increasingly popular in the United States. These demand response programs are typically interruptible load programs where consumers agree to reduce their energy use when requested by the system operator during certain system conditions.

In the future electricity grid, load is expected to be more elastic both in the short-term and in the long-term. In short-term operation, the use of technologies such as smart metering, smart appliances, and electric vehicles could provide consumers with the ability to more actively respond to electricity prices. In long-term planning, load serving entities can invest in distributed generations or energy-efficiency programs to gain more control over their energy needs. Furthermore, should any of the proposed transactive retail markets be implemented, load serving entities will have more information and ability to provide flexibility in the wholesale markets.

With these changes in the future, we believe that load should be allowed to provide flexible bids into the electricity markets. Therefore, in the rest of this dissertation, we model double-sided markets where loads are allowed to actively participate in both forward and spot wholesale markets.

4.2 Need to Co-model Operational Decisions and Investment Planning

As demonstrated and discussed in the earlier chapters, there is a gap between investment planning and operational practices in the electricity industry. Investment planning is often done for the worst case scenarios. For instance, generation capacity planning is done to meet peak load and transmission planning is done to meet N-2 reliability. The issue with worst case planning strategies is that they often result in highly conservative investment decisions that do not account for the value of flexibility.

With the availability of new technologies, the future electricity grid is likely to be more flexible. In addition to the demand flexibility discussed in the previous section, additional grid flexibility can be introduced via smart transmission and distribution technologies. Advanced control, communication, and sensing infrastructures can also be used to provide system operators with more flexibility to quickly respond to changing grid conditions. With the increasing flexibility, it becomes increasingly important for investors and system planners to take into account operational flexibility in making investment decisions. This dissertation attempts to bridge the gap between operational decisions and investment planning by co-modeling operational and investment decision-making.

4.3 Need to Design Forward Energy Markets for Better Resource Adequacy and Risk Sharing

One area of wholesale market design that has received significant attention in recent years is the design of long-term markets for generation resource adequacy. There are several ways in which different regions have attempted to tackle the resource adequacy problem, but there is no clear consensus as to what is the best method to ensure long-term resource adequacy. In this section, we will discuss some of these strategies and describe the strategy proposed in this dissertation.

In some areas, long-term resource adequacy is managed through long-term bilateral contracts between generators and load serving entities. The key issue with using bilateral contracts is that the details of such contracts are often private, and hence information that might be useful for the long-term planning of other stakeholders are not made public. For example, in ERCOT, 90% of generation is contracted for ahead of the spot market but the contract details are not provided to the "public, regulators, and ERCOT's market monitor" [46]. Given that there are often strong substitutionary effects among generation and transmission investment options, the lack of availability of contract details makes it very difficult to make efficient investment decisions.

In northeastern United States, forward capacity markets are used to ensure long-term resource adequacy. The way forward capacity markets work is that the system operators dictate how much capacity each load serving entity is required to purchase in the forward market based on its forecast of future peak load. The effectiveness and efficiency of forward capacity markets as a tool for resource adequacy is a topic of debate [47][48]. One of the key criticisms of this strategy is that the capacity requirements are determined based on "worst case" scenarios (e.g. peak load), and hence do not fully account for the potential of operational flexibility.

In some other regions, long-term resource adequacy is tackled using forward energy-only markets. These forward energy markets can come in different forms. In Columbia, the forward energy market uses physical contracts where generators are required to physically deliver the amount of energy contracted [49]. In Nordpool, the forward energy market uses financial contracts where no physical delivery of energy is involved [50]. Whether such energy-only forward markets are able to ensure long-term resource adequacy is still an open question.

In this dissertation, we propose the use of long-term markets for energy (e.g. 5 years ahead) with mandated participation of load and/or generators. Load serving entities should be required to procure their long-term forecasted electricity demand that should be within a certain range of the actual realized demand. For example, load serving entities could be required to procure sufficient generation 5 year ahead such that the actual required demand falls within plus or minus 15% of the procured demand. In order to encourage load serving entities to provide as accurate a forecast as possible, the load serving entities would be penalized if the demand falls outside the plus or minus 15% range. The rationale behind this penalty is that the load serving entities should be penalized for the underinvestment or overinvestment that occurs due to vastly inaccurate forecasts. A similar regulation should be put in place for generators, where generators are required to contract out a certain percentage of their generation via long-term contracts and be penalized for not meeting those needs. A preliminary framework showing the information exchange for the long-term market is shown in Figure 4.1, where $\lambda_{forward}$ is the forward price of electricity and π is the future marginal penalty that the generation or load serving entities will face if the contracted quantity in the forward market is vastly different from the spot. For example, the penalty to be paid by the load serving entity when real time market has cleared is given by the following equation:

$$\pi \max(|P_{d,forward} - P_{d,spot}| - \epsilon, 0) \tag{4.1}$$

where $P_{d,forward}$ is the contracted long-term demand, $P_{d,spot}$is the actual realized demand during the spot market, and ϵ is the forecast error tolerance (e.g. 15% of $P_{d,forward}$). The load serving entity will only be penalized if the forecast is off by a certain tolerance level.

The benefit of such a system is that it provides bounds to the uncertainty that investment planners face in making investment decision. Information regarding the bounds on uncertainty

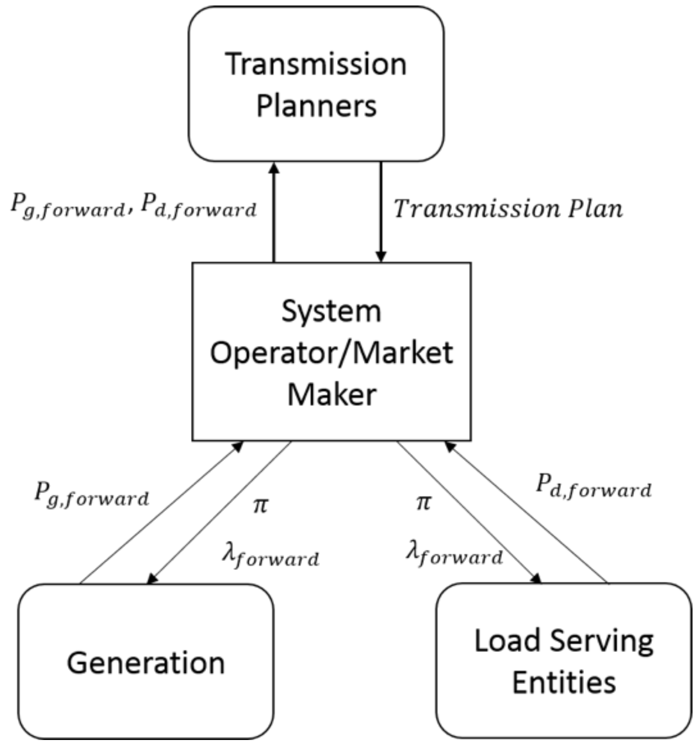

Figure 4.1: Preliminary framework of Information Exchange for Long-Term Market

and on how much customers are willing to pay for demand can allow investment planners to make more efficient and flexible investment decision. In addition, the cost of underinvestment or over-investment is shared by the stakeholders. The framework described above is a preliminary proposal and more work needs to be done to provide a more detailed evaluation of different market designs for long-term markets in the electricity sector.

In the rest of this dissertation, we pay particular attention to the design of forward energy markets. In particular, we test the long-term energy market with mandated participation proposed in this section.

4.4 Develop Robust Modeling Tools to Manage Complexity

As mentioned frequently throughout the previous chapters, the future electricity grid is likely to have a greater diversity of technologies. A result of this greater diversity is that power system operation and planning models will get increasingly complex. In addition to capturing the complexity brought about by the new technologies, market models for the future electricity grid need to capture the temporal and spatial complexity of the electricity industry. We need to develop tools to allow us to model multi-timescales markets with stakeholders operating at different levels of aggregation and with different level of technological sophistication.

In recent years, various tools have been developed to capture some of these complexity in electricity markets. Some of the major tools developed include the AMES wholesale power market testbed and the Electricity Market Complex Adaptive System (EMCAS) software. The AMES testbed is an open source software developed at Iowa State University [51]. This testbed focuses on the modeling of the FERC Standard Market Design. The EMCAS software is a commercial software developed by Argonne National Laboratory [52]. This software captures various aspects needed to model current electricity market design, including the handling of multi-timescales markets. However, with its current feature set, it still does not provide the features required to capture all the complexity of future electricity markets.

Even though there are tools being developed to better model electricity markets, these tools are still limited in scope and do not truly provide sufficient modeling flexibility to capture the complexity of the future electricity grid. In the rest of this dissertation, we contribute to the development of robust modeling tools for market design of the future electricity grid.

Part II

Temporal and Spatial Decomposition for Electricity Market Design

Chapter 5

Mathematical Decomposition for Power System Operation and Planning

In Part I of this dissertation, we focused our study on impediments towards flexibility in the transmission sector. However, many of the policy recommendations made are not transmission specific, but involve changing the way the overall power system markets and operations are designed. In this part of the dissertation, we broaden our focus and extend Model 1 in Part I of the dissertation to include flexible generation and demand. Instead of limiting our case studies to simple test system, in this part of the dissertation, we use mathematical decomposition to directly deal with both the institutional and computational complexity of the power system operation and planning problem.

The overall goal of this part of the dissertation is to demonstrate how mathematical decomposition can be used to not only manage the computational complexity of the power system operation and planning problem, but also to guide market design for distributed decision-making. We demonstrate the use of Non-Convex Generalized Benders Decomposition and Lagrangean Decomposition to temporally and spatially decompose a power system operation and investment problem with flexible transmission, generation, and demand devices that is posed as a non-convex Mixed Integer Non-Linear Programming(MINLP) problem. In our case study, we demonstrate how the temporally decomposed problem can be solved faster than the original problem, even when the original problem is solved using state of the art commercial MINLP solver. In addition, a significant focus of the case study is to demonstrate how mathematical decomposition techniques can be used to gain economic insights that can guide electricity market design. In the first half of this chapter, we provide an overview of the theory behind Benders decomposition and Lagrangean decomposition and discuss the various economic interpretation of the different decomposition strategies. In the second half, we combine the two decomposition techniques to temporally and spatially decompose a power system operation and investment problem.

This part of the dissertation is based on a working paper [53].

5.1 Mathematical Decomposition and Its Economic Interpretation

Optimization decomposition algorithms have traditionally been used as a way to handle large-scale optimization problem. With advances in the field of computing, increasingly complex decomposition algorithm has been developed and implemented in recent years to handle larger and more complicated optimization problems. Most of these newer decomposition strategies are extensions of the three major traditional decomposition methods: Dantzig-Wolfe Decomposition [54], Benders Decomposition [55], and Lagrangean Decomposition [56]. The appropriate decomposition algorithm to use depends on the structure of the problem. All of these decomposition strategy has been used in various work to improve the computational efficiency of different aspects of the power system planning problem [57–59], but few has highlighted the economic interpretation of the decomposition. Therefore, in the remaining of this section, we provide a brief overview of the key decomposition strategies used in this paper (i.e. Benders Decomposition and Lagrangean Decomposition) and a discussion of the economic interpretation and market insights that can be gained through mathematical decomposition.

5.1.1 Generalized Benders Decomposition

Generalized Benders Decomposition (GBD) is particularly appropriate for problems with complicating variables[1] in the form of [55]:

$$\min_{x,y} f(x,y) \ \text{ s.t. } \ G(x,y) \leq 0 \ \ x \in X \ y \in Y \tag{5.1}$$

where y is the complicating variable(s) and the problem is such that when y is fixed, the problem becomes a much easier optimization problem. Many non-linear programming and mixed-integer programming problems can be written in the form above. An extensive exposition of GBD can be found in [55]. For the purpose of this paper, we will focus on the case where:

$$\min_{x,y} \quad f_x(x) + f_y(y) \tag{5.2}$$

$$\text{s.t.} \quad G(x,y) \leq 0 \ \ G_x(x) \leq 0 \ \ G_y(y) \leq 0 \tag{5.3}$$

$$x \in X \ y \in Y \tag{5.4}$$

In the context of the power system operation and planning problem, these complicating variables (y) are typically investment capacity variables (including generation, transmission and responsive load capacity), while the non-complicating variables (x) are the operational variables. Therefore, $f_y(y)$ and $f_x(x)$ are the investment cost and operational cost of the system respectively and $G_y(y)$, $G_x(x)$, and $G(x,y)$ represent the investment constraints, operation constraints, and coupling constraints respectively.

The fundamental idea behind GBD is that the master problem provides the lower bound of the original objective function while the subproblems provide the upper bound [60]. The algorithm ends when the upper bound and lower bound converge to within a certain tolerance limit. A cutting plane approach is used to solve the master problem, where constraints ('cuts') are iteratively added to bound the feasible set or objective function of the original problem based on the results of the

[1]It is often possible to convert problems with complicating variables to problems with complicating constraints by adding new variables. However, for certain problem types this conversion might require the introduction of too many new variables, which makes the decomposition inefficient

subproblem(s). Theoretically, the master problem is the projection of the problem from the full variable space, onto the y space[2]. In our context, the master problem is the investment master problem:

$$\min_{y} \quad f_y(y) + F_{Op} \tag{5.5}$$

$$\text{s.t.} \quad G_y(y) \leq 0 \tag{5.6}$$

$$w(y^{\star,j}) + \lambda^{j}_{InFea}(y - y^{\star,j}) \leq 0 \;\; \forall\, j \in I \tag{5.7}$$

$$f_x(y^{\star,h}) + \lambda^{h}_{Opt}(y - y^{\star,h}) \leq F_{Op} \;\; \forall\, h \in V \tag{5.8}$$

$$y \in Y \tag{5.9}$$

where F_{Op} is the master problem estimation of the operational cost of the system($f_x(x)$). In (5.7), I is the set of Feasibility Benders Cut where each cut represents the first order approximation of the objective function (i.e. $w(.)$) of a feasibility check that was found to be infeasible, $y^{\star,j}$ represents the investment variables obtained from feasibility check j, and λ^{j}_{InFea} is the vector of dual variables obtained from feasibility check j. Similarly, in (5.8), V is the set of Optimality Benders Cut where each cut represents the first order approximation of the objective function (i.e. $f_x(.)$) of one iteration of the operational subproblem, $y^{\star,h}$ represents the investment variables obtained from solving the h-th iteration of the operational subproblem, and λ^{h}_{Opt} is the vector of dual variables obtained from solving the h-th iteration of the operational subproblem. The feasibility check and operational subproblem will be defined next.

The feasibility check is used to ensure that there exists a feasible solution to the operational subproblem for the current investment decision discovered by the master problem. The feasibility check in this case can be written as:

$$w = \min_{x,e} \quad 1^T e \tag{5.10}$$

$$\text{s.t.} \quad e \geq 0 \tag{5.11}$$

[2]see [61] for a more theoretical exposition of the decomposition strategy

$$G_x(x) \leq 0 \tag{5.12}$$

$$G(x, y^\star) \leq e \tag{5.13}$$

$$x \in X \tag{5.14}$$

where e is the vector of slack variables used to relax the coupling constraints and $y^\star$ is the investment decision discovered by the master problem in the latest iteration. If any of the slack variables are greater than zero, the operation subproblem is infeasible and a feasibility Benders Cut is added to the master problem as shown in (5.7). If the operational subproblem is shown to be feasible, we continue to solve the actual subproblem, which can be written as:

$$\min_{x} \quad f_x(x) \tag{5.15}$$

$$\text{s.t.} \quad G_x(x) \leq 0 \tag{5.16}$$

$$G(x, y^\star) \leq 0 \tag{5.17}$$

$$x \in X \tag{5.18}$$

An optimality Benders Cut is added to the master problem as shown in (5.8) each time the operational subproblem is solved. In the context of power system operation and planning, the operation subproblem can typically be decomposed into a series of individual optimal power flow problems. This will be demonstrated later in this part of the dissertation.

Various extensions of GBD has been developed to improve the implementability and performance of GBD for problems with different characteristics (i.e. binary variables, non-convexities etc.). For this paper in particular, an extension of the GBD for non-convex MINLP presented in [62] is used to handle the non-convexity of the power system planning and operation problem used. This will be discussed further in Section 5.2.

5.1.2 Lagrangean Decomposition

Unlike GBD, Lagrangean Decomposition is suitable for problems with complicating constraints. In the context of power system operation and planning, these arise from system level constraints such as power balances in the system. Therefore, Lagrangean Decomposition is commonly used to spatially or functionally decompose power system problems (e.g. [16, 63]). Lagrangean Decomposition is a special case of Lagrangean Relaxation where instead of directly relaxing the complicating constraints, we assign each complicating constraint to one of the subproblems, duplicate the 'outside' variable that appears in the complicating constraint, and add the new complicating constraint equating the duplicated variables to the objective function using the penalty method[56]. This will be demonstrated in the simple example below:

$$\min_{a,b,\hat{s}} \quad f_a(a) + f_b(b) + f_s(\hat{s}) \tag{5.19}$$

$$\text{s.t} \quad G_a(a) \leq 0 \tag{5.20}$$

$$G_b(b) \leq 0 \tag{5.21}$$

$$G_s(a, b, \hat{s}) \leq 0 \tag{5.22}$$

$$a \in A, b \in B, \hat{s} \in \hat{S} \tag{5.23}$$

where a and b are the decision variables for zone A and zone B respectively, while $\hat{s}$ contains the system-wide variables (i.e. zone A + B) . Similarly, (5.20), (5.21) and (5.22) are the zone A constraints, zone B constraints, and system-wide constraints respectively. Now, we assume that there is a system operator that can be tasked with maintaining the system variables and constraints (e.g the Independent System Operator). In this case, we 'assign' the system constraints to the system operator and double the non-system variables that appear in the system constraints. The new overall problem becomes:

$$\begin{aligned} \min_{a,b,\hat{s},a_s,b_s} \quad & f_a(a) + f_b(b) + f_s(\hat{s}) + \lambda_a(a_s - a) \\ & +\lambda_b(b_s - b) \end{aligned} \tag{5.24}$$

$$\text{s.t} \quad G_a(a) \leq 0 \tag{5.25}$$

$$G_b(b) \leq 0 \tag{5.26}$$

$$G_s(a_s, b_s, \hat{s}) \leq 0 \tag{5.27}$$

$$a \in A, b \in B, \hat{s} \in \hat{S} \tag{5.28}$$

where a_s and a_b are duplicated variables of a and b. Typically, not all the variables in a and b will be duplicated, as only those that appear in the complicating constraints will need to be duplicated. The constraints maintaining equality between the duplicated variables are added to the objective function with penalty terms (λ_a and λ_b). The new overall problem can then be easily decomposed into three subproblems. First, the system operator subproblem is:

$$\min_{a_s, b_s, \hat{s}} \quad f_s(\hat{s}) + \lambda_a(a_s) + \lambda_b(b_s) \tag{5.29}$$

$$\text{s.t} \quad G_s(a_s, b_s, \hat{s}) \leq 0 \tag{5.30}$$

$$a_s \in A, b_s \in B, \hat{s} \in \hat{S} \tag{5.31}$$

The subproblem for zone A is:

$$\min_{a} \quad f_a(a) - \lambda_a(a) \tag{5.32}$$

$$\text{s.t} \quad G_a(a) \leq 0 \;\; a \in A \tag{5.33}$$

The subproblem for zone B is:

$$\min_{b} \quad f_b(b) - \lambda_b(b) \tag{5.34}$$

$$\text{s.t} \quad G_b(b) \leq 0 \;\; b \in B \tag{5.35}$$

The subproblems above can be solved iteratively where the multiplier λ_a and λ_b are updated at each iteration using a multiplier update method such as the sub-gradient method [64] or the cutting-plane method [65]. The sub-gradient method of multiplier update used in this dissertation is shown below:

$$\lambda^{k+1} = \lambda^k + \alpha_k(x_a^k - x_b^k) \tag{5.36}$$

where λ^k is the multiplier at the k^{th} iteration, x_a and x_b are the duplicated variables that we want to equalize, and α_k is the k^{th} step size. Prices are adjusted until the constraints maintaining the equality between the duplicated variables are fulfilled.

5.1.3 Economic Interpretation of Decomposition

The role of mathematical decomposition in system design has received increasing notice in recent years. From network architecture [64] to auction design [66], mathematical decomposition can be used to provide insights into how a complex system or problem can be distributed over multiple decision makers.

Benders Decomposition is suitable for vertical decomposition of industry/market structure. In terms of power systems, examples of vertical decomposition include decomposing the power system operation and planning problem into an investment subproblem and an operational subproblems, and separating the power system operation problem into independent unit commitment and economic dispatch problems. In addition, Benders Decomposition provides additional information about the interactions among variables via the cutting planes (i.e. the optimality and feasibility cuts), that could guide pricing decision in an auction/market setting. These interactions have significant implications in an investment setting due to the complementaries or substitution effects of different investment options being considered. Cutting planes reduce the feasible region of the solution which translate to constraining investment options based on information obtained through previous round results. In combinatorial auctions, the dual variable associated with a cut is associated with the opportunity cost of accepting a bid over the others [67]. This interpretation of Benders Cuts will be demonstrated further in the next chapter.

Lagrangean Decomposition has a particularly interesting market interpretation, with strong links to double-sided auction theory. It is frequently likened to a tatonnement procedure [68][69], a price discovery mechanism where prices are iteratively adjusted until supply and demand of a product is balanced. Using the earlier Lagrangean Decomposition example, a_s and b_s can be interpreted as the system's demand for a certain resource, while a and b can be interpreted to be the supply of the resource by zone A and zone B. The prices are adjusted until supply is equal to demand(i.e. $a_s = a$ and $b_s = b$).

Besides the convenient pricing mechanism, Lagrangean Decomposition also provides a framework to explore different potential market structures for distributed decision-making. The flexibility in assigning variables and constraints to different subproblems allows us to create different market structures with different exchanges of information and different services/resources being priced. Unlike Benders Decomposition, Lagrangean Decomposition is suitable for horizontal decomposition of industry/market structure, where the same function is distributed across multiple parties. In terms of power systems, such horizontal decomposition includes distributing power system operation decisions across individual nodes or power system investment decisions across multiple stakeholders. Nested Lagrangean Decomposition can also be used to design more complicated, hierarchical market structures (e.g. a three-tier market structure with nodal exchange, zonal exchange, and system-wide exchange). Furthermore, combining Lagrangean Decomposition with other mathematical decomposition techniques, such as Benders Decomposition, could potentially lead to richer market interpretations.

A demonstration of such economic interpretations on a temporally and spatially decomposed power system investment and operation problem will be presented in the next chapter.

5.2 Power System Investment Problem with Flexible Transmission, Generation and Demand Devices

In this section, we introduce the power system investment problem with possible investments in wind generation, new transmission lines, flexible reactance devices for existing transmission lines (e.g Thyristor Controlled Series Compensator), and responsive load capacity. Two possible decompositions of this problem is also presented. First, the full problem formulation will be given.

The objective function is to maximize social welfare accounting for load utility, operational cost, and investment cost. Writing it in standard form, the maximization problem becomes the following minimization problem:

$$\min_{X^{y}_{invt}, X^{s,y}_{Op}} \quad \sum_{y=1}^{Y} e^{-ry} \Bigg\{ \sum_{s=1}^{S} Pr(s) \Big[\sum_{g=1}^{N_G} c_g(P^{s,y}_{G,g}) \tag{5.37}$$

$$- \sum_{d=1}^{N_D} \Big(U_d(P^{s,y}_{D,d}) - c_{loss,d}(P^{s,y}_{loss,d}) \Big) \Big] \tag{5.38}$$

$$+ \sum_{\hat{l}=1}^{N_{\hat{L}}} c_{invt,\hat{l}}(b^{y}_{line,\hat{l}}) + \sum_{f=1}^{N_L} c_{invt,f}(K^{y}_{Flex,f}) \tag{5.39}$$

$$+ \sum_{g=1}^{N_G} c_{invt,g}(K^{y}_{G,g}) + \sum_{d=1}^{N_D} c_{invt,d}(K^{y}_{D,d}) \Bigg\} \tag{5.40}$$

where X^{y}_{invt} and $X^{s,y}_{Op}$ are the set of investment and operational decision variables respectively. $P_{G,g}$,$P_{D,d}$ and $P_{loss,d}$ represent the power generation, supplied demand, and unmet demand respectively. $b_{line,\hat{l}}$, $K_{Flex,l}$, $K_{G,g}$, and $K_{D,d}$ are the binary variable indicating whether a line is built, new flexible reactance capacity, new generation capacity, and new responsive demand capacity respectively. r is the interest rate. Y is the total number of investment time period, while S is the total number of scenario in each time period. $Pr(s)$ is the total number of times scenario s occurs in an investment time period. N_G, N_D, $N_{\hat{L}}$,N_L are the number of generators, number of loads, number of potential new lines, and number of existing lines respectively. c_g, U_d and $c_{loss,d}$ are the generation cost, demand utility, and cost of loss load respectively, while $c_{invt,\hat{l}}$, $c_{invt,f}$, $c_{invt,g}$ and $c_{invt,d}$ are the annualized new line investment cost, flexible reactance investment cost, generator investment cost and responsive load capacity investment cost respectively.

For this problem, the operational aspect of the problem is captured using a DC power flow. Therefore, the system level constraints in this problem include the nodal power balance equations and the power flow equations. The nodal power balance constraints can be written as:

$$\boldsymbol{G P^{s,y}_{G}} + \boldsymbol{S f^{s,y}_{line}} - \boldsymbol{D P^{s,y}_{D,d}} + \boldsymbol{D P^{s,y}_{loss,d}} = 0 \quad \forall\, s, y \tag{5.41}$$

where the bolded variables indicate matrices/vectors. $\boldsymbol{G}$ and $\boldsymbol{D}$ are 0-1 matrices mapping the vectors of generation and demand variables to the nodes. $\boldsymbol{S}$ is a matrix that is +1 for transmission lines ending at the node and -1 for transmission lines starting at the node. $\boldsymbol{f_{line}}$, $\boldsymbol{P_G}$, $\boldsymbol{P_{D,d}}$, and $\boldsymbol{P_{loss,d}}$ are vectors of transmission line flows, power generation, power demand supplied, and unmet demand respectively.

The power flow equations are written as:

$$f_{line,l}^{t,y} = \frac{\theta_{l,to}^{s,y} - \theta_{l,from}^{s,y}}{x_l - x_{Flex,l}^{s,y}} \quad \forall\, l, s, y \tag{5.42}$$

$$-M(1 - b_{line,\hat{l}}^{y-d_{\hat{l}}}) \leq f_{line,\hat{l}}^{s,y} - \frac{\theta_{\hat{l},to}^{s,y} - \theta_{\hat{l},from}^{s,y}}{x_{\hat{l}}} \leq M(1 - b_{line,\hat{l}}^{y-d_{\hat{l}}}) \qquad \forall\, \hat{l}, s, y > d_{\hat{l}} \tag{5.43}$$

where $\theta_{l,to}$ and $\theta_{l,from}$ are the nodal angle at the ending and starting nodes of the transmission line respectively. $f_{line,l}$ is the line flow for line l. x_l is the reactance of the transmission line and $x_{Flex,l}^{s,y}$ is the flexible reactance setting of the line. $d_{\hat{l}}$ is the construction delay of the new line, and the rest are as defined earlier. The power flow constraints for new lines are written as big-M constraints (where M is a large constant), such that the constraint for each line is only enforced if the line is built.

The generator constraints are written as follows:

$$P_{G,g}^{min} \leq P_{G,g}^{s,y} \leq P_{G,g}^{max} + \gamma_w^{s,y} K_{G,g}^{y} \quad \forall\, g, s, y \tag{5.44}$$

$$K_{G,g}^{y-1} \leq K_{G,g}^{y} \leq K_{G,max,g} \quad \forall\, g, y > 1 \tag{5.45}$$

$$0 \leq K_{G,g}^{y} \leq K_{G,max,g} \quad \forall\, g, y = 0 \tag{5.46}$$

where γ_w is a parameter that captures the level of wind power available at any period of time if the generator is a wind generator. γ_w is any value between 0 and 1 for wind generators, and 1 otherwise. $P_{G,g}^{min}$, $P_{G,g}^{max}$, and $K_{G,max,g}$ are the minimum generation, maximum generation, and maximum investment in generation capacity for generator g respectively. Constraint (5.44) is the operational constraint of the generators, while constraints (5.45) and (5.46) are investment constraints of the generators.

The load constraints are as follows:

$$P_{D,d}^{inelas,s,y} - K_{D,d}^{y} - P_{loss,d}^{t,y} \leq P_{D,d}^{s,y} \leq P_{D,d}^{max,s,y} \, \forall \, d, s, y \tag{5.47}$$

$$K_{D,d}^{y-1} \leq K_{D,d}^{y} \leq K_{D,max,d} \, \forall \quad d, y > 1 \tag{5.48}$$

$$0 \leq K_{D,d}^{y} \leq K_{D,max,d} \, \forall \quad d, y = 0 \tag{5.49}$$

where $P_{D,d}^{max}$ is the maximum load demanded at the given time period, $P_{D,d}^{inelas}$ is the inelastic load demanded at the given time period, $K_{D,max,d}$ is the maximum investment in responsive load capacity, and the rest are as defined earlier. Constraint (5.47) is the operational constraint of the loads, while constraints (5.48) and (5.49) are investment constraints for the responsive loads.

The line constraints are:

$$-K_{line,l} \leq f_{line,l}^{s,y} \leq K_{line,l} \quad \forall \, l, s, y \tag{5.50}$$

$$-K_{line,\hat{l}} b_{line,\hat{l}}^{y-d_{\hat{l}}} \leq f_{line,\hat{l}}^{s,y} \leq K_{line,l} b_{line,\hat{l}}^{y-d_{\hat{l}}} \quad \forall \, \hat{l}, s, y > d_{\hat{l}} \tag{5.51}$$

$$f_{line,\hat{l}}^{s,y} = 0 \quad \forall \, \hat{l}, s, y \leq d_{\hat{l}} \tag{5.52}$$

$$b_{line,\hat{l}}^{y-1} \leq b_{line,\hat{l}}^{y} \quad \forall \, \hat{l}, y > 1 \tag{5.53}$$

$$0 \leq b_{line,\hat{l}}^{y} \quad \forall \, \hat{l}, y = 0 \tag{5.54}$$

$$b_{line,\hat{l}}^{y} \in \{0, 1\} \quad \forall \, \hat{l}, y \tag{5.55}$$

where $K_{line,l}$ is the line flow capacity and the rest or the variables are as defined earlier. (5.50) is the operational line flow constraint for existing lines, while (5.51) and (5.52) are the operational line flow constraints for new potential lines. (5.53), (5.54) and (5.55) are the investment constraints for new potential lines.

Last but not least, the flexible reactance constraints are:

$$0 \leq x_{Flex,l}^{s,y} \leq K_{Flex,l}^{y} \forall \, l, s, y \tag{5.56}$$

$$K_{Flex,l}^{y-1} \leq K_{Flex,l}^{y} \leq 0.5x_l \forall\, l, y > 1 \tag{5.57}$$

$$0 \leq K_{Flex,l}^{y} \leq 0.5x_l \forall\, l, y = 0 \tag{5.58}$$

where (5.56) is the operational flexible reactance constraint and (5.57) and (5.58) are the flexible reactance investment constraints.

5.2.1 Temporal Decomposition

The first decomposition strategy we implemented is to decompose the full problem formulation above temporally to separate the investment problem from the operational problem. Since the problem above is non-convex, we applied the Non-Convex GBD algorithm presented in [62] to this problem. The key difference between the Non-Convex GBD and the traditional GBD is that in Non-Convex GBD the GBD iteration is applied to a convex estimation of the original problem (i.e. the Lower Bounding Problem (LBP)) instead of the original problem. GBD applied to the LBP provides a series of valid investment decisions and lower bounds to the original problem, which is then used to construct the primal subproblems (PP) to find valid upper bounds to the original problem[62].

Convex Relaxation to Obtain Lower Bounding Problem(LBP)

In the problem described above, the non-convex constraint is constraint (5.42). By rearranging the constraint, we observe that the constraint is a bilinear equation:

$$f_{line,l}^{s,y} x_l - f_{line,l}^{s,y} x_{Flex,l}^{s,y} = \theta_{l,to}^{s,y} - \theta_{l,from}^{s,y} \tag{5.59}$$

In order to convert the non-convex bilinear equation to a convex equation, we replace the bilinear function with its McCormick relaxation. Let $v_l^{s,y} = f_{line,l}^{s,y} x_{Flex,l}^{s,y}$, the concave and convex envelopes for the bilinear constraint are as follows:

$$v_l^{s,y} \geq K_{line,l} x_{Flex,l}^{s,y} + K_{Flex,l}^{y} f_{line,l}^{s,y} - K_{Flex,l}^{y} K_{line,l} \tag{5.60a}$$

$$v_l^{s,y} \geq -K_{line,l}x_{Flex,l}^{s,y} \tag{5.60b}$$

$$v_l^{s,y} \leq -K_{line,l}x_{Flex,l}^{s,y} + K_{Flex,l}^{y}f_{line,l}^{s,y} + K_{Flex,l}^{y}K_{line,l} \tag{5.60c}$$

$$v_l^{s,y} \leq K_{line,l}x_{Flex,l}^{s,y} \tag{5.60d}$$

The equations above are linear constraints when the investment variables are held fixed. The LBP can then be obtained by replacing constraint (5.42) in the original full problem with equations (5.60a - 5.60d) and the equation below:

$$f_{line,l}^{s,y}x_l - v_l^{s,y} = \theta_{l,to}^{s,y} - \theta_{l,from}^{s,y} \tag{5.61}$$

Master Problem Formulation(MP)

The LBP is now a mixed-integer linear program. The MP of the LBP can be written as follows:

$$\begin{aligned} \min_{X_{invt}^{y},\nu} \; & \sum_{y=1}^{Y} e^{-ry}\Bigg[\sum_{\hat{l}=1}^{N_{\hat{L}}} c_{invt,\hat{l}}(b_{line,\hat{l}}^{y}) + \sum_{f=1}^{N_L} c_{invt,f}(K_{Flex,f}^{y}) \\ & + \sum_{g=1}^{N_G} c_{invt,g}(K_{G,g}^{y}) + \sum_{d=1}^{N_D} c_{invt,d}(K_{D,d}^{y})\Bigg] + \nu \qquad (5.62) \\ \text{s.t.} \quad & (5.45), (5.46), (5.48), (5.49), (5.53) - (5.55), (5.57), (5.58) \\ & w(X_{Invt}^{\star,j}) + \lambda_{InFea}^{j}(X_{Invt} - X_{Invt}^{\star,j}) \leq 0 \;\; \forall\, j \in I \qquad (5.63) \\ & f_x(X_{Invt}^{\star,h}) + \lambda_{Opt}^{h}(X_{Invt} - X_{Invt}^{\star,h}) \leq \nu \;\; \forall\, h \in V \qquad (5.64) \end{aligned}$$

where ν is the master problem estimation of the operational cost and (5.63) and (5.64) are the infeasibility cuts and optimality cuts as in (5.7) and (5.8). If there are no changes in master problem solutions between iteration, the master problem can be forced to generate new integer realization by adding the following constraint to the problem above:

$$\sum_{\hat{l},y\in\{\hat{l}:b^{y,i}_{line,\hat{l}}=1\}} b^{y,i}_{line,\hat{l}} - \sum_{\hat{l},y\in\{\hat{l}:b^{y,i}_{line,\hat{l}}=0\}} b^{y,i}_{line,\hat{l}} \leq |\{\hat{l} : b^{y,i}_{line,\hat{l}} = 1\}| - 1 \ \ \forall i \in I \cup V$$

Primal Bounding Problem (PBP)

The PBP is obtained by fixing the investment variables in the LBP. The resulting problem is:

$$\min_{X^{s,y}_{Op}} \quad \sum_{y=1}^{Y} e^{-ry} \sum_{s=1}^{S} Pr(s)\Big[\sum_{g=1}^{N_G} c_g(P^{s,y}_{G,g}) - \sum_{d=1}^{N_D} \Big(U_d(P^{s,y}_{D,d}) - c_{loss,d}(P^{s,y}_{loss,d})\Big)\Big] \tag{5.65}$$

$$\text{s.t.} \quad (5.41), (5.43), (5.44), (5.47), (5.50) - (5.52), (5.56), (5.60a) - (5.60d) \tag{5.66}$$

Note that the problem above naturally decomposes into $S \times Y$ number of operational subproblems ($PBP_{s,y}$) for each time period (s, y), $s \in S, y \in Y$. The results of the individual operational subproblems are combined[3] and used to derive the optimality cuts, which is the first order approximation of the operational objective function with respect to the investment variables.

Feasibility Problem(FeaP)

The feasibility problem is similar to the PBP except that slack variables are added to all the inequality constraints and the objective function is to minimize the sum of slack variables(see (5.5)). In this case, we run the feasibility problem only if any of the PBP subproblem is infeasible. Similar to PBP, FeaP can be decomposed into $S \times Y$ number of feasibility subproblems ($FeaP_{s,y}$). The results of the feasibility subproblems are used to derive the feasibility cuts.

[3] In this case, it takes a simple summation of objective function values and Lagrange multipliers for the individual operational subproblems to form the optimality cuts

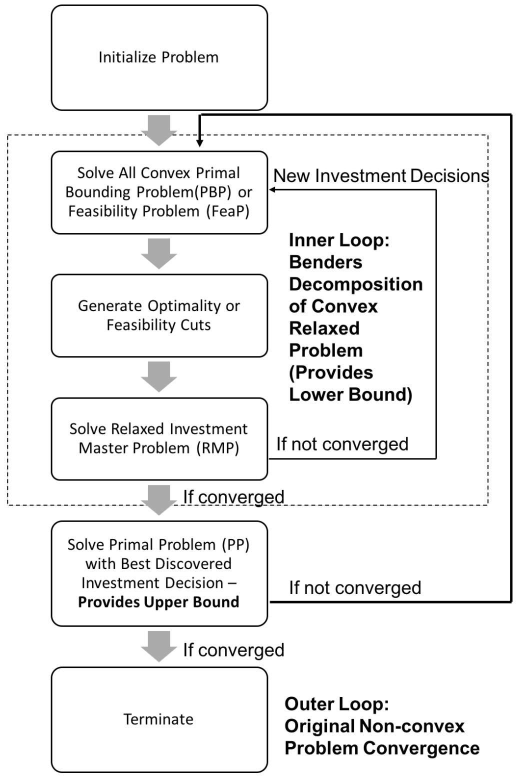

Figure 5.1: Overview of Algorithm Flow for Temporally Decomposed Problem

Primal Problem(PP)

The PP is just the original full problem with the investment variables fixed (i.e. the non-convex version of the PBP).

$$\min_{X_{Op}^{s,y}} \quad \sum_{y=1}^{Y} e^{-ry} \sum_{s=1}^{S} Pr(s) \Big[\sum_{g=1}^{N_G} c_g(P_{G,g}^{s,y}) - \sum_{d=1}^{N_D} \Big(U_d(P_{D,d}^{s,y}) - c_{loss,d}(P_{loss,d}^{s,y}) \Big) \Big] \tag{5.67}$$

$$\text{s.t.} \quad (5.41) - (5.44), (5.47), (5.50) - (5.52), (5.56) \tag{5.68}$$

As with the PBP and FeaP, the problem above naturally decomposes into $S \times Y$ number of operational subproblems($PP_{s,y}$) for each time period $(s, y), s \in S, y \in Y$.

The complete Non-Convex GBD Algorithm is presented in Algorithm 1[4] located at the end of this chapter and a diagrammatic overview of the algorithmic flow for this temporally decomposed

[4]This is a simplified version of the algorithm presented in [62] that has been modified to fit our needs

problem is shown in Fig. 5.1.

5.2.2 Spatial and Temporal Decomposition

In this section the temporal decomposition above is extended further by applying Augmented Lagrangean Decomposition, also known as the Method of Multipliers. Augmented Lagrangean Decomposition is an extension of the basic Lagrangean Decomposition approach described earlier (See [70] for an extensive discussion of this algorithm). The main difference between Augmented Lagrangean Decomposition and the Lagrangean Decomposition approach described earlier is the addition of a quadratic term to the objective function, which makes the objective function strictly convex. Applying Augmented Lagragean Decomposition to the earlier example in Section 5.1, the objective function (5.24) will become:

$$\begin{aligned}\min_{a,b,\hat{s},a_s,b_s} & f_a(a) + f_b(b) + f_s(\hat{s}) + \lambda_a(a_s - a) + \lambda_b(b_s - b) \\ & + \frac{\gamma}{2} \parallel a_s - a \parallel^2 + \frac{\gamma}{2} \parallel b_s - b \parallel^2 \end{aligned} \tag{5.69}$$

where γ is a parameter that can be adjusted to encourage convergence. The new objective function above is no longer separable due to the quadratic term. However, there are various strategies that have been developed to deal with this non-separability [70]. The method we adopt in this part of the dissertation is the alternating direction method. In this method, the quadratic term is duplicated and the subproblems are solved sequentially by fixing the external variables. Going back to the example in Section 5.1, the objective functions of the subproblems will now be:

Subproblem for System Operator:

$$\begin{aligned}\min_{\hat{s},a_s,b_s} & f_s(\hat{s}) + \lambda_a(a_s) + \lambda_b(b_s) \\ & + \frac{\gamma}{2} \parallel a_s - a^k \parallel^2 + \frac{\gamma}{2} \parallel b_s - b^k \parallel^2 \end{aligned} \tag{5.70}$$

Subproblem for zone A:

$$\min_{a} f_a(a) - \lambda_a(a) + \frac{\gamma}{2} \parallel a_s^{k+1} - a \parallel^2 \tag{5.71}$$

Subproblem for zone B:

$$\min_{b} f_b(b) - \lambda_b(b) + \frac{\gamma}{2} \parallel b_s^{k+1} - b \parallel^2 \tag{5.72}$$

where the superscripts $k/k+1$ indicate fixed variables. The constraints remain the same as those shown in Section 5.1. Using the alternating direction method, we alternate between solving the system operator problem and solving the zonal subproblems. At each iteration k, we fix the external variables to the solution obtained from the previous iteration of the external subproblem(s).

The decomposition approach just described is used to spatially decompose the temporally decomposed problem shown in Section 5.2.1. Augmented Lagrangean Decomposition is used to separate each node's problem.

Spatial Decomposition of Operational Problem

First, we decompose the operational problem $PBP_{s,y}$. In order to simplify the decomposition, we introduce a new variable type, which represents the net nodal import:

$$\boldsymbol{E_p^{s,y}} = \boldsymbol{DP_{D,d}^{s,y}} - \boldsymbol{DP_{loss,d}^{s,y}} - \boldsymbol{GP_G^{s,y}} \quad \forall\, s, y \tag{5.73}$$

where $\mathbf{E_p^{s,y}}$ is a $p \times 1$ vector of nodal import where $p \in P$, P is the number of nodes in the system. We add constraint (5.73) to the operational problem and rewrite the system balance constraint (5.41) with the new variable. $PBP_{s,y}$ becomes:

$$\begin{aligned} \min_{X_{Op}^{s,y}} \quad & e^{-ry} Pr(s) \Big[\sum_{g=1}^{N_G} c_g(P_{G,g}^{s,y}) - \sum_{d=1}^{N_D} \Big(U_d(P_{D,d}^{s,y}) - c_{loss,d}(P_{loss,d}^{s,y}) \Big) \Big] && (5.74) \\ \text{s.t.} \quad & (5.43), (5.44), (5.47), (5.50) - (5.52), (5.56)(5.60a) - (5.60d), (5.73) \end{aligned}$$

$$\boldsymbol{Sf_{line}^{s,y}} - \boldsymbol{E_p^{s,y}} = 0 \quad \forall\, s, y \tag{5.75}$$

where (5.75) is the new nodal power balance equation. Now, the nodal export becomes our coupling variable and hence we double the variable and rewrite the objective function of the problem in the Augmented Lagrangean form (the constraints stay the same):

$$\begin{aligned} \min_{X_{Op}^{s,y}} \quad & e^{-ry} Pr(s) \Big[\sum_{g=1}^{N_G} c_g(P_{G,g}^{s,y}) - \sum_{d=1}^{N_D} \Big(U_d(P_{D,d}^{s,y}) - c_{loss,d}(P_{loss,d}^{s,y}) \Big) \Big] \\ & + \sum_{p=1}^{P} \Big[\lambda_p(\hat{E}_p^{s,y} - E_p^{s,y}) + \frac{\gamma}{2} \parallel \hat{E}_p^{s,y} - E_p^{s,y} \parallel^2 \Big] \end{aligned} \tag{5.76}$$

where $\hat{E}_p^{s,y}$ is the duplicated variable. Now, we decompose the problem into a system level subproblem and nodal level subproblems for each node. The system level problem is in charge of system level variables such as line flow, flexible reactance settings, and nodal angles, whereas the individual nodes are in charge of nodal level variables such as generation and demand. The system level problem (PBP_{sys}) can be written as:

$$\min_{X_{Op,Sys}^{s,y}} \quad \sum_{p=1}^{P} \Big[\lambda_p(\hat{E}_p^{s,y}) + \frac{\gamma}{2} \parallel \hat{E}_p^{s,y} - E_p^{s,y,k} \parallel^2 \Big] \tag{5.77}$$

$$\text{s.t.} \quad (5.43), (5.50) - (5.52), (5.56), (5.60a) - (5.60d), (5.75)$$

where $X_{Op,Sys}$ represents only the system level operational variables. The individual node subproblem (PBP_p) can be written as:

$$\begin{aligned} \min_{X_{Op,p}^{s,y}} \quad & e^{-ry} Pr(s) \Big[\sum_{g=1}^{N_{G,p}} c_g(P_{G,g}^{s,y}) - \sum_{d=1}^{N_{D,p}} \Big(U_d(P_{D,d}^{s,y}) - c_{loss,d}(P_{loss,d}^{s,y}) \Big) \Big] \\ & - \lambda_p(E_p^{s,y}) + \frac{\gamma}{2} \parallel \hat{E}_p^{s,y,k+1} - E_p^{s,y} \parallel^2 \end{aligned} \tag{5.78}$$

$$\text{s.t.} \quad (5.44), (5.47), (5.73)$$

where $X_{Op,p}$ represents only the variables in node p. $N_{G,p}$ and $N_{D,p}$ are the number of generators and number of loads in node p respectively. Note that the constraint set only contains the corresponding constraints for generators and loads in node p.

The decompositions strategy for $PP_{s,y}$ is identical to the process above. The only difference is that constraints (5.60a) - (5.60d) are replaced with (5.42).

Spatial Decomposition of Investment Problem

Next, we decompose the investment master problem (MP) In this case, the complicating variables are the generation and responsive load capacity investment decision variables. We duplicate the generation and responsive load capacity investment decision variables and rewrite the objective function of the MP in Augmented Lagrangean form:

$$\begin{aligned}\min_{X^y_{invt},\nu} \sum_{y=1}^{Y} e^{-ry}\Big\{ & \sum_{\hat{l}=1}^{N_{\hat{L}}} c_{invt,\hat{l}}(b^y_{line,\hat{l}}) + \sum_{f=1}^{N_L} c_{invt,f}(K^y_{Flex,f}) \\ & + \sum_{g=1}^{N_G} \Big[c_{invt,g}(K^y_{G,g}) + \lambda_{G,g}(\hat{K}^y_{G,g} - K^y_{G,g}) \\ & + \frac{\gamma}{2} \parallel \hat{K}^y_{G,g} - K^y_{G_g} \parallel^2 \Big] \\ & + \sum_{d=1}^{N_D} \Big[c_{invt,d}(K^y_{D,d}) + \lambda_{D,d}(\hat{K}^y_{D,d} - K^y_{D,d}) \\ & + \frac{\gamma}{2} \parallel \hat{K}^y_{D,d} - K^y_{D_d} \parallel^2 \Big] \Big\} + \nu \end{aligned} \tag{5.79}$$

where $\hat{K}^y_{G,g}$ and $\hat{K}^y_{D,d}$ are the replicated generation and responsive demand capacity investment variable respectively. Similar to the operational problem, we decompose the investment problem into a system level subproblem and nodal level subproblems for each node. The system level problem is in charge of transmission related investment variables, whereas the individual node subproblems are in charge of their own nodal generation and demand investments. The system level problem (MP_{sys}) becomes:

$$\min_{X^y_{invt,s},\nu} \sum_{y=1}^{Y} e^{-ry}\Big\{ \sum_{\hat{l}=1}^{N_{\hat{L}}} c_{invt,\hat{l}}(b^y_{line,\hat{l}}) + \sum_{f=1}^{N_L} c_{invt,f}(K^y_{Flex,f})$$
$$+ \sum_{g=1}^{N_G} \Big[\lambda_{G,g}(\hat{K}^y_{G,g}) + \frac{\gamma}{2} \parallel \hat{K}^y_{G,g} - K^{y,k}_{G_g} \parallel^2 \Big]$$
$$+ \sum_{d=1}^{N_D} \Big[\lambda_{D,d}(\hat{K}^y_{D,d}) + \frac{\gamma}{2} \parallel \hat{K}^y_{D,d} - K^{y,k}_{D_d} \parallel^2 \Big]\Big\} + \nu \tag{5.80}$$
$$\text{s.t.} \quad (5.53) - (5.55), (5.57), (5.58)$$

$$w(X^{\star,j}_{Invt,s}) + \lambda^j_{InFea}(X_{Invt,s} - X^{\star,j}_{Invt,s}) \leq 0 \ \ \forall\, j \in I \tag{5.81}$$

$$f_x(X^{\star,h}_{Invt,s}) + \lambda^h_{Opt}(X_{Invt,s} - X^{\star,h}_{Invt,s}) \leq \nu \ \ \forall\, h \in V \tag{5.82}$$

where $X_{Invt,s}$ is the system level investment variables. The individual node investment subproblems (MP_p) can be written as:

$$\min_{X^y_{invt,p},\nu} \sum_{y=1}^{Y} e^{-ry}\Big\{ \sum_{g=1}^{N_{G,p}} \Big[c_{invt,g}(K^y_{G,g}) - \lambda_{G,g}(K^y_{G,g})$$
$$+ \frac{\gamma}{2} \parallel \hat{K}^{y,k+1}_{G,g} - K^y_{G_g} \parallel^2 \Big]$$
$$+ \sum_{d=1}^{N_{D,p}} \Big[c_{invt,d}(K^y_{D,d}) - \lambda_{D,d}(K^y_{D,d})$$
$$+ \frac{\gamma}{2} \parallel \hat{K}^{y,k+1}_{D,d} - K^y_{D_d} \parallel^2 \Big]\Big\} + \nu \tag{5.83}$$
$$\text{s.t.} \quad (5.45), (5.46), (5.48), (5.49)$$

where $X_{Invt,p}$ represents the investment variables for node p. Once again, only the investment constraints for the investments in node p is included in the problem.

Price Update

The system operator is in charge of updating all the price signals λ in this problem. The updating equation for the price signals is written as:

$$\lambda^{k+1} = \lambda^k + \gamma(x^k - x_d^k) \tag{5.84}$$

where x_d is the duplicated version of coupling variable x and γ is the same γ as used for the quadratic terms in the Augmented Lagrangean version of the objective function. The choice of γ affects the speed of convergence. In this paper, we use a dynamic updating scheme for γ [71]:

$$\gamma^{k+1} = \begin{cases} \gamma^k \tau_{up} & \| r_k \|_2 > \ \mu \| q_k \|_2 \\ \frac{\gamma^k}{\tau_{down}} & \mu \| r_k \|_2 < \| q_k \|_2 \\ \gamma^k & \text{otherwise} \end{cases} \tag{5.85}$$

where $\tau_{up} > 1$, $\tau_{down} > 1$, and $\mu > 1$ are parameters that sets the rate of change of γ, and r_k and q_k are defined as follows:

$$r_k = x^k - x_d^k \tag{5.86}$$

$$q_k = \gamma(x_d^k - x_d^{k-1}) \tag{5.87}$$

In order to speed up convergence, the γ for each coupling variable is allowed to evolve independently according to the updating scheme above. In addition, for every 10 continuous iterations in which there are no change in any of the γ, we reset all γ to:

$$\gamma^{k+1} = (N_{jump})\gamma^0 \tag{5.88}$$

where γ^0 is the initial value of γ and N_{jump} is the number of times in which there are no changes in any of the γ for 10 continuous iterations. This heuristic was found to speed up convergence

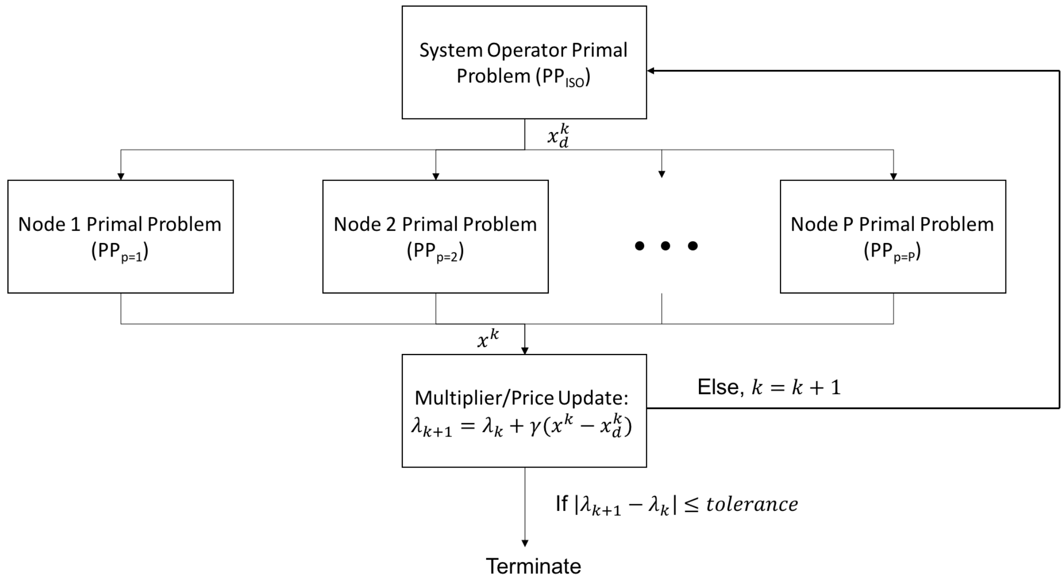

Figure 5.2: Algorithmic Flow for Spatially Decomposed Primal Problem

significantly for certain cases and will be discussed further in the next chapter.

The algorithmic flow for this problem, is very similar to the algorithmic flow for the temporally decomposed problem shown in Fig. 5.1. The main difference is that each of the operational (PBP,PP) and investment subproblems (RMP) are now broken down spatially into nodal subproblems. As an example, Fig. 5.2 illustrates the new algorithmic flow of the primal problem.

Algorithm 1 Algorithm for Non-Convex GBD

Initialize Iteration Counters: $m \leftarrow 0$ $n \leftarrow 1$
Initialize Index Sets: $I^0 = V^0 = U^0 \leftarrow \emptyset$
Initialize Upper Bound: $UB \leftarrow +\infty$
Initialize Bounds on LBP: $UBLBP \leftarrow +\infty$
$LBLBP \leftarrow -\infty$
Set Tolerances $\epsilon_{s,y}$ and ϵ
Initialize X^1_{Invt} and Investment Cost (i.e. Investment only portion of MP's objective function) C^1_{Invt}
repeat
  if $m = 0$ or (MP is feasible and LBLBP $<$ UBLBP and LBLBP $<$ UB $- \epsilon|$LBLBP$|$) **then**
    repeat
      $m \leftarrow m + 1$
      Solve $PBP_{s,y}$ for all $(s, y), s \in S, y \in Y$ with $X_{Invt} = X^m_{Invt}$
      if All $PBP_{s,y}$ are feasible **then**
        Add Optimality Cuts to MP
        $I^m \leftarrow I^{m-1} \cup m$
        if $\sum_{s,y} obj_{PBP_{s,y}} + C^m_{Invt} <$ UBLBP **then**
          UBLBP $\leftarrow \sum_{s,y} obj_{PBP_{s,y}} + C^m_{Invt}$
          $X^\star_{Invt} \leftarrow X^m_{Invt}$ and $m^\star = m$
        end if
      else
        $V^m \leftarrow V^{m-1} \cup m$
        Solve $FeaP_{s,y}$ for all $(s, y), s \in S, y \in Y$
        Add Feasibility Cuts to MP
      end if
      Solve MP
      if MP is feasible **then**
        Set X^{m+1}_{Invt} to the new investment variables
        LBLBP $\leftarrow obj_{MP}$
        $C^{m+1}_{Invt} \leftarrow obj_{MP} - \nu$, where ν is MP's estimation of operational cost
      end if
    until LBLBP $\geq$ UBLBP or MP is infeasible
  end if
  if UBLBP $<$ UB $- \epsilon|$UBLBP$|$ **then**
    Solve $PP_{s,y}$ for all $(s, y), s \in S, y \in Y$ with $X_{Invt} = X^\star_{Invt}$
    $U^m \leftarrow U^{m-1} \cup m^\star$
    if All $PP_{s,y}$ feasible with optimum value $X^\star_{Op}$ and $\sum_{s,y} obj_{PP_{s,y}} <$ UB **then**
      UB $\leftarrow \sum_{s,y} obj_{PP_{s,y}}$
      $X^{op}_{Invt} \leftarrow X^\star_{Invt}$, $X^{op}_{Op} \leftarrow X^\star_{Op}$
    end if
    if $I^m \backslash U^n \neq \emptyset$ **then**
      UBLBP $\leftarrow +\infty$
    else
      Select $i \in R^m \backslash U^n$ where $obj_{PBP}(X^i_{Invt})$ is the smallest
      $X^\star_{Invt} \leftarrow X^i_{Invt}$, UBLBP $\leftarrow obj_{PBP}(X^i_{Invt})$
      $m^\star \leftarrow i, n \leftarrow n + 1$
    end if
  end if
until UBLBP $\geq$ UB $- \epsilon|$UBLBP$|$ and (MP is infeasible or LBLBP $\geq$ UB $- \epsilon|$LBLBP$|$)

Chapter 6

Case Study

In this chapter, we demonstrate the use of the decomposition schemes developed in the previous chapter on a 24-bus test system. First, we simulate the algorithms above to demonstrate that the decomposed problems converge to the ϵ-optimal solution and provide significant computational benefits in the temporally decomposed case. Next, we analyze the decomposed algorithms to generate insights that could guide market design.

6.1 Algorithmic Test on 24-Bus Test System

First, the decomposed algorithms are tested on a modified version of the 24-Bus IEEE Reliability Test System used in [72]. The branch data, generation data, load data, and cost functions for the test system are shown in Appendix 2. The test system is divided into two wind and load region as shown in Fig. 6.1. Historical hourly wind and load data from PJM for years 2012 to 2015 were used to obtain wind and load patterns for this paper [73]. Region A uses wind and load data from the PJM Mid-Atlantic region, whereas Region B uses wind and load data from the PJM West region. As with the previous part of this dissertation, K-means clustering was applied to the historical wind and load data to produce S number of scenarios of correlated wind and load level. The results of the K-mean clustering algorithm is S number of scenarios with correlated wind and load levels given as percentages. The percentages tells us how much of the maximum capacity of

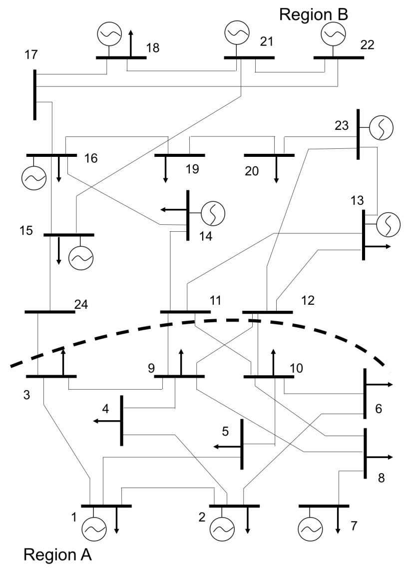

Figure 6.1: 24-Bus Test System

wind or load is generated or demanded in a given region for a given scenario $s \in S$.

We simulate 3 investment cycles (i.e. $Y = 3$), where each investment time period is 4 years apart, and use an interest rate r of 10%. Therefore, we adjust the discount function used in the problem from e^{-ry} to $e^{-4r(y-1)}$ to account for the 4 year cycle. The following happens over the 3 investment cycles:

- 300MW generator at node 22 and 350MW generator at node 23 retire in cycle 1.
- 155MW generator at node 16 and 310MW generator at node 23 retire in cycle 2.
- Maximum load increases by 5% each investment cycle, which causes the linear term of the load utility function to increase by 5% each cycle as well.

The potential investment options considered are:

- As much as 2000MW of wind generation nameplate capacity at nodes 2, 7, 17, 22 and 23 at an annualized cost of $220k/MW
- Up to 20% of the maximum load at each node can be converted to responsive load at an annual cost of $500,000/MW. Note that a significant portion of the load is already price-

Table 6.1: Potential New Line Addition

	From	To	Reactance (p.u.)	Capacity (MW)	Investment Cost (M$/MW-year)
1	1	2	0.0139	100	0.7
2	1	5	0.0845	100	4.3
3	2	4	0.1267	100	6.4
4	7	8	0.0614	100	3.1
5	8	9	0.1651	100	8.4
6	8	10	0.1651	100	8.4
7	16	17	0.0259	250	1.3
8	21	22	0.0678	250	3.4
9	15	21	0.0490	250	2.5
10	16	19	0.0231	250	1.2
11	17	22	0.1053	250	5.3
12	12	23	0.0966	250	4.9
13	13	23	0.0865	250	4.4

Table 6.2: Potential Flexible Reactance Addition

	From	To	Flexible Capacity (p.u.)	Investment Cost (M$/p.u.-year)
1	15	21	0.0245	20
2	15	24	0.0260	20.8
3	16	17	0.0130	10.4
4	16	19	0.0116	9.6
5	17	18	0.0072	5.6
6	17	22	0.0527	42.4

sensitive in the problem setup. The differences between minimum and maximum loads given in Table 6.7 gives us the loads that are already elastic.

- 13 potential new lines as shown in Table 6.1
- 6 potential flexible reactance devices on existing lines as shown in Table 6.2.

The updating parameters used for the Lagrangean Decomposition are as follows:

- $\tau_{up} = \tau_{down} = 2$
- $\gamma = \mu = 5$ for operational problems
- $\gamma = \mu = 100$ for investment problems.

The original full problem was solved with BARON [74], a leading commercial MINLP solver, using CPLEX as its linear programming solver. The decomposed problems were solved with CPLEX [75] as the linear solver, GUROBI [76] as the mixed integer linear program solver, and BARON as the non-linear programming solver. We used an absolute tolerance of 0.2% for all optimization problems and all simulations were done on an Intel Core i7-4790 CPU at 3.6GHz with 16 GB RAM.

6.1.1 Computational Efficiency of Temporally-Decomposed Problem

As mentioned earlier, one of the basic purposes of mathematical decomposition is to improve the computational efficiency of the problem. In terms of computational efficiency, there is a trade-off between communication overhead and distributed processing. In our case, we find that the temporally decomposed problem is significantly more computationally efficient as compared to solving the original non-decomposed problem using BARON. However, the temporally and spatially decomposed problem is significantly slower, due to the high number of iterations needed for convergence of the spatially decomposed problem. For the purpose of market design, computational efficiency is not a direct concern, however, the number of iterations required for convergence provides some information about the ease or difficulty of price discovery.

Fig. 6.2 shows the computational time required for the original problem versus the temporally decomposed problem for different number of scenarios plotted on a logarithmic scale. From the graph, we can see that the computational time for the original problem grows exponentially with increasing problem size while the computational time for the temporally decomposed problem grows linearly with increasing problem size. This indicates that the temporally decomposed problem is significantly more computationally efficient and scalable as compared to the original problem.

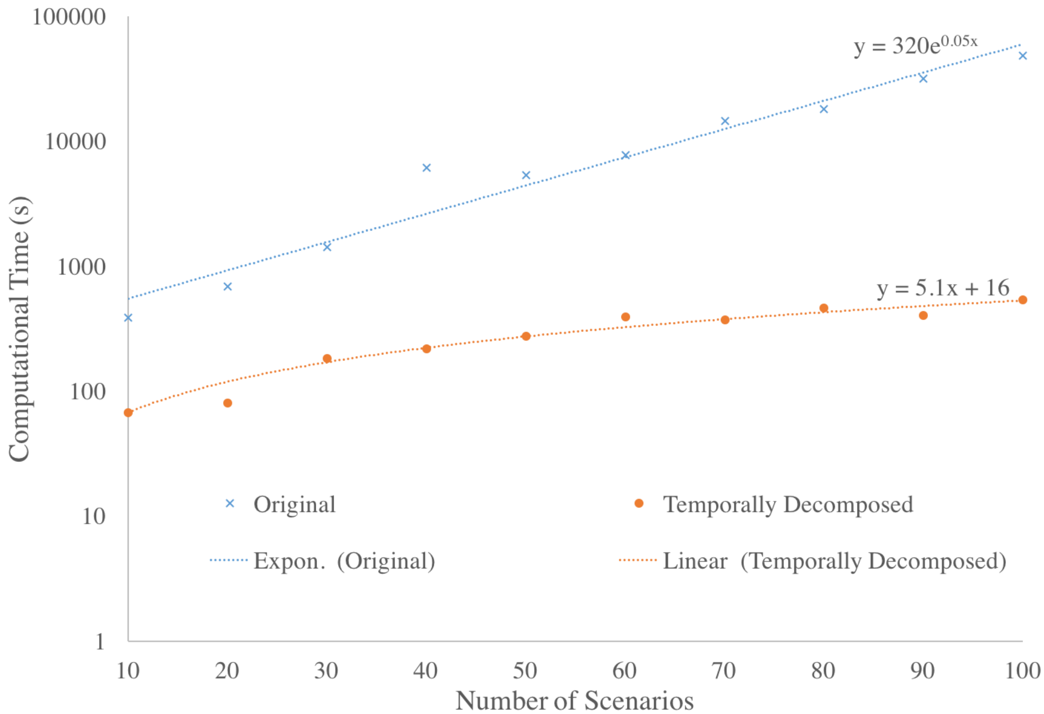

Figure 6.2: Comparison of Computational Time Required for Original Problem versus Temporally Decomposed Problem(Logarithmic Scale)

Table 6.3: Comparison of Convergence Time, Lower Bound, and Upper Bound for Original Problem and Decomposed Problem with 50 Scenarios

	Original	Temporally Decomposed	Temporally and Spatially Decomposed
Time(s)	5363	262	96778
Lower Bound ($B)	-2.275	-2.275	-2.273
Upper Bound ($B)	-2.271	-2.270	-2.269

6.1.2 Comparison of Decomposed Problem Solution with Original Problem Solution

Next, we compare the solutions of the original problem, the temporally decomposed problem, and the temporally and spatially decomposed problem with 50 scenarios. The convergence time, lower bound, and upper bound for the different problems are shown in Table 6.3. From the table, we can observe that the lower bounds and upper bounds are very similar in all three cases, which suggests

Table 6.4: Comparison of Investment Decisions(FR denotes Flexible Reactance)

	Original	Temporal Decomposition	Temporal and Spatial Decomposition
Cycle 1 Investments			
FR 2	0.026	0.026	0.026
FR 3	0.002	-	0.01
FR 4	0.012	0.012	0.012
FR 5	-	-	0.007
Line 4	1	1	1
Line 9	1	1	1
Cycle 2 Investments			
Line 1	1	1	1
Gen Node 7	414	446	283
Flex Load Node 4	15	-	17
Cycle 3 Investments			
FR 1	0.025	0.025	0.025
FR 6	-	-	0.003
Line 7	-	1	-

that the problem converged to similar solutions. Fig. 6.3 and Fig. 6.4 show the convergence of the temporally decomposed problem and the temporally and spatially decomposed problem respectively. Note that there are only a small number of data points for UBP because the non-convex primal problem is only solved after the convex relaxed problem has converged. The implication of this is discussed later in the discussion on approximate pricing. Fig. 6.5 shows the stabilization of prices from the convergence of the spatially decomposed operational problem (PBP_{sys}, PBP_p)

The investment decisions found at convergence for the three different algorithms are shown in Table 6.4. We observe that there are small differences in investment decisions, even though the lower and upper bounds of the results for the three different algorithms are fairly similar. This is likely due to close substitutes in potential investment options. In the real world, there are likely to be other factors that could help investment planners decide between investments that are close substitutes. Such factors could include environmental impacts and ease of financing.

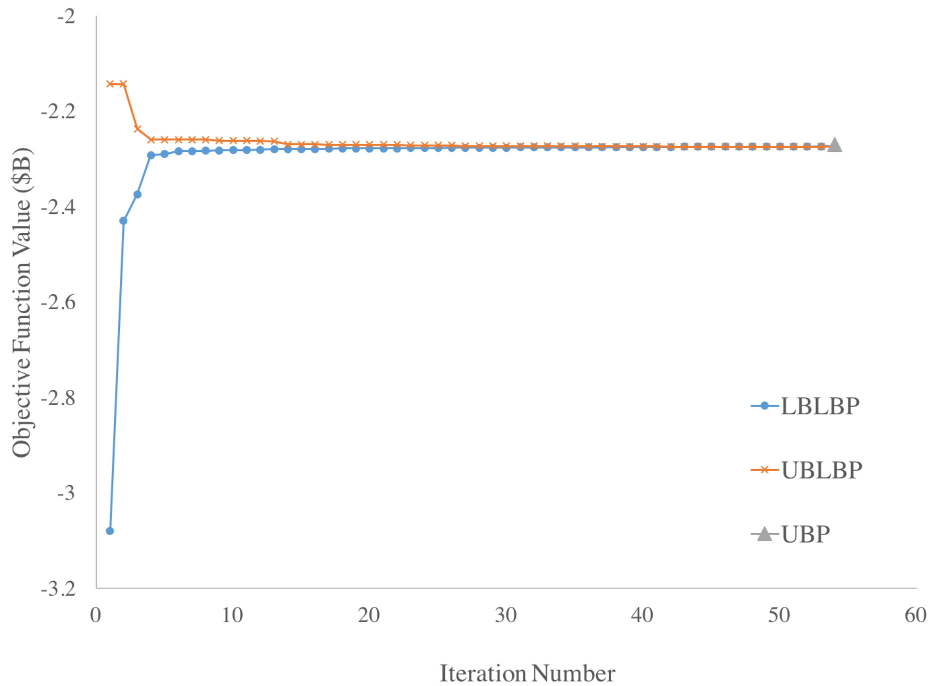

Figure 6.3: Convergence of Temporally Decomposed Problem with 50 Scenarios

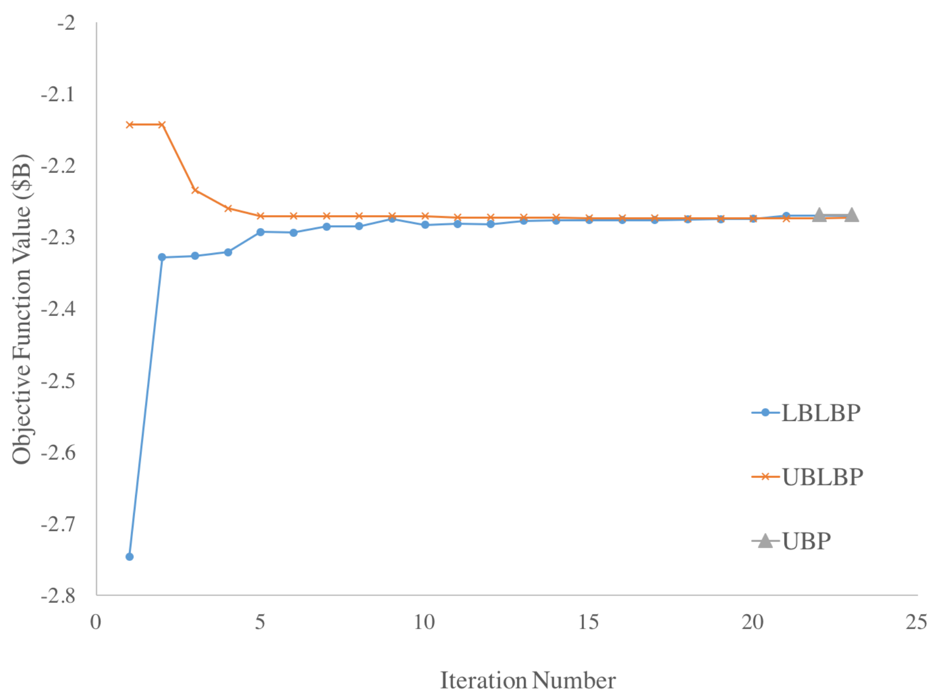

Figure 6.4: Comparison of Temporally and Spatially Decomposed Problem with 50 Scenarios

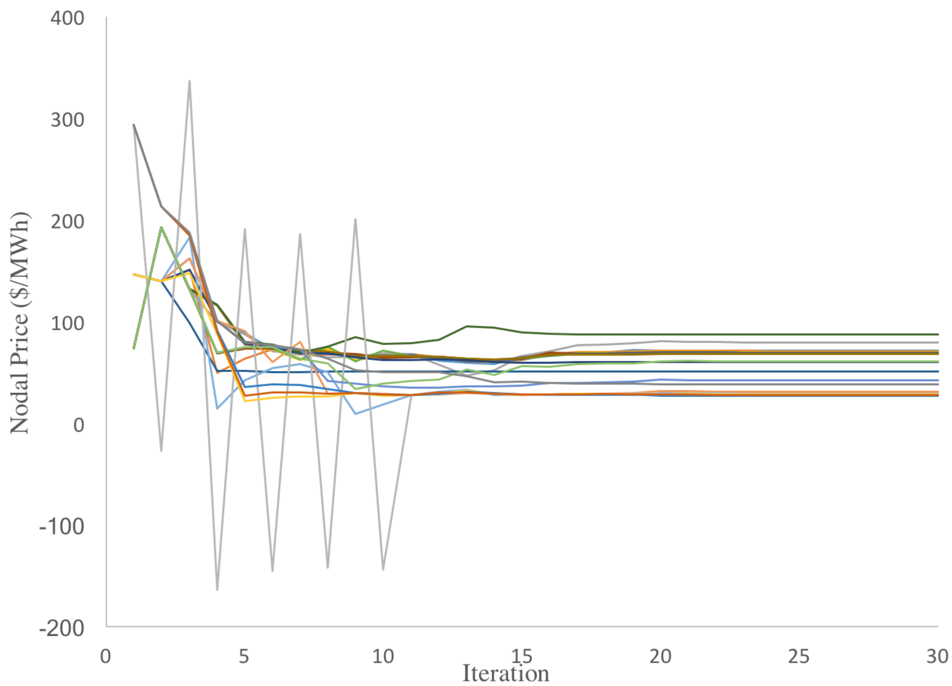

Figure 6.5: Example of Stabilization of Nodal Prices for One Scenario

6.1.3 Optimality

In the results above, we observe that the final lower and upper bounds of the objective function values for all three cases are very similar, which suggests that the decomposed algorithms were able to find the ϵ-optimal solution to the full problem. In [62], it was proven that if the Non-Convex GBD algorithm converges finitely with a feasible solution, the solution found is an ϵ-optimal solution to the original problem. In this dissertation, we did not attempt to mathematically prove that the spatially and temporally decomposed algorithm provides an ϵ-optimal solution. The proof of optimality is left for future work.

6.2 Market Insights

As mentioned before, a key focus of this paper is to demonstrate the economic and market insights that can be gained through mathematical decomposition. In this subsection, we will highlight some key insights that can be gained not only from the decomposition scheme presented, but also through the process of developing the decomposition strategy.

6.2.1 Market Structure

The market structure suggested by the temporally and spatially decomposed problem is a coordinated forward electricity market and investment auction as shown in Fig. 6.6. Based on the Benders Decomposition of the problem, capacity prices obtained from the operational problems are needed to provide the operational information required for investment decision making. Realistically, perfect information on operational details cannot be obtained ahead of time due to the real-time nature of electricity flow and demand. However, a well-designed forward electricity market should provide forward electricity prices that could provide some information to guide decision making during the investment auction. Even though these forward prices do not tell us everything about actual operational conditions, it provides a good indicator of what real-time prices could look like and provides an opportunity for investor to manage risk.

Due to the nature of electricity power flow and the lumpy nature of power system investments, any additional infrastructure in the power system could have a significant impact on electricity prices. Each additional power system investment can significantly alter power flow and optimal prices in the system such that forward prices determined prior to the investment are no longer accurate signals of real-time operating conditions. Therefore, as demonstrated by Benders Decomposition, there needs to be a feedback process between the forward energy market and investment planning, such that forward price signals account for investment decisions and vice versa. Note that the key difference between the market structure suggested here and the forward capacity markets being implemented by ISO-NE and PJM is that the market structure indicated here is a forward energy market and not a capacity market. More work needs to be done to better understand how this coordination between forward energy market and power system transmission and generation investment planning can be best achieved in actual power systems and whether they would perform better in the long run as compared to capacity markets.

The spatial decomposition used in this case allows us to delegate generation and demand operation and investment decisions to the nodes, assuming that appropriate price signals are given by the market coordinator/system operator. Depending on the market complexity desired, the problem can be decomposed into zones instead of nodes, with each zone consisting of multiple nodes. Furthermore, Lagrangean Decomposition can be use to further decompose the problem to introduce hierarchical market structures such as that shown in Fig 6.7, where the nodal problem is further decomposed into individual generation and demand problems coordinated by a nodal/zonal coordinator. An example of how the nodal problem can be decomposed into individual generator and demand sub-problems can be seen in [16].

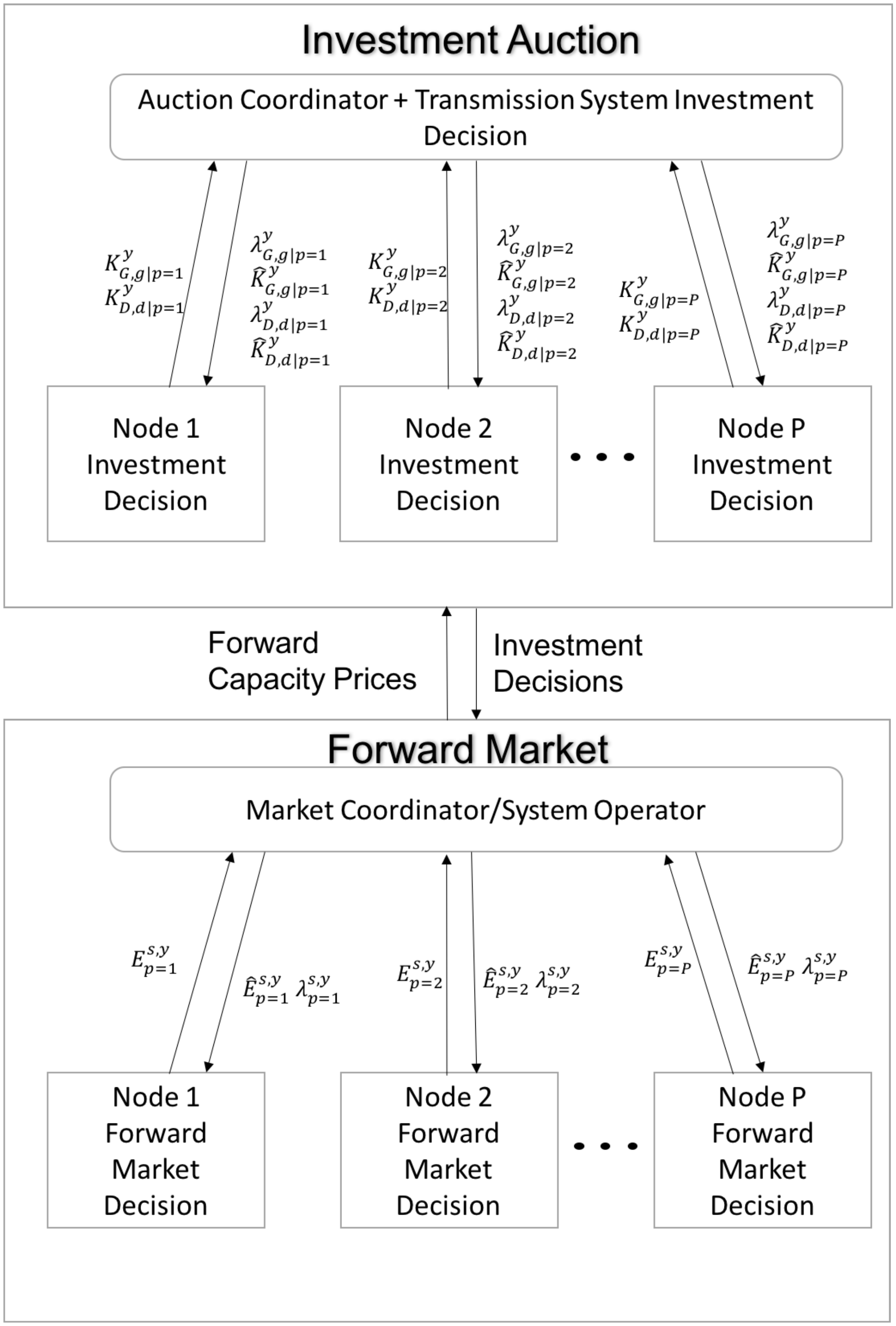

Figure 6.6: Market Structure Suggested By Temporally and Spatially Decomposed Problem

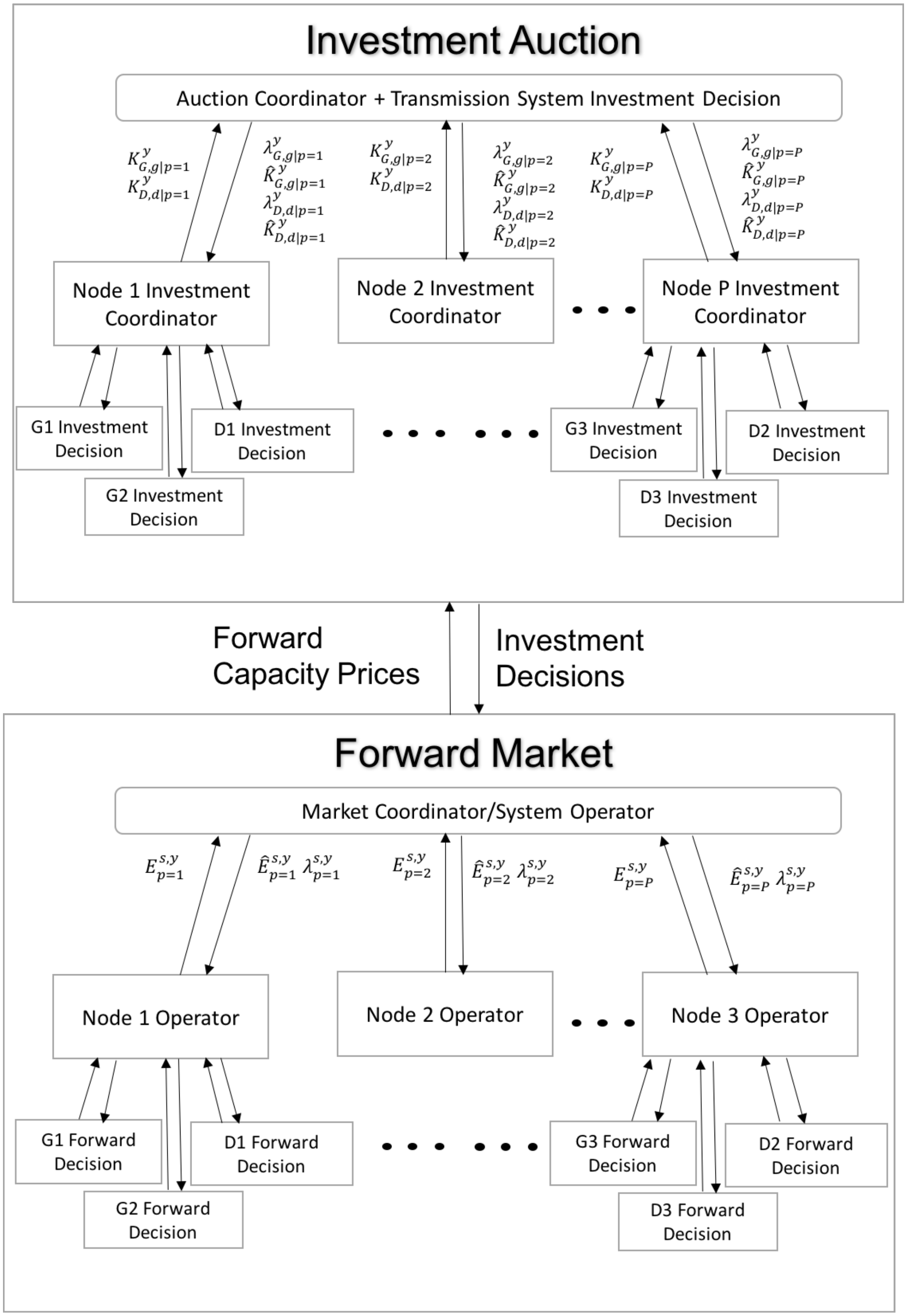

Figure 6.7: Extended Hierarchical Market Structure

6.2.2 Pricing and Externalities

The decomposition schemes presented give us some idea on potential pricing schemes and auction rules for the investment auction and forward market. Different decomposition and multiplier updates methods lead to different pricing strategies. The Augmented Lagrangean Decomposition scheme demonstrated in this chapter has two pricing components - the multiplier λ and the penalty parameter γ. The multiplier λ is the actual price signal that is updated based on the mismatch in demand and supply for the corresponding resource/services, while the penalty parameter γ provides market participants with an extra signal that represents the velocity of convergence. This information regarding the velocity of convergence, along with information regarding the mismatch in supply and demand, provides individual stakeholders with additional information to improve their bids in subsequent iterations. With current technological availability, the iterative approach towards price discovery and market clearing could be easily implemented for markets that do not have to clear in real-time, such as the forward market and investment auction discussed here. For real-time markets that needs to clear within seconds, the functional clearing approach such as that proposed in [16] could be used.

The set of Benders Cuts provides information regarding the substitution and complementary effects among investment options. The complex interactions among different investment options could be difficult to discern from the Benders Cut with continuous investment options. However, for transmission investments with binary investment options, the interpretation can be relatively straightforward. To illustrate this, consider two optimality Benders Cut obtained through the benders decomposition process with only two binary line investment options:

$$f_x(X^{\star,1}_{Invt,A}, X^{\star,1}_{Invt,B}) + \lambda^1_{Opt,A}(X_{Invt,A} - X^{\star,1}_{Invt,A}) + \lambda^1_{Opt,B}(X_{Invt,B} - X^{\star,1}_{Invt,B}) \leq F_{Op} \tag{6.1}$$

$$f_x(X^{\star,2}_{Invt,A}, X^{\star,2}_{Invt,B}) + \lambda^2_{Opt,A}(X_{Invt,A} - X^{\star,2}_{Invt,A}) + \lambda^2_{Opt,B}(X_{Invt,B} - X^{\star,2}_{Invt,B}) \leq F_{Op} \tag{6.2}$$

where (6.1) and (6.2) are the optimality cuts obtained from the first and second iteration of the Benders Decomposition, and $X_{Invt,A}$ and $X_{Invt,B}$ are binary variables for two line investment options. Now, assume that the parameters for the optimality cuts obtained from the first two iterations of the algorithm are as shown in Table 6.5.

Table 6.5: Parameters for Benders Cut Interpretation Illustrative Example

h	$X^{\star,h}_{Invt,A}$	$X^{\star,h}_{Invt,B}$	λ^h_A	λ^h_B
1	0	0	negative value	positive value
2	1	0	negative value	negative value

Keeping in mind that the goal of the investments is to minimize operation cost (F_{Op}), the negative multiplier value associated with Line A in (6.1) suggests that Line A is a beneficial investment option whereas the positive multiplier value associated with Line B suggests that Line B is not a beneficial investment option. However, in the second cut obtained when Line A is already built, the multiplier value associated with Line B becomes negative, which suggests that it is now beneficial to build Line B as well. Taken together, this set of benders cut suggests that Line A and Line B are complementary investments. More work needs to be done to better understand how such information could be helpful in enabling the formation of socially-beneficial cooperative investment alliances during investment auctions and also in helping system operators value complementary investments.

6.2.3 Approximate Pricing

In the Non-Convex GBD algorithm adopted in this chapter, a convex relaxation of the original non-convex problem is used as an approximate to the original problem and to speed up convergence. In the algorithm, the original non-convex version serves only as a check to the investment decisions obtained through solving the convex relaxation of the problem. This leads to the following question: As the power system become increasingly complex, what is the minimum level of complexity that needs to be modeled and considered in designing markets and pricing schemes. Non-convexities have traditionally been difficult to price. The information available for forward markets and investment markets that occur long before the actual real-time transaction are inherently highly uncertain and imperfect. In such situations, using an approximate, simpler model for market clearing might prove to be good enough. For multi-temporal markets, a series of increasingly complex system and market model could be used as we move from long-term planning to real-time operation. These series of markets should be designed to be consistent with each other, such that the prices obtained by the long-term market are a reasonable approximation of real-time market prices.

6.2.4 'Behind the Scene' Insights

Researchers generally only report results of successful decomposition attempts and the resulting insights. Unfortunately, some of the most important insights when using mathematical decomposition for market design are gained through the process of decomposition. 'Failed', behind-the-scene, decomposition attempts are typically not discussed even if they provide important insights into market design. Here, we discuss some of the insights that were gained during the process of decomposing this problem.

Firstly, it is easy to start the decomposition process with preconceived expectations of how the final decomposition should look like. Occasionally, the problem structure is such that the preconceived expectations can be met, however, in some situations, the preconceived expectations cannot be supported by the underlying mathematical structure of the problem. If one finds it hard to decompose a problem in a certain way using sound mathematical decomposition techniques, it could suggest that the complicating constraints or variables cannot be adequately captured using prices. For instance, we attempted to apply Lagrangean Relaxation to spatially decompose the operational problem such that network flow is managed in a distributed manner instead of through a system operator. This was proposed in [77] and successfully done in [78] where the DC power flow constraints were successfully handled in a distributed manner by the generations and loads subproblems, without the need for a system operator subproblem. However, in attempting to apply that to the problem in this part of the dissertation, we find that the additional complexity brought about by flexible reactance devices made it such that it is no longer simple or practical to distribute the power flow constraints. Therefore, we choose to have the power flow constraints managed by the system operator sub-problem instead. This suggests that it is difficult to design a market without a system operator or market coordinator managing the system level power flow constraints when there are flexible reactance devices in the system.

Next, introducing new variables to the optimization problem can simplify the decomposition and allow for different market structure. The introduction of new variables is particularly helpful in designing hierachical market structure. For instance, instead of decomposing the problem such that each generator and load has its own subproblem, we introduce a new variable representing the net nodal import and decompose the problem nodally. In doing so, we were able to simplify the decomposition of the problem and reduce the number of complicating variables that need to be coordinated on the overall system level. As suggested earlier in Fig. 6.7, the problem can be decomposed further into individual generator and load subproblems with a nodal coordinator, resulting in a hierachical market structure. With the future electric power system becoming increasing complex, a hierachical market structure is likely to be preferable to a single layered market structure, as it allows for localized complexity to be isolated such that the complexity of each level of the market is manageable.

Finally, the tuning of parameters for the decomposition algorithms could provide information about potential areas of concern in designing pricing schemes. In tuning the update velocity parameter (γ) for the operational sub-problem, it was discovered that a straightforward use of a fixed γ can be used under most normal operating scenarios. However, for scenarios that have insufficient generation resulting in unusually high nodal prices at some locations, careful tuning of the parameter γ is required to ensure that convergence occur within a reasonable number of iterations. The 'jump' in γ shown in (5.88) was found to greatly speed up convergence under such scenarios through our experimentations. This suggests that if such an iterative market clearing/auction process is to be implemented, special care needs to be taken to ensure that the price updating scheme works in both normal operating conditions and contingency situations.

6.3 Limitations of Mathematical Decomposition for Market Design

Even though mathematical decomposition can provide insights into market structure and pricing, there are some limitations that practitioners should be aware of. First, as mentioned earlier, one of the key benefits of using mathematical decomposition for market design is that the resulting distributed decision-making model is provably optimal under certain conditions. However, real world conditions deviate significantly from these conditions and are more complicated. Some aspects of the real world that were not captured in this work include gaming behaviors among agents, different risk preferences, and stochasticity.

Another limitation of using mathematical decomposition for market design is that the information exchange requirement of the market structure suggested by the decomposition process might not be easily implemented in the real world. There is a need to translate the insights generated from mathematical decomposition into more practical market designs that can actually be implemented. For example, to practically implement the market structure proposed in Fig. 6.6, we need to figure out how to actually achieve the coordination between investment and forward markets. Questions such as "what kind of contracts are needed" and "how frequently should forward market clearing occur" will need to be answered.

6.4 Conclusions

As the power system becomes increasingly complex, more sophisticated market structure and pricing strategy need to be developed to allow stakeholders to manage this complexity in a efficient and effective manner. In this part of the dissertation, we demonstrate how mathematical decomposition can be a tool not only to improve the computational efficiency of power system decision problems, but also to help provide insights that could guide market design. We show how a temporally decomposed power system investment and operation problem can be solved in a more computationally efficient manner as compared to the original full version of the problem. In addition, we demonstrate how spatial and temporal decomposition can be used to generate market insights that could guide future market design.

As discussed earlier, mathematical decomposition relies on various assumptions that are often not reflective of the real world. Therefore, it should not be used as the only tool to guide market design. Instead, it should be used as a tool to generate initial insights into potential market structure and pricing solutions to guide future studies. It is best used in conjunction with other tools in a market designers toolbox such as simulation, human experiments, econometrics, and market equilibrium analysis. In the next and final part of this dissertation, we will demonstrate how simulations can be used to guide market design.

6.5 Appendix 2: Data for Part II of Dissertation

Table 6.6: 24 Bus Test System Generation Data

Node	Capacity (MW)	a ($/$MW^2$)	b ($/$MW$)
1	40	0.0230	71
1	152	0.0215	24
2	40	0.0155	71
2	152	0.0370	24
7	300	0.0320	34
13	591	0.0310	33
15	60	0.0335	41
15	155	0.0350	20
16	155	0.0255	20
18	400	0.0365	10
21	400	0.0285	10
22	300	0.0065	24
23	310	0.0220	20
23	350	0.0280	19

Table 6.7: 24 Bus Test System Load Data

Node	Max Load (MW)	Min Load (MW)	a (\$/MW^2)	b (\$/MW)
1	220	100	-0.0270	116
2	200	100	-0.065	60
3	360	250	-0.0155	88
4	150	80	-0.0260	20
5	150	80	-0.0170	64
6	280	120	-0.0185	38
7	250	120	-0.0205	58
8	350	180	-0.0130	68
9	350	180	-0.0365	136
10	380	180	-0.0275	138
13	530	250	-0.0295	86
14	390	180	-0.0075	90
15	640	310	-0.0305	40
16	200	100	-0.0285	126
18	660	320	-0.0355	54
19	360	200	-0.0125	64
20	260	120	-0.0200	38

Table 6.8: 24 Bus Test System Branch Data

From	To	Reactance (p.u.)	Capacity (MW)
1	2	0.0139	100
1	3	0.2120	100
1	5	0.0845	100
2	4	0.1267	100
2	6	0.1920	100
3	9	0.1190	100
3	24	0.0839	200
4	9	0.1037	100
5	10	0.0883	100
6	10	0.0605	100
7	8	0.0614	100
8	9	0.1651	100
8	10	0.1651	100
9	11	0.0839	200
9	12	0.0839	200
10	11	0.0839	200
10	12	0.0839	200
11	13	0.0476	250
11	14	0.0418	250
12	13	0.0476	250
12	23	0.0966	250
13	23	0.0865	250
14	16	0.0389	250
15	16	0.0173	250
15	21	0.0490	250
15	24	0.0519	250
16	17	0.0259	250
16	19	0.0231	250
17	18	0.0144	250
17	22	0.1053	250
18	21	0.0259	250
19	20	0.0396	250
20	23	0.0216	250
21	22	0.0678	250

Part III

Simulation-Based Electricity Market Design

Chapter 7

Bottom-up Market Model for Power System Operation and Planning

In Part I and Part II of this dissertation, we used optimization models of varying complexity to study the power system operation and planning problem and gained insights into potential market design and pricing decisions. In this part of the dissertation, we demonstrate how a bottom-up simulation-based approach can provide the flexibility to further evaluate some of the market insights gained in the previous parts of this dissertation.

We combine agent-based modeling with a state-machine driven simulation to model different market structures consisting of a spot market, a forward market, and an investment auction. The goal is to demonstrate how simulation-based modeling techniques can be used to test different transactive energy market structures and market rules by relaxing various assumptions, with a focus on how investment decisions for generators and transmission technologies are impacted by different market structures. We seek to demonstrate how simulation-based transactive energy market studies can be used to better understand the potential externalities of different market frameworks such as how risk is distributed across stakeholders, and who are the winners/losers. Some of the policy insights and proposals from the earlier parts of the dissertation are integrated in the model developed in this chapter. In particular, we integrated the regulatory mandate that requires load to purchase a certain portion of their load in the forward market as proposed in Part I of this dissertation. We also evaluate a potential market model with coordinated forward energy market and investment planning as suggested in Part II of this dissertation.

In this chapter, we present a brief background on simulation-based transactive energy market design and develop the models used in this part of the dissertation. This part of the dissertation is part of a working paper [79] that was submitted with the final report for the Carnegie Mellon University - National Institute of Standards and Technology Smart Grid In a Room Simulator project [80].

7.1 Simulation-based Transactive Energy Market Design

Fundamentally, transactive energy markets need to have four key traits:

1. It provides the necessary market signals to enable distributed decision-making at value.
2. It respects private information, while ensuring that information required for coordination is shared.
3. It enables market interactions across multiple timescales.
4. It aligns private objectives with public objectives to ensure that the power system continues to operate in a reliable and efficient manner.

In this section, we will discuss how simulation can be used to model transactive energy markets that have these traits, in order to highlight potential areas of concern for further evaluation.

7.1.1 Agent-based Modeling for Distributed Decision-Making

Agent-based modeling is particularly helpful for modeling the first two traits mentioned above as it is designed to model distributed, autonomous decision making [21]. In agent-based modeling, each agent can be modeled with its own embedded intelligence and autonomous decision making capability. Each agent is given its own private objective function, private constraints, and learning capabilities based on historical market performance. In addition, private versus public information are defined as part of the agent characteristics and hence information privacy and exchanges can be carefully controlled by model designers.

Out of the four traits mentioned earlier, the fourth trait is the most difficult to achieve and evaluate, as it depends on market design decisions and also on stakeholder behaviors. Design decisions that can have a significant impact on whether public and private objectives are aligned include market pricing decisions, information exchanges, and management of risks and uncertainties. Stakeholders behaviors that can have a significant impact on the alignment of public and private objectives include anti-competitive behaviors and price responsiveness. The agent-based modeling framework provides model designers with tremendous flexibility and control over how agents make decisions and interact, which allows for different assumptions on stakeholder behaviors and market designs to be tested. This gives us the ability to evaluate potential misalignments in private and public objectives and other unexpected market behaviors.

7.1.2 Multiple Timescale Handling with State Machines

Multi timescale markets are key to ensuring that long-term and short-term objectives are aligned in a transactive energy market. Increasingly, researchers are recognizing the need for well functioning forward markets to provide investment signals to ensure that an appropriate level of generation and transmission investments is made (e.g. [8] and [81]). Previous work on agent-based multi-timescale modeling includes [22], which focuses on the interactions between the day-ahead market and the spot market, and [82], which focuses on the interactions between forward and spot markets. A transactive energy market is likely to have markets operating at several time scales (e.g. annually, monthly, daily, hourly) and there need to be a simulation framework that is sufficiently robust to handle multiple timescales.

One robust strategy of simulating multiple timescale systems is the use of state machine driven simulations as implemented in the Carnegie Mellon University - National Institute of Standards and Technology Smart Grid In a Room Simulator(CMU-NIST SGRS) [83]. An intuitive way to model multi-timescale markets using state machines is to define interactions happening at one

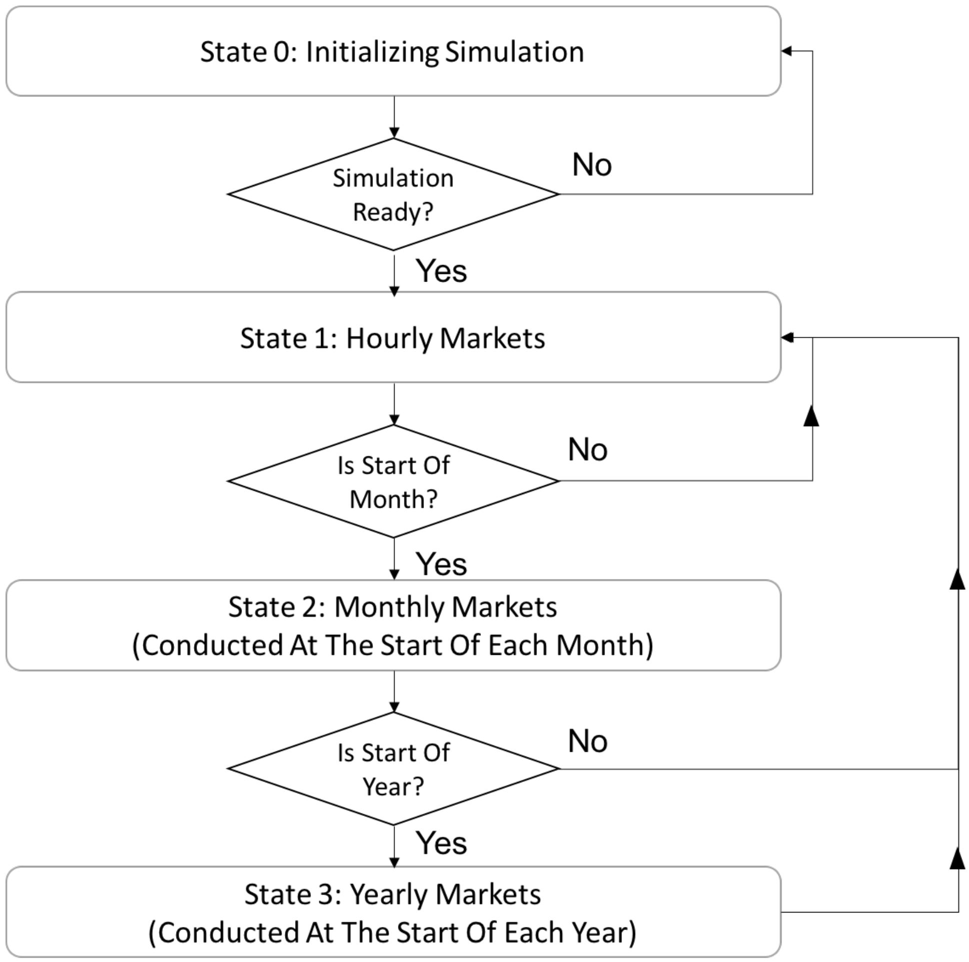

Figure 7.1: Algorithmic Flow for State Machine Based Multiple Timescale Market Simulation

timescale to one state. For instance, decisions that need to be made every hour are assigned to state 1 and decisions that need to be made evey year are assigned to state 2. Fig. 7.1 demonstrates the algorithmic flow of a state machine based multiple timescale market simulation.

7.1.3 Simulation Platforms

In recent years, there has been increasing efforts to develop simulation tools that can aid in transactive energy market design. Some examples include the AMES Wholesale Power Market Testbed developed at Iowa State University [84] and the C2 Wind Tunnel Co-Simulation Tool developed at Vanderbilt University [85]. These two simulation platforms represent two ends of a spectrum.

On one end of the spectrum, we have the AMES Testbed which is designed specifically to model a Federal Energy Regulatory Commission proposed wholesale market design and is primarily used to test various variations of the proposed market design. On the other end of the spectrum, we have the C2 Wind Tunnel Co-Simulation Tool which is designed to be a highly flexible co-simulation platform designed to simulate any complex system with heterogeneous system components.

This paper uses the state-machine based CMU-NIST Smart Grid in a Room Simulator mentioned earlier [83], which is a flexible simulation platform designed specifically to model distributed decision-making in an electricity grid. The Smart Grid In a Room Simulator is a scalable agent-based simulation framework built on MATLAB. It provides a simulation platform for researchers and policy-makers to test different distributed market and control algorithms. Users are in charge of modeling the agents as state machines and defining the necessary information exchanges among agents. At each step of the simulation, the decision-making process of each individual agent depends on the state the agent is in.

7.2 Test Market Model

In this section, we detail the spot market, forward market and investment market models used in this paper. In order to simplify the problem, we assume risk neutral market stakeholders without any form of anti-competitive behavior. The modeling efforts are focused on the following three market design decisions:

1. As proposed in Part I of this dissertation [1], it is assumed that there is a regulatory mandate that requires at least 75% of load to be purchased in the forward market as a strategy to encourage forward market participation. Any deviations from this mandate result in a penalty.

2. Three different transmission cost recovery policies are considered: short-run congestion revenue based cost recovery, short-run plus forward congestion revenue based cost recovery, and regulated fixed return. Details of the three different policies will be discussed later.

3. We consider three different market interaction models: a spot only market with investment auction, spot market with forward market that is independent of the investment auction, and spot market with forward market that is coordinated with the investment auction. Details of the three different interaction models will be discussed later.

Relatively simple stakeholder behaviors are assumed for modeling decisions not directly relevant to the three market design decisions above.

7.2.1 Generator Model

For the generator spot market, we assume perfectly competitive bids in the form of short-run marginal cost bids for the spot market. A linear short-run marginal cost function is used:

$$C_{G,SRMC}(x_G) = a_G x_G + b_G \tag{7.1}$$

where x_G is the amount of power generated and a_G and b_G are cost function parameters.

Similarly, we assume that the forward market bids are long-run marginal cost bids. The long-run marginal cost function differs from the short-run marginal cost function in that it includes the marginal cost of investment as generation capacity is assumed to be flexible in the long-run.

$$C_{G,LRMC}(x_G) = a_G x + b_G + c_G \tag{7.2}$$

where c_G is the annualized marginal cost of generation capacity investment given in \$/MWh

In terms of the generator investment decisions, we assume that the generator's goal is to maximize expected profit. The generator investment problem is as follows(Gen_{Invt}):

$$\begin{aligned}\max_{P^n_{G,SR}, P^n_{G,Tot}, K_G} \sum_{n=1}^{N} E\Big[&\lambda^n_{LR}(P^n_{G,Tot} - P^n_{G,SR}) + \lambda^n_{SR,est} P^n_{G,SR} - \frac{1}{2} a^n_G (P^n_{G,Tot})^2 \\ &- b^n_G P^n_{G,Tot}\Big] - C_G K_G \end{aligned} \tag{7.3}$$

$$
\begin{aligned}
\text{s.t} \quad & P^n_{G,Tot} < K_{G,base} + K_G & \text{for } n = 1 : N \qquad (7.4)\\
& P^n_{G,SR} + P^n_{G,Fwd} = P^n_{G,Tot} & \text{for } n = 1 : N \qquad (7.5)\\
& K_{G,bid,min} \le K_G \le K_{G,bid,max} & (7.6)\\
& P^n_{G,SR}, P^n_{G,Tot}, K_G \ge 0 & \text{for } n = 1 : N \qquad (7.7)
\end{aligned}
$$

where λ^n_{LR} and $\lambda^n_{SR,est}$ is the forward nodal price and estimated spot nodal price respectively for time period n, C_G is the annualized marginal cost of capacity given in \$/MW that is scaled based on the number of operational time periods considered, $P^n_{G,SR}$, $P^n_{G,Fwd}$ and $P^n_{G,Tot}$ are the estimated residual short-run generation, forward contracted generation, and estimated total real-time generation respectively for time period n, $K_{G,base}$ and K_G are the existing and new generation capacity respectively, N is the number of operational time periods considered, $K_{G,bid,max}$ and $K_{G,bid,min}$ are the maximum and minimum bids respectively, and the rest are as defined earlier.

Constraint (7.4) represents the capacity constraint of the generator, while (7.6) represents the investment limits of the generator. Constraint (7.5) defines the relationship between forward generation, estimated residual short-run generation, and estimated total real-time generation.

The generator is modeled as a two-state state machine. The first state involves decisions occurring on the hourly timescale, while the second state involves decisions occurring on the annual timescale. When the decisions are made depends on the market structure and hence we will defer discussion of the agent states to Section 7.3

7.2.2 Load Model

For the load spot market decision, we assume that the load contains a fixed portion and a responsive portion. For the responsive portion of the load, the load marginal utility function:

$$U_L(x_L) = a_L x_L + b_L \tag{7.8}$$

where x_L is the amount of load consumed including both responsive and fixed load and a_L and b_L are the utility function parameters. For the responsive portion of the load, we assume that the load will be shed as long as the marginal responsive load payment is greater than or equal to the marginal utility. Therefore, the marginal cost function of load shedding at any given time n can be written as:

$$
\begin{aligned}
S_L(x_{Flex,L}) &= -a_L x_{Flex,L} + (a_L x^n_{max,L} + b_L) && (7.9)\\
&= a_{L,Flex} x_{Flex,L} + b^n_{L,Flex} && (7.10)\\
\text{where} \quad a_{L,Flex} &= -a_L\\
b^n_{L,Flex} &= a_L x^n_{max,L} + b_L
\end{aligned}
$$

where $x_{Flex,L}$ is the quantity of load being shed and $x^n_{max,L}$ is the maximum load demanded at time n. This cost function along with the fixed load quantity is submitted to the market operator as part of the spot market bids.

The load forward market decision is affected by the regulatory mandate suggested earlier. In this case, the load has to decide how much to purchase from the forward market, while considering the uncertainty in actual real-time demand. The load forward profit maximization decision problem is as follows($Load_{Fwd}$):

$$
\begin{aligned}
\max_{\substack{P^{n,s}_{D,SR}, P^n_{D,Fwd},\\ P^{n,s}_{D,Ex}, P^{n,s}_{D,Flex}, \epsilon^{n,s}}} \quad & E \sum_{s=1}^{S} \frac{1}{S} \Big[R_D(P^{n,s}_{D,SR} - P^{n,s}_{D,Ex}) - \lambda^n_{SR,est} P^{n,s}_{D,SR} - \frac{1}{2} a^{n,s}_{L,Flex} (P^{n,s}_{D,Flex})^2 \\
& - b^{n,s}_{L,Flex} P^{n,s}_{D,Flex} - \lambda_\epsilon P^{n,s}_{D,max} \epsilon^{n,s} \Big] + R_D P^n_{D,Fwd} - \lambda^n_{LR} P^{n,s}_{D,Fwd} \qquad (7.11)
\end{aligned}
$$

$$
\begin{aligned}
\text{s.t.} \quad & P^{n,s}_{D,SR} + P^n_{D,Fwd} + P^{n,s}_{D,Flex} - P^{n,s}_{D,Ex} = P^{n,s}_{D,max} && \text{for } s = 1:S && (7.12)\\
& \text{if} \quad 1 - \frac{P^n_{D,Fwd}}{P^{n,s}_{D,max}} > Tol, \quad \epsilon^{n,s} = 1 - \frac{P^n_{D,Fwd}}{P^{n,s}_{D,max}} - Tol \\
& \text{else} \quad \epsilon^{n,s} = 0 && \text{for } s = 1:S && (7.13)\\
& P^{n,s}_{D,SR} \leq P^{n,s}_{D,max} && \text{for } s = 1:S && (7.14)\\
& P^{n,s}_{D,Flex} \leq p_{Flex} P^{n,s}_{D,max} && \text{for } s = 1:S && (7.15)
\end{aligned}
$$

$$P_{D,SR}^{n,s}, P_{D,Fwd}^{n}, P_{D,Ex}^{n,s}, P_{D,Flex}^{n,s} \geq 0 \qquad \text{for } s = 1:S \tag{7.16}$$

where $P_{D,Fwd}^{n}$ is the load to be purchased in the forward market for time period n, $P_{D,SR}^{n,s}$ is the anticipated load purchase in the spot market for scenario s of time period n, $P_{D,Flex}^{n,s}$ is the anticipated flexible load dispatch for scenario s of time period n, $P_{D,max}^{n,s}$ is the maximum load demanded for scenario s or time period n, R_D is the retail electricity price paid by customers to the load serving entity, p_{Flex} is the percentage of load that is flexible, and S is the total number of load scenarios simulated by the load for planning purposes. Tol is the forward load purchase error tolerance level set by the regulatory mandate such that if the regulatory mandate requires at least 75% of the load to be purchased in the forward market, $Tol = 1 - 0.75 = 0.25$. $P_{D,Ex}^{n,s}$ is the amount of load purchased in the forward market in excess of the maximum load demanded at a given time for scenario s of time period n, it is only non-zero if the maximum load demanded is less than the forward load purchased. $\epsilon^{s,n}$ is as defined in the conditional constraint(7.13) and it represents the forward load purchase error in excess of the tolerance level for scenario s of time period n.

The conditional constraint (7.13) can be written as the following integer linear constraints to facilitate optimization:

$$1 - \frac{P_{D,Fwd}^{n}}{P_{D,max}^{n,s}} \leq Tol + m \tag{7.17}$$

$$1 - \frac{P_{D,Fwd}^{n}}{P_{D,max}^{n,s}} - Tol \leq \epsilon^{n,s} + (1 + Tol)(1 - m) \tag{7.18}$$

$$1 - \frac{P_{D,Fwd}^{n}}{P_{D,max}^{n,s}} - Tol \geq \epsilon^{n,s} - (1 + Tol)(1 - m) \tag{7.19}$$

where m is a binary variable.

The forward load bids submitted by the loads are fixed forward power demand for each time period (i.e. $P_{D,Fwd}^{n}$). Since the forward load price is affected by the estimated spot prices and vice versa, an iterative price discovery process is needed to settle the forward market. This will be described further in Section 7.3.

7.2.3 Transmission Model

In this model, we consider investments in both new line capacity and flexible line reactance capacity. We assume that transmission owners do not actively participate in spot and forward markets. However, they make investment decisions on new line capacity or flexible reactance capacity based on forward and spot markets results. The transmission owner investment problem is dependent on the transmission cost recovery method being considered.

Regulated Fixed Return

The first cost recovery method being considered is where the transmission owner of each line or flexible reactance device is guaranteed a regulated rate of fixed return by the system operator. In this case, we assume that the transmission owner's bid is just the annualized cost of investment:

$$Bid = C_L(K_L) \tag{7.20}$$

where K_L is the transmission line capacity or flexible reactance capacity and $C_L(.)$ is the annualized investment cost function of the investment option.

Short-run Congestion Revenue Only Cost Recovery

The second cost recovery method being considered is where the transmission owner of each line or flexible reactance device is given rights to the short run congestion charges of the line. The short-run congestion charges are assumed to be the shadow prices or Lagrange multiplier associated with the transmission capacity constraint or flexible reactance capacity constraint of the spot market clearing problem. In this case, the transmission owner's bid function is assumed to be:

$$Bid = \frac{C_L(K_L)}{K_L} \tag{7.21}$$

Forward and Short-run Congestion Revenue Based Cost Recovery

The final cost recovery method is where the transmission owner is given rights to both the forward and short-run congestion charges of the line. Similar to the short-run congestion charges, the long-run congestion charges are assumed to be the shadow prices associated with the transmission capacity constraint or flexible reactance capacity constraint of the long-run market clearing problem. In this case the transmission owner's bid is defined as follow:

$$Bid = \frac{C_L(K_L) - \sum_{n=1}^{N} \mu_{LR}^n K_L}{K_L} \tag{7.22}$$

where μ_{LR} is the forward congestion charges obtained from the forward market clearing.

7.2.4 System Operator Model

Now, we will discuss how the various markets are cleared by the system operator or market coordinator. The forward market is cleared using a DC optimal power flow given generation and load bids in the forward market. The generator bid submitted by generator g for the forward market for operational period n consists of the bid function parameters (a_G^g, b_G^g, c_G^g) and the generator's capacity ($K_{G,Tot}^g$). The load bid submitted by load d for the forward market for operational period n consists of the forward demand ($P_{D,Fwd}^{n,d}$). The forward market clearing problem for an operational period n is written as ($MarClr_{Fwd}$):

$$\min_{\substack{P_{G,Fwd}^{n,g}, \theta^{n,i}, \\ f_{line}^{n,l}, r_{flex}^{n,l}, P_{D,Fwd,Cl}^{n,d}, \\ P_{D,loss}^{n,d}}} \sum_{g=1}^{N_g} \left[\frac{1}{2} a_G^g (P_{G,Fwd}^{n,g})^2 + (b_G^g + c_G^g) P_{G,Fwd}^{n,g} \right] + \sum_{d=1}^{N_d} V_{LL} P_{D,loss}^{n,d} \tag{7.23}$$

$$\text{s.t.} \quad \mathbf{A_G P_{G,Fwd}^n} - \mathbf{A_D P_{D,Fwd,Cl}^n} + \mathbf{A_L f_{line}^n} = \mathbf{0} \tag{7.24}$$

$$P_{D,loss}^{n,d} + P_{D,Fwd,Cl}^{n,d} = P_{D,Fwd}^{n,d} \quad \text{for } d = 1:N_d \tag{7.25}$$

$$f_{line}^{n,l} = \frac{\theta^{n,i=line_{from,l}} - \theta^{n,i=line_{to,l}}}{x_{line}^l - r_{flex}^{n,l}} \text{ for } l = 1:N_l \tag{7.26}$$

$$0 \leq P_{G,Fwd}^{n,g} \leq K_{G,Tot}^{g} \quad \text{for } g = 1 : N_g \tag{7.27}$$

$$0 \leq r_{flex}^{n,l} \leq K_{flex}^{l} \quad \text{for } l = 1 : N_l \tag{7.28}$$

$$-K_{line}^{l} \leq f_{line}^{n,l} \leq K_{line}^{l} \quad \text{for } l = 1 : N_l \tag{7.29}$$

$$-\pi \leq \theta^{n,i} \leq \pi \quad \text{for } i = 1 : N_i \tag{7.30}$$

$$P_{D,loss}^{n,d}, P_{D,Fwd,Cl}^{n,d} \geq 0 \quad \text{for } d = 1 : N_d \tag{7.31}$$

where $P_{G,Fwd}^{n,g}$ represents the cleared forward generation for generator g for operational period n, $P_{D,Fwd,Cl}^{n,d}$ represents the cleared forward demand for load d for operational period n, $P_{D,loss}^{n,d}$ represents the fixed load requested that needs to be shed for load d[1], $\theta^{n,i}$ represents the nodal angles at node i, $f_{line}^{n,l}$ represents the line flows for line l, $r_{flex}^{n,l}$ represents the change in line reactance achieved by controlling the flexible reactance devices at line l, V_{LL} is the cost of not fulfilling any fixed demand, N_g, N_i, N_d and N_l represent the number of generators, number of nodes, number of loads, and number of transmission lines in the system respectively, $\mathbf{A_G}$ is a $N_i \times N_g$ matrix that is 1 if the generator is at the corresponding node and zero otherwise, $\mathbf{A_D}$ is a $N_i \times N_d$ matrix that is 1 if the load is at the corresponding node and zero otherwise, $\mathbf{A_L}$ is a $N_i \times N_L$ matrix that is 1 if the line is exiting the node and -1 if the line is entering the node, $\mathbf{P^n_{G,Fwd}}$, $\mathbf{P^n_{D,Fwd,Cl}}$ and $\mathbf{f^n_{line}}$ are the vectors of cleared forward generation, cleared forward demand, and line flows respectively, x_{line}^{l} is the original reactance of transmission line l, $line_{from,l}$ is the index of the node that line l is exiting from, $line_{to,l}$is the index of the node that line l is entering, K_{flex}^{l} is the flexible reactance capacity at line l, K_{line}^{l} is the transmission line capacity at line l, and the rest are as defined earlier. Constraint (7.24) represents the nodal power balance for the system. Constraint (7.25) ensures that the forward load bids are accounted for whether they are fulfilled by the market or not. Constraint (7.26) represents the line flow equations. Constraints (7.27), (7.28), and (7.29) are the capacity constraints of the different system components. Constraint (7.30) represents the nodal angle limits.

For the spot market clearing, we assume that the amount of generation that has been contracted

[1]In the forward market, the entire forward demand bid is considered to be fixed

in the forward market has already been paid for and hence there are no incremental cost for generation up to the amount that has already been contracted for in the forward market. In addition, a portion of the demand is flexible/responsive. The generator bid submitted by generator g for the spot market for operational period n consists of the bid function parameters (a_G^g, b_G^g) and the generator's capacity ($K_{G,Tot}^g$). The load bid submitted by load d for the spot market for operational period n consists of the cost function parameters for the cost of shedding the elastic portion of the demand ($a_{L,Flex}^{n,d}$, $b_{L,Flex}^{n,d}$), total demand including both inelastic and elastic demand ($P_{D,max}^{n,d}$) and the inelastic demand ($P_{D,min}^{n,d}$). The spot market clearing problem is written as($MarClr_{Spot}$):

$$\min_{\substack{P_{G,SR}^{n,g},\theta^{n,i},\\ f_{line}^{n,l},r_{flex}^{n,l},P_{D,SR,Cl}^{n,d},\\ P_{D,loss}^{n,d},P_{D,Flex}^{n,d}\\ P_{G,Fwd,Use}^{n,g}}} \sum_{g=1}^{N_g}\left\{\frac{1}{2}a_G^g[(P_{G,SR}^{n,g})^2-(P_{G,Fwd,Use}^{n,g})^2]+b_G^g(P_{G,SR}^{n,g}-P_{G,Fwd,Use}^{n,g})\right\}$$

$$+\sum_{d=1}^{N_d} V_{LL}P_{D,loss}^{n,d}+b_{L,Flex}^{n,d}P_{D,Flex}^{n,d}+\frac{1}{2}a_{L,Flex}^{n,d}(P_{D,Flex}^{n,d})^2 \tag{7.32}$$

$$\text{s.t.}\quad \mathbf{A_G P^n_{G,SR}} - \mathbf{A_D P^n_{D,SR,Cl}} + \mathbf{A_L f^n_{line}} = \mathbf{0} \tag{7.33}$$

$$P_{D,loss}^{n,d}+P_{D,SR,Cl}^{n,d}\cdots$$

$$+P_{D,Flex}^{n,d}=P_{D,max}^{n,d}\quad \text{for } d=1:N_d \tag{7.34}$$

$$f_{line}^{n,l}=\frac{\theta^{n,i=line_{from,l}}-\theta^{n,i=line_{to,l}}}{x_{line}^l-r_{flex}^{n,l}}\ \text{for } l=1:N_l \tag{7.35}$$

$$0\le P_{G,SR}^{n,g}\le K_{G,Tot}^g\quad \text{for } g=1:N_g \tag{7.36}$$

$$0\le P_{G,Fwd,Use}^{n,g}\le P_{G,Fwd}^{n,g}\quad \text{for } g=1:N_g \tag{7.37}$$

$$P_{G,Fwd,Use}^{n,g}\le P_{G,SR}^{n,g}\quad \text{for } g=1:N_g \tag{7.38}$$

$$0\le r_{flex}^{n,l}\le K_{flex}^l\quad \text{for } l=1:N_l \tag{7.39}$$

$$-K_{line}^l\le f_{line}^{n,l}\le K_{line}^l\quad \text{for } l=1:N_l \tag{7.40}$$

$$-\pi\le\theta^{n,i}\le\pi\quad \text{for } i=1:N_i \tag{7.41}$$

$$P^{n,d}_{D,Flex} \leq P^{n,d}_{D,max} - P^{n,d}_{D,min} \text{ for } d = 1 : N_d \tag{7.42}$$

$$P^{n,d}_{D,loss} + P^{n,d}_{D,SR,Cl} \geq P^{n,d}_{D,min} \text{ for } d = 1 : N_d \tag{7.43}$$

$$P^{n,d}_{D,loss}, P^{n,d}_{D,SR,Cl}, P^{n,d}_{D,Flex} \geq 0 \quad \text{for } d = 1 : N_d \tag{7.44}$$

where $P^{n,g}_{G,SR}$ is the generation cleared in the spot market for generator g during operational period n, $P^{n,d}_{D,SR,Cl}$ represents the cleared short-term demand for load d during operational period n, $P^{n,d}_{D,Flex}$ represents the elastic load not consumed for load d during operational period n, $P^{n,g}_{G,Fwd,Use}$ represents the generation that has been cleared in the forward market that is actually needed in the spot market for generator g during operational period n, $\mathbf{P^n_{G,SR}}$ and $\mathbf{P^n_{D,SR,Cl}}$ are the vectors are cleared generation and load in the spot market during operational period n, and the rest are as defined earlier. Constraint (7.33) represents the nodal power balance for the system. Constraint (7.35) represents the line flow equations. Constraints (7.36), (7.39), and (7.40) are the capacity constraints of the different system components. Constraint (7.41) represents the nodal angle limits. Constraints (7.37) and (7.38), along with the objective function, ensure that the forward generation that is already contracted is used as far as possible. Constraints (7.34), (7.42) and (7.43), along with a sufficiently high value for V_{LL} ensure that flexible demand is used before fixed load is shed.

The investment auction is a combined generation and transmission investment auction. Generators bid in new generation capacity based on the expected spot and forward nodal prices as shown in Gen_{Invt}, while transmission bids depend on the transmission cost recovery policy. The exact mechanism in which the investment auction is carried out depends on whether generation or transmission investments are prioritized as will be discussed next.

Generation-First Investment Auction

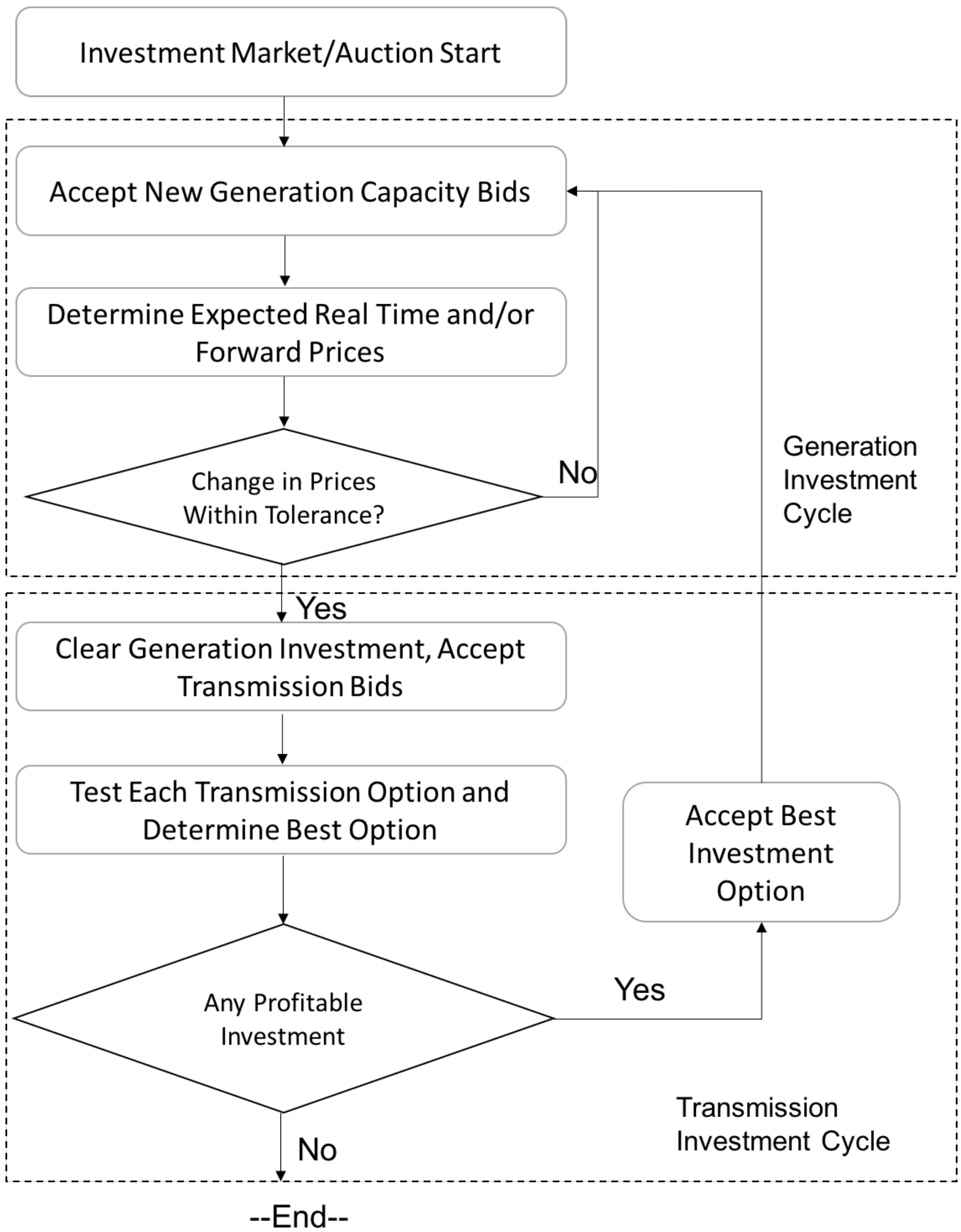

Figure 7.2: Algorithmic Flow for Generation First Investment Auction

The algorithmic flow for the case where generation is prioritized is shown in Fig. 7.2. In this situation, generators begin each investment auction by submitting capacity bids based on Gen_{Fwd}, using the expected spot prices and/or forward prices provided by the market coordinator or system operator. The market coordinator determines the expected spot prices by running a series of spot market clearing problem using different possible load scenarios. The load scenarios for each operational time period are drawn from a normal distribution using the mean and standard deviation of expected load for the given time period. The hourly mean and standard deviation of expected load for all the operational time periods considered are supplied by the loads, based on their best estimates of their own expected power demand. At each generation investment cycle, the expected spot prices are updated based on new generation capacity proposed until the change in prices between iterations are within a certain tolerance level. Once the changes in prices are less than a certain tolerance level, the corresponding generation capacity bids become the cleared generation capacity that generators are committed to building and the transmission investment cycle begins. In addition, after the first iteration within an investment cycle, generation capacity bids for subsequent iterations are bounded by the following rules:

$$K_{G,bid,max} = K_{G,previous} \tag{7.45}$$

$$K_{G,bid,min} = \begin{cases} 0.75K_{G,previous} & K_{G,previous} > 0.2K_{G,max} \\ 0 & \text{otherwise} \end{cases} \tag{7.46}$$

where $K_{G,previous}$ is the generation investment bid at the previous iteration and the rest are as defined earlier. The bidding rule above is designed to prevent huge fluctuations in bids that prevent convergence. As an example of this bidding process, Fig. 7.3 shows the generator investment bids for iterations over multiple investment cycles for one of the simulation conducted in the case study. In this simulation, the generator capacity cleared at the end of each investment cycle is 105 MW for investment cycle 1, 151MW for investment cycle 2, and 207MW for investment cycle 3.

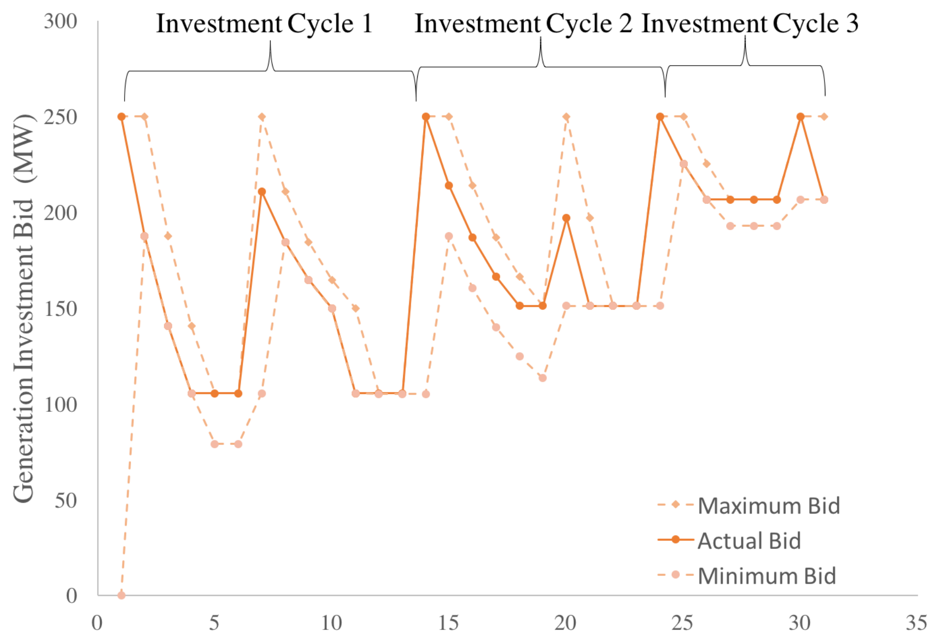

Figure 7.3: Example of Generator Investment Bids for Iterations Over Multiple Investment Cycles

For the transmission investment cycle, transmission owners submit investment bids for both line capacity or flexible reactance as described earlier. At each transmission investment cycle, only the most profitable investment option is accepted before returning to the generation investment cycle and the entire investment auction ends if there are no profitable transmission investment options remaining. The method in which the profitability of different investment options are determined depends on the transmission cost recovery method under consideration:

- *Regulated Fixed Return*: In this case, the market coordinator is provided with the entire investment cost of the transmission investment option. The profitability of investment option ll is defined as:

$$Profit^{ll} = Cost_{pre} - Cost_{post}^{ll} - C_L^{ll}(K_L^{ll}) \tag{7.47}$$

where $Cost_{pre}$ is the total annual cost of power system operation without investment ll, $Cost_{post}^{ll}$ is the total annual cost of power system operation with investment ll, and $C_L(K_L^{ll})$ is the cost of investment submitted to the market coordinator through the transmission bids as shown in (7.20).

- *Short-run Congestion Revenue Only Cost Recovery*: In this case, the transmission bids represent the minimum cumulative congestion price that the transmission owner needs to be willing to make the investment. In other words, the transmission owner will only invest in investment ll if and only if:

$$\frac{C_L^{ll}(K_L^{ll})}{K_L^{ll}} \leq \sum_{n=1}^{N} \mu_{SR}^{ll,n} \tag{7.48}$$

where $\mu_{SR}^{ll,n}$ is the shadow price associated with the transmission capacity constraint or flexible reactance capacity constraint obtained through the spot market clearing problem, and the left hand side of the equation is the transmission bid as shown in (7.21). If this condition holds, the profitability of the investment option from the system point of view is defined to be:

$$Profit^{ll} = Cost_{pre} - Cost_{post}^{ll} - \sum_{n=1}^{N} \mu_{SR}^{ll,n} K_L^{ll} \tag{7.49}$$

- *Forward and Short-run Congestion Revenue Based Cost Recovery*: In this case, the transmission bids represent the minimum cumulative short-run congestion price that the transmission owner needs to be willing to make the investment, after accounting for forward congestion revenue. Note that transmission owners are only compensated based on the short-run congestion price if the capacity constraint is active in the spot market but inactive in the forward market. If the capacity constraint is active in the forward market, the transmission owner is compensated based on the forward congestion price. The transmission owner will only invest in investment ll if and only if:

$$\frac{C_L^{ll}(K_L^{ll}) - \sum_{n=1}^{N} \mu_{LR}^{ll,n} K_L^{ll}}{K_L^{ll}} \leq \sum_{n=1}^{N} \mu_M^{ll,n} \tag{7.50}$$

where

$$\mu_M^{ll,n} = \begin{cases} \mu_{SR}^{ll,n} & \mu_{LR}^{ll,n} = 0 \\ 0 & otherwise \end{cases} \tag{7.51}$$

and $\mu_{LR}^{ll,n}$ is the shadow price associated with the transmission or flexible reactance capacity constraint obtained through the forward market clearing problem and the left hand side of the equation is the transmission bid as shown in (7.22). If this condition hold, the profitability of the investment option from the system point of view is defined to be:

$$Profit^{ll} = Cost_{pre} - Cost_{post}^{ll} - \sum_{n=1}^{N} \mu_O^{ll,n} K_L^{ll} \tag{7.52}$$

where

$$\mu_O^{ll,n} = \begin{cases} \mu_{SR}^{ll,n} & \mu_{LR}^{ll,n} = 0 \\ \mu_{LR}^{ll,n} & otherwise \end{cases} \tag{7.53}$$

Transmission-First Investment Auction

The algorithmic flow for the case where transmission is prioritized is shown in Fig. 7.4. In this situation, transmission owners begin each investment auction by submitting bids based on the expected spot prices and/or forward prices provided by the market coordinator and the transmission cost recovery method. The transmission investment cycle is repeated until there are no longer any profitable investment options before moving on to the generation investment cycle. The generation investment cycle repeats as in the generation-first investment auction until the changes in prices between iterations are less than a certain tolerance level. The investment auction alternates between the transmission and generation investment cycles until there are no longer any profitable transmission investment option.

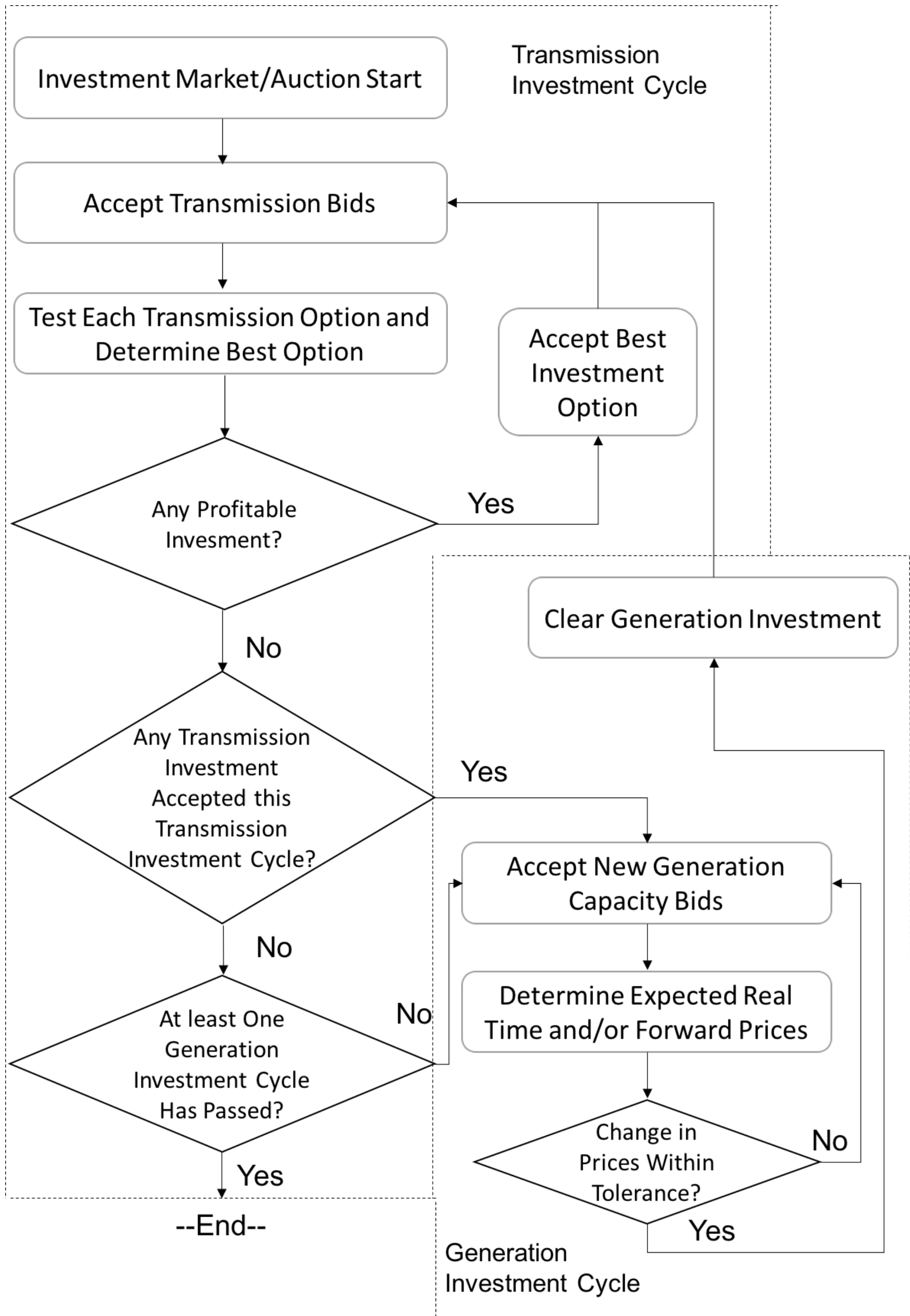

Figure 7.4: Algorithmic Flow for Transmission First Investment Auction

7.2.5 Load Forecast Module

Since the focus of this dissertation is not on load forecasting, we did not attempt to find the best load forecasting model for our purpose. Instead, we adopt a modified version of the load modeling strategy presented in [86] in this paper. As with [86], we model the daily load for each month using the first principal component of the daily load for the month:

$$\mathbf{L_d} = \mu_\mathbf{m} + \mathbf{w_d^T v_m} \tag{7.54}$$

where L_d is a 24×1 vector representing hourly loads for a day, γ_m is a 24×1 vector representing the mean daily loads for the month, v_m is a 24×1 is the principal components of the daily load for the month, and w_d is a 24×1 vector representing a daily stochastic process.

The parameters γ_m and v_m are calibrated using historical data. Instead of explicitly modeling the daily stochastic process w_d as in [86], we fit a simpler autoregressive model of order 1 to the weights associated with the principal components:

$$w_d^t = w_d^{t-1} + \epsilon^t + constant \tag{7.55}$$

where t is the time step and ϵ is a white noise process with a mean of zero.

7.3 Market Interactions

In this section, we discuss the market interactions happening at different timescale for the three different market interaction models being considered.

7.3.1 Spot Only Market with Investment Market

For the spot only market, a forward market does not exist. Therefore, at every time t, the generators and loads submit their generation and load bids for time t to the system operator and the system operator clears the market using $MarClr_{Spot}$. At the start of each year (i.e $t = 0, N, 2N, 3N...$), an investment auction is conducted based on the auction format presented in Fig. 7.2 or Fig. 7.4. This auction is conducted a year ahead such that any investment decisions made at time t becomes operational at time $t + N$. During the auction, the system operator/market coordinator calculates estimated spot market prices for time between $t + N$ and $t + 2N$ by running S scenarios of spot market clearing for each of the time between $t + N$ and $t + 2N$ and taking the average price for each time period. The anticipated loads for each scenario are obtained by drawing randomly from a normal distribution with mean and standard deviation given by the expected hourly load and standard deviation for the specific load. Note that an independent mean and standard deviation is given for each hourly load between time $t + N$ and $t + 2N$. A time-line of this interaction is shown in Fig. 7.5, while a summary of the market interactions for the spot only market is shown in Table 7.1 at the end of this chapter.

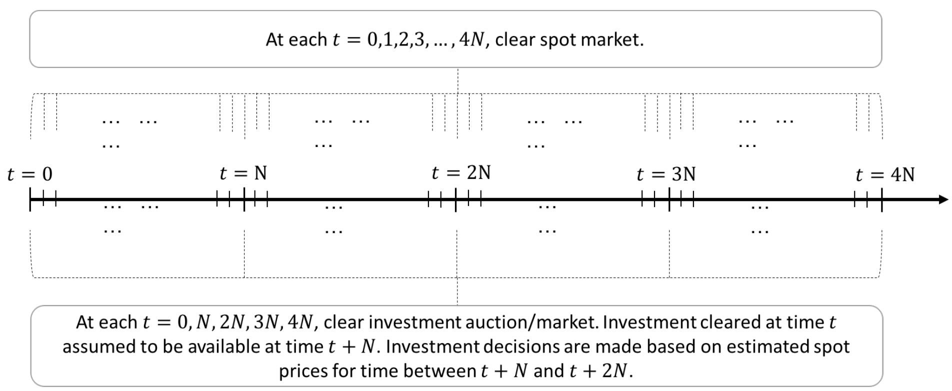

Figure 7.5: Spot Only Simulation Time-line

7.3.2 Spot Market with Independent Forward and Investment Markets

In this case, we assume that a forward energy market exists and that there is a regulatory mandate that requires at least 75% of the load to be purchased in the forward market to encourage market participation. As discussed earlier, any deviation from this mandate results in a penalty. We assume that the forward market is conducted $2N$ time-step ahead to ensure that when the investment auction at time $t = 0, N, 2N, 3N$ etc. is held, forward market for time between $t + N$ and $t + 2N$ has been cleared. For every time t, the generators and loads submit their spot market bids for time

t and forward market bids for time $t + 2N$. The system operator clears the spot market for time t using $MarClr_{Spot}$. Since the loads forward purchase decision is dependent on both the forward price and anticipated spot price, and vice versa, the forward market needs to be cleared via an iterative price discovery process. The forward price is obtained by solving $MarClr_{Fwd}$ based on the forward bids, while the estimated spot price is obtained by running S scenarios of anticipated real-time loads and taking the average spot price. This forward price and estimated spot price is returned to the load to allow it to adjust its forward bids by solving $Load_{Fwd}$. The iterative price discovery process continues until the change in prices between two iterations is less than a certain tolerance level. In addition, in order to promote price stabilization, within a single market clearing cycle, the forward load purchase bids are only allowed to decrease or stay the same over iterations.

The investment auction process is similar to the process discussed earlier for the spot market. The only difference is that the forward price, generation and loads are accounted for by the individual stakeholders decision making. A time-line of this interaction is shown in Fig. 7.6, while a summary of the market interactions for the spot only market is shown in Table 7.2 at the end of this chapter.

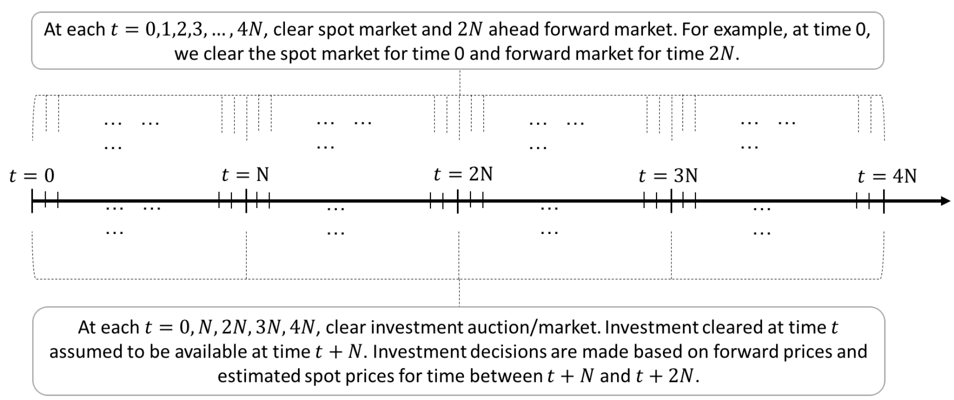

Figure 7.6: Spot Market with Independent Forward and Investment Market Simulation Time-line

7.3.3 Spot Market with Coordinated Forward and Investment Markets

In this case, we assume that a forward energy market exists as with the previous case. However, the forward energy market in this case is coordinated with the investment markets such that forward market for time between $t+N$ and $t+2N$ is cleared during the investment auction market at time $t = 0, N, 2N, 3N$ etc. A time-line of this interaction is shown in Fig. 7.7, while a summary of the market interactions for the spot only market is shown in Table 7.3 at the end of this chapter.

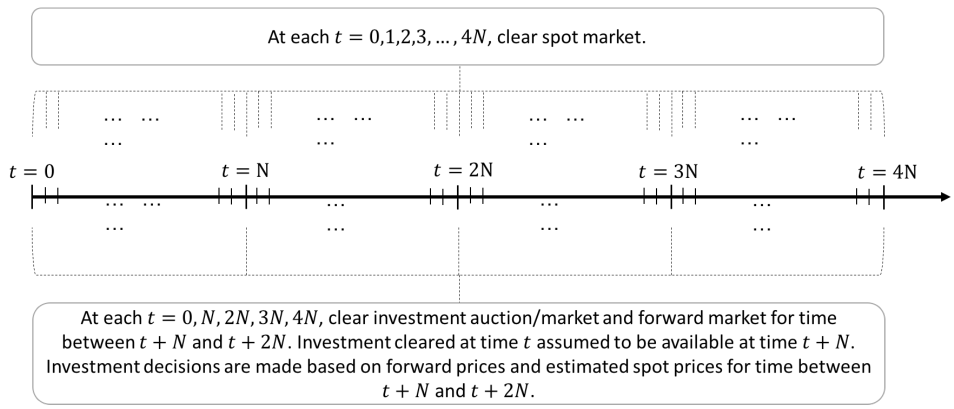

Figure 7.7: Spot Market with Coordinated Forward and Investment Market Simulation Time-line

Table 7.1: Summary of Interaction for Spot Only Market with Investment Market

	Generator	Load	Transmission	ISO
State 0	-	Use load forecast module to provide S simulated load series. Send signal to ISO to indicate that initialization is completed.	-	Once 'initialization completed' signal is received from all loads, send signal to start simulation and move to State 1.
State 1	Submit spot market bid.	Submit inelastic and elastic real time demand, and cost function parameters of cost of shedding elastic load as shown in (7.10).	-	Clear short-run market as in $MarClr_{Spot}$. Send appropriate time signal to repeat state 1 until the time step corresponds to the start of a new year. At the start of a new year, send signal to move to State 2 and start investment auction.
State 2	Solve investment problem Gen_{Invt} and submit new generation capacity bid.	Submit hourly mean and standard deviation of expected load for operational periods considered.	Submit transmission bids as in Section 7.2.3	Conduct investment auction as in Fig. 7.2 or Fig. 7.4. Calculate and provide estimated spot prices for time between $t+N$ and $t+2N$ to generators, loads, and transmissions at each iteration. Once investment auction ends, send signal to move to State 1

Table 7.2: Summary of Interaction for Independent Forward and Investment Markets Market

	Generator	Load	Transmission	ISO
State 0	Same as Table 7.1			
State 1	Submit spot market bid for time t and forward bid for time $t + 2N$.	Submit forward load bid for time $t+2N$ by solving $Load_{Fwd}$. Submit inelastic and elastic real time demand, and cost function parameters of cost of shedding elastic load as shown in (7.10) for time t. Submit hourly mean and standard deviation of expected load for time $t + 2N$	-	Clear short-run market for time t along with forward market for time $t + 2N$ using $MarClr_{Spot}$ and $MarClr_{Fwd}$ respectively Provide forward prices and estimated spot prices for the time $t + 2N$ to loads. Forward market takes a few iteration to clear as described in Section 7.3. Send appropriate time signal to repeat state 1 until the time step corresponds to the start of a new year. At the start of a new year, send signal to move to State 2 and start investment auction.
State 2	Same as Table 7.1			

Table 7.3: Summary of Interaction for Coordinated Forward and Investment Markets Market

	Generator	Load	Transmission	ISO
State 0	Same as Table 7.1			
State 1	Same as Table 7.1			
State 2	Solve investment problem Gen_{Invt} and submit new generation capacity bid. Submit forward market bids for time between $t + N$ and $t + 2N$	Submit hourly mean and standard deviation of expected load for operational periods considered. Submit forward load bids for time between $t + N$ and $t + 2N$ by solving $Load_{Fwd}$.	Submit transmission bids as in Section 7.2.3	Conduct investment auction as in Fig. 7.2 or Fig. 7.4. Calculate and provide estimated spot and cleared forward prices for time between $t + N$ and $t + 2N$ to generators, loads, and transmissions at each iteration. Once investment auction ends, send signal to move to State 1

Chapter 8

Case Studies

The simulation framework described in the previous chapter is tested on a modified version of the 24-Bus IEEE Reliability Test System used in [72]. We tested 12 different cases with different market structures:

1. Spot Only + Investment Market
   (a) Generation First Investment Auction
      i. Regulated Fixed Return Based Cost Recovery (1F)
      ii. Short Run Congestion Revenue Based Cost Recovery (1M)
   (b) Transmission First Investment Auction
      i. Regulated Fixed Return Based Cost Recovery (1F)
      ii. Short Run Congestion Revenue Based Cost Recovery (1M)
2. Spot + Independent Forward and Investment Markets
   (a) Generation First Investment Auction
      i. Regulated Fixed Return Based Cost Recovery (2F)
      ii. Forward and Short Run Congestion Revenue Based Cost Recovery (2M)
   (b) Transmission First Investment Auction

i. Regulated Fixed Return Based Cost Recovery (2F)

ii. Forward and Short Run Congestion Revenue Based Cost Recovery (2M)

3. Spot + Coordinated Forward and Investment Markets

   (a) Generation First Investment Auction

      i. Regulated Fixed Return Based Cost Recovery (3F)

      ii. Forward and Short Run Congestion Revenue Based Cost Recovery (3M)

   (b) Transmission First Investment Auction

      i. Regulated Fixed Return Based Cost Recovery (3F)

      ii. Forward and Short Run Congestion Revenue Based Cost Recovery (3M)

8.1 Test System

The branch data, generation data, load data, and cost functions for the test system are shown in Appendix 3. The test system is the same test system used in Part II of this dissertation (Fig. 6.1). Historical hourly load data from PJM for years 2012 to 2015 were used to calibrate the load forecast model in this paper [73]. Region A uses load data from the PJM Mid-Atlantic region, whereas Region B uses load data from the PJM West region. The load model was fitted using normalized historical data to capture the load pattern. We consider 25 different load scenarios by generating 25 load series using the load model(i.e. $S = 25$). The normalized load series generated by the load model is then scaled up by multiplying the load series by the maximum nodal load as shown in Table 8.8

To simplify simulations, within each year, we simulate only one representative day for each of the four seasons (i.e. $N = 4 \times 24$ hours), and 4 years in total (i.e. $t \in 1 : 4N$). The interest rate is assumed to be 10% per year. In addition, we assume that the maximum nodal load increases by 2% per year.

The investment options being considered along with their annualized investment cost are shown in Table 8.1, Table 8.2, and Table 8.3.

Table 8.1: Potential Generation Addition

	Node	Capacity (MW)	Investment Cost (k$/MW-year)	a_G (\$/MW^2)	b_G (\$/MW)
G1	1	250	286	0.013	24
G2	14	250	286	0.013	24
G3	18	250	286	0.013	24
G4	22	250	694	0.044	10
G5	10	250	694	0.044	10

Table 8.2: Potential New Line Addition

	From	To	Reactance (p.u.)	Capacity (MW)	Investment Cost (M$/year)
T1	6	10	0.0605	100	3.1
T2	7	8	0.0614	100	3.1
T3	8	10	0.1651	100	8.4
T4	20	23	0.0216	250	1.1
T5	15	21	0.0490	250	2.5

Table 8.3: Potential Flexible Reactance Addition

	From	To	Flexible Capacity (p.u.)	Investment Cost (M$/p.u.-year)
F1	15	24	0.0260	20.8
F2	16	17	0.0130	10.4
F3	17	18	0.0072	5.6

8.2 Investment Decisions

The investment decisions resulting from the simulations are shown in Table 8.4. The table shows the year in which the transmission investments become operational and generation capacity in year 2 to year 4 for G1 and G2. Generation investment options G3 to G5 were not invested in for any cases. Since investment decisions made at the start of the first investment decision cycle ($t = 0$) are only made available in year 2, no new transmission or generation capacity is available in year 1. The labels for the cases and investment options in Table 8.4 are as shown in the start of this chapter.

Table 8.4: Investment Decisions For Different Simulation Cases

		Transmission Investment Year Available								Generation Capacity (MW in Year2/Year3/Year4)	
		T1	T2	T3	T4	T5	F1	F2	F3	G1	G2
Gen. First	1F		3		2	2			2	141/141/141	141/141/141
	2F		2		2	2				105/105/151	105/105/105
	3F	3	2		2	2	2	2	2	141/141/141	141/141/141
	1M								2	141/141/141	141/202/202
	2M		4					3	2	105/151/151	105/151/207
	3M				2	2	2	2		141/141/141	141/141/141
Trans. First	1F	2	2		2	2	2			105/105/105	59/59/59
	2F	2	2		2	2	2			79/79/79	45/45/45
	3F	2	2		2	2	2	2	2	105/105/105	73/73/73
	1M						2		2	141/141/141	141/202/202
	2M		2					2	2	105/105/105	105/151/193
	3M		4			2	2		2	188/188/188	188/188/188

Before we continue with the discussion of the result, we want to highlight the fact that in the model presented in this paper, generation and transmission owners make investment decisions based on expected operational revenue for the initial year of operation only. The underlying assumption is that since we assume that load increases over the years, if the investment decision is profitable in the initial year of operation, it should be profitable in subsequent years. This is not always a valid assumptions for real-world investment decision. However, for the purpose of this case study, this assumption is used to simplify the problem and analysis.

8.3 Implications of Market Structure and Market Design on Investment Decisions

Several observations can be made by comparing the resulting investment decisions for different market structures in Table 8.4. These observations and their policy implications are discussed next.

8.3.1 Prioritizing Generation vs. Transmission Investments

The order in which generation and transmission investments are made have a significant impact on resulting investment decisions. This is because generation and transmission investments, in some situations, can be substitutionary investments. This substitutionary effect is particularly obvious when we compare the resulting investment decisions of the generation-first and transmission-first simulations for Cases 1F, 2F, and 3F. In general, the generation-first simulations result in greater generation investment than the transmission-first simulations. Similarly, the transmission-first simulations result in greater and earlier transmission investments when compared to the generation-first simulations.

Traditionally, the electricity industry in the United States uses an integrated resource planning process to centrally plan generation and transmission investments. Under such a framework, it is relatively easy to take into account substitutionary effects of different investment types. However, with greater deregulation and decentralization of electricity operation and planning, the question of how to design markets to take into account these substitutionary effects become a more challenging problem. As demonstrated in this case study, different investment clearing schemes favor different investment types. It is extremely unlikely that any investment market design for the future could truly be 100% technology neutral. However, it is important for market designers and policy makers to understand the biases of any market mechanisms to ensure that any biases align with broader societal objectives.

8.3.2 Different Market Interaction Models

The risk profiles of different investment options are strongly affected by the different market interaction models considered. We defer discussion of the risk profiles brought about by different market structure to Section 8.4. In this section, we focus on the difference between investment decisions for the cases with the independent forward and investment markets and investment decisions for the cases with the coordinated forward and investment markets. From Table 8.4, it can be observed that cases with coordinated forward and investment markets generally result in more investments in generation and transmission when compared to the cases with independent forward and investment markets. In the cases with independent forward and investment market, investment decisions are made based on forward prices and quantities that are cleared prior to the investment cycle. New generation or transmission investments are unable to take advantage of the forward market in the initial year of operation. In the cases with coordinated forward and investment market, the forward market under consideration clears as investment markets clear and hence new investments are accounted for in the forward market. In this case study, this coordination results in greater overall investment level.

The impact of the timing of market interactions on investment decisions is amplified in the stylized market interaction models used in this paper. However, it is still a valid concern in real world market design. In designing electricity markets for the future, such impacts can be reduced by careful market design that accounts for how investment decisions interact with the broader market framework. Liquid markets with multiple time-scales that allow market participants to continually adjust their market decisions with new information could allow new transmission and generation investments to integrate into the broader market more smoothly. Alternatively, researchers could explore whether a one-time market adjustment process could be designed to allow for reallocation of resources with the addition of new capacity, such a one-time market process could be loosely modeled after the “initial public offering" process in financial stock markets.

8.3.3 Regulated vs. Congestion Revenue Based Cost Recovery for Transmission Investment

Comparing the cases with regulated transmission cost recovery and the cases with congestion revenue-based cost recovery in Table 8.4, it can be observed that the cases with congestion revenue based cost recovery result in lower transmission investment levels. This seems to affect the level of transmission line investments more than it affects flexible reactance device investments. This could be due to the lumpy nature of transmission line investments. Often, the installation of a new line eliminates congestion on the particular line, which wipes out real-time congestion charges. The effects of flexible reactance devices are more marginal and does not entirely eliminates real-time congestion charges.

There are two reasons why a transmission investment that is profitable in the regulated cost recovery cases is not profitable in the congestion revenue based cost recovery cases:

1. The expected total congestion revenue is less than what is required by the transmission owners for profitability. In other words, conditions (7.48) or (7.50) is not valid.

2. After accounting for the congestion charges that needs to be paid to the transmission owners, the cost is greater than the benefits to the system. In other words, the profit calculated in (7.49) or (7.52) is negative.

Numerical examples of these two cases will be shown in Section 8.4. From a market design standpoint, the first case could be mitigated by supplementing congestion revenue based compensation with an additional fixed compensation. The second case could be mitigated by only awarding partial rights to the congestion charges. Regardless, the result suggests that congestion revenue only based cost recovery for transmission investment do not accurately reflect the value of transmission investments.

8.4 Risk Profiles of Different Market Structures

In order to study the risk profiles of the different market structures, we run 100 spot market scenarios for each hour of each year using the forward market decisions and investment decisions for the different cases found in the earlier simulations. We use the same simplification used earlier and simulate only one representative day for each of the four seasons within each year (i.e. $N = 4 \times 24$ hours). Therefore a total of 9600 observations are simulated for each year (i.e.$100 \times N$). In this section, we only consider the cases where generation investments are prioritized.

8.4.1 Nodal Price Comparison

First, we compare and contrast the nodal prices obtained for Cases 1F, 2F, and 3F to evaluate how the different market interaction models affect nodal prices. We use nodal prices for the last year of the simulations (year 4) for this section since the system at year 4 would have been able to take advantage of the results of all 3 investment cycles.

We calculate the mean nodal spot price for each hour and compare the mean nodal spot prices obtained for the different cases. Fig. 8.1 shows the distributions of the differences in mean nodal spot prices for Case 2F and Case 1F, whereas Fig. 8.2 shows the distributions of the differences in mean nodal spot prices for Case 3F and Case 1F. From both histograms, it can be observed that the nodal spot prices for cases with a forward market (Cases 2F and 3F) are typically lower than the nodal spot prices for the case with a spot market only (Case 1F). The differences in prices between Case 2F and Case 1F are generally larger than the differences in prices between Case 3F and 1F. In addition, we observe a pattern of larger variances in the differences in nodal prices for nodes in Region A as compared to the differences in nodal prices for nodes in Region B. In Fig. 8.1 and Fig. 8.2, the bluer bars correspond to nodes in Region A (i.e. nodes 1 to 10). We can observe that the bluer bars have greater spread in both Fig. 8.1 and 8.2. This suggests that there are zonal/regional differences in market behaviors in response to market structure.

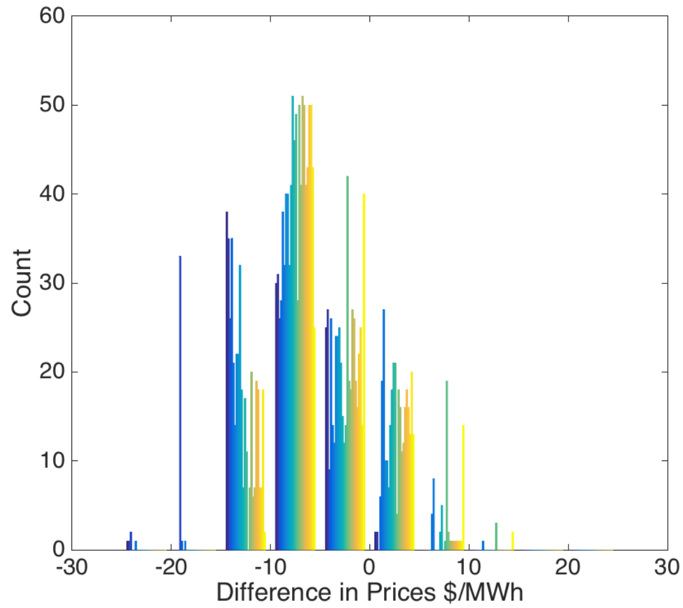

Figure 8.1: Distributions of Differences between Mean Nodal Spot Price in Case 2F and Case 1F in Year 4 for the 24 Nodes (Negative values indicate that prices for 2F < prices for 1F)

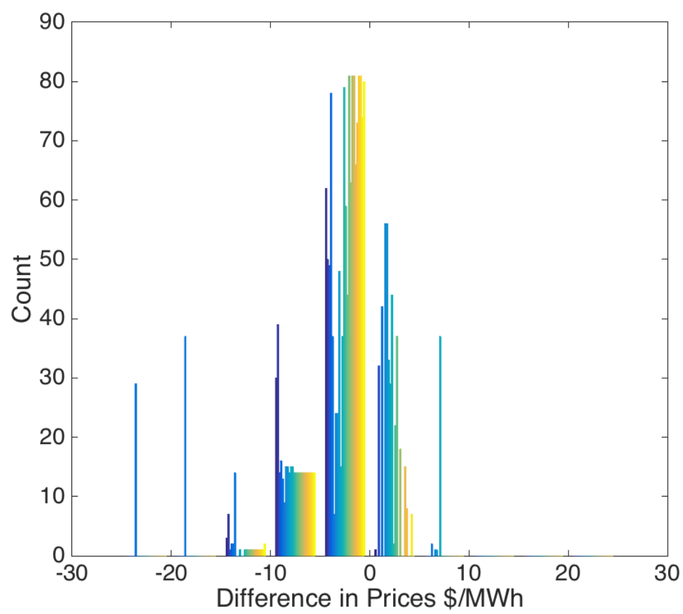

Figure 8.2: Distributions of Differences between Mean Nodal Spot Price for Case 3F and Case 1F in Year 4 for the 24 Nodes (Negative values indicate that prices for 3F < prices for 1F)

Next, we compare the forward price and mean nodal spot price for each hour for Case 2F and Case 3F in Fig. 8.3 and 8.4 respectively. We find that the average spot prices are generally higher than the forward price. In addition, the variances of the differences in spot and forward prices in Fig. 8.3 and Fig. 8.4 demonstrate the same zonal/regional patterns as described earlier.

To further quantify the differences in spot and forward prices, we calculate the expected forward risk premium for the two cases using the following equation:

$$E(\text{RiskPremia}) = E[\frac{\lambda_{SR} - \lambda_{LR}}{\lambda_{LR}}] \tag{8.1}$$

Based on this equation, the risk premium is positive if expected spot price is greater than forward price and negative otherwise. The overall expected forward risk premium is 2% for Case 2 and 20% for Case 3.

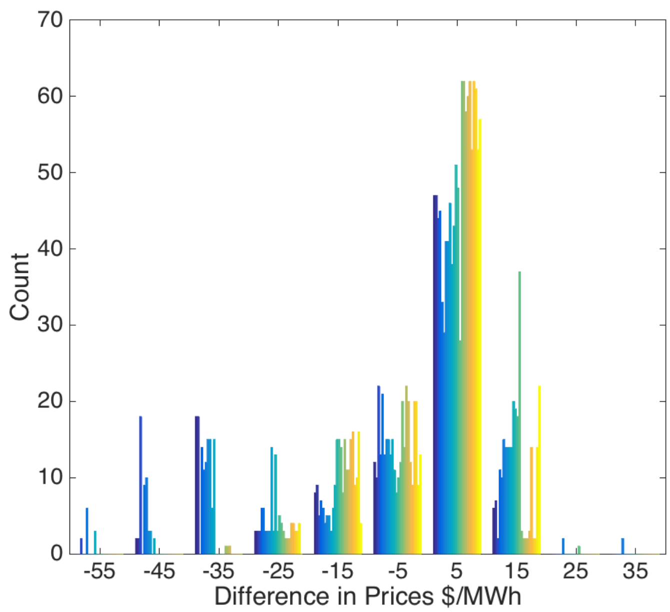

Figure 8.3: Distributions of Differences in Forward Nodal Price and Mean Nodal Spot Price for Case 2F in Year 4 for the 24 Nodes (Negative values indicate that forward price is less than spot price)

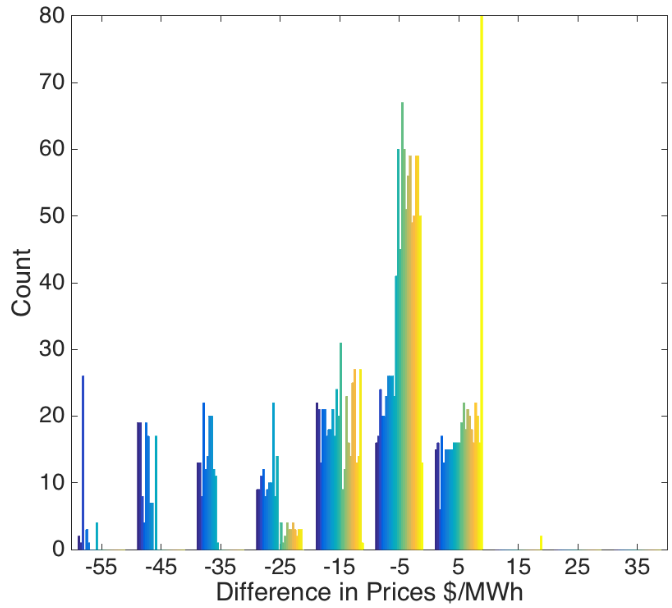

Figure 8.4: Distributions of Differences in Forward Nodal Price and Mean Nodal Spot Price for Case 3F in Year 4 for the 24 Nodes (Negative values indicate that forward price is less than spot price)

Various econometric studies have been done to evaluate the risk premium for actual forward electricity markets [50][87], however, most of the results of these studies do not provide a fair comparison to the results of the models in this paper as the forward market structures studied are very different. The only forward market structure we could find that is similar to what is being proposed in this dissertation is the Colombian forward electricity market structure that was started in 2010 [49]. In the Colombian forward electricity market, the forward market clearing occurs 1-2 years ahead and 100% of regulated load is required to be purchased in the forward market [49]. This is similar to the forward market design used in this paper where forward market clearing occurs 1 or 2 years ahead and 75% of load is required to be purchased in the forward market. [88] did an econometric study of the Colombian forward market and found that the forward risk premium averages about 2.14%. This is consistent with the risk premium found in Case 2F of this study, but lower than the average risk premium found in Case 3F. We will attempt to explain the higher risk premium for Case 3F in the next section.

8.4.2 Load Comparison

In Fig. 8.5 and Fig.8.6, we compare the percentage of load that is purchased in the forward market for Case 2F and Case 3F in year 4. We observe that the average load percentage purchased through the forward market is generally greater for Case 2F than for Case 3F. The overall average load purchased through the forward market is 88% for Case 2F and 80% for Case 3F. We hypothesize that the differences in percentage of load purchased in the two different forward market could be a reason for the difference in risk premium between Case 2F and Case 3F. In Case 3F, the lower demand in the forward market results in higher reliance on the more volatile spot market, which in turn causes the higher risk premium.

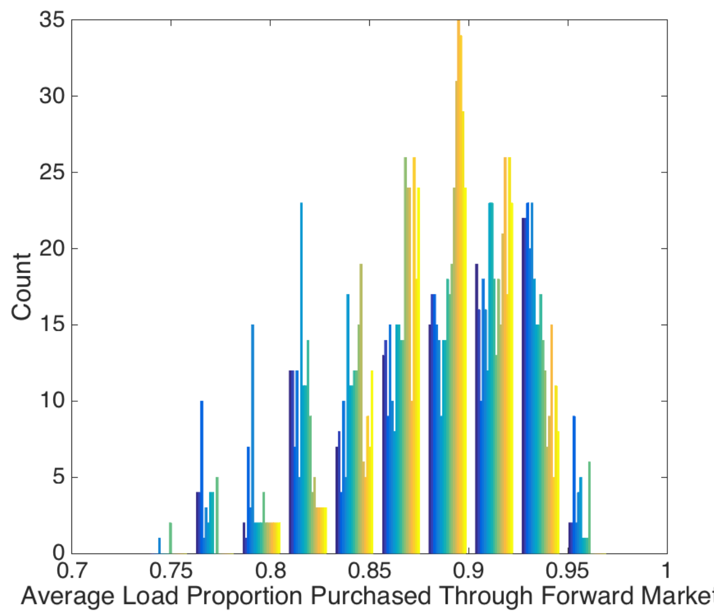

Figure 8.5: Distributions of Proportion of Load Purchased Via Forward Market for Case 2F in Year 4 for the 17 Loads

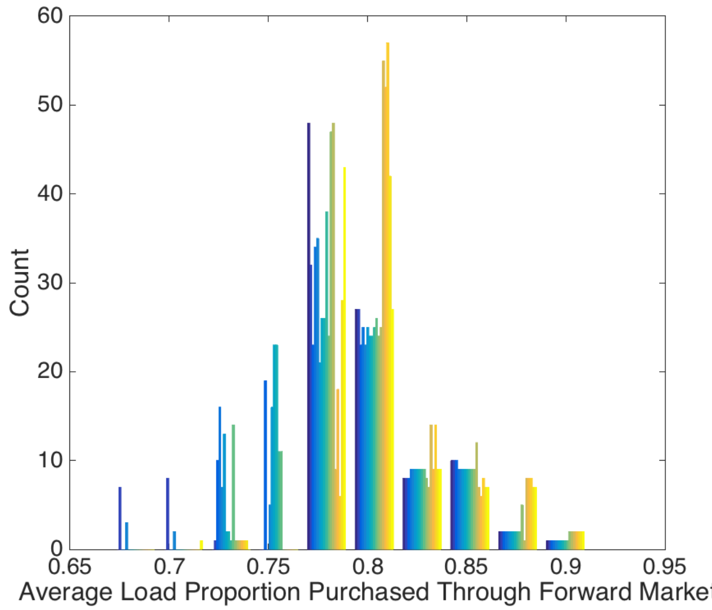

Figure 8.6: Distributions of Proportion of Load Purchased Via Forward Market for Case 3F in Year 4 for the 17 Loads

Next, we calculate the overall load profit for year 4 for Cases 1F, 2F and 3F. The load profit is calculated using the profit function defined in the objective function in (7.11). The overall load profits for Region A and Region B are calculated independently and shown in Fig. 8.7 and Fig. 8.8 respectively. In both regions, we observe that the profit for Case 3F is generally higher than the profit for Case 2F, and the profit for Case 2F is generally higher then the profit for Case 1F. As expected, Case 1F with only a spot market has the greatest variance in overall load profit. In fact, for Region A, the load profit was negative for some scenarios in Case 1F. This results suggest that the coordinated forward and investment market structure (3F) is the most favorable market structure for loads, while the spot only market structure (1F) is the least favorable market structure for loads.

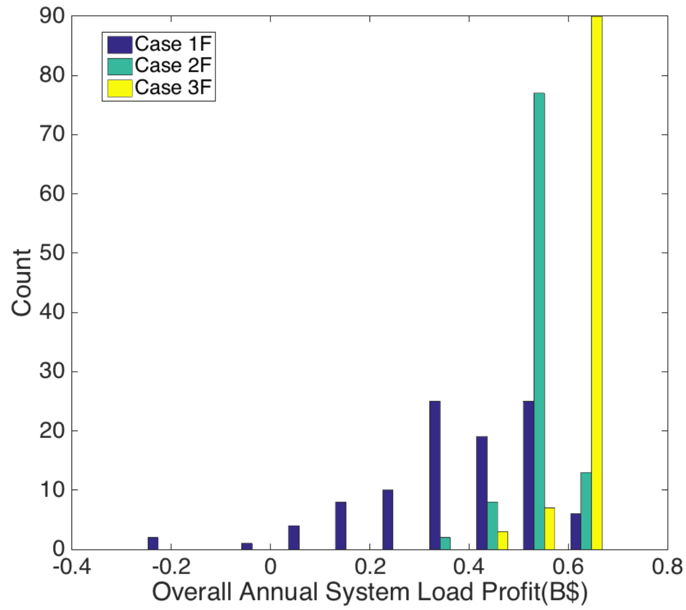

Figure 8.7: Distributions of Total Load Profit for Loads Located in Region A for Cases 1F, 2F, and 3F in Year 4

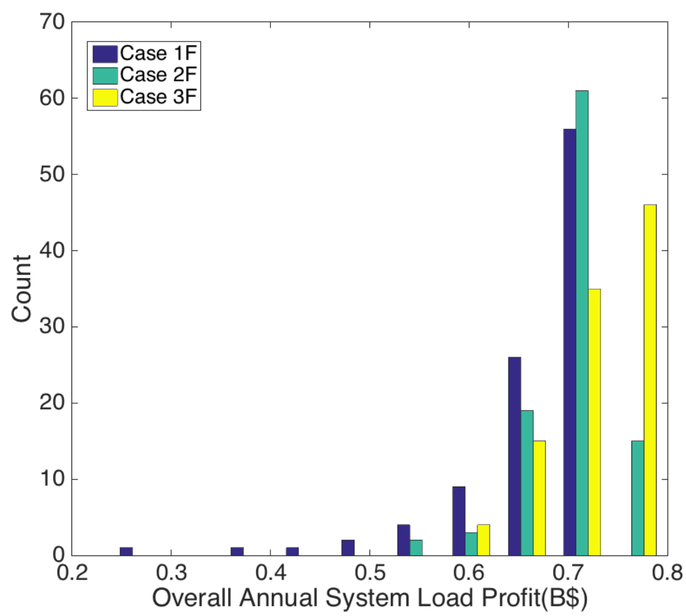

Figure 8.8: Distributions of Total Load Profit for Loads Located in Region B for Cases 1F, 2F, and 3F in Year 4

Table 8.5: Mean Generation Profit

	Mean (k$)	
	G1	G2
1F	130	-16
2F	30	-22
3F	96	-31
1M	150	130
2M	8.7	32
3M	120	-28

8.4.3 Generation Profit Comparison

In this section, we evaluate the profitability of the new generation investments for Cases 1F to 3F and 1M to 3M for year 4. The distributions of the generation profit for G1 and G2 in year 4 for the different cases are shown in Fig. 8.9, Fig. 8.10, Fig. 8.11 and Fig. 8.12. Note that the generation profit accounts for the annualized cost of investment. To better quantify the generation profit, the average generation profit for G1 and G2 for the different cases are shown in Table 8.5.

From the table and histograms, it can be observed that the spot only market structure (1F/1M) is the most favorable market structure for generators. This makes sense as from Fig. 8.1 to Fig. 8.4 we know that the spot-only market structure results in the highest nodal prices. In the previous section, we find that the worst market design for loads is the spot only market design. The fact that the most favorable market structure for generators is also the worst for loads highlights an important point in market design - there are always winners and losers. In this model, we assume that generators bid in a perfectly competitive manner. If generators have market power and is able to bid strategically, the results could potentially be very different.

Another observation from the table and histograms is that on average, G2 is not profitable for Cases 1F, 2F, 3F, and 1M. This is a result of interactions between generation and transmission investments. Even though the generation investment was profitable during the generation investment cycle in which it is made, the addition of new transmission investments reduces the nodal prices at G2 making it unprofitable. Such interactions are likely to increase with a greater variety of grid technologies. How to best consider such interactions between generation and transmission investments is still an open research question in power markets design.

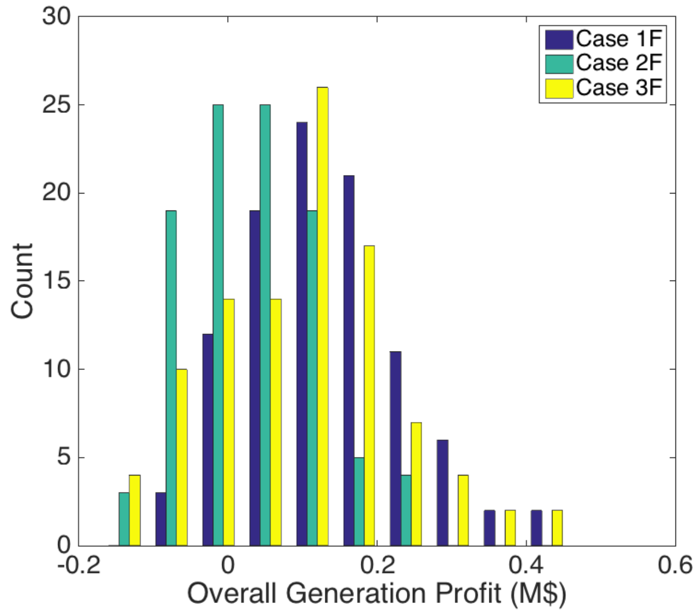

Figure 8.9: Distribution of Generator Profit per MW Capacity for Generator G1 for Cases 1F, 2F, and 3F in Year 4

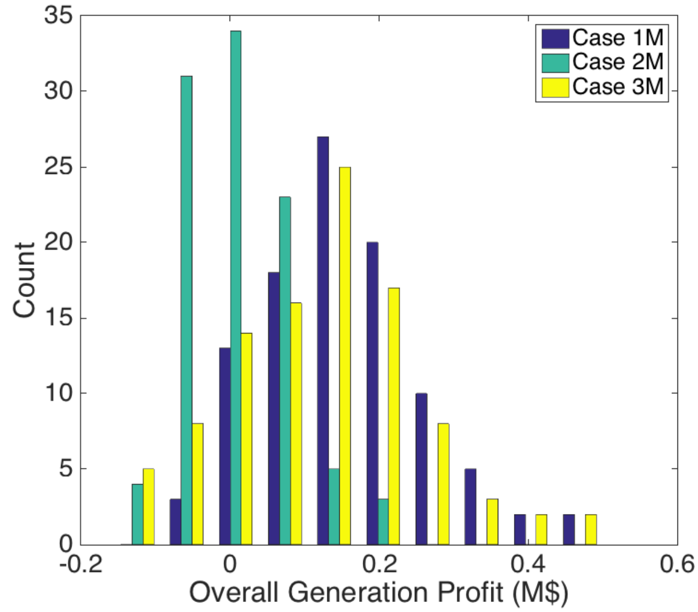

Figure 8.10: Distribution of Generator Profit per MW Capacity for Generator G1 for Cases 1M, 2M, and 3M in Year 4

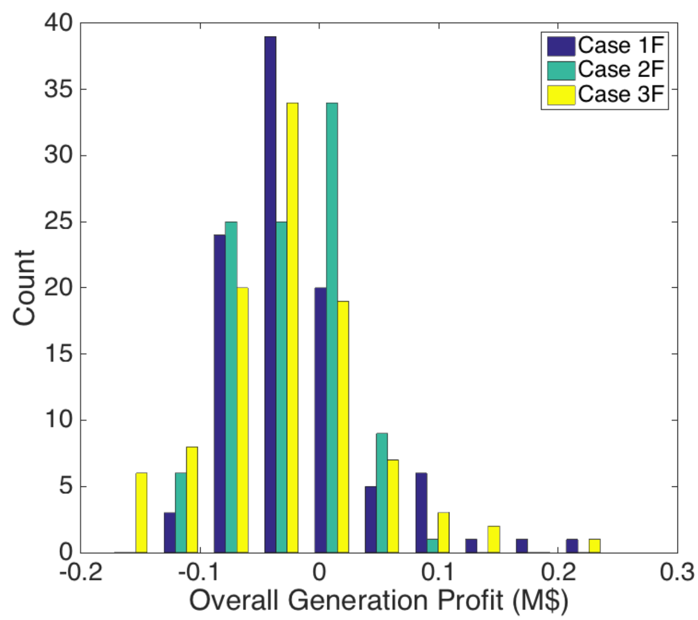

Figure 8.11: Distribution of Generator Profit per MW Capacity for Generator G2 for Cases 1F, 2F, and 3F in Year 4

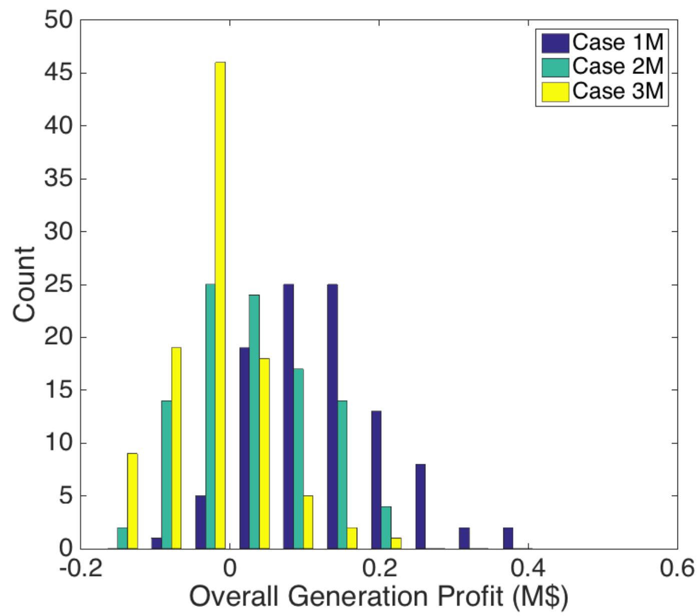

Figure 8.12: Distribution of Generator Profit per MW Capacity for Generator G2 for Cases 1M, 2M, and 3M in Year 4

8.4.4 Transmission Revenue Comparison

Finally, we evaluate three of the transmission investment options in greater detail. The three transmission investment options (T4, T5, and F3) are selected as they are most frequently invested in in year 2. The mean and standard deviation of the expected congestion revenue for the three investment options in year 2 is shown in Table 8.6. From the table, it can be observed that the standard deviation for congestion revenue is zero in some cases. This occurs under two conditions:

1. There is no congestion as in T4 and T5 in Case 1F.

2. There are no scenarios in which the transmission line flow is constrained in the spot market but not constrained in the forward market. In such situations, the only congestion revenue is obtained from the forward market clearing, which is fixed and hence has zero variability.

For Cases 1F, 2F, and 3F, congestion revenue does not matter as the transmission owners are assured cost recovery through the regulated rate of return. Therefore, as expected, the congestion revenue shown in Table 8.6 for the three cases are in some cases less than the investment costs

Table 8.6: Mean and Standard Deviation of Expected Congestion Revenue for T4, T5, and F3 for Y2(* Indicates That the Investment Was Not Installed and Hence the Congestion Revenue Shown is Pre-Installation)

	Mean(Standard Deviation)		
	M$		k$
	T4	T5	F3
1F	0 (0)	0 (0)	16 (11)
2F	96 (0)	78 (0)	580 (2.7)*
3F	1.2 (0)	29 (0)	0.01 (0.1)
1M	110 (55)*	110 (45)*	1100 (460)
2M	130 (27)*	75 (0)*	600 (13)
3M	1.3 (0)	21 (0)	0.1 (0.2)*

shown in Table 8.2 and Table 8.3 earlier. As mentioned in Section 8.3.3, there are two reasons why transmission investments that are profitable in the regulated cost recovery case are not profitable in the congestion revenue based cost recovery cases. Examples of the first reason can be seen in investments T4 and T5 for Case 1M. From the results for case 1F, we can observe that if T4 or T5 is built, congestion revenue will go to zero, and hence congestion revenue alone is insufficient to make T4 and T5 profitable in case 1M from the point of view of the transmission owners. Examples for the second reason can be seen in investments T4 and T5 for Case 2M. From the results for case 2F, we can observe that even if both T4 and T5 are built, the congestion revenues are high enough such that both lines are profitable from the point of view of the transmission owners. However, from the point of view of the system operator, the amount of congestion charges that will be paid out is less than the cost savings to the system due to the lines and hence it is not profitable from the system point of view. Some potential solutions for this has been discussed in Section 8.3.3.

8.5 Limitations

Through the case studies, we have demonstrated how agent-based simulations can be a useful tool to gain insights into various market designs. In this section, we will highlight some of the key limitations of using agent-based simulations for market design.

First, the performance and results of the simulations are tied to system parameters and assumptions. With electricity markets, any model developed needs to be specific to the system conditions of the market of interest. Market and system conditions in New England are very different from conditions in Texas, and there is probably not going to be a one-size-fit-all model or solution. The extent to which market behaviors observed in case studies using a specific test system is generalizable to other test systems depends on the root cause of the market behaviors. For instance, in our case studies, the observations made regarding transmission cost recovery are likely to be generalizable since the root cause of the observed behaviors is technology related (i.e. the lumpiness of transmission line). Observations made regarding risk premium, losers, and winners, are more difficult to generalize since they are brought about by complex interactions among the different agents within a specific system.

Second, mathematical and computational models are simplifications of the real world and hence behaviors observed in models might not be directly translatable to the real world. Stylized models such as those used in this dissertation are useful as a starting point to evaluate potential effects of different market designs, but it can be difficult to evaluate whether certain effects are due to the simplifications made by the stylized models or by the market features being tested. Ideally, we will want to follow up the simulations using stylized models with simulations using more complex models that better reflect the real world, or with pilot testing.

8.6 Conclusion

In this part of the dissertation, we develop an agent based modeling model to simulate different market structures with different combinations of spot energy market, forward energy market, and investment auctions. The forward market design used is similar to the recently introduced forward market design used in Colombia [49], where load is mandated to purchase a certain percentage of their load from the forward market conducted 1-2 years ahead. In addition, we modeled different cost recovery mechanisms for transmission investment cost recovery. Using a case study, we demonstrate how simulation-based modeling techniques can be used to better understand potential winners/losers and risk profiles of different market design options. The policy implications of our findings and open research questions have been discussed in Section 8.3 and Section 8.4.

As mentioned earlier, we tested two key policy recommendations or design suggestions obtained from Part I and Part II of this dissertation. The results show that the risk premium brought about by the mandated load participation in long-term market as proposed in Part I of the dissertation is dependent on the broader market structure. The risk premium shown in one of our model is consistent with the risk premium found in a similar market structure implemented in Colombia [88]. The coordinated forward and investment market model as proposed in Part II shows mixed results. This proposed forward market model appears to favor loads more than the independent forward market model. However, its effects on generation and transmission investment decisions and returns are mixed. As mentioned earlier, the coordinated and independent forward market models presented in this dissertation are highly stylized models. In real world market design, the level of interactions among forward and investment markets will depend on how often market participants are allowed to adjust their forward market decisions to respond to new information in the market. Also, we suggested the possibility of a one-time market adjustment process that is specifically design to allow for reallocation of resources with each addition of new capacity.

8.7 Appendix 3: Data for Part III of the Dissertation

Table 8.7: 24 Bus Test System Generation Data

Node	Capacity (MW)	a_G (\$/MW^2)	b_G (\$/MW)
1	40	0.0230	71
1	152	0.0215	24
2	40	0.0155	71
2	152	0.0370	24
7	300	0.0320	34
13	591	0.0310	33
15	60	0.0335	41
15	155	0.0350	20
16	155	0.0255	20
18	400	0.0365	10
21	400	0.0285	10
22	300	0.0065	24
23	310	0.0220	20
23	350	0.0280	19

Table 8.8: 24 Bus Test System Load Data

Node	Max Load (MW)	a (\$/MW^2)	b (\$/MW)
1	198	-0.0270	116
2	180	-0.065	60
3	324	-0.0155	88
4	135	-0.0260	20
5	125	-0.0170	64
6	252	-0.0185	38
7	225	-0.0205	58
8	315	-0.0130	68
9	315	-0.0365	136
10	342	-0.0275	138
13	477	-0.0295	86
14	351	-0.0075	90
15	576	-0.0305	40
16	180	-0.0285	126
18	594	-0.0355	54
19	324	-0.0125	64
20	234	-0.0200	38

Table 8.9: 24 Bus Test System Branch Data

From	To	Reactance (p.u.)	Capacity (MW)
1	2	0.0139	100
1	3	0.2120	100
1	5	0.0845	100
2	4	0.1267	100
2	6	0.1920	100
3	9	0.1190	100
3	24	0.0839	200
4	9	0.1037	100
5	10	0.0883	100
6	10	0.0605	100
7	8	0.0614	100
8	9	0.1651	100
8	10	0.1651	100
9	11	0.0839	200
9	12	0.0839	200
10	11	0.0839	200
10	12	0.0839	200
11	13	0.0476	250
11	14	0.0418	250
12	13	0.0476	250
12	23	0.0966	250
13	23	0.0865	250
14	16	0.0389	250
15	16	0.0173	250
15	21	0.0490	250
15	24	0.0519	250
16	17	0.0259	250
16	19	0.0231	250
17	18	0.0144	250
17	22	0.1053	250
18	21	0.0259	250
19	20	0.0396	250
20	23	0.0216	250
21	22	0.0678	250

Part IV

Conclusion

Chapter 9

Conclusions and Future Work

With the introduction of new transmission, generation, and demand technologies, the electric power system is becoming increasingly complex. New market and regulatory tools need to be developed to be able to deal with the increased flexibility and complexity of the future electricity grid. In this concluding chapter, we will discuss the work presented in this dissertation in the context of a broader market design framework and highlight the key contributions of this dissertation

9.1 Market Design for Complex Socio-Technical Systems

The overall contribution of this dissertation to the design of future electricity markets is in developing and demonstrating tools that can be part of a broader market design framework. In Fig. 9.1, we present an overall market design framework for the future electricity grid. We believe that the market design framework presented here is relevant to market design for any complex socio-technical systems, and not just for electricity grids.

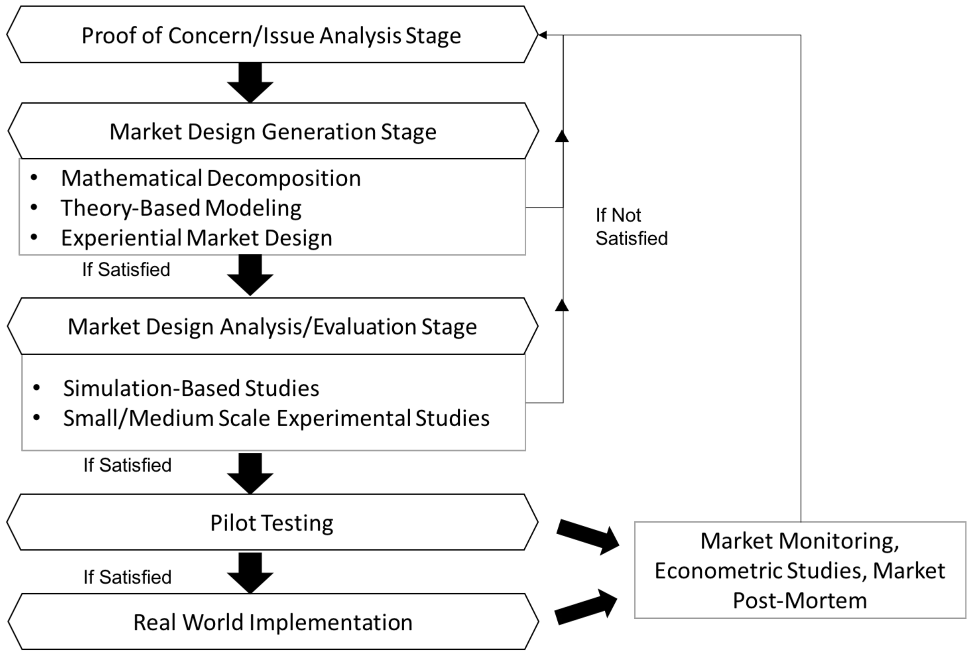

Figure 9.1: Overall Market Design Framework

The first stage of market design is what we call the “proof of concern" stage or issue analysis stage. In this stage, the goal is to find potential areas of concern in the market and to frame the problem. These concerns could arise due to various reasons, such as the introduction of new technology into the power system, or undesirable market behavior observed through market testing. One way in which one can frame potential market problems is through the use of “toy problems" as done in Part I of this dissertation. The purpose of these “toy problems” is to demonstrate potential areas of concerns using simple examples that are easily understood. Generating such "toy problems” is as much of an art as it is a science, and the process of generating the problem can often give practitioners a better understanding of the issue at hand.

Once the market problems we are trying to solve have been defined, we move on to the market design generation stage. In this stage, the goal is to generate market designs that could solve the issues at hand. There are various ways in which market designs can be generated. They could be based on economic theory or they could be based on the experiences of market experts. Part II of this dissertation demonstrates how mathematical decomposition can be used to generate insights that could help make market design decisions. Used in conjunction with economic theory and expert experience, mathematical decomposition can be used to generate promising market designs.

Once a specific market design or a set of potential market designs is selected, we move on to the market design analysis/evaluation stage. In this stage, the goal is to conduct studies to evaluate the proposed market designs. This can be done either through experimental studies with actual human participants, or through simulation-based studies as presented in Part III of the dissertation. With advances in computing, simulation-based studies are the most scalable, cost-effective option to test different market designs. At this stage the potential externalities, risk profiles, and unintended consequences of the different market designs being proposed can be evaluated. If any undesirable market behavior is discovered at this stage, we can go back to the initial issue analysis stage to deal with the undesirable behavior.

Once we are satisfied with the performance of the simulation or experimental model, it is recommended that an initial limited pilot test of the market design be conducted if possible. In some cases, this might not be possible and a complete implementation of the market design needs to be introduced at once. Regardless, whether it is a pilot test or complete implementation of the new market design, a market monitoring and data collection system needs to be in place so that the market data can be analyzed to ensure that it is functioning as expected.

Regardless of how well studied a certain market design is, it is likely that unexpected behaviors will emerge during actual implementation. Therefore, market design is inherently an iterative process, where practitioners will likely have to tweak different market components over time. The framework presented in Fig. 9.1 provides a systematic approach to market design.

9.2 Models for Power System Planning and Operations

Besides the broader contribution of this dissertation to market design for complex socio-technical systems, this dissertation also contributes to the development of various models for power system planning and operations. All the models presented in this dissertation are mixed-integer, non-linear, and non-convex due to the modeling of transmission investments as lumpy investments and the consideration of flexible reactance devices. The resulting models are therefore more complex than traditional DC transmission and generation investment models. The reason for developing and using a more complex model for our case studies is to ensure that the market design tools presented in this dissertation are flexible enough to handle the increasing complexity in the power system.

In Part I of this dissertation, we developed two transmission investment models. The first model captures the value of operational flexibility by accounting for short-run uncertainties characterized through K-means clustering, whereas the second model captures the value of investment flexibility by accounting for long-run uncertainties characterized through markov processes. In addition, different operational frameworks with different levels of flexibility were considered. The models were used to understand how different operational frameworks handle uncertainties and how different levels of information uncertainties affect investment decisions.

The models in Part I were only used to solve simple examples on a 2-Bus Test System. In Part II of this dissertation, we expanded the model in Part I to account for potential investments in generation and flexible transmission devices. The model was decomposed temporally and spatially to allow us to generate insights that could guide market design. The temporally decomposed model is highly computationally efficient and can be solved faster than the corresponding centralized problem using a leading MINLP solver. The temporally and spatially decomposed model is computationally inefficient, but it allows us to generate greater insights into different potential market structures.

In the final part of this dissertation, agent-based models where each agent is modeled as a state-machine were developed. The agent-based models are highly flexible and were used to test various spot, forward, and investment market configurations. In addition, the models were used to test various transmission cost recovery methods.

9.3 Market Insights

The models discussed in the previous section were used to gain insights into different aspects of electricity market design through case studies. More often than not, these insights lead to further research questions. Some of the key market insights gained are presented below:

- System flexibility is key in the face of uncertainties. Flexible operational frameworks, such as the corrective N-1 operational framework, along with the availability of flexible loads, can reduce the need for redundant investments. In addition, improvements in system flexibility also increase the value of investments in more modular flexible devices.

- There needs to be a strategy for long-term information exchange in the system so that stakeholders are provided with better information about long-term uncertainties. Well designed forward markets are needed in the system. Simulations show that even the simple forward market models tested in this dissertation provide significant benefits to transmission investment cost recovery and load profits. Interestingly, the forward market tested in this dissertation is detrimental to generators' profits.

- A regulatory mandate that requires load serving entities to purchase a certain percentage of their load in the long-term forward market (1-5 years ahead) is a promising strategy for forward market design. In fact, a similar design has been used in Colombia since 2010 with promising results [49]. However, more work needs to be done to better understand whether such a market structure is feasible in the United States.

- There needs to be a feedback process between forward energy market and investment planning. In testing a coordinated forward energy and investment market model, we find that such a coordinated market model generally results in higher investment levels. In actual real-world market design, the level of feedback between forward energy market and investment planning depends on the ability for market participants to adjust their forward decisions in response to new information in the market. This could potentially be achieved through liquid, multiple time-scale markets. In addition, it might be interesting to study the potential of a one-time forward market adjustment process, similar to the "initial public offering" process in the financial stock market, to allow for reallocation of resources with the addition of new capacity.

- A potential hierarchical market structure is proposed in Fig. 6.7.

- Various pricing insights were gained from the decomposition schemes. However, more work needs to be done to translate these insights into practical pricing strategies. For example, how can we use the penalty term that represents the velocity of convergence in the decomposed problem to improve price discovery in real-world markets or auctions? How can information regarding the substitutionary and complementary effects among different investment options obtained through Benders Cuts be used to potentially form socially beneficial cooperative investment alliances?

- Non-convexities have traditionally been difficult to price. In the Non-Convex GBD algorithm adopted in Part II of this dissertation, a convex relaxation of the non-convex problem is used as an approximation to the original problem to ease computation. This leads to the question of what is the minimum level of complexity that needs to be modeled in designing electricity markets and pricing schemes.

- The potentially substitutionary effects of generation and transmission investments mean that the order of investments can have significant impacts on overall investments in the system. It is unlikely that any investment market protocol could be truly 100% technology neutral. Therefore, it is important for market designers to understand the biases of any investment protocol to ensure that any investment bias introduced to the system align with the broader societal objectives.

- Congestion revenue based cost recovery appears to result in under investments in transmission lines due to two reasons. First, the lumpiness of investments often results in post-investment congestion revenue of zero. Second, in some situations, transmission owners are willing to make the investment based on expected congestion revenue, but the congestion revenue that needs to be paid out by the system operator to the transmission owner does not justify the investment. The availability of long-run congestion revenue via the forward market helps with the first situation. In the second situation, some cases could potentially be resolved by rewarding only partial rights to the congestion revenue, such that the transmission owners receive a percentage of the congestion revenue that makes it profitable to both the transmission owners and system operators.

9.4 Concluding Remarks

In this concluding chapter, we have discussed the contributions of this dissertation in terms of model development and market insights, and in the context of an overall framework for market design. On the highest level, this dissertation is about developing and demonstrating market design tools that can handle the increasing level of complexity in the electric power system. This dissertation takes some initial steps in demonstrating how tools such as mathematical decomposition and computer simulations can be used to gain insights into market design for the future electricity grid. However, more work remains to be done. In particular, we believe that there should be greater exploration of the potential of mathematical decomposition as a tool for market design, especially in terms of market pricing.

In addition, we believe that one of the biggest challenges in the design of future electricity markets is that it is currently difficult to compare studies done by different researchers due to the variety of tools being used. Simulation-based studies like the one used in this dissertation are particularly notorious for being difficult to interpret. Therefore, one key research focus in the near future for the electricity market design community should be to develop a common evaluation framework to compare the different market design ideas being tested by the broader research community and to develop best practices for electricity market design.

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