Essays on Unit Commitment and Interregional Cooperation in Transmission Planning

by

Saamrat Kasina

A dissertation submitted to The Johns Hopkins University in conformity with the requirements for the degree of Doctor of Philosophy.

Baltimore, Maryland

July, 2017

© Saamrat Kasina 2017

All rights reserved

Abstract

One of the most challenging problems in the power industry is deciding which transmission lines to build. The process of answering this question leads to some very interesting and complex optimization problems. Answers to subsidiary questions about the detail of generator operations to simulate, generator siting, environmental regulations, political boundaries, and the ways in which these factors interact with each other, together inform the decision of building transmission lines. For example, carbon taxes may favor transmission expansion to areas with high levels of renewable energy, and consequently, fast ramp-rate generation may be desired to balance the variable nature of renewable energy sources.

Transmission investment decisions can have far-reaching consequences for investors and a host of other entities connected to the electric grid. In addition to being expensive and time-consuming to build, these lines influence other transmission and generation investments, operations, and electricity prices.

This work presents a series of essays on the transmission planning problem. There are two main themes: the effects of short-term operations, and the effects of political

ABSTRACT

boundaries, on long-term transmission plans. Contributions of these essays include the following:

1. An alternative formulation of the Unit Commitment (UC) problem that solves faster than the standard UC formulation, and UC approximations that improve computational performance while maintaining high fidelity in the quality of the solution (reduction of binary variables and tightening of constraints).
2. Demonstrating how to bridge the gap between short-term (hours) operational models and long-term (years) transmission and generation co-optimization models, using an application of the U.S. Western Interconnection.
3. Demonstrating that short-term operational constraints have the potential to affect long-term transmission and generator investments. As an example, we find that, when operational constraints such as ramp-rates and minimum-run capacities are considered, transmission investment can sometimes act as a substitute to generation investments.
4. A novel formulation of the noncooperative regional transmission planning problem that shows how regional transmission operators acting in their own self-interest can negatively impact transmission investments.
5. Demonstrating that adjoining transmission operators can both benefit from cooperating with each other in the transmission planning process. Interestingly, we find that it is not enough to focus on seam lines connecting two regions.

There are lines internal to each region that have interregional benefits and are identified only though a cooperative planning process.

6. Approximations of the non-cooperative transmission planning model that aid scale-up of this framework to large data-sets, further improving computational performance.

Limitations of these models, practical issues involved, and future research directions are discussed in the concluding chapter.

Together, these essays illuminate the effects of operational constraints and political boundaries on transmission planning, and encourage decision makers to consider them in their planning processes.

Primary Reader: Dr. Benjamin F. Hobbs

Secondary Readers: Dr. Hugh Ellis
Dr. Sauleh Siddiqui

Dedication

To my wonderful Mother, Father, and Brother. Any amount of gratitude I show you is inadequate.

Acknowledgments

This thesis would not have been possible if not for the incredible support system I have had in Baltimore and elsewhere. Foremost, I would like to thank my advisor, Dr. Ben Hobbs. He is an excellent scientist and an incredible teacher. He inspires me with his humility, hard work, and integrity. My admiration and respect for him have only grown with time. I thank him from the bottom of my heart and look forward to more exciting times working with him.

I would also like to thank my committee members - Dr. Paul Ferrarro, Dr. Hugh Ellis, Dr. Dan Robinson, Dr. Erica Schoenberger, Dr. John Boland, Dr. Tak Igusa, and Dr. Sauleh Siddiqui. Dr. Hugh Ellis has always pushed me to think hard about my work, especially in validating results, and adapting the models in this thesis to real-life applications. Dr. Sauleh Siddiqui is a veritable well of knowledge on equilibrium problems. I thank him for patiently answering my questions and discussing MPECs and EPECs with me the many times I dropped by his office. Dr. Erica Schoenberger taught the *Environmental History* class, which I took in my first semester at Hopkins. The first 10 minutes of every class was “silly questions” time.

Because of her, I am able to ask questions without feeling scared of looking stupid. I would also like to thank Jean-Paul Watson of the Sandia National Laboratories for showing by example what constitutes an excellent researcher.

I spent the previous summer interning at the firm E3, in San Francisco. Specifically, I would like to thank Ren Orans, Michelle Chait, Fritz Kharl, and DoGEE alumnus Jeremy Hargreaves for their patience, collegiality, and guidance.

My stay in Baltimore would not have been the same without friends from DoGEE - Dano, Mike, Steven, Stephanie, Robin, Jon, Cindy, Elina, Fengwei, Liang, Pengcheng, Qingyu, Brent, Tania, Emily, Marie, Hardik, and Jessica. Especially Dano, Robin, and Cindy read parts of this thesis, and it is better because of their feedback. I would also like to express my deep appreciation for my friend, roommate, and officemate Marc Beaudin, who spent a considerable amount of his time and energy proofreading this thesis and checking all the equations. I am constantly amazed at how much he can accomplish.

I also thank Anya Castillo and Francisco (Pancho) Muñoz for being both mentors and friends. They encouraged me to explore my ideas, and I could always turn to them with questions. I would also like to thank Chris Kelly for inspiring me with his imagination and sheer brilliance. I will miss our long conversations over beer at CVP, about topics ranging from water quality assessment to global politics.

My friends Venkat, Srinivas, Abdul, and Balaji are some of the most generous people I know and I am lucky to be their friend. I would be remiss not to thank my friends Sid, Saumya, Hareesh, and Akshay for their friendship and support. I cannot thank these guys enough for all the fun and laughter.

I would not have been able to complete even a fraction of this thesis, if not for my best friend, Sarita. I thank her for all the times she encouraged me to continue when I felt like giving up. My time in Baltimore was so much more fun because she was here.

I would also like to thank my brother, Prathap, and his wife, Sneha. My brother always inspired me, and stood by me. I drew enormous courage knowing that he had my back. His wife is an equally marvelous woman. I have great memories of my visits to them in New Haven — winter afternoons spent reading game theory papers at their home, cafes, and the Yale library.

Lastly, I would like to thank my parents. I owe everything to them. My mother is an amazing woman — extremely intelligent and full of laughter, love, courage, and kindness. She inspires me everyday to be a better person. My dad inculcated a sense of freedom, intellectual pursuit, and steadfastness in me since I was a kid. His support for me is unwavering. Together, they are the bedrock of my life.

This work was made possible by funding from the Consortium for Electric Reliability Technology Solutions (CERTS) of The U.S. Department of Energy (DoE), and from the Sandia National Laboratories.

Contents

Abstract ii

Acknowledgments vi

List of Tables xvi

List of Figures xviii

1 Introduction 1

- 1.1 Motivation 1
- 1.2 Scope and contribution 5
  - 1.2.1 Chapters 2 and 3: Unit commitment approximations in transmission planning 5
  - 1.2.2 Chapters 4 and 5: Cooperation in interregional transmission planning 7

2 Unit Commitment Approximations for Generator Production Cost-

ing **9**

2.1 Abstract 9

2.2 Notation 10

2.2.1 Sets and Indices 10

2.2.2 Parameters 10

2.2.3 Variables 11

2.3 Introduction 12

2.4 Preliminaries 17

2.4.1 Definitions 17

2.4.2 The role of Valid Inequalities in MILP solvers 17

2.5 Model formulations 18

2.5.1 Base Case Unit Commitment (BCUC) 18

2.5.2 Base Case Relaxed Unit Commitment (BCRUC) 20

2.5.3 Tight Unit Commitment (TUC) 20

2.5.4 Tight Relaxed Unit Commitment (TRUC) 23

2.5.5 Tight Partially Relaxed Unit Commitment (TPRUC) 23

2.5.6 Load Duration Curve (LDC) 24

2.5.7 Augmented Load Duration Curve (LDC’) 25

2.6 Experimental design and assumptions 25

2.7 Results and discussion 28

2.7.1 Indices measuring model performance 28

2.7.2 Comparison of BCUC and TUC formulations 29
2.7.3 Total system costs 31
2.7.4 Hourly energy prices 33
2.7.5 Time to solve 34
2.7.6 Comparison of linear approximations 36
2.7.7 Estimating a new generator's profit 39
2.7.8 Increasing net load variability due to wind 41
2.8 Conclusion 45

3 Transmission Planning with Intertemporal and Generator Operational Constraints 48

3.1 Abstract 48
3.2 Notation 49
3.2.1 Sets and Indices 49
3.2.2 Parameters 50
3.2.3 Variables 51
3.3 Introduction 52
3.4 Two stage stochastic transmission planning 56
3.4.1 Transmission planning model ignoring inter-temporal operational constraints 57
3.4.2 Transmission planning model with unit commitment constraints 60
3.5 Case study: WECC 21-zone network 62

3.6 Results from a deterministic case-study 64
3.6.1 Generator flexibility in the short-run (hours) affects long-run (years) transmission plans: Changes in first stage investments 64
3.6.2 Economic regret 67
3.6.3 Operations are more accurately depicted due to UC constraints 69
3.6.3.1 Where and why do we see these changes? - The example of coal units and carbon prices 72
3.6.3.2 Economic regret faced by the system at different midrange carbon taxes 75
3.7 Five-scenario stochastic two-stage program 77
3.7.1 Scenarios' description and probabilities used 77
3.7.2 Does UC change stochastic 10-year and 20-year investments? . 80
3.7.2.1 Effect on stage 1 investments 80
3.7.2.2 Effect on stage 2 investments 83
3.8 Conclusions 87

4 An Equilibrium Model For Noncooperative Interregional Transmission Planning 90
4.1 Abstract 90
4.2 Notation 91
4.2.1 Sets and Indices 91
4.2.2 Parameters 92

4.2.3 Variables 93

4.3 Introduction 94

4.3.1 Problem definition 94

4.3.2 Relationship with previous work 98

4.3.3 Scope 100

4.4 Single-ISO MPEC: Non-cooperative transmission planning 101

4.4.1 Lower-level problem: Generator investments and energy market equilibrium 104

4.4.2 Upper Level Problem: ISO maximizing surplus of players within its region 106

4.4.3 Solving the individual ISO's MPEC 108

4.4.3.1 Lower level's dual constraints 108

4.4.3.2 Strong duality condition 109

4.4.3.3 Linearizing the non-linear terms in strong duality condition 110

4.5 Multi-ISO EPEC: Non-Cooperative transmission planning 111

4.6 Cooperative transmission planning 113

4.7 Case study 114

4.7.1 Test case 115

4.7.2 Results and discussion 116

4.7.2.1 Changes in transmission and generation investments 116

4.7.2.2 Value of Cooperation 120
4.7.2.3 Using this framework to evaluate side-payment agreements 122
4.7.2.4 Computational performance 123
4.8 Conclusion 124

5 McCormick Envelopes to Approximate Large-Scale Interregional Non-cooperative Transmission Planning Models 126

5.1 Abstract 126
5.2 Introduction 127
5.3 All nonlinear terms in the objective function cannot be linearized . . 129
5.4 Why we do not see these nonlinear objective function terms in a competitive market model 131
5.5 McCormick envelopes 134
5.6 McCormick envelopes for the bilinear terms 136
5.7 Quality of the single MCC envelope (MCC_1) for the 17-bus CAISO dataset 139
5.8 Tightening McCormick envelopes 140
5.8.1 Does spurious splitting matter? 144
5.8.2 Additional constraints needed to correctly split the variables . 144
5.9 Performance of piece-wise McCormick approximation 146
5.9.1 Changes in line investment and overall surplus 146

5.9.2 Effect of approximations' quality on EPEC solution 148
5.10 Increase in size of approximations 149
5.11 Conclusion 150
6 Conclusion 152
6.1 Summary and contributions 153
6.1.1 Improved approximations of unit commitment 153
6.1.2 Noncooperative vs cooperative transmission planning 158
6.2 Computational difficulties 164
6.3 When is the additional effort justified? 165
6.4 Limitations of the studies 166
6.5 Future research 168
Appendix 171
Bibliography 176
Vita 197

List of Tables

2.1 Comparing Base Case and TUC MILP performance 30
2.2 Percentage errors in estimating total system costs. TRUC had a maximum error of 0.59% while TPRUC (with only 19.4% of the number of binary variables), had a maximum error of 0.38%. 33
2.3 Time to solve $(s)^*$ 36
2.4 Time to solve $(s)^*$ models with high penetration of variable renewables. 45

3.3 Levels of uncertain parameters in each of the five scenarios. L, M, H indicate Low, Medium, and High respectively. The values can be found in Table 4.1 of [1]. 78
3.4 Two sets of probabilities were tested with and without UC Constraints 79
3.5 Set 1 probabilities: 1st stage generation investment changes (with UC - without UC). Less investment in CCGT units and less investment overall. Wind investment changes geographically. 82
3.6 Set 2 probabilities: 1st stage generation investment changes (with UC - without UC). Less investment in CCGT units and more investment in wind is observed. 83
3.7 Changes in stochastic solutions based on the probability set. 87

4.1 Region-wise transmission investment. † indicates a seam line while * indicates a region's internal line that is built only in the cooperative framework. 117
4.2 Generation Investment Changes 119
4.3 Change in Annualized Investment Cost and Energy Prices by Region (Cooperative - Non Cooperative) 120
4.4 Breakdown of Annualized Value of Cooperation [Δ Surplus (Cooperative-Noncooperative)] 121

5.1 Comparing primal solutions from two MPECs - Lines chosen to be built 139

5.2 Error in Objective value from two MPECs, calculated by imposing the upper level solution from the approximation upper level solution on the original single-ISO MPEC. 140
5.3 Primal Solutions: Comparison of the approximations' transmission investments with the original recommendations. 147
5.4 Percentage underestimation of Objective value: Imposing approximation upper level solution on original MPEC. Green indicates a reduction in error. For all four models, it is assumed that the other player builds no transmission lines. 147
5.5 Error in Objective value - Imposing approximated EPEC solution on EPEC 149
5.6 Size of the problem increases with complexity of McCormick envelopes 150

6.1 Generator data (size $1x$) for Unit Commitment models from Chapter 2. 171
6.2 Changes in 1st stage energy mix (annual operations) in the deterministic case study from section 3.6. The plotted values were filtered for values below 400 GWh for ease of display. 172
6.3 2nd stage generation investment changes (with UC - without UC) for Set 1 probabilities. Overall, we see that there is less investment across all technologies. 173
6.4 2nd stage generation investment changes under Set 2 probabilities **without** Unit Commitment. Compare this with Table 6.5. 174
6.5 2nd stage generation investment changes under Set 2 probabilities **with** Unit Commitment. Compare this with Table 6.4. 175

List of Figures

2.1 Hypotheses shown as arrows: In comparison, Hypothesis 1 is (in most cases) proven mathematically (for total cost); the magnitude of the change in solution (total cost, primal variables, prices, net revenues) is assessed through numerical experiment. Hypothesis 2 is assessed through numerical experiment. 26
2.3 RMSE in price prediction from TRUC and TPRUC. 34
2.5 Percentage error in total cost from linear approximations relative to UC ($1x$). Negative error implies the model under-estimates system costs compared to base case UC. 38
2.6 RMSE in prices from linear approximations relative to UC. 39
2.7 A small generator's gross margin (Revenue — Operating Cost) as predicted by UC linear approximations for $1x$ system. For larger system sizes, we expect TRUC's performance to improve as its RMSE reduces. 40
2.8 Load profiles with and without wind 42

3.1 Two-Stage stochastic model schematic. Squares represent decision nodes. Uncertainty is depicted by the chance node (circle) and the branches represent scenarios. 57
3.2 21-zone network representation of the Western Interconnection [1]. . . 63
3.3 Changes in Stage 1 transmission investment: Left panel shows investments (wind farms in green and gas plants in blue) without UC and right panel shows investments with UC. See Table 3.1 for generation investment changes. 65
3.5 Example of how UC affects short-runs operations depiction. These are operations in Colorado without and with UC. Results are from Stage 1 operations from a deterministic 'Economic Recovery' case. We see that UC now forces the model to make coal plants' dynamics more realistic in terms of starting up, shutting down, and ramping. 71

3.6 Effects of carbon tax upon the capacity factor (CF) of coal plants (2024, WECC 1 Economic Growth scenario, no unit commitment constraints) 73
3.7 Effects of unit commitment constraints upon the capacity factor (CF) of coal plants under alternative CO2 prices, and the resulting impacts on transmission investments. A positive value indicates that coal is operated more with the addition of UC constraints as compared to without. Green denotes change in Stage 1 transmission plans. 74
3.8 10-year transmission investments (here-and-now decisions) with and without UC (Set 2 probabilities). 81
3.9 20-year transmission investments (wait-and-see decisions) with and without UC using two sets of probabilities for the 'WECC 1: Economic Recovery' scenario. **Left panel**: Green line indicates that the line is built with UC constraints, but not without. These are using Set 1 probabilities. **Right panel**: Red line indicates the line that is not built with UC constraints, but is built without, i.e., it is a sub-optimal line. These are using Set 2 probabilities. 84
3.10 Second stage generation changes with Set 1 probabilities. Solar investments change geographically, more wind investments, and gas units change operations. The data is shown in Table 6.3 of the appendix. . 85
3.11 Second stage generation changes with Set 2 probabilities. Gas operations change geographically and wind investment is being concentrated. 86

4.1 Transmission planning regions in USA [2]. 96
4.2 Hierarchical structure of a single region's transmission planning problem. Region_i (its planner) is in the upper level and the generators and consumers of the entire market (all regions) are in the lower level. . . 103
4.3 Time line of transmission investments, generation investments, and system operation 103
4.4 Hierarchical structure of Multi-ISO transmission planning problem. All ISOs are in separate upper level problems, and there is a single energy market in the lower level they interact with and it consists of generators and consumers in all regions. 113
4.5 Transmission investments change with cooperative transmission planning. ▲ and - - - indicate nodes and lines of Region 1. ■ and — represent Region 2. Parallel lines between two nodes indicate transmission investment. Lines connecting ▲ and ■ are seams lines. Only bus numbers are indicated for clarity. 118

5.1 4-bus example network with two regions. Green (solid) indicates buses and lines in Region 1 and Black (dashed) indicates Region 2. 132
5.2 McCormick envelopes [3]. 135

Chapter 1

Introduction

1.1 Motivation

The U.S. electric transmission grid is a vast network with more than 200,000 miles of high-voltage transmission lines [4]. This grid delivers electricity from generators to distributors, who in turn deliver it to wholesale and retail consumers. The United States electric grid is mainly comprised of three regions - The Eastern Interconnection, The Western Interconnection, and the Texas Interconnection. Transmission or generator outages have the potential to ripple through these interconnections, leaving a significant number of people, industries, and public service providers without power. In 2003, a software bug in the alarm system at a control room in Ohio ultimately led to a blackout affecting 45 million people across eight states in Northeastern U.S.A.

and an additional 10 million people in Canada [5]. Outside the U.S.A, in India in 2012, a combination of weather, political, infrastructural, and electrical causes led to an imbalance between electricity generation and demand. These disturbances cascaded over the Indian electric grid, and caused the largest blackout in the history of the world, affecting 620 million people [6].

An argument has been made that the U.S. has under-invested for years in transmission [7] [8], and that we need to make up for that, including proposals for "supergrids" [9] [10] to take advantage of renewable and load diversity. Currently, transmission makes up 18% of the total annual capital expenditure [11], and transmission charges make up 9% of the U.S. average electricity [12]. But transmission's importance may be greater than its fraction of the cost. In fact, [13] argues that transmission is the most important issue to be dealt with in integrating renewable energy sources.

Traditionally the majority of transmission upgrades in the U.S. were performed by vertically integrated utilities (VIUs) to meet grid reliability standards set by the North American Electric Reliability Corporation (NERC). The objective of these standards was to ensure grid stability and reliability for smooth power delivery from generators to consumers. Deregulation of the power sector started changing the focus of transmission planning. Federal Energy Regulatory Commission (FERC) Order 888 sought not only to promote competition in the wholesale market by providing non-discriminatory access to transmission — thereby separating the transmission planning process from generators and consumers — but also gave utilities the right to recover costs of transmission investments from energy consumers. This emphasis on transmission costs and their recovery is inextricably tied to the question of who benefits from transmission. As a result, it became important to understand the benefits of transmission investment and to compare these with the corresponding costs [14].

Interest in new methods of transmission planning was also fueled by the push to integrate more renewables into the energy mix. High-quality renewables are often located far from load centers in the USA. For example, states like Wyoming and Idaho have outstanding wind generation potential [15], but the development of these resources would require investment in high-voltage transmission lines from the wind farms to the load-pockets that can use the generated energy. Recognizing that transmission investment was no longer driven by just reliability, ISOs focused more on public-policy driven transmission planning.

While some ISOs have developed new methodologies to plan for transmission investments driven by both reliability standards and policy, there is a current lack of industry standard to achieve this [16] [17]. Moreover, most ISOs still follow simple production costing methodologies [14] that ignore the chronological nature of electricity demand and the physical nature of generators. This lack of a comprehensive view on how to plan for transmission is due, in no small part, to the complexity of the issues being considered. This complexity arises due to multiple factors, including the following:

1. Transmission upgrades are costly. A poor planning process might result in

over-investment ("stranded" assets whose costs exceed their benefits) or under-investment (which can result in inefficient operations, such as extensive wind curtailment, as in Texas in the 2000s [18] or presently in China [19], and solar curtailment, as in India now [20]), as well as inefficient siting of generators.

2. Power cannot be directed manually. The grid is governed by the laws of physics (Kirchhoff's laws).

3. Transmission lines take time to be built. The process of planning, getting approval, and building a transmission line is a 7-10 year long process. Thus, planners need to commit to investment decisions without knowledge of the political, regulatory and economic landscape 10 years later.

Keeping these complexities in view, there was increased interest in new, comprehensive economic transmission planning methods. For instance, [21] proposed a market-driven model that estimates probabilistic uncertainty in nodal prices and used this to find which upgrades are needed. However, the study does not consider future policy uncertainty nor allows for multiple rounds of investment as happens in reality, where decisions are made and revised gradually over time. A two-stage stochastic model that lets planners consider uncertainty and allows for multiple rounds of investments was proposed in [22], which was then expanded upon by including Kirchhoff Voltage Laws and by applying the framework to a larger test system in [23].

1.2 Scope and contribution

There are multiple system-level metrics that can be used to measure the impact of potential infrastructure additions (in this case, transmission lines) and operations on the system. Some of these metrics are vulnerability, resilience, reliability, and economic performance. Most studies focus on endogenously evaluating system performance in terms of a subset of these metrics. For example, [24] and [25] include $n-k$ reliability constraints[1] into economic evaluations of system operations.

The main focus of this thesis is *economic* electric transmission planning - i.e., estimating the benefits and costs of transmission additions using mathematical models with the ability to decide when, where, and what line investments are required. The specific chapters in this thesis and the questions addressed within these chapters are:

1.2.1 Chapters 2 and 3: Unit commitment approximations in transmission planning

Planning models, in general, have two components that interact with each other: an investment component that proposes candidate investments in generation and transmission, and an operations component that simulates system operational costs with those investments. In a competitive market framework, the model's objective is usually to maximize the system's net economic benefits (surplus) given the physical constraints on the system. Traditionally, in order to reduce computational costs, load duration curves (LDC) were used to represent load in capacity-expansion models [26], [27]. In such models, generators are considered to be infinitely flexible within their capacity bounds, i.e., there is an implicit assumption that ramp rates, start-up costs, and other intertemporal constraints have little impact on the solution. But [28], [29], and [30] demonstrate the importance of using chronological data and Unit Commitment (UC) constraints in capacity expansion problems. We address this issue in Chapters 2 and 3:

---

[1] Reliability constraints that ensure that blackouts do not occur even when k components of the system are disrupted.

Chapter 2 Since embedding a full UC formulation into a capacity expansion model is impractical given the computational burden of UC problems, we develop UC approximations that give tight relaxations of the full UC Mixed Integer Linear Program (MILP). In this chapter, we ask the following questions:

- Does a linear approximation of UC exist that can predict system energy costs and energy prices?
- How accurately do these approximations (linear and mixed-integer) predict energy prices, decisions, and total system costs relative to full UC models?

Chapter 3 We embed a linear UC approximation developed in Chapter 2 into a multi-stage stochastic transmission planning model such as in [22] and

[23].[2] In this chapter, we address the following questions:

- Does modeling UC have the potential to change transmission and generation investments. If yes, then under what conditions is this potential the greatest?
- What is the value of considering UC in long-term transmission planning processes?

1.2.2 Chapters 4 and 5: Cooperation in interregional transmission planning

In Chapter 3, the transmission expansion model we use is a single optimization model that assumes perfect competition (i.e., players are price takers) and that all players' decisions occur simultaneously. Another important assumption is that there is one central transmission planner (or multiple planners with side-payments, both being equivalent in this context). But in reality, there are multiple regional transmission planning agencies (usually defined by the boundaries of their respective control regions) with little to no coordination among themselves during planning. We address this issue in Chapters 4 and 5.

Chapter 4 We develop and explore a mathematical program that defines the relationship between transmission planners, regional boundaries, generation investments, and the energy market equilibrium. The problem is modeled as a bi-level problem with the transmission planner as the leader, and the generation planners and market operator as followers. In this chapter, we ask the following questions:

---

[2] The WECC 21-zone test-case used in Chapter 3 was compiled by Yueying (Jasmine) Ouyang, Jonathan Ho, and Qingu Xu.

- How are the transmission plans from a noncooperative planning process and a cooperative planning process different from each other?
- What is the value of cooperation among multiple planners in transmission planning?

Chapter 5 This chapter aids in the scale up of the equilibrium problems developed in Chapter 4 to larger test cases. These are mixed-integer non-convex problems that are difficult to solve in mathematical programming, due to their irregular and disconnected feasible spaces. We develop approximations (based on McCormick envelopes [31]) of the noncooperative transmission planning problem faced by each regional planner. In this chapter, we ask the following questions:

- How can McCormick envelopes be used to model convex approximations of the regional transmission planner's optimization problem as developed in Chapter 4?
- Can the tightness of these approximations be improved?
- What are the trade-offs associated with a tighter approximation?

Chapter 2

Unit Commitment Approximations for Generator Production Costing

2.1 Abstract

The generator unit commitment (UC) problem, being a large mixed-integer problem (MIP), is often impractical to solve as a subproblem of market simulation or planning optimization models because of the many operating hours that must be considered. This paper presents a tight formulation of the UC problem and two computationally efficient extensions of this formulation - an LP and an MILP. First, we formulate a MILP that defines a tighter constraint set than the standard formulation in literature [32]. Second, we consider its LP relaxation. This LP is the limiting case as unit size

shrinks to zero: start-up and minimum-run levels are treated as continuous variables. Third, an alternative approximation based on an hour-sampling technique restricts unit commitment variables to be binary only for some generators in crucial intervals, reducing the dimensionality of the traditional UC problem. We use test cases to compare the costs, market prices, and generator profits from these approximations with those from full UC models, and indicate that our methods outperform other approximations in the literature, such as load a duration curve method, in terms of accuracy of predicting the aforementioned metrics. Our formulations solve 1-4 orders of magnitude faster than the full UC MIP.

2.2 Notation

2.2.1 Sets and Indices

G Set of Generators g

H Set of Hours h

2.2.2 Parameters

α_g	Incremental fuel consumption of g [Th/MWh]
β_g	Fixed term of fuel consumption of g [Th/h]
γ_g	Fuel consumption of g during start-up [Th]

θ_g	Fuel consumption of g during shut-down [Th]
C_g^{fuel}	Cost of fuel consumed by g [€/Th]
C_g^{om}	Cost of operation and maintenance of g [€/MWh]
Q_g^{min}	Minimum power output from generator g [MW]
Q_g^{max}	Maximum power output from generator g [MW]
D_h	Demand in hour h [MW]
UR_g	Maximum Up-Ramp of g [MW]
DR_g	Maximum Down-Ramp of g [MW], a negative quantity
SRR_g	Maximum 10-min ramp of g [MW]
X_R	Required operating reserve as fraction of demand

2.2.3 Variables

$q'_{g,h}$	Rampable output from generator g in hour h [MW]
$q_{g,h}$	Power generated from generator g in hour h [MW]
$\overline{q}_{g,h}$	Upper-Bound on output from generator g in hour h [MW]
$r_{g,h}$	Spinning reserve from generator g in hour h [MW]

$u_{g,h} \in \{0,1\}$: 1 if generator g is running in hour h

$y_{g,h} \in \{0, 1\}$: 1 if generator g is started up in hour h

$z_{g,h} \in \{0, 1\}$: 1 if generator g is shut down in hour h

$c^y_{g,h}$ Fuel consumed if unit is started-up in hour h [Th]

$c^z_{g,h}$ Fuel consumed if unit is shut-down in hour h [Th]

2.3 Introduction

Unit commitment (UC) models solve important operations problems in the power industry. In the US deregulated markets, for example, a central operator collects supply bids or cost information from generators, and runs an area-wide UC model. The UC model then specifies a schedule for commitments and generation that minimizes overall system costs, recognizing various physical constraints such as generator capacity, transmission line loading limits, and generator minimum-run capacities. Schedules are generated in day-ahead markets (24 h horizon) and in real-time for fast start units (1-2 h horizon), to minimize the cost of electricity provision.

Advances in mixed integer programming (MIP) software have allowed the industry to move from the Lagrangian relaxation (LR) methods that were used before the 1990s, to more flexible and comprehensive formulations in market operations [33]. PJM has estimated that moving from LR to MIP-based methods led to savings of $100 million per year [34]. Despite these computational advances, however, solving large-scale unit commitment models is still a challenge. As the system size increases, MIP's Branch-and-Bound algorithm faces larger decision trees, which increases solution times. This computational cost has limited the application of UC models in market simulation and planning models because analyses of policies and investments may require thousands of simulations to represent varying load, wind, and solar conditions across operating hours for all years over a planning horizon.

Planning models usually have two components that interact with each other: an investment component that proposes candidate investments in generation and transmission, and an operations component that simulates system operational costs with those investments. In a competitive market, the model's objective is usually to minimize the overall cost to the system (investment and operations), subject to system constraints. Traditionally, as mentioned in Chapter 1, in order to increase computational efficiency, load duration curves (LDC) were used to represent load in capacity expansion models [26], [27]. In such models, generators were sorted in ascending order of marginal costs and dispatched in merit-order (cheapest-first). However, dispatching units solely based on merit-order removes load chronology thereby ignoring dynamic constraints, such as ramping limits, and costs, such as start-up costs, assuming an insignificant impact on solutions.

But [28], [29], and [30] demonstrated that it is important to use chronological data and capture inter-temporal constraints, such as minimum-run capacity and ramp-rates in capacity expansion problems. For example, system costs and greenhouse gas emissions increase by 17% and 34% respectively, when inter-temporal constraints are considered [30]. Therefore, the flexibility of units and its on-off operations can significantly affect the estimated profits in generation investments as shown in [35]. All this points towards a need to more accurately model generator operational characteristics. Indeed, looking at including wind variability in generation planning models, [36] specifically argued for "*less computationally costly approaches that can adequately account for the mixed-integer nature of generating units and chronology of net-demand.*"

In the past, studies have tried to solve the unit commitment problem faster by reducing the number of binary variables in the formulation [32]. Using decomposition methods such as the Benders' algorithm [37], is another way to manage the burden of solving large UC problems [38]. Planning models that ignore inter-temporal constraints include a method to reduce the computational burden by adjusting the level of operational detail. For example, [39] uses 12 non-chronological hours to represent the future, while [40] uses 38 such hours.

In addition to planning models, market-simulation models that predict future prices and generator outputs need to model operational details such as start-ups and ramps. This becomes especially pertinent as the penetration of renewable energy generation increases [41]. Since integrating full UC models into these planning and simulation models is not practically possible, it is useful to have tight approximations of the UC problem that can estimate start-up costs and quickly bound the full UC model. Recent research that extends UC to consider uncertainty in wind output [42] or fuel prices [43] further accentuates the need to develop efficient and accurate approximations to UC problems.

In this study, we propose three models, the second and third of which are the proposed approximations. Our first model is a Tight Unit Commitment (TUC) formulation. TUC is a MILP that gives the same optimal solution as the standard formulation in the literature, but includes constraints that define a tighter constraint set. Second, in the Tight Relaxed Unit Commitment (TRUC), the binary variables are relaxed in the TUC formulation, and we look at the resulting LP relaxation. Unit running variables, $u_{g,h}$, are now treated as continuous variables and this can be seen as representing the limiting case in which the size of an individual generating unit becomes very small. Our third model, the Tight Partial Relaxed Unit Commitment (TPRUC), is a version of TRUC where the commitment decisions of a subset of generating units are represented by binary variables in a subset of hours. This approach reduces the dimensionality of the UC problem, thereby giving rise to a smaller MILP while still capturing the discrete nature of the problem in the most crucial periods. In this study, these crucial periods are assumed to be intervals where load changes most rapidly.

In Section 2.4.1, we present some preliminary definitions to clarify the idea of valid inequalities. Then, in Section 2.5.1, we describe the basic unit commitment model followed by its linear relaxation, BCRUC, in Section 2.5.2. We then present the TUC formulation in Section 2.5.3 and in Section 2.5.4, its linear relaxation, TRUC. Our third model, TPRUC, is presented in Section 2.5.5 followed by a discussion on load duration curves in Section 2.5.6. We describe our test case in 2.6 and describe the different systems we use to compare the performance of the models. We present results in Section 2.7. First, in Section 2.7.2, we show that TUC solves faster than the base case MILP formulation (while giving the same primal and dual solution) for every system size we test. In Section 2.7.3, we compare the performance of the base case formulation, TRUC, and TPRUC in terms of how accurately they predict total system costs and hourly energy prices. We also see how these metrics change with the size of the system. We see that, in TPRUC, with a small fraction of the total number of binary variables, we are able to solve the full UC MILP to a high degree of accuracy while still reducing computational times significantly. In Section 2.7.6, we compare the performance of all the linear models - the base case relaxation, TRUC, and a load duration curve approach, in terms of the accuracy with which they predict total system costs, hourly energy prices, and a new generator's short-run profits. In Section 2.7.8 we introduce renewables into the system making the net demand profile more variable. While comparing the performance of TUC, TPRUC, and TRUC, we show that this variability makes the models solve much slower, further bolstering the need for efficient approximations of the UC formulation. We conclude in Section 2.8.

2.4 Preliminaries

2.4.1 Definitions

Definition 2.4.1. Valid Inequalities [44]

An inequality $\alpha u \leq \beta$ is valid for a set $K \subset \mathbb{R}^d$ if it is satisfied by every point $\overline{u} \in K$.

Definition 2.4.2. Convex Hull [45]

The convex hull of a set C, denoted **conv** C, is the set of all convex combinations of points in C

$$\textbf{conv}\ C = \left\{ \sum_{i=1}^{k} \theta_i x_i | x_i \in C, \theta_i \geq 0, i \in \mathbb{N}, i \leq k, \sum_{i=1}^{k} \theta_i = 1 \right\}$$

2.4.2 The role of Valid Inequalities in MILP solvers

There are many general types of valid inequalities (e.g., Gomory cuts [46], Rounding Cuts [47]), many of which are employed by state-of-the-art MILP solvers (e.g., CPLEX, GUROBI) to get tight relaxations at the root node, while solving MILPs. Modern solvers rarely employ an elementary Branch-and-Bound approach [48] to solving MILPs, but rather use some variation (or a combination) of techniques that are based on Branch-and-cut process [49]. At every node, the MILP is relaxed, checked for integrality, and if possible, valid inequalities or cuts are added. These cuts serve to shrink the feasible size of the LPs eliminating points that are not valid for the MILP, but if left untrimmed, could spawn sub-trees of their own.

In addition to the cuts that are added by the solver, valid inequalities can be added by the user depending on the specific structure of the problem being solved. These can help trim portions of the branch-and-cut tree and help in quicker convergence of the MILP solution. Simply put, valid inequalities are used to cut away parts of the polytope of the LP relaxation without cutting away any valid point of the MILP.

2.5 Model formulations

In this section, we present the models we use in this case study. We make two modeling assumptions to simplify our case study: 1) ignore minimum-on and -off time constraints (i.e., refractory periods after a generator is turned on or off); 2) assume start-up costs are constant for a unit (i.e., no warm-start capability). These assumptions can be revised as needed.[1]

2.5.1 Base Case Unit Commitment (BCUC)

This is the formulation against which we compare the performance of our models. This is a standard UC model in literature from [32]. The formulation was modified to include spinning reserve requirements and to make minimum-up and -down times 1 h. The objective function and constraints of the basic unit commitment model are:

$$\text{MIN} \quad \sum_{g,h} \{ \, C_g^{fuel} (\beta_g u_{g,h} + c_{g,h}^{y} + c_{g,h}^{z} + \alpha_g q_{g,h}) + C_g^{om} q_{g,h} \} \tag{2.1}$$

---

[1] Also see Section 6.4.

$$\text{s.t.} \quad \sum_g q_{g,h} = D_h \ \ \forall h \tag{2.2}$$

$$\sum_g \overline{q}_{g,h} \geq (1 + X_R) D_h \ \ \forall h \tag{2.3}$$

$$\overline{q}_{g,h} - q_{g,h} \leq SRR_g \ \ \forall g, h \tag{2.4}$$

$$c^y_{g,h} \geq \gamma_g (u_{g,h} - u_{g,h-1}) \ \ \forall g, h \tag{2.5}$$

$$c^z_{g,h} \geq \theta_g (u_{g,h-1} - u_{g,h}) \ \ \forall g, h \tag{2.6}$$

$$u_{g,h} Q^{min}_g \leq q_{g,h} \leq \overline{q}_{g,h} \ \ \forall g, h \tag{2.7}$$

$$0 \leq \overline{q}_{g,h} \leq u_{g,h} Q^{max}_g \ \ \forall g, h \tag{2.8}$$

$$\overline{q}_{g,h} - q_{g,h-1} \leq u_{g,h-1} UR_g + Q^{min}_g (u_{g,h} - u_{g,h-1}) + Q^{max}_g (1 - u_{g,h}) \ \ \forall g, h \tag{2.9}$$

$$\overline{q}_{g,h} - q_{g,h} \leq DR_g u_{g,h} + Q^{min}_g (u_{g,h-1} - u_{g,h}) + Q^{max}_g (1 - u_{g,h-1}) \ \ \forall g, h \tag{2.10}$$

$$\overline{q}_{g,h} \leq Q^{max}_g u_{g,h} + Q^{min}_g (u_{g,h} - u_{g,h+1}) \ \ \forall g, h \tag{2.11}$$

$$q_{g,h}, \overline{q}_{g,h}, c^y_{g,h}, c^z_{g,h} \geq 0 \ \ \forall g, h \tag{2.12}$$

$$u_{g,h} \in \{0, 1\} \ \ \forall g, h \tag{2.13}$$

The objective (2.1) minimizes the costs of start-ups and commitment, energy production, and of non-fuel operation and maintenance. Constraint (2.2) specifies that the sum of generation should meet hourly demand. The spinning reserve requirement and the spinning reserve capacity that can be provided by a generator are specified by (2.3) and (2.4), respectively. Start-up costs are stipulated by (2.5), while (2.6) dictate costs of shutting down. Constraints (2.7), and (2.8) are the generator's minimum and maximum production capacity constraints. Constraints (2.9) and (2.10) are the inter-temporal ramp constraints while (2.11) constrains the maximum capacity of a generator in an hour with whether it is being started up in an hour or not. Constraints (2.12) and (2.13) specify non-negative and binary variables respectively. Other constraints such as transmission limits can be included in the model, but are omitted here for simplicity.[2]

2.5.2 Base Case Relaxed Unit Commitment (BCRUC)

A common UC approximation is to relax all integer variables [50] [51] [52]. We call this the Base Case Relaxed Unit Commitment (BCRUC), which amends the base case UC model from section 2.5.1 by replacing constraint (2.13) with the following constraint:

$$0 \leq u_{g,h} \leq 1 \ \ \forall g, h \tag{2.14}$$

2.5.3 Tight Unit Commitment (TUC)

Now, we present a MILP UC formulation that gives the same solution as the base case, but defines a tighter constraint set and provides a tighter relaxation than the base case.[3]

$$\text{MIN} \quad \sum_{g,h} \{ \, C_g^{fuel}(\beta_g u_{g,h} + \gamma_g y_{g,h} + \theta_g z_{g,h} + \alpha_g q_{g,h}) + C_g^{om} q_{g,h} \} \tag{2.15}$$

---

[2] We address this limitation in the next chapter.

[3] We show results from numerical experiments supporting this in Section 2.7. For example, BCUC and TUC, both report an objective value of 13572.25 k€/week and solve in 449 and 132 s respectively for our smallest test case. Details of the test cases are given in Section 2.6.

$$\text{s.t.} \quad \sum_g q_{g,h} = D_h \;\; \forall h \tag{2.16}$$

$$r_{g,h} + q_{g,h} \leq u_{g,h} Q_g^{max} \;\; \forall g, h \tag{2.17}$$

$$\sum_g r_{g,h} \geq X_R D_h \;\; \forall h \tag{2.18}$$

$$u_{g,h} - u_{g,h-1} = y_{g,h} - z_{g,h-1} \;\; \forall g, h \tag{2.19}$$

$$q_{g,h} - q^{'}_{g,h} = u_{g,h} Q_g^{min} \;\; \forall g, h \tag{2.20}$$

$$(r_{g,h} + q^{'}_{g,h}) - q^{'}_{g,h-1} \leq UR_g u_{g,h-1} \;\; \forall g, h \tag{2.21}$$

$$q^{'}_{g,h} - (r_{g,h-1} + q^{'}_{g,h-1}) \geq -DR_g u_{g,h} \;\; \forall g, h \tag{2.22}$$

$$r_{g,h} + q^{'}_{g,h} \leq u_{g,h-1}(Q_g^{max} - Q_g^{min}) \;\; \forall g, h \tag{2.23}$$

$$r_{g,h-1} + q^{'}_{g,h-1} \leq u_{g,h}(Q_{g,h}^{max} - Q_{g,h}^{min}) \;\; \forall g, h \tag{2.24}$$

$$r_{g,h} \leq u_{g,h-1} SRR_g \;\; \forall g, h \tag{2.25}$$

$$r_{g,h} \leq u_{g,h} SRR_g \;\; \forall g, h \tag{2.26}$$

$$r_{g,h} \leq u_{g,h+1} SRR_g \;\; \forall g, h \tag{2.27}$$

$$u_{g,h} \in \{0, 1\} \;\; ; \;\; q_{g,h}, q^{'}_{g,h}, r_{g,h} \geq 0 \;\; \forall g, h \tag{2.28}$$

$$0 \leq y_{g,h}, z_{g,h} \leq 1 \tag{2.29}$$

Objective (2.15) minimizes the fixed cost of running the unit, start-ups, shut-downs, and the variable costs of operation and maintenance. Constraint (2.16) ensures that supply and demand of energy is balanced in every hour. Constraint (2.17) is the upper bound on the amount of reserve and energy that can be produced from a generator g in any given hour. Constraint (2.18) ensures that there is enough reserve capacity in the system and (2.19) defines the relationship between start-up, shut-down and the binary variables u_{gt} that represent whether the generator is online (1) or offline (0). Constraint (2.20) defines the relationship between the total energy produced from the generator and the rampable part of the output $q^{'}_{g,h}$. Constraints (2.21) and (2.22) limit the amount by which generation can be ramped up and down respectively. These constraints also leave headroom in both directions for deliverable reserves. Notice that these two constraints would not change the primal MILP solution if the binary variables, $u_{g,h}$, were removed from their respective RHS's. By explicitly linking a generator's running status, $u_{g,h}$, to its ramp capability, the root relaxation of this MILP has a comparatively smaller feasible set, which helps in solving the MILP faster (and we prove this using numerical experiments in Section 2.7). We follow a similar strategy and add more valid inequalities (2.23) - (2.27). Constraint (2.23) limits the value of $r_{g,h}$ and $q^{'}_{g,h}$ during start-ups. Similarly, (2.24) constrains these values during shut-down. Equations (2.25) - (2.27) constrain the amount of reserve that can be provided in any given hour. Constraint (2.28) specifies that $u_{g,h}$ are binary variables, and reserve and energy outputs cannot be negative. Constraint (2.29) bounds the start-up and shut-down variables.

As mentioned above, in this formulation, the constraints on ramping, on reserves, and on energy produced during startups and shutdowns, all define a tighter constraint set.[4] All constraints are linked to the start-up or shut-down variables and reduce the feasible space of the relaxed LP at every node of the branch-and-bound process in addition to shrinking the size of the binary tree, ultimately accelerating the convergence process.

---

[4] See footnote 3.

2.5.4 Tight Relaxed Unit Commitment (TRUC)

The Tight Relaxed Unit Commitment (TRUC) is the LP relaxation of TUC (section 2.5.3). This is a tighter relaxation than the linear relaxation of the base case formulation, i.e., BCRUC. We show this using numerical experiments in Section 2.7.6. The TRUC model is relevant for evaluating the effects of inter-temporal constraints in long-term planning models, as described in Section 2.3.

2.5.5 Tight Partially Relaxed Unit Commitment (TPRUC)

The Tight Partial Relaxed Unit Commitment (TPRUC) is an extension of TRUC. In this, we assume that some hours or sequences of hours are more sensitive than others for UC. For example, if an operator knows, by experience, that start-ups of plants A, B and C in hours $h \in \mathbf{H}'$ are most likely important (for example, the set of hours that experience the steepest increase in load over their preceding hours), commitment variables for those units in those times can be modeled as binary variables in TPRUC.

This partial relaxation approach is similar to the relax-and-fix idea originally proposed by [53], in which a model is run with integrality constraining only a subset of the actual binary variables. This takes advantage of the tight linear formulation without the computational burden of solving the full MIP UC of Section 2.5.1. TPRUC is formulated as follows:

$$\text{Min } (2.15)$$

$$\text{s.t. } (2.16) - (2.27), (2.29)$$

$$q_{g,h}, q^{'}_{g,h}, r_{g,h} \geq 0 \;\; \forall g, h \tag{2.30}$$

$$u_{g,h} \in \{0, 1\} \;\; \forall \;\; g \in G^{'}, h \in H^{'} \tag{2.31}$$

$$0 \leq u_{g,h} \leq 1 \;\; \forall \;\; g, h \tag{2.32}$$

Here $G^{'}$ is the subset of generators and $H^{'}$ is the subset of hours for which the corresponding start-up variables, $u_{g,h}$, are binary. This leads to smaller MIPs which can potentially solve faster, as branch-and-bound explores a smaller tree.

2.5.6 Load Duration Curve (LDC)

Many market and planning models ignore intertemporal constraints, and assume generators are dispatched in merit-order (i.e, cheapest first) based on marginal cost [54] [55] [56]. This model, LDC, ignores all intertemporal constraints and, start-up, shut-down, and running costs. The LDC model under-estimates the system cost due to the artificial flexibility bestowed to the system, such as assuming infinite ramp rates and no refractory period after a unit is started-up or shut-down.

2.5.7 Augmented Load Duration Curve (LDC')

The augmented load duration curve (LDC') approach is a commonly used variant of the LDC approach, LDC' [57]. Here, the data is again non-chronological, but the generators' heat-rates (α_g) are adjusted upwards based on their estimated number of start-ups and shut-downs [57]. Here, we use start-ups and shut-downs from the base case UC to do this adjustment.

In Figure 2.1, we summarize our hypotheses and the relationships among the different model formulations, in terms of their respective estimates of total system costs, and computation time.

2.6 Experimental design and assumptions

Our three formulations are tested on a system with 11 thermal generators from [58].[5] The time-frame considered is 168 hours (1 week) and the models are solved simultaneously for the week, not a sequence of 24 h models. The average hourly demand is 3.5 GW and the spinning reserve capacity required is set as a fraction, $X_R = 0.02$, of total demand in each hour. To sample for a subset of important hours for TPRUC, we select the 60 hours of the total 168 hours whose (absolute value of) net-demand ramps over their previous hours are higher than 1 standard deviation or more from the mean hourly net-demand ramps. In other words, these 60 hours see the steepest

---

[5] Generator data is presented in Table 6.1 of the appendix.

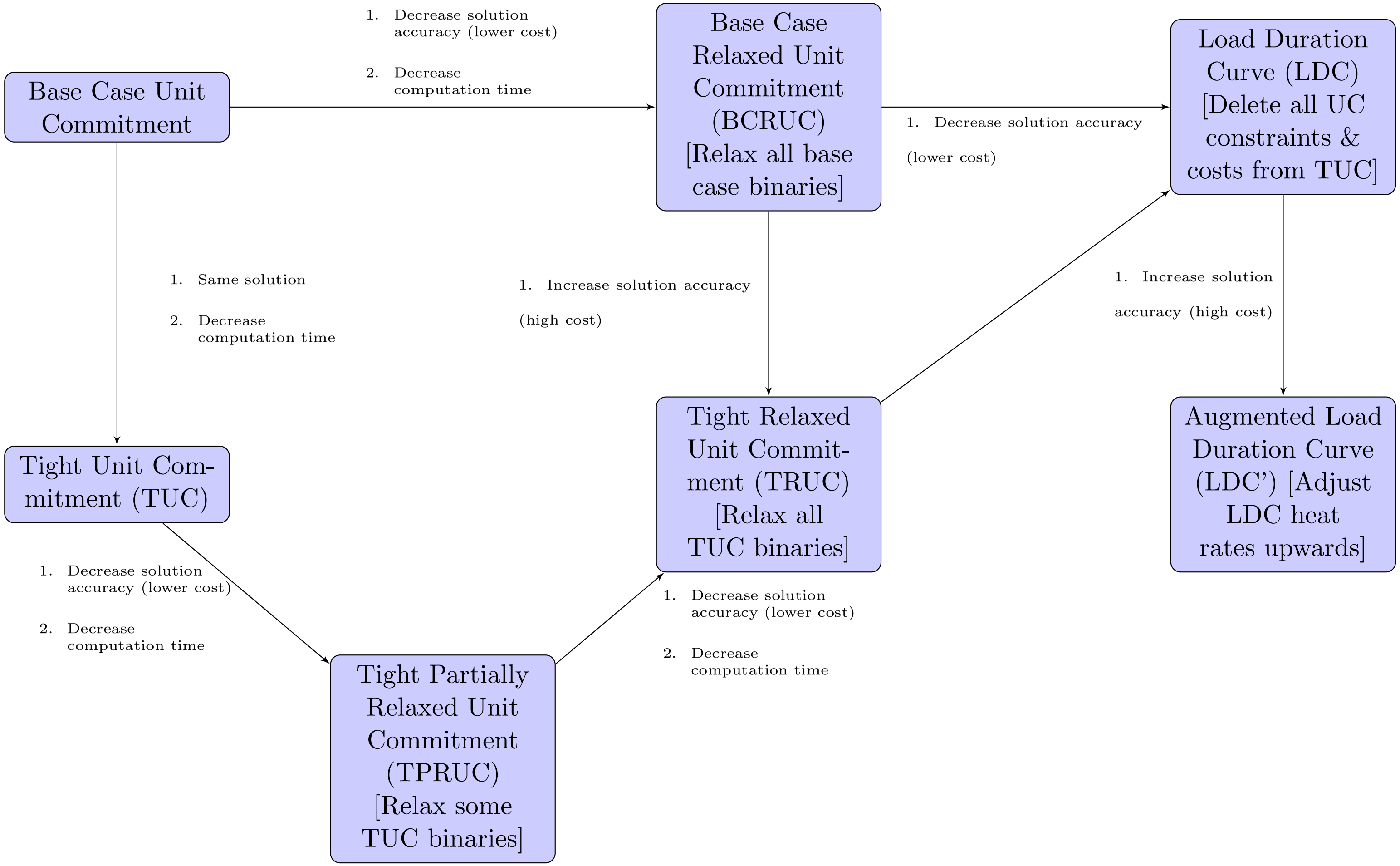

Base Case Unit Commitment
1. Decrease solution accuracy (lower cost)
2. Decrease computation time
Base Case Relaxed Unit Commitment (BCRUC) [Relax all base case binaries]
1. Decrease solution accuracy
(lower cost)
Load Duration Curve (LDC) [Delete all UC constraints & costs from TUC]
1. Same solution
2. Decrease computation time
1. Increase solution accuracy
(high cost)
1. Increase solution
accuracy (high cost)
Tight Unit Commitment (TUC)
Tight Relaxed Unit Commitment (TRUC) [Relax all TUC binaries]
Augmented Load Duration Curve (LDC') [Adjust LDC heat rates upwards]
1. Decrease solution accuracy (lower cost)
2. Decrease computation time
1. Decrease solution accuracy (lower cost)
2. Decrease computation time
Tight Partially Relaxed Unit Commitment (TPRUC) [Relax some TUC binaries]

Figure 2.1: Hypotheses shown as arrows: In comparison, Hypothesis 1 is (in most cases) proven mathematically (for total cost); the magnitude of the change in solution (total cost, primal variables, prices, net revenues) is assessed through numerical experiment. Hypothesis 2 is assessed through numerical experiment.

net-demand ramps over their preceding hours in the week. Within these hours, we constrain only the commitment variables for mid-and peak-load units (Gas and Oil units) to be binary. The reasoning behind this is that in these hours, base load units will be committed to their full capacity and will not be cycled, while the mid and peaker units will be cycled, shut-down, or started-up. This reduces the number of binary variables from 1848 (11 × 168) to 360 (6 × 60), an 80.5% reduction.

We also test the performance of these models on larger systems. The original 11-generator system is considered to be size $1x$. We test the performance of our formulations on six different system sizes. A system double this size, $2x$, has double the number of generators (and double the number of binary variables) as $1x$, double the system capacity (MW), and double the hourly load. For example, a 100 MW coal generator from $1x$ is represented by two 100 MW coal generators in $2x$, both with the same characteristics as the original 100 MW generator. In order to compare the results, we divide the objective values from every model by the system size factor (2 in this example). This increases the size of the TUC and TPRUC models (which associate binary variables with generators), but not the TRUC model (since all variables are continuous; as a result, two 100 MW generators of a given type with the same costs, can still be exactly represented as a single 200 MW generator. That is, any level of unit commitment and dispatch for the single 200 MW generator can be represented by a TRUC version with two 100 MW generators, and the same cost will occur, and vice versa.). We solve all the MILP models (base case, TUC, TPRUC) with priority constraints [59]. These constraints break ties between units that have exactly the same characteristics.

We test each of these approximations on system sizes $1x$, $2x$, $3x$, $4x$, $7x$, and $10x$ and evaluate their performance in terms of how accurately they estimate overall system cost, hourly prices, and weekly profits for each generator type, as obtained by the original full UC model. These results are shown in Section 2.5.1. We also show the time each model takes to solve for each system size. In Section 2.5.4, we compare our linear approximation (TRUC) with other linear approximations from literature, a Relaxed Unit Commitment (RUC) [32] and a Load Duration Curve (LDC) method [60] and show that it outperforms them in predicting system cost, and energy prices for the larger test cases.

2.7 Results and discussion

2.7.1 Indices measuring model performance

The metrics used to compare model performances in this case study are described below:

Total systems costs: This is the objective function of the models. This measures the total cost to the system of meeting load and having enough capacity to meet spinning-reserve requirements. The base case values set the standard and cost-estimates from other models are compared to these.

RMSE in price prediction: This is the Root Mean Square Error (RMSE) [61] of hourly energy prices across the operating horizon (a week, in this case study) from each model when compared with the actual hourly energy prices (as predicted by the base case formulation). The lower the RMSE, the better the prediction.

Time to solve: This is the CPU time taken for a model to solve (to optimality — a 0.00% MIP gap — in some cases, and to a pre-specified gap in some cases.[6]). This is measured in seconds. The smaller this value, the faster the model solves, and the better the associated model is in this metric.

Generators short-run profits: These is a generator's short-run profit. It is measured by calculating the generator's revenue (using prices from the energy balance constraint) minus the costs of energy production across all the hours in a week (the operating horizon in this case study) while correcting for make-whole payments.[7] The closer a model's estimate of these profits to the actual profits (as estimated by the base case), the better the model is in this metric.

2.7.2 Comparison of BCUC and TUC formulations

To show that the Tight Unit Commitment formulation (TUC) is indeed tighter than the base case formulation, we ran the test systems of all sizes ($1x$ - $4x$, $7x$, $10x$) with a condition to exit the solution process if the relative optimality gap drops below 0.1% or reaches a time-limit of 1000 s, whichever condition is met first.

---

[6] See Table 2.3 for more details

[7] See Section 2.7.7 for more details.

		Base Case		TUC	
Sys. size	No. of Binaries	MIP Gap (%)	Time (s)	MIP Gap (%)	Time (s)
$1x$	1848	0.00	449	0.00	132
$2x$	3696	0.098	911	0.098	313
$3x$	5544	0.092	971	0.09	223
$4x$	7392	0.093	551	0.076	448
$7x$	12936	12.5	1000	0.08	598
$10x$	18480	0.485	1000	0.073	925

Table 2.1: Comparing Base Case and TUC MILP performance

In Table 2.1, we see that for every size we tested, TUC performed better[8]. Specifically, for the larger test-systems ($7x$ and $10x$), TUC reached the gap of 0.1% without hitting the time-limit of 1000s. For these two sizes, the base case MILP formulation reaches the time-limit and reports gaps of 12.5% and 0.485% respectively, which are much larger than those reported by TUC.

---

[8] All runs were done with default CPLEX 12.6.3 settings. The performance of CPLEX could potentially be improved by parameter tuning. Also see Section 6.2.

2.7.3 Total system costs

As the system size increases, the (normalized) cost decreases for the full UC problem (Figure 2.2). This is expected as, with increasing size, the system is more granular, giving the MIP flexibility to allocate resources more efficiently thereby lowering costs. For example, suppose a single 100 MW generator served a 50 MW load. Then, in a $2x$ system, two 100 MW generators must serve a 100 MW load. Since only one of these is required for this task, start-up and other fixed costs can be ignored for the second generator. For TRUC, the same total system cost is predicted for all sizes. This is necessarily the case, as in this system, TRUC's results depend only on the total capacity of each generator type, not on the size of the individual units (see Section 2.6). As hypothesized earlier, TRUC's cost appears to be a limit that the other models approach as system size increases.[9]

In Section 2.7.2, we saw a MILP formulation that solves faster than the base case (from Section 2.5.1). Now, from Figure 2.2, we see that, with a careful, yet simple, selection of hours, we can get a MILP that accurately captures system costs from the full MILP base case formulation (Section 2.5.1). TPRUC estimates system costs better than TRUC (closer to the base case cost estimates). This is to be expected as TRUC is a relaxation of TPRUC and hence, under-estimates the objective function. The percentage errors of TRUC and TPRUC's cost estimation are shown in Table

---

[9] We do not show total system cost estimates from BCRUC, LDC, and LDC' in this plot. They are shown in Section 2.7.6 when their performance is compared to TRUC.

[10] All sizes in Base Case were solved to less than a MILP gap of 0.1%.

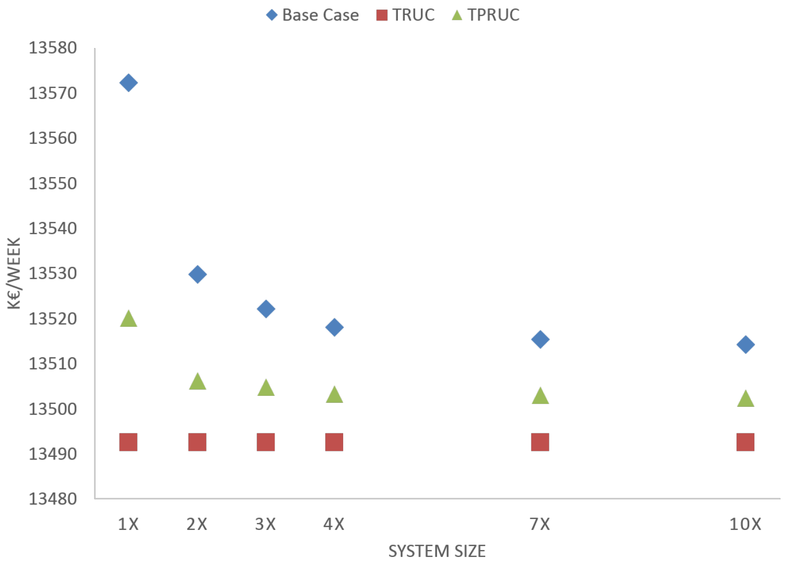


Figure 2.2: Total cost as a function of system size.[10]

2.2. From the table, we see that TRUC estimates costs for all system sizes with a $\geq$ 99.4% accuracy and with TPRUC, this accuracy increases to 99.6%. Furthermore, we see that in this case study, for the largest test case ($10x$), with TPRUC and just 19.4% of binary variables of the full UC MILP, we are able to capture the objective value with a $\geq$ 99.9% accuracy.

---

[11] All TPRUC sizes were solved to optimality. Error is calculated against the full UC MILP Base Case results which were solved to a gap less than 0.09% without a time-limit. For example, the size 10x took 8995s or approx. 2.5h to get to 0.083% gap. See Table 2.3.

Size	TRUC	TPRUC [11]
$1x$	0.59%	0.38%
$2x$	0.28%	0.17%
$3x$	0.22%	0.13%
$4x$	0.19%	0.11%
$7x$	0.17%	0.09%
$10x$	0.16%	0.09%

Table 2.2: Percentage errors in estimating total system costs. TRUC had a maximum error of 0.59% while TPRUC (with only 19.4% of the number of binary variables), had a maximum error of 0.38%.

2.7.4 Hourly energy prices

Figure 2.3 shows the RMSE in hourly price predictions from TRUC and TPRUC. As system size increases, TRUC gets better at predicting prices (lower RMSE with increasing size). TPRUC estimates prices better than TRUC for every system size. For the largest size, $10x$, TPRUC predicts average price with an error of only €0.4/MWh. Indeed, this reduction in price-prediction RMSE can be clearly seen in the Price Duration Curves shown in Fig. 2.4. As the system size increases, TRUC and TPRUC converge towards the actual price curve.

---

[12] UC refers to the actual prices (from Base Case).

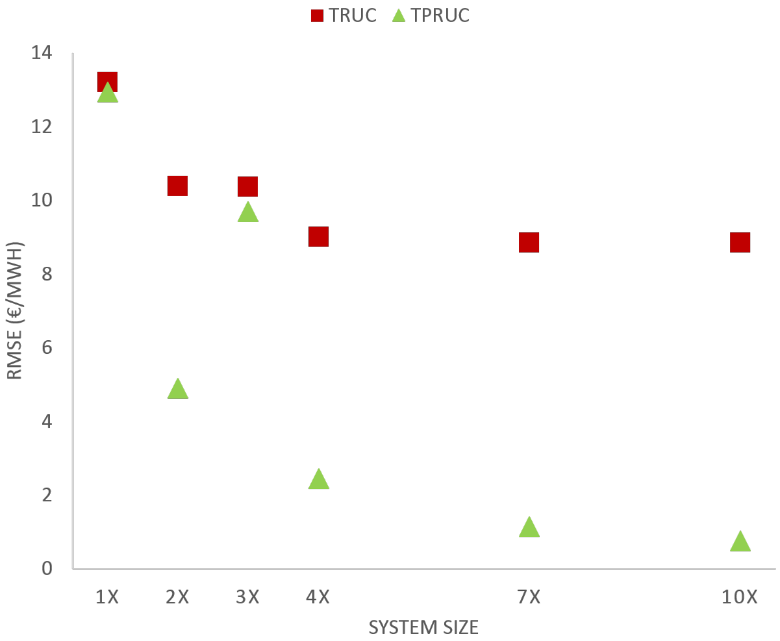
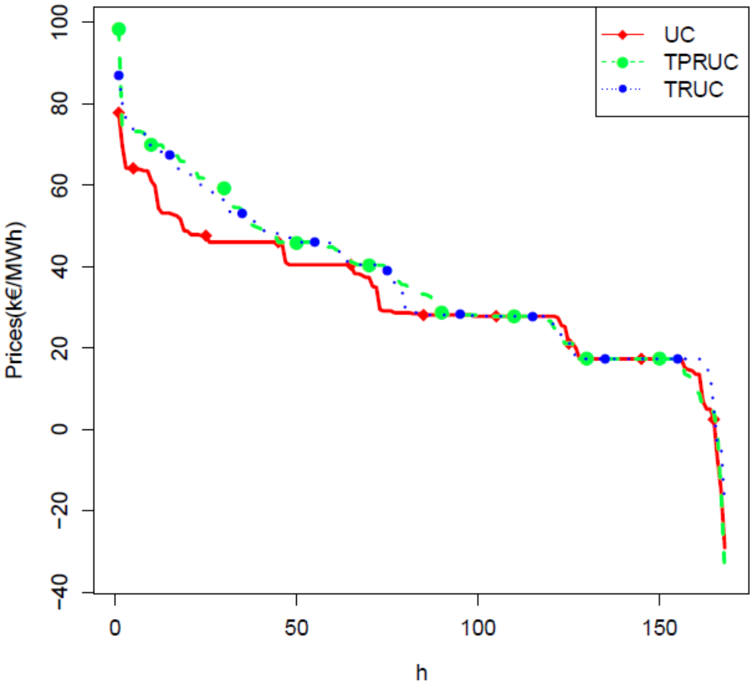


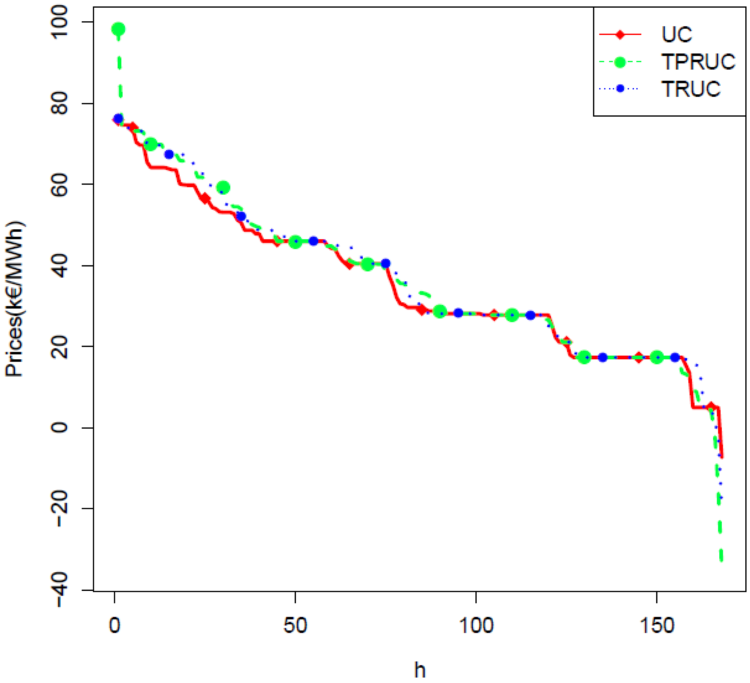
Figure 2.3: RMSE in price prediction from TRUC and TPRUC.

2.7.5 Time to solve

We also look at the time taken to solve these models as one of the goals of these approximations is to accurately mimic the full UC while reducing computational effort. From Table 2.3, we see that, TRUC and TPRUC solve faster than the base case UC. For example, for size $2x$, TUC, TPRUC, and TRUC's solution times are 1-4 orders of magnitude faster than full UC. In general, for all sizes, we see that the LP (TRUC) solves fastest, followed by the MILPs, TPRUC and TUC. All models were solved on a Windows 7 PC with an Intel Core i7-860 Processor 2.80 GHz processor and 8 GB RAM using CPLEX 12.6.3.



(a) Size $1x$ Price Duration Curve.



(b) Size $10x$ Price Duration Curve.

Figure 2.4: Price duration curves for systems of sizes $1x$ and $10x$.[12]

Model	$1x$	$2x$	$3x$	$4x$	$7x$	$10x$
Base Case	449	1470	1434	1305	4540	8995
TUC	132	313	223	448	598	949
TPRUC	8	32	176	351	4472	3094
TRUC	< 1	3	5	19	54	75

Table 2.3: Time to solve $(s)^*$

*Size $1x$ was solved to optimality for all models. For sizes $2x$-$10x$, Base Case and TUC were solved to a $\leq 0.09\%$ gap. TPRUC was solved to optimality for all sizes. TPRUC Sizes $7x$ and $10x$ solve to 0.09% gap in 145 s and 259 s respectively. UC sizes $2x$-$10x$ were solved with priority constraints, which break ties between units that have exactly the same characteristics. Without these constraints, UC $2x$-$10x$ took more than 10000 s to solve.

2.7.6 Comparison of linear approximations

TPRUC allows system operators to incorporate their insights by giving them the ability to use binary variables for the subsets of units and hours they think are important. But the models are still MIPs and can become difficult to solve for large systems. Thus, having good linear UC approximations is both useful and practical because, in addition to being relatively faster to solve (compared to MIPs), they can quickly provide valuable insights into overall system costs and unit scheduling by providing lower bounds to the system costs of the full UC problem. Furthermore, they can be incorporated into decomposition techniques such as Benders decomposition [62] (that require subproblems to be convex, and so we cannot use MIPs) where, if used in the subproblem, they can generate valid cuts because they are convex. These cuts can then be used to guide the convergence of the master problem.

We compare our LP (TRUC) to two LP models used in the power industry literature - Relaxed Unit Commitment (BCRUC), a load duration curve (LDC) approach [55]. A BCRUC model is the full UC model (here, the Base Case model from Section 2.5.1) with relaxed integrality constraints (Equation(2.12)). The LDC model sorts load non-chronologically such that intertemporal and fixed costs are ignored. It is widely used in market and planning models [54] [55] [56] due to its simplicity and computational efficiency. As mentioned in section 2.5.7, LDC' is a variant (also non-chronological) of LDC, but with adjusted heat-rates based on start-up frequency [57]. Here, we use start-ups and shut-downs from the base case UC for Size $1x$ to do this adjustment. We compare these linear models on the basis of how accurately they estimate system costs and prices.

Figure 2.5 shows the error in estimating total costs for the $1x$ and $10x$ system sizes by the linear models. We see that TRUC estimates total costs better the other linear approximations. With TRUC, we are able to capture more than 99.4% of the total system costs for the $1x$ system.[13] From Figure 2.2, we know that, as system size increases, the base case UC's costs approach the results from the TRUC model, therefore, TRUC's accuracy can only improve. Hence, we see that TRUC's error in predicting system costs reduces even further from 0.59% for the $1x$ system to 0.16% for the $10x$ system. Note that the strength of this model is that it is a (suboptimal) LP formulation that attempts to capture the solutions from an MIP without using

---

[13] These are all LP approximations, so by definition they under-estimate costs of the cost-minimizing UC MILP.

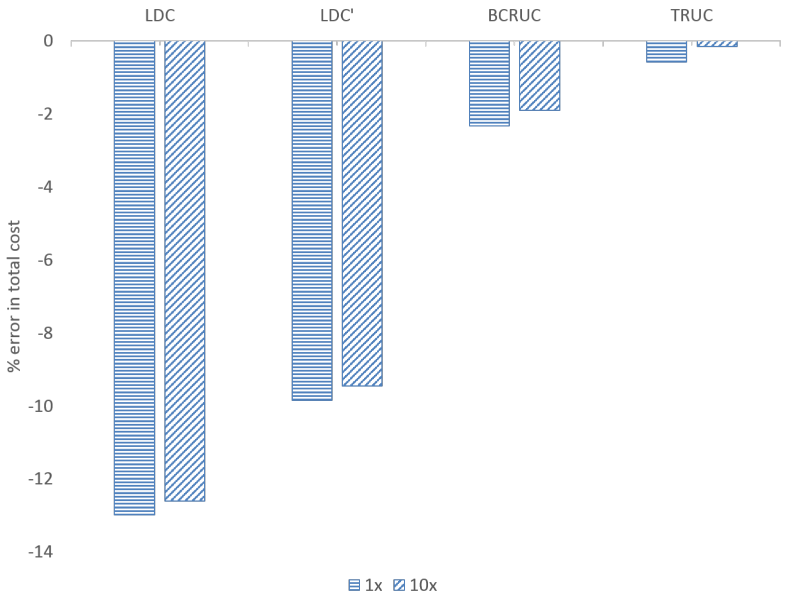


Figure 2.5: Percentage error in total cost from linear approximations relative to UC ($1x$). Negative error implies the model under-estimates system costs compared to base case UC.

integer variables. Thus, for a small reduction in the quality of the solution, we gain a significant advantage in computational performance as evidenced by the solution times in Table 2.3.

Estimating energy prices is crucial as they determine generator margins which in turn affect generator investments [35]. The ability to accurately predict generator margins is valuable in any market simulation tool. In this test case, prices are calculated as the marginal cost of serving load, fixing the values of all binary variables [63].

From Figure 2.6, we see that, as system size increases, TRUC's price estimates improve as shown by the decreasing RMSE. For the smaller test cases, the simple relaxation (BCRUC) has the least error. LDC's price-prediction is poor and its RMSE increases with system size.

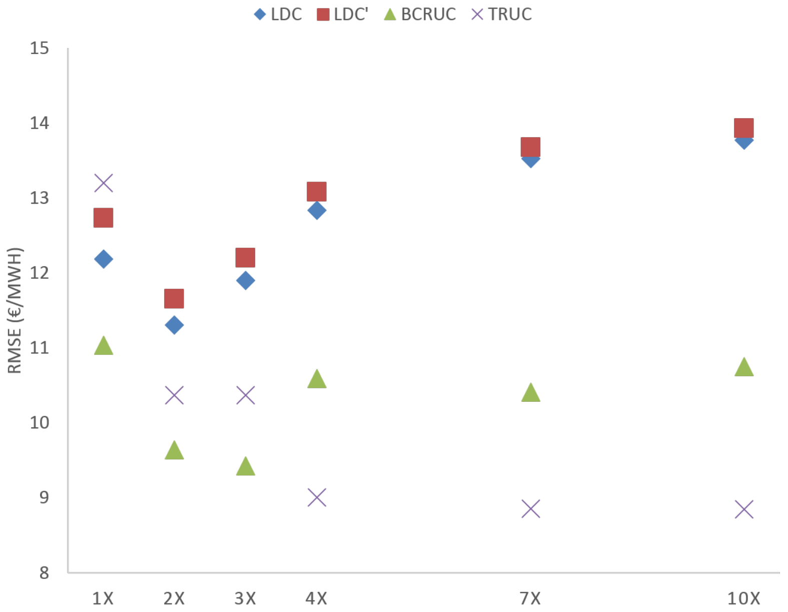


Figure 2.6: RMSE in prices from linear approximations relative to UC.

2.7.7 Estimating a new generator's profit

Short-run profits[14] provide incentives for future investments. These profits in turn depend on both energy prices over time and costs to generators. Gross margin (revenue minus operating cost) provides an integrated index of the effect of these factors on generator profitability.

As mentioned in Section 2.3, LDC and LDC' are commonly used to represent operations within planning models. We compare the performance of TRUC against these models, in terms of estimating investment profitability, by examining the gross margin of small increments in capacity (10 MW) of each type. Repeating this process for all technologies, we calculate weekly margins for these 10 MW capacity generators after correcting for make-whole payments.[15]

---

[14] Not to be confused with long-run profits, which subtracts capital costs from gross margin.

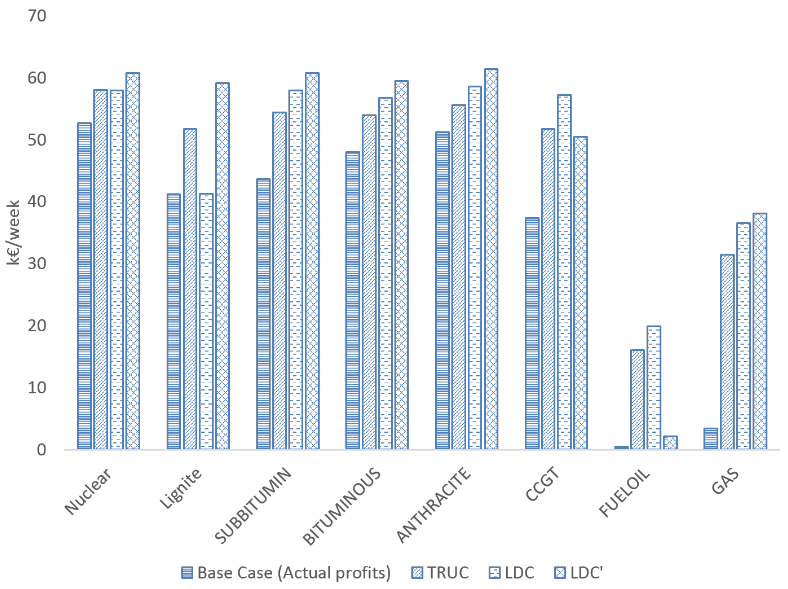


Figure 2.7: A small generator's gross margin (Revenue — Operating Cost) as predicted by UC linear approximations for 1x system. For larger system sizes, we expect TRUC's performance to improve as its RMSE reduces.

From Figure 2.7, we see that while all linear approximations generally overestimate generator profits, TRUC predicts profits best, except in two cases. These are for a small Lignite generator (where LDC performs better than TRUC) and for a small Fuel Oil generator (where LDC' performs better). In addition to better profit-predictions, TRUC is the only model to correctly order the profitability of the two most (Nuclear, Anthracite) and two least profitable units (Gas, Fuel oil). Gas and Fuel oil are expected to be the least earning as they are on the margin most of the time while Nuclear and Anthracite are base-loaded.

---

[15] MIPs, being non-convex, can result in market prices that yield negative short-run margins for some generators [63]. Make-whole payments are additional payments made to generators after-the-fact, to cover losses they may have incurred due to such prices. We calculate make-whole payments for each 10 MW unit separately for each day, consistent with US market practices.

2.7.8 Increasing net load variability due to wind

The US and other countries around the world are witnessing an increasing share of their energy needs being met from variable renewable variable sources such as wind and solar. Keeping this in view, it is important to explore how the accuracy of UC approximations is affected by a generation mix with a large amount of variable renewables. We do this by modifying our models such that the thermal generators now have to meet net demand (i.e, Demand − Wind Output). The load and the net load profiles used in this case study are shown in Figure 2.8. Wind energy now meets 13% of the total weekly demand lowering the average hourly demand (3.50 GWh to 3.04 GWh) and increasing its standard deviation (0.67 GWh to 0.76 GWh). Additionally, demand becomes more volatile. Its volatility[16] is now 0.37 GWh compared to 0.19 GWh in the case without wind. Since wind energy is modeled as negative load (and in this case is always less than total hourly load), we implicitly assume no wind curtailment.[17]

---

[16] As measured by the average of the absolute value of the hourly ramp in net load.

[17] This is a restrictive condition and system costs might be reduced by allowing spillage.

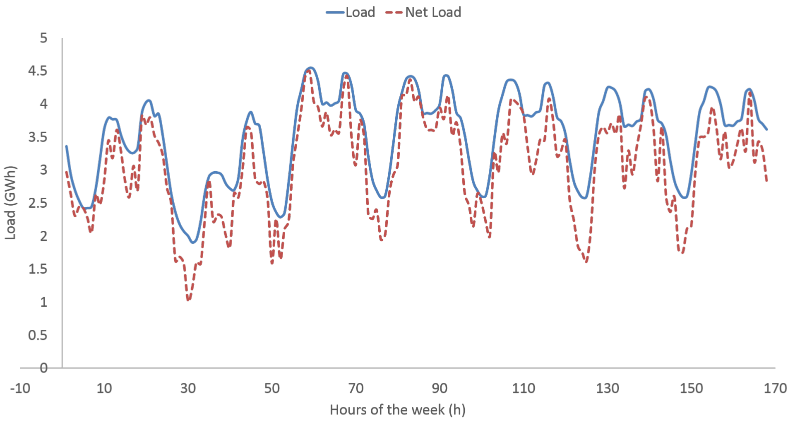


Figure 2.8: Load profiles with and without wind

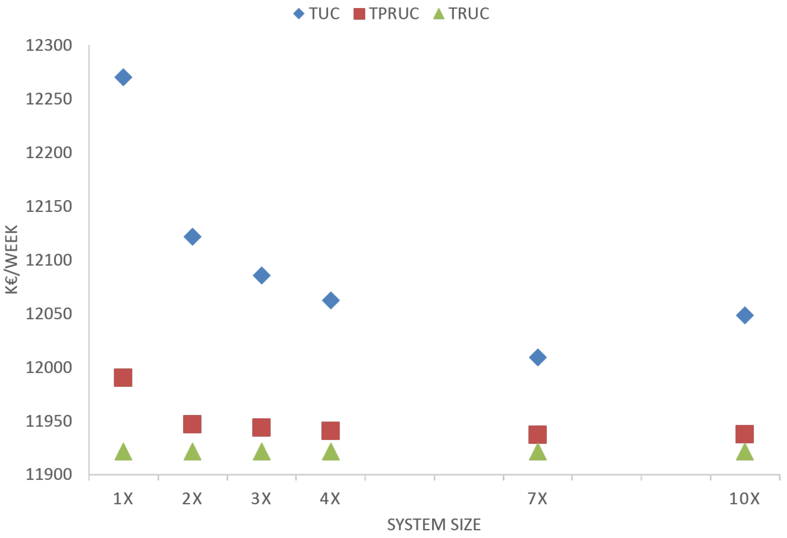


Figure 2.9: Total cost with wind as a function of system size.[18]

Figure 2.9 shows the total cost to the system as estimated by TUC, TPRUC, and TRUC. All TUC models were solved to a 1% MILP relative optimality gap. For the 10x TUC case, although it might appear that the system cost is greater than that of 7x, this is within the aforementioned 1% optimality gap. It is not possible for an optimal 10x solution to be worse than an optimal 7x solution as the former model has fewer constraints than the latter (See Section 2.7.3 for a more detailed explanation). Given the optimality gap for the 10x solution, the true optimum for this system size could be in the range of [11,928 k€/week, 12,009 k€/week].[19]

The relative performance of the UC models is similar in both the with (Figure 2.2) and without wind (Figure 2.9) cases.[20] In both cases, the actual cost to the system (as predicted by TUC) decreases with increasing system size and TRUC's cost appears to be a limit that the other models approach as system size increases. Additionally, similar to the case without wind, by designating the commitment variables of a subset of generators in specific hours as binary,[21] TPRUC provides a better estimate of total system costs compared to TRUC. However, when compared to the case without wind, the errors in predicting total system costs increase for both TPRUC and TRUC. For the smallest system size, 1x, TPRUC and TRUC underestimate costs by 2.3% and

---

[18] For the 10x TUC case, although it might appear that the system cost is greater than that of 7x, this is within the aforementioned 1% optimality gap.

[19] The minimum value of the interval being 1% less than the current 10x TUC solution and the maximum value being the 7x TUC solution.

[20] TUC and BCRUC give the same objective values and we have shown that these formulations describe the same feasible region.

[21] Similar to the case without wind, we designate as binary the commitment variables of mid- and peak-load units in the 50 hours that experience the steepest net-load ramps.

2.8% as opposed to 0.4% and 0.6% respectively in the case without wind.[22] It should be noted that this is a worst-case scenario estimate for TPRUC and TRUC since all TUC models in the case with wind were solved to a larger optimality gap (1% gap) when compared to the case without wind (0.09%). As TUC is solved to smaller optimality gaps, TPRUC and TRUC's system cost estimates can only improve.

The main difference, though, between running the full MILP TUC model with and without wind is the computation cost. In this case study, TUC takes much longer to solve when wind is added to the energy mix (see Table 2.4).[23] For example, for size $1x$, TUC takes 10 times longer to solve the case with wind than the one without, even with a more powerful computer and an optimality gap of 1%. TRUC, being an LP, still solves much faster than the MILP models.[24] The increases in TUC computation times reinforce the importance of efficient unit commitment approximations.

---

[22] These errors decrease with increasing system size as shown in Figure 2.9 and the associated footnote.

[23] All models with modified net load profile were solved on a Windows Server 2012 with 112 GB RAM and an AMD Opteron 6274 2.20 GHz processor. The specifications of this computer are different (and much higher) than the one on which test cases without wind were solved.

[24] We believe this increase in computation time will be exaggerated even further for BCRUC based on the differences in the time taken to solve in the case without wind. However, we were not able to solve the BCRUC case to reasonable optimality gaps for this case study.

Model	$1x$	$2x$	$3x$	$4x$	$7x$	$10x$
TUC	1267	2564	8196	10000	10000	10000
TPRUC	132	15411	264	263	318	622
TRUC	2	9	38	139	619	256

Table 2.4: Time to solve $(s)^*$ models with high penetration of variable renewables.

*Stopping criteria for all TUC models was a time limit of 10000 s or a gap of 0.1%, whichever condition was met first. For TPRUC, sizes $1x$ and $2x$ were solved to optimality. System sizes $3x$-$10x$ were solved to a $\leq 0.1\%$ gap. TPRUC was solved to optimality for all sizes. TPRUC Sizes $1x$ and $2x$ solve to 0.1% gap in 145 s and 281 s respectively. Similar to Section 2.7.3, all MILP models of sizes $2x$-$10x$ were solved with priority constraints, which break ties between units that have exactly the same characteristics. Without these constraints, TUC $2x$-$10x$ took more than 10000 s to solve.

2.8 Conclusion

There are important trade-offs between accuracy and computational burden in unit commitment (UC) models. Approximations that capture most of the characteristics of unit commitment, but solve quickly, can be useful. Each approximation has advantages and disadvantages that need to be considered, keeping the size of the problem, the available computational resources, and the purpose of the analysis in mind.

We presented a MILP UC formulation (which we call TUC), that defines a tighter constraint set than the standard UC formulation from literature. We showed that this solves faster than the base case.[25] We then relaxed this MILP and showed that the resulting LP, TRUC, compares well with common linear approximations from literature such as those based on load duration curves (models LDC and LDC' from

---

[25] When using the default settings of an out-of-box solver such as CPLEX 12.6.3.

Sections 2.5.6 and 2.5.7) and a linear relaxation (BCRUC from Section 2.5.2) of the base case MILP. This was measured in terms of reduced error in estimating system costs and hourly energy prices. TRUC has the advantages of being an LP, including solving many orders of magnitude faster than the full UC model, and easier scaling-up to larger system sizes. We also saw that, for problem size $1x$, TRUC's estimates of system costs were within 1% of those predicted by the full UC, and this improved for larger systems (see Figures 2.2 and 2.5). Comparatively, the errors for system cost estimates from LDC and LDC' were around 13% and 10% respectively for the $1x$ system.

We also used selective hour-sampling to extend TRUC to TPRUC by including binary commitment variables for a subset of hours that experience steep load ramps. We have shown that TPRUC is a smaller MIP that solve faster than the full UC while capturing system characteristics, such as total costs and energy prices, better than TRUC. Additionally, we have shown that the approximations correctly identify the two most profitable and the two least profitable generators.[26] Overall, these approximations are helpful steps towards fulfilling the need to have models that approximate UC quickly.

The tight linear approximation of the UC model we presented in this chapter, TRUC, can be thought of as starting a series of small plants with similar characteristics instead of one big generator. Hence, it is likely to be most useful in large systems, in which individual generators tend to be aggregated anyway. The advantages of TRUC are likely to be particularly important for a multistage stochastic planning model, such as [64], where the planning component of the problem is already complex.[27] Embedding a linear UC approximation such as TRUC, which is an LP, yet estimates system costs (to within 1% accuracy in our case study), energy prices (error for $10x$ system was €0.4/MWh), and generator profits more accurately than current linear models from literature (LDC and LDC'), into a multistage stochastic planning model enables us to determine the effect of UC constraints on long-term generation and transmission investments. We do this in the next chapter along with addressing some of the limitations of the approximations we presented in the current chapter, i.e., lack of a network with realistic data, lack of transmission constraints, and the lack of renewable energy sources in the energy mix.

---

[26] Although TRUC over-estimates generator profits for the smallest size $1x$, it performs better than currently used linear approximations. Furthermore, we expect TRUC's estimates of generator profits to become more accurate with increasing system size due to the decreasing RMSE in hourly price estimation.

---

[27] In such cases, TRUC also readily fits into a decomposition approach, such as Benders' decomposition, which require subproblems to be convex, and has been previously used to solve such problems [65] [66].

Chapter 3

Transmission Planning with Intertemporal and Generator Operational Constraints

3.1 Abstract

In the previous chapter, we presented a tight linear relaxation of the unit commitment (UC) problem. We showed that for large systems, this approximation estimates system costs with a $\geq$ 99.8% accuracy. We also showed that it estimates average hourly prices and generator profits better than linear approximations that are commonly used in the literature. In this chapter, we use this LP formulation, TRUC,

to demonstrate the effects of UC on long-term transmission and generation planning. We compare the results from a transmission planning model that includes UC constraints (in the form of TRUC), with those from a traditional transmission planning model, where operations are represented using a load duration curve that ignores inter-temporal constraints such as ramp rates and minimum-run capacities. We find that UC's potential to affect long-term transmission plans is the greatest when there are slow-moving generators in the mix that are cycled.

3.2 Notation

3.2.1 Sets and Indices

$\mathbf{B}$	Set of buses b
$\mathbf{H}$	Set of hours h
$\mathbf{L}$	Set of all transmission lines l
$\mathbf{L_E}$	Set of all existing transmission lines
$\mathbf{L_N}$	Set of all new transmission lines
$\mathbf{T}$	Set of (time) stages t (three stages).
$\mathbf{R}$	Set of internal-regions r (For Renewable Portfolio Standard constraint)
$\mathbf{G}$	Set of generators g

GR	Set of renewable generators gr ($GR \subset G$)
S	Set of scenarios s. A scenario is a distinct set of constraint and objective function parameters for a future stage ($t = 2, 3$).

3.2.2 Parameters

$B_l^{E/N}$	Susceptance of existing (E) and new lines (N)
$C_{l,t,s}^{Z}$	Cost of building line l in stage t and scenario s
$C_{b,g,t,s}^{X}$	Cost of building unit g at bus b in stage t and scenario s
$C_{b,g,t,s}^{Y}$	Marginal Cost of generating energy from unit g, bus b, stage t, scenario s
$C_{b,g,t,s}^{SU/SD}$	Cost of starting-up/shutting-down unit g, bus b, stage t, scenario s
$P_{t,s}$	Scenario probabilities
$VOLL_{b,t,s}$	Value of Lost Load in bus b, stage t, and scenario s
$QP_{b,g}^{min}$	Minimum-run capacity as a fraction of total capacity
$Q_{b,g}^{min}$	Minimum-run capacity of generator g
$X_{b,g}^{1}$	Existing capacity of generator g and bus b
POR_g	Planned Outage Rate of generator g
FOR_g	Forced Outage Rate of generator g

$X^R_{b,g,t}$	Capacity being retired in stage t (exogenous)
$\overline{X}_{b,g,t,s}$	Maximum capacity of generator g allowed at bus b
R_g	Fraction of capacity that can provide reserves
X_R	Fraction of load that contributes to reserve requirement
$RP_{b,g}$	Fraction of maximum capacity that can be ramped up or down for unit g
$M_{b,l}$	Line-incidence matrix mapping buses to lines. 1 and -1 indicate to and from buses respectively.
M	A large scalar (Big-M)
$D_{b,h,t,s}$	Load at bus b, hour h, stage t, and scenario s
RPS_r	State-mandated fraction of yearly load that must come from renewables
$\overline{F}^{E/N}_{l,t,s}$	Maximum flow on existing (E) and new lines (N)
$\underline{F}^{E/N}_{l,t,s}$	Minimum flow on existing (E) and new lines (N)

3.2.3 Variables

$z_{l,t,s}$	$\{0,1\}$: Invest in line l in stage t, scenario s
$x_{b,g,t,s}$	Capacity of generator g built at bus b
$q_{b,g,h,t,s}$	Output from g in hour h in stage t and scenario s

$l_{b,h,t,s}$	Curtailment at bus b in hour h, stage t, scenario s.
$p^{min}_{b,g,h,t,s}$	Minimum-run capacity online in hour h from g in stage t and scenario s
$r_{b,g,h,t,s}$	Reserves in hour h from generator g in stage t and scenario s
$\overline{x}_{b,g,t,s}$	Generator g's capacity in stage t and scenario s
$p^{SU}_{b,g,h,t,s}$	Capacity started up in hour h from generator g in stage t and scenario s
$p^{SD}_{b,g,h,t,s}$	Capacity shut down in hour h from generator g in stage t and scenario s
$f^{E/N}_{l,h,t,s}$	Flow on existing (E) and new (N) lines in hour h, stage t, scenario s
$\theta_{b,h,t,s}$	Bus angle at bus b, hour h, stage t, and scenario s

3.3 Introduction

There is growing evidence supporting the inclusion of UC constraints in long-term generation and transmission planning models [30] [36] [29]. Despite this, due to the computational difficulties associated with solving UC problems, limited studies have focused on short-term operational constraints in the context of planning. Up until the early 2000s, large-scale UC problems (without planning) were complex enough, that it was necessary to use techniques such as Lagrangian Relaxation (LR) [67] [68] or Benders' decomposition [69] [70], to solve them. However, development of faster computers, and algorithmic advances in Mixed Integer Programming (MIP) techniques starting in late 1980s [71] [72] made large-scale MIPs more tractable and efficient to solve. These algorithms were also applied to problems in the power industry and (as mentioned in Chapter 2) by 2006 it was estimated that the transition from LR to MIP-based methods had led to savings of \$100 million per year for the PJM market alone [34]. This new tractability of UC problems allowed recent studies such as [30] and [36] to re-assess planning methods and the effect of generator operational constraints on them. Ref. [36] especially found that while UC has the potential to affect investments, there is currently a dearth of models that account for the discrete nature of generators and commitment decisions. In Chapter 2, we developed one such model (TRUC) that adequately approximates the full UC MILP (capturing $\geq 99\%$ of the total system costs) while remaining tractable enough computationally to be used within large-scale investment planning models. The goal of this chapter is to bridge the gap between UC and planning models and determine whether UC has the potential to affect long-term investments and, if yes, to explore its conditions and causes.

If UC does indeed affect planning decisions, it would mean that the recommendations from load duration curve (LDC) methods, that are commonly used for planning currently, are suboptimal. These suboptimal solutions can in turn again lead to inefficient generation and transmission siting and inefficient operations. The potential savings from using more accurate investment models could be significant.

Contributions

The contributions of this chapter are as follows:

1. In our experience,[1] even with a decomposition approach such as Benders [73], that separates large MIPs into smaller problems, a planning problem with an embedded full MILP UC model could not be solved a reasonable time. In this chapter, we address this issue by incorporating approximated UC constraints (using TRUC) into a multi-stage stochastic transmission planning model [22] [65] and applying it to a large region (the U.S. Western Interconnection).
2. We investigate whether UC has the potential to affect long-term investments in planning models when compared to using a simple load duration curve-based method. If it does have the potential, we explore the conditions under which investments change.
3. We recognize that integrating UC and planning models has some practical disadvantages. First, it increases the number of constraints and variables in an already complex planning model. Second, more data is required as the operational characteristics of each unit (e.g. minimum-run and ramp capabilities) are needed to include chronology into the model. We evaluate these trade-offs by quantifying "regret" i.e., the additional cost the system incurs if it implements decisions recommended by a model that uses a simple LDC curve to represent

---

[1] Results not shown.

operations in a planning model.

4. We consider uncertainty in the form of future scenarios in a two-stage stochastic planning model with recourse, and show that short-term operational constraints have the potential to change both the deterministic and the stochastic investment solutions. We also found that the solution is sensitive to the probabilities assigned to the individual scenarios.

First in Section 3.4, we present an overview of a two-stage stochastic planning model from literature [64] [22]. In this model, operations are depicted using a load duration curve, and intertemporal constraints as well as fixed costs such as start-up and shut-down costs are ignored. Then, in Section 3.4.2, we present the modified two-stage stochastic transmission and generation planning model with UC constraints. Short term start-up and shut-down costs, and ramping constraints are depicted in this model using the linear relaxation, TRUC, of the Tight Unit Commitment formulation presented in Section 2.5.4. We compare results from these two models in a deterministic setting (no uncertainty in the future) in Section 3.6, and show that UC indeed has the potential to change long-term transmission and generation investments. In Section 3.6.3, we show an example of how UC changes the depiction of unit operations within planning models. Then, in Section 3.6.3.1, we present results from a sensitivity analysis to determine the conditions under which UC affects transmission plans. We expand the deterministic case study to a stochastic framework by considering regulatory and policy uncertainty in Section 3.7. We also show that the probabilities assigned to scenarios has an effect on how UC changes investment recommendations.

3.4 Two stage stochastic transmission planning

The two-stage stochastic transmission planning model we use is based on models proposed previously in literature [64] [22]. It has two stages of investment - investments that have to be made today (here-and-now) while considering an uncertain future[2], and recourse decisions (including operations and investments in future years) that can be made upon realization of the future. The timeline of the model is shown in Figure 3.1. In the first stage, t_1, - today - the only decisions made are investments (generation and transmission). These decisions are made before uncertainty is revealed and are represented by I. We assume that these investments take 10 years to build and come online in the next stage - Stage 2 (t_2, 10 y from today). This is a typical lead time for large power plants and new transmission. At the beginning of t_2, uncertainty is revealed and we know which scenario has materialized. In this stage, we simulate 10 years of systems operations while a second round of generation and transmissions investments (i.e., recourse investments) are made for any realizable scenario. These two decisions (Investments and Operations for every possible scenario) are shown as $I(s) + O(s)$ in Figure 3.1. These investments come online at the beginning of Stage

---

[2] In this case-study, scenarios are considering to be possible futures with a range of possible technological, policy, and economic developments. There are multiple uncertain parameters in each scenario - fuel prices, capital costs, renewable policy etc.

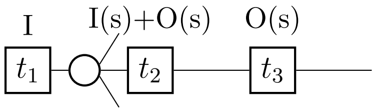


Figure 3.1: Two-Stage stochastic model schematic. Squares represent decision nodes. Uncertainty is depicted by the chance node (circle) and the branches represent scenarios.

3 (t_3, 20 y from today) after a 10 year construction period. In this stage, the grid, with all the new generation and transmission investments, is operated for a period of 30 years without new investments or remaining uncertainty.

3.4.1 Transmission planning model ignoring inter-temporal operational constraints

This is a two-stage stochastic planning model from literature [64] [1]. We compare transmission and generation investments, and generator operations from this model to the modified planning model (with UC constraints) presented in Section 3.4.2.

$$\text{Min} \quad P_{t,s}\Big[\sum_{l,t,s} C^{Z}_{l,t,s} z_{l,t,s} + \sum_{b,g,t,s} C^{X}_{b,g,t,s} x_{b,g,t,s} + \sum_{b,g,h,t,s} C^{Y}_{b,g,t,s} q_{b,g,h,t,s} + \sum_{b,h,t,s} VOLL_{b,t,s} l_{b,h,t,s}\Big] \tag{3.1}$$

$$\text{s.t.,} \quad r_{b,g,h,t,s} + q_{b,g,h,t,s} \leq (1 - POR_g)(1 - FOR_g)\overline{x}_{b,g,t,s} \quad \forall b, g, h, t, s \tag{3.2}$$

$$\overline{x}_{b,g,2,s} = X^{1}_{b,g} + x_{b,g,1} - \sum_{t=1}^{2} X^{R}_{b,g,t} \quad \forall b, g, s \tag{3.3}$$

$$\overline{x}_{b,g,3,s} = X^1_{b,g} + x_{b,g,1} + x_{b,g,2,s} - \sum_t X^R_{b,g,t} \quad \forall b, g, s \tag{3.4}$$

$$\overline{x}_{b,g,t,s} \leq \overline{X}_{b,g,t,s} \quad \forall b, g, t, s \tag{3.5}$$

$$r_{b,g,h,t,s} \leq R_g \overline{x}_{b,g,t,s} \quad \forall b, g, h, t, s \tag{3.6}$$

$$\sum_g q_{b,g,h,t,s} - \sum_l M_{b,l}(f^E_{l,h,t,s} + f^N_{l,h,t,s}) + l_{b,h,t,s} = D_{b,h,t,s} \ \ \forall b, h, t, s \tag{3.7}$$

$$\sum_{b,g} r_{b,g,h,t,s} \geq X_R D_{b,h,t,s} \ \ \forall h, t, s \tag{3.8}$$

$$\underline{F}^E_l \leq f^E_{l,h,t,s} \leq \overline{F}^E_l \quad \forall l \in L_E, h, t, s \tag{3.9}$$

$$z_{l,t,s} \underline{F}^N_{l,t,s} \leq f^N_{l,h,t,s} \leq z_{l,t,s} \overline{F}^N_{l,t,s} \quad \forall l \in L_N, h, t, s \tag{3.10}$$

$$\sum_{b \in B(r), gr, h} q_{b,gr,h,t,s} \geq RPS_r \sum_{b \in B(r)} D_{b,h,t,s} \ \ \forall r, t, s \tag{3.11}$$

$$q_{b,g,h,t,s}, r_{b,g,h,t,s}, x_{b,g,t,s} \geq 0 \ \ \forall b, g, h, t, s \tag{3.12}$$

$$z_{l,t,s} \in \{0, 1\} \ \ \forall l, t, s \tag{3.13}$$

The objective function (3.1) minimizes investment costs of new transmission and generation, variable operating costs of existing and new generators, and monetary penalties from lost load. Constraints (3.3)-(3.4) are inventory constraints that enforce relationships between total capacity in different years: the capacity at any stage is a function of investments and retirements from previous stages. Constraint (3.5) enforces upper-bounds on the amount of new capacity that can be built in every stage for each generator type. Constraint (3.6) limits the quantity of spinning reserve provided by a generator to a fraction of its capacity. Constraint (3.7) is the Kirchhoff's

Current Law (KCL) which ensures that the net injections and withdrawals at every bus in every hour are equal.[3]. Constraint 3.8 ensures that there is enough spinning reserve capacity available and constraints (3.9) and (3.10) impose thermal limits on flows on existing and new lines respectively. Constraint (3.11) enforces Renewable Portfolio Standards (RPS) on the energy produced annually across WECC. This constraint ensures that a fraction of the total electricity generated is from renewable sources. This is consistent with WECC's policies, where multiple states have their own renewable standards. For example, the state of California has set itself a goal of procuring 33% of its electricity by 2020 and 50% by 2030 [76]. Lastly, constraints (3.12) and (3.13) enforce non-negativity on energy and reserve variables, and restrict transmission investments to binary variables. To run a deterministic case, the weights assigned to the scenarios, $P_{t,s}$, become zero for all, except for the selected scenario.

The difference between the above model and those from [64] and [22] is in the depiction of generator operations. The aforementioned studies use non-chronological hours and ignore inter-temporal constraints, whereas we include them, by embedding the TRUC formulation (Section 2.5.4 from Chapter 2) into this two-stage stochastic transmission planning model.

---

[3] This is a DCOPF approximation of the Optimal Power Flow (OPF) problem embedded within the long-term transmission planning problem. Considering line-flow losses would modify this constraint. See references [74] and [75] for a full explanation of linearized DCOPF model, including assumptions, approximations, and derivations from the ACOPF model.

3.4.2 Transmission planning model with unit commitment constraints

This is the two-stage stochastic planning model that is modified to include UC constraints. This is done by embedding the TRUC formulation from Section 2.5.4 into the planning model from Section 3.4.1.

$$\text{Min} \quad P_{t,s}\Big[\sum_{l,t,s} C^{Z}_{l,t,s} z_{l,t,s} + \sum_{b,g,t,s} C^{X}_{b,g,t,s} x_{b,g,t,s} + \sum_{b,g,h,t,s} C^{Y}_{b,g,t,s} q_{b,g,h,t,s} +$$

$$\sum_{b,h,t,s} VOLL_{b,t,s} l_{b,h,t,s} + \sum_{b,g,h,t,s} \frac{C^{SU}_{b,g,t,s}}{Q^{min}_{b,g,t,s}} p^{SU}_{b,g,h,t,s} + \sum_{b,g,h,t,s} \frac{C^{SD}_{b,g,t,s}}{Q^{min}_{b,g,t,s}} p^{SD}_{b,g,h,t,s}\Big] \tag{3.14}$$

$$\text{s.t.,} \quad \text{Constraints}(3.3) - (3.5), (3.7) - (3.13)$$

$$p^{min}_{b,g,h,t,s} \leq QP^{min}_{b,g} \overline{x}_{b,g,t,s} \quad \forall b, g, h, t, s \tag{3.15}$$

$$p^{min}_{b,g,h,t,s} \leq q_{b,g,h,t,s} \quad \forall b, g, h, t, s \tag{3.16}$$

$$r_{b,g,h,t,s} + q_{b,g,h,t,s} \leq (1 - POR_g)(1 - FOR_g) \frac{p^{min}_{b,g,h,t,s}}{QP^{min}_{b,g}} \quad \forall b, g, h, t, s \tag{3.17}$$

$$r_{b,g,h,t,s} \leq R_g \frac{p^{min}_{b,g,h,t,s}}{QP^{min}_{b,g}} \quad \forall b, g, h, t, s \tag{3.18}$$

$$p^{min}_{b,g,h,t,s} - p^{min}_{b,g,h-1,t,s} = p^{SU}_{b,g,h,t,s} - p^{SD}_{b,g,h-1,t,s} \quad \forall b, g, h, t, s \tag{3.19}$$

$$\big(r_{b,g,h,t,s} + q_{b,g,h,t,s} - p^{min}_{b,g,h,t,s}\big) - \big(q_{b,g,h-1,t,s} - p^{min}_{b,g,h-1,t,s}\big) \leq RP_{b,g} \left(\frac{p^{min}_{b,g,h,t,s}}{QP^{min}_{b,g}} - p^{min}_{b,g,h,t,s}\right) \quad \forall b, g, h, t, s \tag{3.20}$$

$$\left(q_{b,g,h,t,s} - p^{min}_{b,g,h,t,s}\right) - \left(q_{b,g,h-1,t,s} - p^{min}_{b,g,h-1,t,s}\right) \geq -RP_{b,g}\left(\frac{p^{min}_{b,g,h-1,t,s}}{QP^{min}_{b,g}} - p^{min}_{b,g,h-1,t,s}\right) \quad \forall b,g,h,t,s \tag{3.21}$$

$$q_{b,g,h,t,s} - p^{min}_{b,g,h,t,s} \leq \frac{p^{min}_{b,g,h,t,s}}{QP^{min}_{b,g}} - \frac{p^{SU}_{b,g,h,t,s}}{QP^{min}_{b,g}} \quad \forall b,g,h,t,s \tag{3.22}$$

$$q_{b,g,h,t,s} - p^{min}_{b,g,h,t,s} \leq \frac{p^{min}_{b,g,h,t,s}}{QP^{min}_{b,g}} - \frac{p^{SD}_{b,g,h,t,s}}{QP^{min}_{b,g}} \quad \forall b,g,h,t,s \tag{3.23}$$

$$p^{min}_{b,g,h,t,s}, p^{SU}_{b,g,h,t,s}, p^{SD}_{b,g,h,t,s} \geq 0 \;\; \forall b,g,h,t,s \tag{3.24}$$

The objective of the planning model is to minimize investment costs of new transmission and generation, operating costs of existing and new generators, monetary penalties from lost load, and costs of generator start-up and shut-down. This is given by the objective function (3.14). The new variable $\frac{p^{min}_{b,g,h,t,s}}{QP^{min}_{b,g}\overline{x}_{b,g,t,s}}$ is equivalent to the relaxed binary variable $u_{g,h}$ from the TRUC formulation of Chapter 2 (Section 2.5.4). The continuous non-negative variable $p^{min}_{b,g,h,t,s}$ is upper-bounded by the must-run (minimum-run) capacity of the generator, $QP^{min}_{b,g}\overline{x}_{b,g,t,s}$. This relationship is given by constraint (3.15). Constraints (3.16) and (3.17) define the lower and upper-bounds respectively on the energy produced from a generator in any given hour. Observe how the latter constraint is different from constraint (3.2). Similar to the valid inequalities from the previous chapter (Section 2.5.3), the RHS of constraint (3.17) depends on the fraction of generator capacity running. Constraint (3.18) limits the quantity of spinning reserve provided by a generator. The upper-bound on the spinning reserve from a generator depends on the fraction of the capacity that is running, $p^{min}_{b,g,h,t,s}$. Constraint (3.19) ensures that the additional capacity started up in hour h, is consistent with the values of the start-up and shut-down variables. Constraints (3.20) - (3.21) are the inter-temporal ramping constraints. These constraints leave enough head-room for reserves while ramping up, and ensure that the generator's ramping capability is consistent with the running capacity in that particular hour. Constraints (3.22) and (3.23) ensure that the maximum output from a unit is consistent with the capacity that is started-up or shut-down in that particular hour. Variables indicating capacity that is running, started-up, and shut-down in a given hour are defined as non-negative values in constraint (3.24).

3.5 Case study: WECC 21-zone network

The data-set used for this case study is a 21-bus representation of the Western Interconnection (the area managed by the Western Electricity Coordinating Council or WECC). It is a reduced network derived from a 300-bus model of WECC, that was developed by a team from the Johns Hopkins University (JHU) in collaboration with a team from the Arizona State University (ASU).[4] A map of this network is shown in Figure 3.2. A detailed description of the data-set can be found in [77].

Chronological load data was sampled to find one day matching peak load from the North-West (winter-peaking), one day matching peak load South-West US (summer-peaking), and one day that matches WECC-wide average load. This brought our

---

[4] Yueyang (Jasmine) Ouyang, Jonathan Ho, Qingyu Xu, and Pearl Donohoo-Valett from JHU. Yujia Zhu and Dan Tylavsky from ASU.

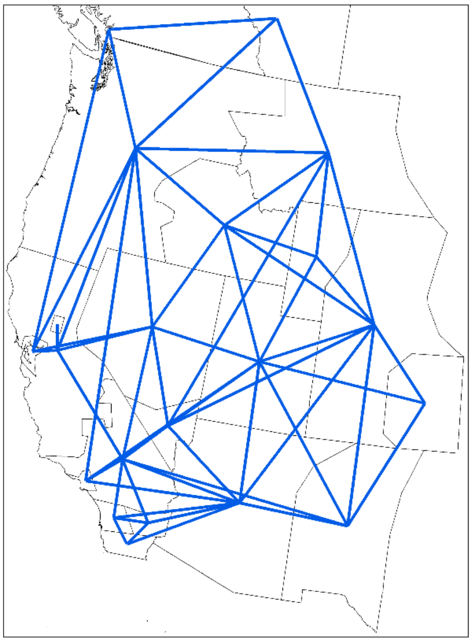


Figure 3.2: 21-zone network representation of the Western Interconnection [1].

total sampled hours to 72 (three days). A load duration curve was constructed and the number of hours with load greater than two standard-deviations away from the average load were counted. This fraction (in a year) of peak-load hours was used to assign weights to the sampled peak-days (assuming one day contains a maximum of one peak-hour). The remaining weight was divided up equally among the hours of the average day. Additionally, wind and solar data were scaled in the selected days to match annual regional averages.

3.6 Results from a deterministic case-study

In a deterministic model (as opposed to a stochastic or probabilistic model), the effect of a single scenario is considered. All parameters in the model are treated as known, with no uncertainty assumed about the future. In the following simple deterministic example, using the 21-bus network and a two-stage deterministic model, we show how UC affects long-term transmission and generation investments. The parameters that we used for the deterministic case study are from the 'Economic Recovery' planning scenario from the WECC Scenario Planning Steering Group study [78]. Details of this scenario (and the others used in the stochastic case) can be found in Section 3.7.1 and [1].

3.6.1 Generator flexibility in the short-run (hours) affects long-run (years) transmission plans: Changes in first stage investments

In this section, we show that operational constraints indeed have the potential to affect both the 1st and 2nd stage transmission and generation investments suggested by the models.

Figure 3.3 shows the effects of operational constraints on Stage 1's transmission

---

[5] These were filtered for values smaller than 10 MW.

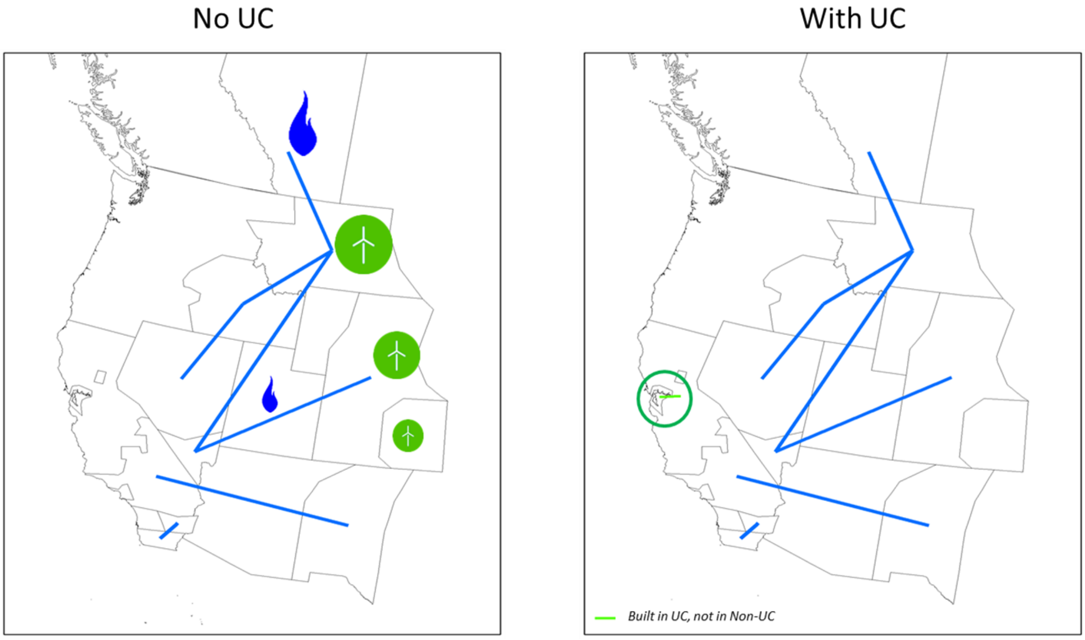


Figure 3.3: Changes in Stage 1 transmission investment: Left panel shows investments (wind farms in green and gas plants in blue) without UC and right panel shows investments with UC. See Table 3.1 for generation investment changes.

Zone	Wind	Gas CCGT
Alberta	0	-767
Colorado	-26	0
Montana	-424	0
Utah	0	-493
Wyoming & Colorado	-154	0

Table 3.1: First-stage generation investment changes (With UC - Without UC) in the deterministic case (in MW). A negative value means that less capacity is built when UC constraints are added to the planning model.[5]

investments and Table 3.1 details the changes to Stage 1's generation investments. In Figure 3.3, on the left are the lines and (additional) generation that are built without UC constraints (using the model from Section 3.4.1), while the right panel represents investments with Unit Commitment (using the model from Section 3.4.2). We see that one extra line is built today (in Stage 1, corresponding to the first 10 years) when you add UC constraints to the planning model. This line (circled in green in the right panel) is built in lieu of extra generation capacity that is built in if a LDC is used (highlighted in the left panel of Figure 3.3 and detailed in Table 3.1). Uneconomical wind farms in Wyoming, Montana, and Colorado along with gas plants in Alberta, and the Wyoming & Colorado zone are built. With UC, we build less of these units and instead build one extra transmission line (marked in green).

Here, short-term operational constraints favor transmission as an alternative to generation investment.[6] This need not always be the case as transmission investments are lumpy by nature (high fixed costs for a line and binary variables mean that partial lines cannot be built). When investments are lumpy, transmission need not be the only alternative to constrained generation. More flexible generation can be built (as opposed to the high costs that will be incurred if a transmission line has to be built) or existing generators can be operated more. In other cases, renewables can be built either locally or elsewhere if congestion on the lines allows shipment of power to the place it is needed. Indeed, in the following sections, we will see some of these results under varying conditions.

3.6.2 Economic regret

If only a load duration curve is used, it is sufficient for the planner to know the capacity of every plant. But to include short-term operational constraints into long-term planning models, planners require estimates of start-up and shut-down costs, minimum-run capacities, and a host of other generator operational details. This additional data procurement costs the planner - in terms of data collection and modeling effort. In order to determine the circumstances under which use of the model is justified, we quantify the economic regret, or the loss of economic efficiency from using a suboptimal transmission system (from the simple LDC model).

---

[6] In results not shown here, the second stage generation and transmission investments change as well.

We define economic regret as the cost difference between the UC planning model, and the Stage 1 LDC planning model results applied to the UC planning model. It is an estimate of the monetary cost the system incurs from basing first-stage investments on the results of an inaccurate LDC model rather than the more accurate (UC) model. There are three possible outcomes:

1. 1st stage decisions of the LDC planning model and UC model are the same $\implies$ No economic regret.

2. 1st stage decisions differ, but the LDC first stage decisions result in the same cost as the UC model solution when tested on the UC model. This means the set of LDC first stage transmission investments is an alternate optima for the UC model. $\implies$ No economic regret.

3. 1st stage decisions differ, and the LDC first stage decisions result in a higher cost than the UC model solution when tested on the UC model. This means the set of LDC first stage transmission investments is a suboptimal solution for the UC planning model. $\implies$ Positive economic regret.

In the case study above, we found that the 1st stage transmission investments were different in the LDC model when compared with the UC planning model (See Figure 3.3). One less transmission line was built, and when this set of suboptimal first stage transmission investments was imposed on the UC planning model, the economic regret was found to be \$731 Million. This is 7% of today's (Stage 1's) transmission investment cost.

So, in this case study, the planning committee needs to assess the additional effort involved in moving to more accurate models that consider unit commitment, against \$ 731 M, which is the regret the decision makers potentially faces from using less-accurate planning models.

3.6.3 Operations are more accurately depicted due to UC constraints

In addition to generation and transmission investments, the overall energy generation mix changes in terms of location and type of generators. As an example, Stage 1's major energy mix changes (with UC — without UC) are shown in Figure 3.4. In Alberta, with UC, we observe an increase in Combustion Turbine (CT) generation and a reduction in Combined Cycle Gas Turbines (CCGT) generation, when compared to the LDC model's generation mix. We see less coal operated in Arizona/NE New Mexico while more coal operated in Western Wyoming and Wyoming/Colorado. Overall, the imposition of UC constraints and costs causes the yearly generation mix to shift from slow-ramping and inflexible coal generation to faster and flexible CCGTs and CTs.

At the root of all these generation and transmission changes are differences in unit-level generator operations (within the planning model), including the effects of

---

[7] Also see Table 6.2 in the appendix.

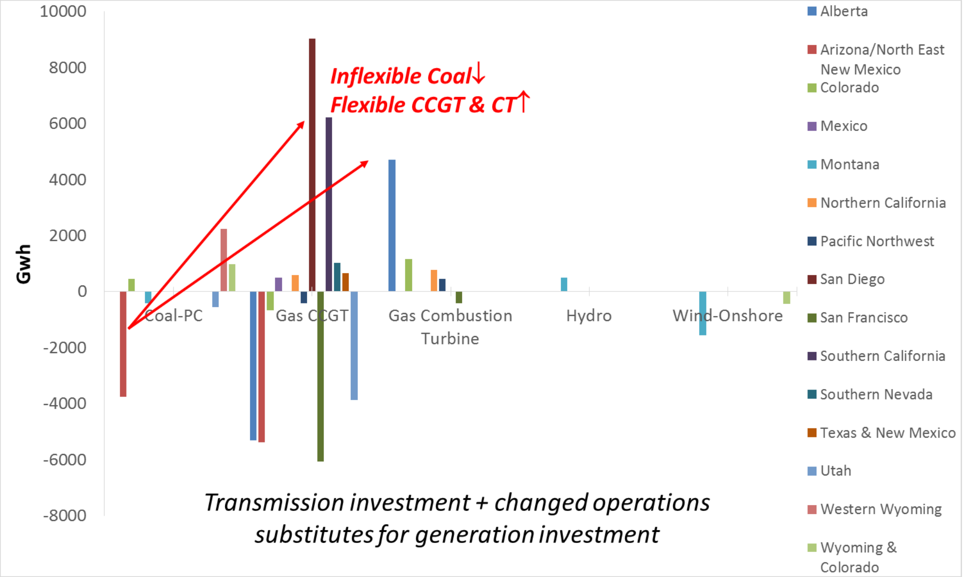


Figure 3.4: Changes in Stage 1 operations by generator type and zone (With UC minus Without UC).[7]

start-up costs, minimum-run, and ramp-rate constraints. Figure 3.5 illustrates unit-level changes by comparing the operations of generators at a single bus (Colorado) with and without UC constraints. It should be noted that the total output from generators in Colorado differ between the with and without UC cases (Figure 3.5).

Coal-powered units are slow-ramping and, because of their operating constraints, cannot be shut down for a few hours in between operations. In Figure 3.5, we can see the LDC model starts up and shuts down the coal capacity twice in a day, and ramps it rapidly. This is not actually feasible. So, including UC constraints rectifies the traditional LDC models' representation of coal operations. We note more uniform ramping characteristics, and reduced short-span shutdowns. These basic changes in operations, such as the ones shown in Figure 3.5, occur in all buses, stages, and

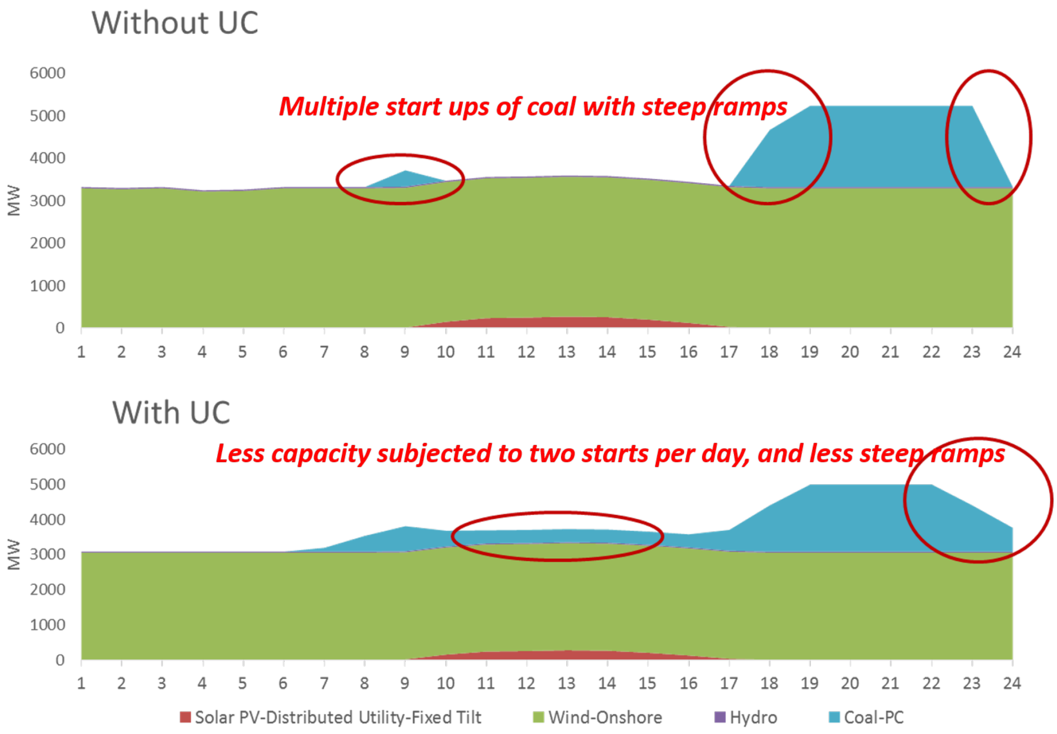


Figure 3.5: Example of how UC affects short-runs operations depiction. These are operations in Colorado without and with UC. Results are from Stage 1 operations from a deterministic ‘Economic Recovery’ case. We see that UC now forces the model to make coal plants’ dynamics more realistic in terms of starting up, shutting down, and ramping.

scenarios simulated, and they have the potential to change the relative economic attractiveness of operating different technologies. For example, as we see from Figure 3.5, imposing UC constraints makes coal less valuable (less flexible), and either increases its costs (generate more when not needed, as in the second figure) or causes it to be used less in favor of more flexible technologies (not shown here). This change in technologies' relative economic attractiveness, can in turn, change the investments needed to economically meet demand.

3.6.3.1 Where and why do we see these changes? - The example of coal units and carbon prices

As we will show in this section, UC's potential to affect long-term investments is the greatest when slow-moving generators (e.g. coal units) appear in the energy mix *and* are cycled frequently. For example, consider the effect of increasing the carbon tax. As Figure 3.6 shows, as carbon taxes increase, coal's capacity factor decreases, indicating it is gradually priced out of the energy mix.[8] The UC constraints interact with the tax in interesting ways. Figure 3.7 shows how the addition of UC constraints changes coal units' capacity factors at each level of carbon tax. A positive change implies that with UC constraints, coal is being run more and a negative change implies that coal is being run less.

At low carbon taxes ($0 and $20/ton), coal usage increases with UC constraints.

---

[8] The deterministic model was re-run with different carbon price trajectories for CO_2. For the previous results, a carbon tax of $59/ton was used.

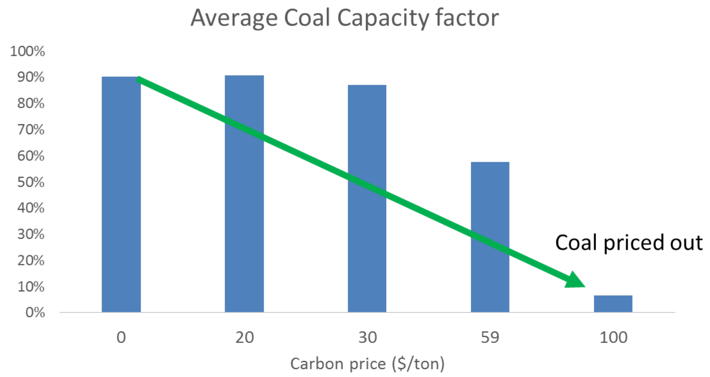


Figure 3.6: Effects of carbon tax upon the capacity factor (CF) of coal plants (2024, WECC 1 Economic Growth scenario, no unit commitment constraints)

This is because, in these cases, coal is cheap, and since it carries no/low penalties, coal-powered units operate for longer than without UC due to constraints on shutting-down and ramping.[9] We see this effect in Figure 3.7 above. For medium carbon taxes ($30 and $59/ton), coal is used less than the case without UC. In these cases, coal plants are not started up as often as it would have been without UC. For the highest carbon tax ($100/ton), the coal unit is run longer. This is because at this high penalty, it is being used only as a peaker unit, and at these times, the ramp constraints keep it on for longer.

What is interesting are the cases when UC shows the potential to change investments. Today's (Stage 1) transmission investments change with the addition of UC constraints only in the medium carbon tax range (marked in green in Figure 3.7). This occurs when coal is started-up less frequently and, when running, is being cy-

---

[9] The coal results are all only for existing units. We assume new coal units cannot be built in WECC.

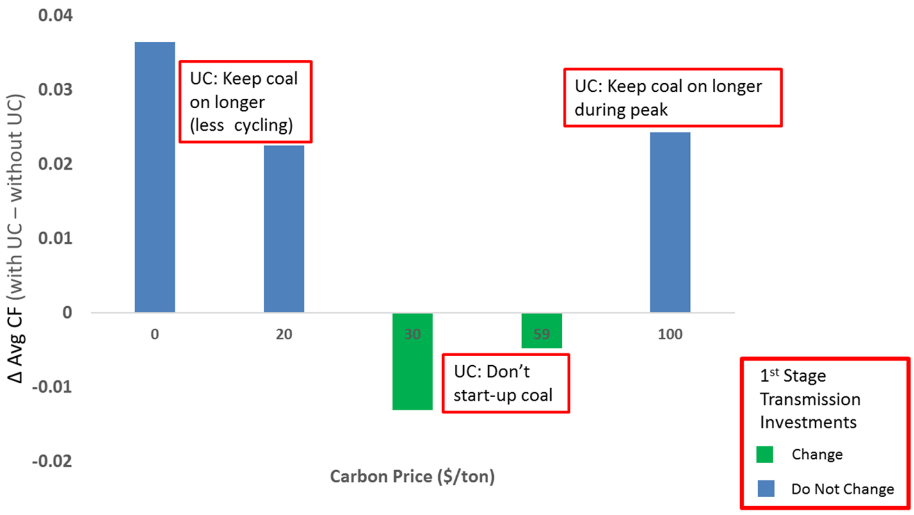


Figure 3.7: Effects of unit commitment constraints upon the capacity factor (CF) of coal plants under alternative CO2 prices, and the resulting impacts on transmission investments. A positive value indicates that coal is operated more with the addition of UC constraints as compared to without. Green denotes change in Stage 1 transmission plans.

cled. This may be intuitive because, at very low and very high carbon taxes, coal is either completely base-loaded (no cycling) or completely priced out of the energy mix (very little overall share of the mix; used just for peak). In both these cases, UC constraints do not matter as much because the units are rarely ramped or started up. It is in the mid-ranges that carbon tax changes investments because this is when coal plants (and other slow-moving inflexible units) are being cycled enough while having a sizable share in the energy mix to make a difference to the long-term relative attractiveness of technologies when UC is considered.

3.6.3.2 Economic regret faced by the system at different mid-range carbon taxes

In the mid-range of carbon taxes, as shown in Section 3.6.3.1, there is a strong possibility that the inclusion of UC will change Stage 1 transmission investments. We showed the economic regret faced by the system at one carbon tax ($59/ton in Section 3.6.2). In this section, we calculate the economic regret[10] faced by the system at different mid-range carbon taxes, to further understand how the extent of coal unit cycling affects transmission investments.

Table 3.2 shows that as carbon tax increases, economic regret first increases and then decreases.[11] Again, this is intuitive as units are slowly moving up the merit-order

---

[10] Here, economic regret is defined as the cost difference between the UC planning model, and the Stage 1 transmission investments from the LDC planning model imposed on the UC planning model.

[11] This economic regret is calculated at the given carbon taxes and the effect of UC might change under different carbon taxes.

Carbon tax ($/ton)	Economic Regret (ER)[*] (in $ Million)	ER (as a percentage of Stage 1 transmission investment cost)
45	177.5	1.3 %
50	329.4	3.2 %
59	731.0	7 %
65	321.1	2.3 %
70	334.7	2.4 %

Table 3.2: Economic regret for medium range carbon taxes calculated as a percentage of Stage 1 transmission investment cost without UC. It should be observed that this economic regret is calculated at the given carbon taxes and the effect of UC might change under different carbon taxes. For example, the same two sets of transmission investments (one each from a model with UC and without UC) can result in different economic regrets at different carbon taxes.

[*] Calculated using the assumed carbon tax.

— from being completely baseloaded to being used as peakers. As they move up, the amount they are cycled first increases and then decreases. This further confirms that it is the intersection of inflexible generation with cycling that causes UC to change investments.

3.7 Five-scenario stochastic two-stage program

The above deterministic model had only one scenario.[12] We now add four scenarios to this,[13] and show results from the corresponding two-stage stochastic program under two sets of weights assigned to each scenario. Details of these scenarios and probabilities are given in Section 3.7.1. The goal of the stochastic model is to determine if UC still has the potential to change the transmission plans compared to a LDC model when the future looks uncertain. In this model, we explicitly take that uncertainty into account.

3.7.1 Scenarios' description and probabilities used

The five scenarios we use were developed by the WECC Scenario Planning Steering Group [78]. Every uncertain future parameter (natural gas prices, carbon tax, load growth, state RPS, federal RPS etc.) could take on three values - Low (L), Medium (M), and High (H), depending on the scenario. Table 3.3 gives an overview of the

---

[12] Multiple solutions were discussed, each being from a deterministic model with a different carbon tax.

[13] Table 3.4 shows the probabilities we use.

Uncertain Parameters	Scenarios				
	Base Case	WECC 1: Econ- -omic Recovery	WECC 2: Clean Energy	WECC 3: Short-Term Consumer Costs	WECC 4: Long-Term Societal Costs
Gas Prices	M	H	M	M	L
Carbon Prices	M	M	H	L	H
Load Growth	M	H	H	L	L
State RPS	M	M	H	L	H
Federal RPS	M	M	H	M	H
Wind Capital Cost	M	H	L	H	L
Geothermal Capital Cost	M	M	L	M	M
Solar Capital Cost	M	M	L	H	M
Demand Growth Rate	M	H	H	L	L
In-state RPS	M	M	L	M	H
IGCC with CCS Capital Cost	M	M	L	M	M

Table 3.3: Levels of uncertain parameters in each of the five scenarios. L, M, H indicate Low, Medium, and High respectively. The values can be found in Table 4.1 of [1].

five scenarios. The values of these levels can be found in Table 4.1 of [1].

These five scenarios were considered by WECC in their 2013 transmission plan [78]. ‘Base case’ is a Business-As-Usual scenario, where all parameters take the medium-level values. In ‘Economic Recovery’, there is high load growth (including high growth of peak demand). Gas prices and wind capital costs are also high. In the ‘Clean Energy’ scenario, it is assumed that capital costs of low-carbon sources of energy such as wind, geothermal, and solar are cheaper to build. In addition to high carbon prices, high State and high Federal RPS standards incentivize new renewable sources development. In ‘Short-term consumer costs’, economic growth in Western

No.	Scenarios	Set 1	Set 2
1	Base Case	0.2	0.2
2	WECC 1: Econ Recovery	0.2	0.1
3	WECC 2: Clean Energy	0.2	0.1
4	WECC 3: Short-Term Consumer Costs	0.2	0.47
5	WECC 4: Long-Term Societal Costs	0.2	0.13

Table 3.4: Two sets of probabilities were tested with and without UC Constraints

US is restrained and proven and low-risk technologies are favored [78]. Wind and solar plants are more expensive to build, whereas load growth and carbon prices are low. In 'Long-term societal costs', consumers are willing to pay a higher cost for more environmentally friendly sources of energy. This is characterized by reduction in gas prices, increase in price of carbon and aggressive RPS requirements. See Table 3.3 for a comparison of the scenarios.

Table 3.4 shows the two sets of probabilities that are used in the results here. In Set 1, all scenarios are equally weighted, while in Set 2, the probabilities are a result of a moment-matching linear program that minimizes the squared error between the expected mean of seven parameters in all scenarios, and the mean of the parameters across the five scenarios. An additional constraint in this LP is that every scenario has to have a minimum assigned probability of 0.1.[14]

---

[14] This moment-matching was done by Qingyu Xu, a graduate student at The Johns Hopkins University. More details of the moment-matching method can be found in [1].

3.7.2 Does UC change stochastic 10-year and 20-year investments?

We find that Unit Commitment (UC) indeed has the potential to change the transmission and generation investment decisions from a two-stage stochastic program that uses LDC to depict operations. First, we look at Stage 1 investments change under both sets of probabilities shown in Table 3.4.

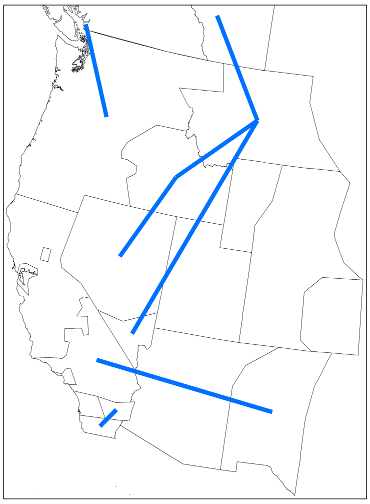
3.7.2.1 Effect on stage 1 investments

In Figure 3.8, blue lines indicate 10-year transmission investments recommended by both models — one using Set 1 weights and the other using Set 2 weights. Under Set 1 weights, there is no change in today's transmission investments. All the lines that are recommended without UC are also recommended with UC. These lines are shown in Figure 3.8a.[15]. We do see differences in generation investment though. Less CCGT is built and (slightly) more wind is built. These values are shown in Table 3.5.

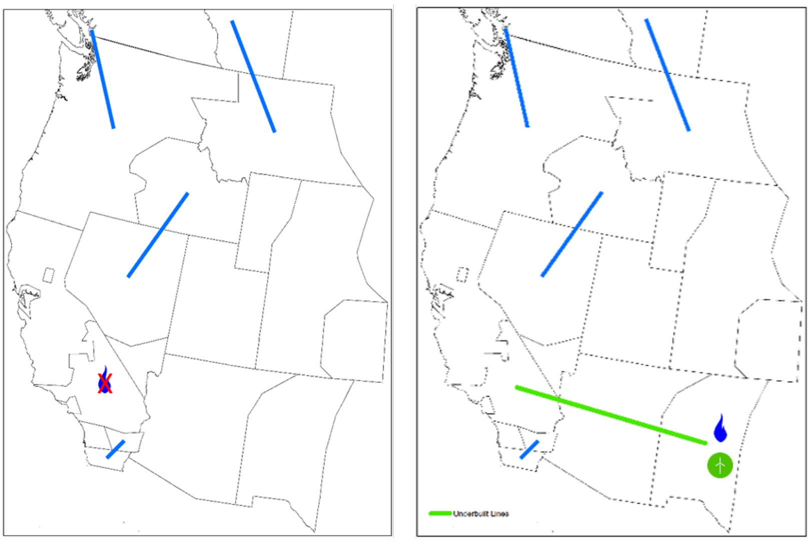
From Figure 3.8b, we see that under the second set of weights (Set 2), Unit Commitment constraints favor building a transmission line (shown in green), and building gas and wind plants in Texas/New Mexico and then shipping power to Southern California instead of building gas units locally (as is the case without Unit Commitment). We also see the associated generation investment changes in Table 3.6. Overall, less

---

[15] Only one panel is shown as line investments are the same with and without UC



(a) No change in transmission investments with and without UC (Set 1 probabilities)



(b) With UC constraints (right), one additional line is built instead of local generation under an alternative set of probabilities when compared to the without UC case.

Figure 3.8: 10-year transmission investments (here-and-now decisions) with and without UC (Set 2 probabilities).

Zone	Wind	Gas CCGT
Alberta	0	-767
Montana	-54	0
Texas & New Mexico	-161	0
Western Wyoming	0	33
Wyoming & Colorado	259	0

Table 3.5: Set 1 probabilities: 1st stage generation investment changes (with UC - without UC). Less investment in CCGT units and less investment overall. Wind investment changes geographically.

gas capacity (CCGT) is built and more wind capacity is built with UC than without.

Summarizing the impacts on 1st stage transmission and generation investments, UC affected Stage 1's transmission investments only under one set of probabilities (Set 2), but generation investment was affected under both sets. Although the magnitudes varied, overall, totaling investments over the WECC-region, less gas was invested in and more wind was favored. Furthermore, with Set 2 probabilities, we saw that UC can not only favor transmission as an alternative to local generation investment, but result in more renewable sources investment than without UC.

Zone	Wind	Gas CCGT
Alberta	0	-774
Montana	-57	0
Southern California	0	-3750
Texas & New Mexico	3736	1220
Western Wyoming	0	40

Table 3.6: Set 2 probabilities: 1st stage generation investment changes (with UC - without UC). Less investment in CCGT units and more investment in wind is observed.

3.7.2.2 Effect on stage 2 investments

When UC constraints are added, Stage 2 generation and transmission investments change as well. As an example of these changes, Figure 3.9 shows the second-stage transmission changes for the 'WECC 1: Economic Recovery' scenario under both sets of probabilities. From the left panel of Figure 3.9, we see that under one set of probabilities (Set 1), UC builds one additional line (connecting Texas/New Mexico and Wyoming). At the two ends of this line, we see that less gas and wind is built in Wyoming and less gas, but more wind is built in Texas/New Mexico. Across the entire region though, less wind, less solar, and less CCGT investment takes place with UC when compared to without UC. There is also a geographical change in where these

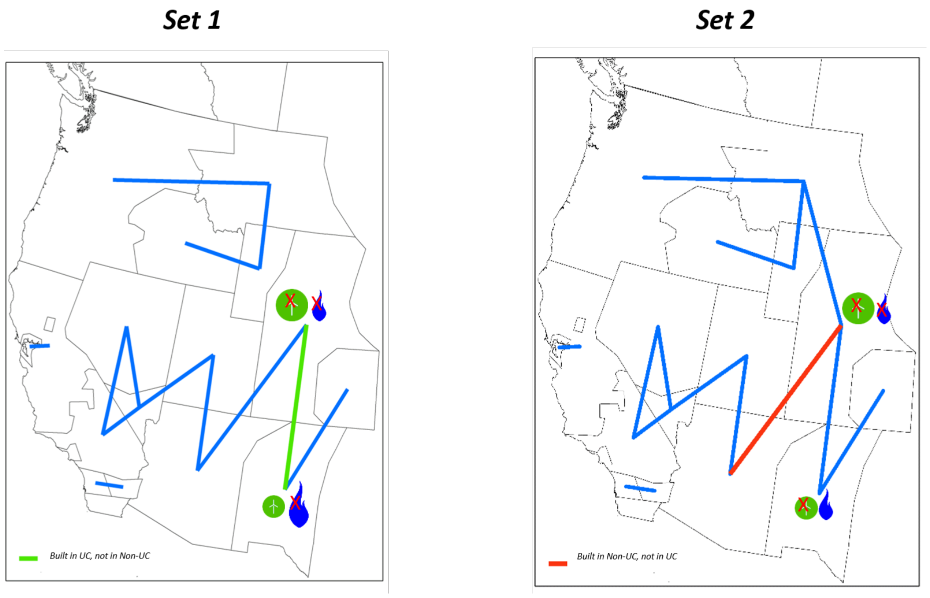


Figure 3.9: 20-year transmission investments (wait-and-see decisions) with and without UC using two sets of probabilities for the 'WECC 1: Economic Recovery' scenario. **Left panel**: Green line indicates that the line is built with UC constraints, but not without. These are using Set 1 probabilities. **Right panel**: Red line indicates the line that is not built with UC constraints, but is built without, i.e., it is a sub-optimal line. These are using Set 2 probabilities.

investments take place. This is shown in Figure 3.10.[16]

In terms of transmission changes under Set 2, one less line is built with UC than without. It is interesting to note the effects of UC on 2nd stage generation investments under the second set of probabilities (Set 2) — The overall pattern of less generation investment is similar to Set 1. Here, it is less wind, less CCGT, and less CT investment. This is shown in Figure 3.11. But along with geographical

---

[16] Data is given in Table 6.3 of the appendix.

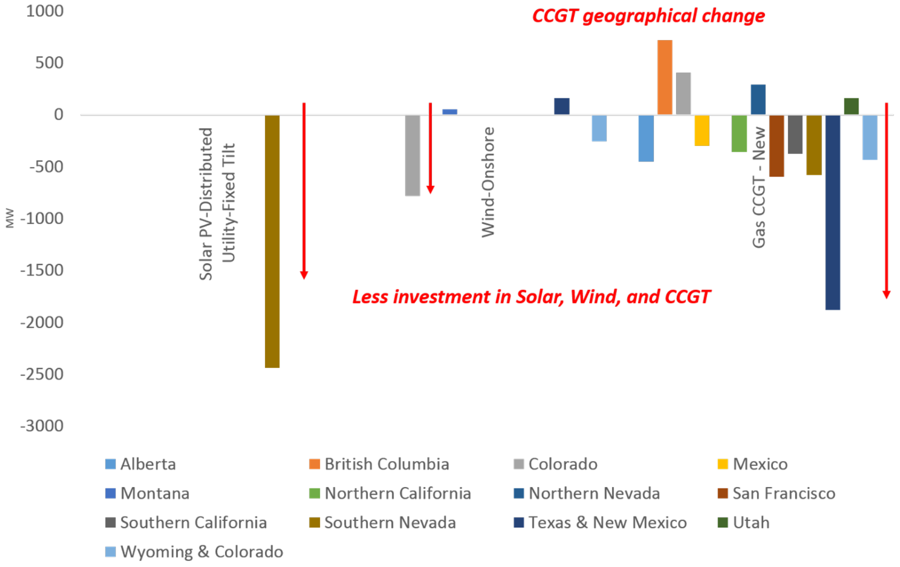


Figure 3.10: Second stage generation changes with Set 1 probabilities. Solar investments change geographically, more wind investments, and gas units change operations. The data is shown in Table 6.3 of the appendix.

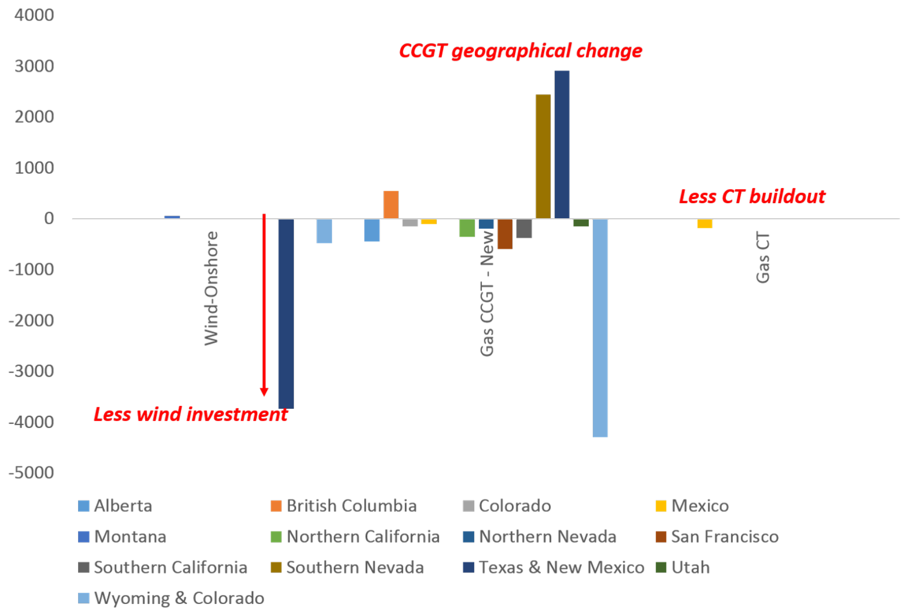


Figure 3.11: Second stage generation changes with Set 2 probabilities. Gas operations change geographically and wind investment is being concentrated.

changes, preferences for technologies change at each bus. For example, consider the Texas/N Mexico zone (bottom-right) in Figure 3.9. We see that under Set 1, at this location, UC prefers more wind and less CCGT, while under Set 2, UC builds less wind and more CCGT. Stage 2 generator investments, under Set 2 probabilities, with and without UC are shown in Tables 6.5 and 6.4 of the appendix respectively.

Summarizing the effects of UC on second stage generation investments, overall, less generation is invested in. When investments happen with UC, they are at different locations when compared to those from a no UC model. We also saw that UC affects second stage transmission investments differently under different scenario-weights. Under Set 1, it favored building an extra line, while under Set 2, it favored building one less. For convenience, the effects of UC on generation and transmission investments in the five-scenario 2-stage stochastic model are summarized in Table 3.7.

	Set 1	Set 2
Stage 1 Transmission	No Change	1 extra line
Stage 1 Generation	More wind Less CCGT	More wind Less CCGT
Stage 2 Transmission	1 extra line	1 less line
Stage 2 Generation	Less solar Less wind Less CCGT	Less wind Less CCGT Less CT

Table 3.7: Changes in stochastic solutions based on the probability set.

3.8 Conclusions

In conclusion, we showed how to represent chronological operational constraints within long-term multi-stage transmission planning models. We also showed that Unit commitment has the potential to change today's (Stage 1) and future (Stage 2) transmission and generation investments, potentially increasing costs, as measured by economic regret. This regret is the economic cost of basing today's transmission investments on results from an inaccurate LDC model. Specifically, we find that:

- If slow-moving generators are expected to be in the energy mix with the potential of being cycled (for example, in scenarios with a medium carbon-tax where coal is cycled), it is important to consider UC constraints as these are the scenarios where transmission investments are most likely to change.

- Depending on the solar, wind, hydro profiles, the changes to investments can be as follows:
    - Transmission can be considered an alternative to generation.
    - The set of generation investments shifts to more flexible units.
    - A different mix of generators (technology + geographically) can be built, and power can be shipped to load-centers instead of local generation investment.
    - More investment in renewable power generation is favored.
- There is a cost to not considering operational constraints in planning. In the simple deterministic 'Economic Recovery' case, this economic regret was found to be approximately $700 million when one of the eight transmission lines is foregone.
- The solution is sensitive to factors that affect the merit-order (e.g., Carbon tax, different weights to scenarios).
- Although this is not a focus of this chapter, I confirm that considering uncertainty is important [22]. Stochastic 1st stage investments can be different from deterministic 1st Stage investments, confirming findings in previous papers as well [22] [65] [64].

- Stochastic 1st stage investments with UC can be *very* different from each other depending on our estimates of scenario probabilities.

Overall, based on the results in this chapter, we recommend including Unit Commitment constraints in long-term planning models. The benefits of including UC are potentially the highest, in grids where the energy mix contains slow-moving generators that are cycled. We find that the recommendations from planing models which consider future uncertainty, also are affected by UC constraints.

Chapter 4

An Equilibrium Model For Noncooperative Interregional Transmission Planning

4.1 Abstract

Optimization methods for regional transmission planning overlook the boundaries between transmission planning entities and do not account for lack of coordination. The practical result of those boundaries is inefficient plans because one planning region may disregard the costs and benefits its network changes impose on other regions. We develop a bi-level model that represents multiple noncooperative transmission plan-

ners in the upper level together with consumers and generators for the entire region in the lower level. We find that the transmission plans from such a framework can differ significantly from those from a cooperative framework and have fewer net benefits. Importantly, we find that cooperation among transmission planners leads to increased competition among generators from adjoining regions, which in turn leads to more efficient generator investments. We prove that the system-wide benefits from cooperation among transmission planners is always positive. We then calculate the value of this cooperation for a small test case with two transmission planners, while also identifying the market parties who gain - and those who lose - from this cooperation.

4.2 Notation

4.2.1 Sets and Indices

K	Set of technologies k
B	Set of buses b
H	Set of hours h
$B(i)$	Set of buses in region i
$L(i)$	Set of transmission lines owned by ISO_i
$K(b)$	Set of generators at bus b

$b \in L(i)$	Set of buses incident upon $L(i)$
$l \in B(i)$	Set of lines incident upon $B(i)$
S_i	Seam lines of region i

4.2.2 Parameters

$D_{b,h}$	Demand [MW]
B_l^E	Susceptance of existing line l
B_l^N	Susceptance of possible new line l
$M_{b,l}$	Line Incidence Matrix
$\underline{F}_l^E; \overline{F}_l^E$	Bounds on flow on existing line l [MW]
$\underline{F}_l^N; \overline{F}_l^N$	Bounds on flow on new line l [MW]
$CX_{b,k}$	Annualized cost of building tech k at b [\$/MW]
$CY_{b,k}$	Marginal cost of generating energy [\$/MW]
CZ_l	Annualized cost of building line l [\$]
$W_{b,k,h}$	Capacity factor of unit k at bus b
$X_{b,k}$	Existing capacity of unit k at bus b [MW]
$\overline{X}_{b,k}$	Maximum possible capacity of k at b [MW]

δ	Discount factor
N	Number of sampled hours
P	8760/N
T_I	Length of time (y) after today when generation and transmission investments come online
T_O	Length of time (y) for which operations are assumed after investments come online
$VOLL_b$	Value of Lost Load [\$/MW]

4.2.3 Variables

$x_{b,k}$	Capacity of technology k built in bus b [MW]
$y_{b,k,h}$	Energy output from k in hour h and bus b [MW]
z_l	$\{0, 1\}$: 1 if line l is built
$f^E_{l,h}$	flow on existing line l in hour h [MW]
$f^N_{l,h}$	flow on new line l in hour h [MW]
$l_{b,h}$	Load curtailed b and hour h [MW]
$\theta_{b,h}$	Phase angle in bus b and hour h
$p_{b,h}$	Price at bus b in hour h [\$/MWh]

4.3 Introduction

4.3.1 Problem definition

In 1996, the Federal Electricity Regulatory Committee (FERC) issued orders 888 and 889 that resulted in the unbundling of generation, transmission, and distribution assets [79]. Now, in the US, no one entity controls all aspects of the market, and administrative bodies called the Independent System Operators (ISOs) operate the energy market as a neutral third party by taking supply side bids from generators and demand side bids from consumers. An additional responsibility of ISOs is to plan for transmission expansion. But since they are not responsible for generation planning, ISOs have to take generators' and consumers' response to network additions and transmission prices into account when evaluating potential grid reinforcements [65]. On the other hand, in regions where utilities are still vertically integrated, transmission planning is undertaken by the utilities themselves.

Transmission planning is inherently complex. Several factors contribute to this complexity, including:

1. Transmission upgrades are costly. A poor planning process might result in over-investment ("stranded" assets whose costs exceed their benefits) or under-investment (which can result in inefficient operations, such as extensive wind curtailment, as in Texas in the 2000s [18] or presently in China [19] and solar

curtailment, as in India now [20]), as well as inefficient siting of generators.

2. Power flows are governed by the laws of physics (Kirchhoff's laws).
3. One region's grid and dispatch decisions affect other regions' costs and benefits.

Notwithstanding these difficulties, US regional transmission planning entities (see Fig. 4.1) each have planning processes for transmission investment in their control regions. But these processes usually focus on the benefits of investments to the planner's own region without considering (a) the reactions of generator investment to these investments (i.e., no transmission-generation co-optimization), or (b) the effect of the proposed lines on dispatch and transmission investment in other regions (which in turn may affect the planner's own region). Examples of such processes are [80] and [81]. In fact, FERC order 1000 [82] recognizes the latter problem by explicitly obligating public utility transmission providers to set-up processes that can identify *"possible transmission solutions that may be located in neighboring transmission planning regions"*. The adoption of this order by FERC is an acknowledgment of the need to consider spillover benefits and costs in other regions, including their quantification and use as a basis for cost allocation. But current interregional transmission planning initiatives such as [83] and [84] often ignore the political boundaries within which individual ISOs operate, focusing on identifying lines that "benefit" the entire system without recognizing that it may be difficult to finance and permit lines that benefit multiple regions. For instance, [83] develops transmission plans for

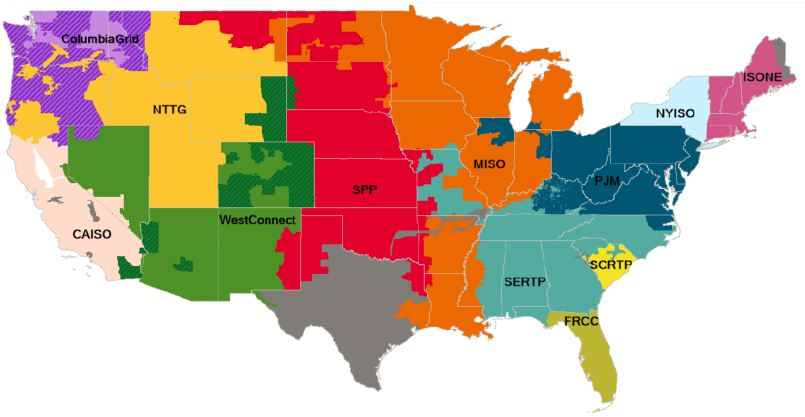


Figure 4.1: Transmission planning regions in USA [2].

the western interconnection using simple production costing and implicitly assuming a single planner. The Eastern Interconnection Planning Collaborative (EIPC) [84] does the same for its region.

Many researchers have also proposed solving a single optimization problem to identify transmission reinforcements that would enhance the system's "total economic surplus" or "social welfare". This is generally done by solving a single cost minimization Mixed Integer Program (MIP) that minimizes the cost of generator investments, transmission investments, and generator dispatch. Such a cost minimizing model is used because under certain assumptions, it can be shown that the investments resulting from cost minimization are same as the investments from multiple profit-maximizing players' problems. Some of these assumptions are:

1. The players all behave competitively, i.e., they act as if they maximize their individual profit subject to fixed prices.

2. They all hold the same beliefs about future load growth, fuel prices, and environmental policies.
3. They all take decisions simultaneously.
4. There is a single market operator who is also the grid planner.
5. There is no significant spillover of benefits or costs to neighboring regions.

This equivalence can mathematically be proven by showing that the Karush-Kuhn-Tucker (KKT) conditions of the single problem and the individual players' KKT conditions are the same. More details can be found in [85].

But using such a model for a large region encompassing multiple transmission planning entities might not be a good way to identify lines that will end up getting built, given regional planners' imperfect cooperation and focus on benefits within their region. Evidence for the divergence of local and market-wide benefits is provided by some promising instances of interregional cooperation and information exchange in transmission planning. For example, MISO and SPP had to re-evaluate proposed interregional lines upon observing that the estimates of some lines' benefits differed significantly when evaluated by regional models versus an interregional model [86]. Therefore, there is a need for modeling frameworks that explicitly take into account this inconsistency between one subregion's incentives and the overall benefits to all the subregions. Addressing this inconsistency is considered difficult. For example, FERC commissioner at the time, Philip Moeller, has been quoted as saying, *"There* *are so many benefits to interregional transmission, but they're so hard to identify and to figure out how to get them built...but it's where there's a lot of inefficiencies."* [87].

Models that identify transmission lines that get built when regional planners *do not* cooperate with each other can serve as a way to delineate the benefits each regional planner may gain by cooperating with other regional planners. At the same time, such models can be used to identify different side payment arrangements among the planners that could result in benefits for all regions (a strict Pareto improvement). In this chapter, we develop such models representing centralized and noncooperative planning processes, and compare their results.

4.3.2 Relationship with previous work

A classic paper in multi-player transmission expansion is [88] which models different State Electricity Boards in India playing a cooperative game (with side payments amongst the states), where the objective of each state is to maximize its gain by choosing either to act on its own or join a coalition. The drawbacks of this study are that the gains of the coalitions and players are known beforehand and are not considered endogenous to the problem. Furthermore, each state is modeled as controlling both the generation and transmission within its boundaries. While this was (and still is) true in India, much of the US is now deregulated, with generators separated from transmission operators. Another example is [89], which also looks at coalition formation when being in a coalition means sharing the costs of building transmission lines connecting the coalition's member regions. Unlike the models we propose, that study does not take generators' response to transmission investments into account, and the only transmission decisions made by the model concern lines connecting different regions, and not lines within a region.

A more recent study dealing with multiple planners is [90] where the authors propose a three-stage equilibrium model to identify transmission investments that result from a game among different planners. The study assumes that there is a supra-player at a level above the planners whose objective is to invest in cross-border transmission lines that maximize the welfare of the interregional system and who correctly anticipates how each planner will react to its proposed plans by investing in its regional non-seam lines. In this chapter, we present a more general framework in which every potential line addition is the responsibility of just one of the non-cooperative planners with no supra-player, and it can be easily extended to depict multiple cost-sharing arrangements. We also consider generators' reaction (investing in generation) to the transmission investments being made by the regional planners. Furthermore, ref. [90]'s assumptions might lead to two regions being forced to build and share the costs of a line which neither of them would want to build in the absence of the supra-player. This cannot happen in our model. In addition to this, while [90] treats transmission investment decisions as continuous variables, we treat them as discrete i.e., it is not possible to build fractions of a line.

4.3.3 Scope

We address the need for a model that represents the independence of planners in different regions by modeling multiple players in the market (ISOs, generators, and consumers) while also recognizing that individual regional planners have their own planning processes that focus primarily on benefits for their own region. We model this interaction as a Nash noncooperative game.

Our models and results are organized as follows. In section 4.4, we develop the mathematical structure of a single regional planner's optimization problem where the goal of the ISO is to maximize the surplus of its region. That surplus is defined as the combined surplus of the generators and consumers in the region and the planner's own surplus (Here, for simplicity, we generalize the concept of a regional planner to that of an ISO where the ISO controls investment in transmission lines in its control region and its surplus arises from its operation of the spot markets.) These problems are structured as Mathematical Programs with Equilibrium Constraints (MPECs). In section 4.5, we expand this model to the case where there are multiple regional planners who simultaneously (but separately and noncooperatively) make their individual investment decisions, each anticipating the spot market's reaction to their decisions. This problem has the structure of an Equilibrium Program with Equilibrium Constraints (EPEC).

Then in section 4.7, in a case-study using a 17-bus system based on the CAISO network, we show how this multi-planner EPEC can be solved. Consistent with the Nash noncooperative game framework, this is done assuming that each region assumes that other regions do not change their strategies (the transmission lines they build). We then consider whether the transmission plans differ from a noncooperative planning process differ from plans based upon a single-central planner. We also ask what the value is, if any, of regional planners cooperating with each other when considering transmission investments.

4.4 Single-ISO MPEC: Non-cooperative transmission planning

We start by modeling a single regional planner's (ISO's) problem as a co-optimization in which the ISO makes transmission investments anticipating how generators and consumers (in all the regions) respond to those investments. Generators respond to transmission investments by building generation capacity they see as profitable and operating their units economically. Consumers respond by consuming energy (demand is assumed to be inelastic here, but more general formulations can have elastic demand).

The ISO's objective is to maximize the economic surplus of all players within its region. We consider this to be a combination of the consumers', generators', and the ISO's own economic surpluses. Consumer surplus can be thought of as the monetary gain by consumers from buying power at prices less than the maximum they would have willingly paid.[1] Generators' profit can similarly be thought of as their net monetary gain from selling power at prices higher than what they would have willingly produced at minus expenditures from new generation capacity investments.[2] The ISO only controls line investments within its control-region and its surplus can be thought of as its net monetary gain from acting as a price-taking spatial arbitrager and transmission investor. We arbitrarily allocate any lines connecting buses in two regions to one of the two regions.

The structure of the problem lends itself naturally to a hierarchical model where the regional planner (ISO) is in the upper level making decisions knowing that its objective function (the regional surplus) is affected by outcomes of the generation investment and spot market equilibrium model in the lower level. So, the problem facing each ISO has the structure shown in Fig. 4.2. The subscript i in ISO$_i$ indicates this is a single region's optimization problem.

These bi-level hierarchical problems are also called MPECs since a portion of the ISO's constraints corresponding to market operations is itself an equilibrium problem [91]. Bi-level problems have been used to depict the structure of leader (here, the ISO) and followers (here, generators and consumers in the entire market) since at least 1934, when the economist von Stackelberg published his book *Market Structure*

---

[1] Consumer surplus is the integral of the consumers' demand function from 0 to the quantity (q) purchased, minus the cost of purchasing q.

[2] Producer surplus is the difference between what the producers got paid for selling quantity q to consumers and the sum of the integral of their supply curve from 0 to q and expenditures from generator investments.

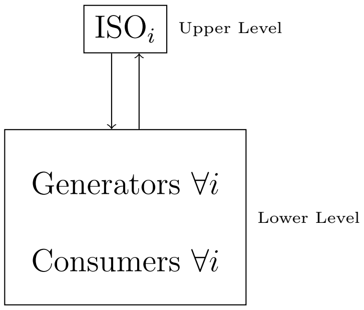


Figure 4.2: Hierarchical structure of a single region's transmission planning problem. Region$_i$ (its planner) is in the upper level and the generators and consumers of the entire market (all regions) are in the lower level.

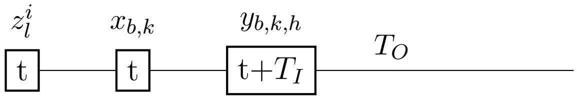


Figure 4.3: Time line of transmission investments, generation investments, and system operation

and Equilibrium [92] [93]. Therein, he described the hierarchical problems that came to be known as Stackelberg games, which are sequential games in which the leader moves first knowing how followers would react. The followers then react naively, taking prices as exogenous not realizing that their actions affect market outcomes.

In the U.S. power sector, the need for such hierarchical equilibrium models has increased since the market was unbundled [94]. Now there are multiple players in the market, each trying to make the best decisions possible for themselves while in some cases anticipating other players' reactions. The structure of MPECs naturally fits many of these problems. For instance, [95] uses MPECs to analyze market power in oligopolistic power markets and [96] uses them to model optimal bidding strategies by generators in the day-ahead energy market. [97] models and solves an MPEC where in the upper level, a strategic generator makes investment and operation decisions anticipating how the market clears in response to her decisions. Similarly, [98] also models a strategic generator looking to invest, but the generator now faces uncertainty regarding rival generators' actions. When transmission operators are explicitly modeled in multi-level models, they are generally modeled as a single entity controlling all regions [99] or as the spot market operator in the lower level [100].

We now present our lower and upper level formulations for the single-ISO case in sections 4.4.1 and 4.4.2 respectively.

4.4.1 Lower-level problem: Generator investments and energy market equilibrium

The lower-level problem is a manifestation of the ISO's belief that in the future (once it commits to investing in the lines it plans to invest in and communicates that to the lower level), the generation market operates based on certain assumptions. These assumptions were listed above (Section 4.3) and they allow the lower-level player problems (Generators and Consumers) to be combined into a single cost-minimization optimization (a linear program, LP) [85].[3] Their lower-level equilibrium problem is as follows (dual variables are shown to the right of constraints):

---

[3] This is the case if demand is considered to be inelastic. If demand is linear, it is a quadratic program (QP), and if elastic, it is an nonlinear program (NLP) [101].

$$\text{Min} \quad \sum_{b,k} CX_{b,k} x_{b,k} + P\Big[\sum_{b,k,h} CY_{b,k} y_{b,k,h} + \sum_{b,h} VOLL_b l_{b,h}\Big] \tag{4.1}$$

$$\text{s.t.} \quad \sum_{k \in K(b)} y_{b,k,h} - \sum_{l} M_{b,l}(f^E_{l,h} + f^N_{l,h}) + l_{b,h} = D_{b,h} \ : (p_{b,h}) \ \ \forall b, h \tag{4.2}$$

$$\underline{F}^E_l \leq f^E_{l,h} \leq \overline{F}^E_l \ : (\xi^-_{l,h}, \xi^+_{l,h}) \ \ \forall l \in E, h \tag{4.3}$$

$$z^*_l \underline{F}^N_l \leq f^N_{l,h} \leq z^*_l \overline{F}^N_l \ : (\beta^-_{l,h}, \beta^+_{l,h}) \ \ \forall l \in N, h \tag{4.4}$$

$$f^E_{l,h} - B^E_l \sum_b M_{b,l} \theta_{b,h} = 0 \ : (\lambda^E_{l,h}) \ \ \forall l \in E, h \tag{4.5}$$

$$-(1 - z^*_l)M \leq f^N_{l,h} - B^N_l \sum_b M_{b,l} \theta_{b,h} \leq (1 - z^*_l)M : \quad (\lambda^{N-}_{l,h}, \lambda^{N+}_{l,h}) \ \ \forall l \in N, h \tag{4.6}$$

$$0 \leq y_{b,k,h} \leq W_{b,k,h}(x_{b,k} + X_{b,k}) \ : (\phi^-_{b,k,h}, \phi^+_{b,k,h}) \ \ \forall b, k, h \tag{4.7}$$

$$0 \leq x_{b,k} + X_{b,k} \leq \overline{X}_{b,k} \ : (\alpha^-_{b,k}, \alpha^+_{b,k}) \ \ \forall b, k \tag{4.8}$$

$$0 \leq l_{b,h} \leq D_{b,h} \ : (\nu^-_{b,k}, \nu^+_{b,k}) \ \ \forall b, h \tag{4.9}$$

The lower level is a DCOPF approximation [74] of the transmission-constrained market equilibrium problem with generation investment.[4] The lower-level objective is to minimize the cost of operating existing and new generation, investing in new generation, and from lost load over the planning horizon.[5]

Constraint (4.2) ensures that demand is met at every bus in every hour, or that a loss in load occurs and is penalized. Constraints (4.3) and (4.4) restrict flows on existing and new lines to be within their thermal limits. Constraints (4.5) and (4.6) ensure that line flows on all lines obey Kirchhoff's Voltage Law (KVL). Constraints (4.7) - (4.9) impose upper bounds on generation output, investment and load curtailment. For simplicity, active power losses on lines are neglected, although other Stackelberg models include them [102].

---

[4] The assumptions on which this model is based are listed in Section 4.3 and in [85].

[5] For simplicity, we assume that both generation and transmission investments are decided today, i.e., as soon as the new transmission plans are announced, generators react and decide their investments accordingly. We further assume their construction time is the same and they come online after T_I years. We then assume the system is operated for T_O years after the investments come online (Fig. 4.3). The model can be easily changed to reflect alternative assumptions without loss of generality.

The dual variable of the power balance constraint at each bus b, $p_{b,h}$, is its Locational Marginal Price (LMP) in hour h. The asterisks on transmission investment variables z_l^* in constraints (4.4) and (4.6) indicate that they are viewed by the lower-level problem as fixed at the values decided by the upper level. Note that since load can be curtailed, the lower-level problem is feasible for any feasible solution, $\hat{z}_l$, of the upper level problem.

4.4.2 Upper Level Problem: ISO maximizing surplus of players within its region

The above optimization problem [(4.1) - (4.9)] defines the reaction of generators and the energy market given transmission investment z_l^* from the upper level. The leader's (regional ISO's) objective (4.10) is to maximize the total surplus within its region i, subject to this reaction.

The upper level problem is given in equations (4.10) - (4.12).

$$\text{Max} \quad P\Big[\sum_{\substack{h \\ b \in B(i) \\ k \in K(i)}} (p_{b,h} - CY_{b,k}) y_{b,k,h} + \sum_{\substack{h \\ b \in B(i)}} (VOLL_b - p_{b,h}) D_{b,h} -$$

$$\sum_{\substack{h \\ L \in L(i)}} (f^E_{l,h} + f^N_{l,h}) \sum_{b \in B(L(i))} M_{b,l} p_{b,h} \Big] - \sum_{l \in L(i)} CZ_l z_l \tag{4.10}$$

$$\text{s.t.,} \quad z_l \in \{0, 1\} \tag{4.11}$$

$$\text{The equilibrium problem } [(4.1) - (4.9)] \tag{4.12}$$

The surplus of a region is the total surplus of the region's producers, consumers, and the ISO's own surplus. In the objective (4.10), the regional generators' surplus is the profit they make by selling their marginal-costed production at their respective bus LMPs. The consumer surplus is the benefit from load served (not curtailed) minus expenditures, and the ISO's own surplus is from congestion rents. Congestion rent is the money collected by the owners of the rights to a transmission line (in this chapter, the ISO). Typically, this amount is equal to the flow on the line times the energy price differential across the line [103]. The interpretation here is that the ISO collects congestion rents and passes them on to consumers in its region. Equation (4.11) constrains line investment variables to binary variables. The ISO's strategic planning model is constrained by the lower-level solution given by (4.12).

4.4.3 Solving the individual ISO's MPEC

Bi-level MPECs such as the one described in (4.10) - (4.12) are optimization problems that are constrained by equilibrium problems. Here, the lower-level problem [equations (4.1) - (4.9)] is a LP and hence could be replaced by its KKT conditions. Equivalently, it can also be replaced by the combined set of its primal constraints, dual constraints, and strong duality condition [104].[6] We do this for the single-ISO MPEC by writing out the lower-level problem's dual constraints and strong duality condition. These, when combined with the primal constraints [(4.2) - (4.9)], can then be inserted into the constraint set of the upper level problem which can then be solved as a single optimization problem.

4.4.3.1 Lower level's dual constraints

$$CX_{b,k} - \sum_{h} \phi^{+}_{b,k,h} W_{b,k,h} - \alpha^{-}_{b,k} + \alpha^{+}_{b,k} = 0 \ \ \forall b,k \tag{4.13}$$

$$CY_{b,k}P - \phi^{-}_{b,k,h} + \phi^{+}_{b,k,h} + p_{b,h} = 0 \ \ \forall b,k,h \tag{4.14}$$

$$VOLL_{b}P + p_{b,h} - \nu^{-}_{b,h} + \nu^{+}_{b,h} = 0 \ \ \forall b,h \tag{4.15}$$

$$\begin{aligned}\sum_{l} M_{b,l}\left(-\lambda^{E}_{l,h} B^{E}_{l}\right) + \sum_{l} M_{b,l}\left(\lambda^{N-}_{l,h} B^{N}_{l}\right) - \\ \sum_{l} M_{b,l}\left(\lambda^{N+}_{l,h} B^{N}_{l}\right) = 0 \ \ \forall b,h\end{aligned} \tag{4.16}$$

$$-\sum_{b} p_{b,h} M_{b,l} + \lambda^{E}_{l,h} - \xi^{-}_{l,h} + \xi^{+}_{l,h} = 0 \ \ \forall l \in E, h \tag{4.17}$$

---

[6] This would not be the case if the lower problem were an NLP.

$$-\sum_{b} p_{b,h} M_{b,l} - \lambda^{N-}_{l,h} + \lambda^{N+}_{l,h} - \beta^{-}_{l,h} + \beta^{+}_{l,h} = 0 \;\; \forall l \in N, h \tag{4.18}$$

Additionally, in equations (4.19) - (4.20), dual variables $\lambda^{N-}_{l,h}$, $\lambda^{N+}_{l,h}$ are constrained to be zero when there is no investment in the corresponding transmission line.

$$\lambda^{N-}_{l,h} \leq z_l M \tag{4.19}$$

$$\lambda^{N+}_{l,h} \leq z_l M \tag{4.20}$$

Here M is a very large scalar. Everything is now tied together by adding the following non-linear strong duality condition which equates the lower-level problem's primal and dual objective values at the optimal solution.

4.4.3.2 Strong duality condition

$$\begin{aligned} &\sum_{b,k} CX_{b,k} x_{b,k} + P \sum_{b,k,h} CY_{b,k} y_{b,k,h} + P \sum_{b,h} VOLL_b l_{b,h} = \\ -&\sum_{b,k,h} \phi^{+}_{b,k,h} W_{b,k,h} X_{b,k} - \sum_{b,k,h} p_{b,h} D_h + \sum_{l,h} \beta^{-}_{l,h} z_l \underline{F}^{N}_{l} - \sum_{l,h} \beta^{+}_{l,h} z_l \overline{F}^{N}_{l} - \\ &\sum_{b,k} \alpha^{+}_{b,k} (\overline{X}_{b,k} - X_{b,k}) - \sum_{b,h} \nu^{+}_{b,h} D_h - \sum_{l,h} \xi^{+}_{l,h} \overline{F}^{E}_{l,h} + \sum_{l,h} \xi^{-}_{l,h} \underline{F}^{E}_{l,h} \end{aligned} \tag{4.21}$$

The resulting problem is a Mixed Integer Quadratically Constrained Quadratic Program, which is more difficult to solve to global optimality than LPs or MILPs due to the presence of bilinear terms in (4.21). We simplify the solution process by linearizing as many non-linear terms as possible in the model.

4.4.3.3 Linearizing the non-linear terms in strong duality condition

We replace constraint (4.4) in the lower-level constraints with two equivalent constraints. These are:

$$\underline{F}_l^N \leq f_{l,h}^N \leq \overline{F}_l^N \ : (\beta_{l,h}^-, \beta_{l,h}^+) \ \forall l \in N, h \tag{4.22}$$

$$z_l^* \underline{M}_l^N \leq f_{l,h}^N \leq z_l^* \overline{M}_l^N \ : (\gamma_{l,h}^-, \gamma_{l,h}^+) \ \forall l \in N, h \tag{4.23}$$

Two new dual variables $\gamma_{l,h}^-, \gamma_{l,h}^+$ now enter the associated dual constraint (4.18) which now becomes:

$$-\sum_b p_{b,h} M_{b,l} - \lambda_{l,h}^{N-} + \lambda_{l,h}^{N+} - \beta_{l,h}^- + \beta_{l,h}^+ - \gamma_{l,h}^- + \gamma_{l,h}^+ = 0 \ \forall l \in N, h \tag{4.24}$$

To describe the relationship between z_l and $\gamma_{l,h}^-, \gamma_{l,h}^+$, we add two constraints:

$$\gamma_{l,h}^- \leq (1 - z_l) M \tag{4.25}$$

$$\gamma_{l,h}^+ \leq (1 - z_l) M \tag{4.26}$$

This results in the exactly linearized strong duality condition (4.27).

$$\begin{aligned} &\sum_{b,k} CX_{b,k} x_{b,k} + P \sum_{b,k,h} CY_{b,k} y_{b,k,h} + P \sum_{b,h} VOLL_b l_{b,h} = \\ &-\sum_{b,k,h} \phi_{b,k,h}^+ W_{b,k,h} X_{b,k} - \sum_{b,k,h} p_{b,h} D_h + \sum_{l,h} \beta_{l,h}^- \underline{F}_l^N - \sum_{l,h} \beta_{l,h}^+ \overline{F}_l^N - \\ &\sum_{b,k} \alpha_{b,k}^+ (\overline{X}_{b,k} - X_{b,k}) - \sum_{b,h} \nu_{b,h}^+ D_h - \sum_{l,h} \xi_{l,h}^+ \overline{F}_{l,h}^E + \sum_{l,h} \xi_{l,h}^- \underline{F}_{l,h}^E \end{aligned} \tag{4.27}$$

Summarizing, the single-ISO MPEC's constraints are all linear now and the problem is summarized below:

$$\begin{aligned}
&\text{Minimize} \quad (4.10) \\
&\text{s.t.} \quad (4.2)-(4.3),(4.5)-(4.9),(4.24) && \text{(Lower primal constr.)} \\
&(4.13)-(4.17),(4.19),(4.20),(4.25),(4.26) && \text{(Lower dual constr.)} \\
&(4.27) && \text{(Strong duality)}
\end{aligned}$$

Note that we still have non-linearities in the single-ISO MPEC's objective function (4.10) in the form of bilinear terms.[7] These bilinear terms make the problem a non-convex MINLP, and problems of this type are in general more difficult to solve than comparitively sized LPs and MILPs [105]. While state-of-the-art solvers such as CPLEX and Gurobi can solve LPs and MILPs efficiently, their ability to solve non-convex MINLPs is limited [106].

4.5 Multi-ISO EPEC: Non-Cooperative transmission planning

The next step is to expand this single-ISO framework to the multi-ISO case by combining all individual ISO's MPECs into a single framework (see Fig. 4.4). In effect, we are trying to find an equilibrium for the situation where each regional ISO is trying to make transmission investments that maximize its own regional surplus. Problems with this structure, where there are multiple leaders (ISOs) and a single follower (the market), are called Equilibrium Programs with Equilibrium Constraints (EPECs).

---

[7] In the next chapter, we show that this objective function cannot be exactly linearized.

EPECs have been used to model many energy market applications. For example, [95] solves a series of MPECs with each MPEC depicting a generator's bidding problem in an oligopolistic market while anticipating rival generators' reactions. [107] generalizes this by optimizing generators' bids while also considering demand stochasticity, making this a stochastic EPEC. Other examples are [100] and [95] which model generators with the knowledge that their output affects transmission prices (the price of moving power from one bus to another).

EPECs can be solved in a variety of ways, the most popular method being diagonalization, which is what we use in this study. Diagonalization is a variant of the Gauss-Siedel method [108], which is used to find solutions of simultaneous equations. In essence, diagonalization solves the MPEC of one leader at a time, assuming that the strategies of the other leaders are fixed. The leaders' strategies are updated at each iteration to the most recently computed values. This is done iteratively until there is no change in the leaders' strategies from one iteration to the next. For an overview of this and other methods used to solve EPECs, see [94]. MPECs in general are non-convex. So, the corresponding EPEC (when using diagonalization) might not converge. For example, while [95] reports that their diagonalizations converged for every test case they used, [109] reports that their diagonalization did not converge for certain instances. Non-convergence does not necessarily imply that a pure-strategy equilibrium does not exist. It could be that though one or more equilibria exist, the algorithm fails to converge to one of them.

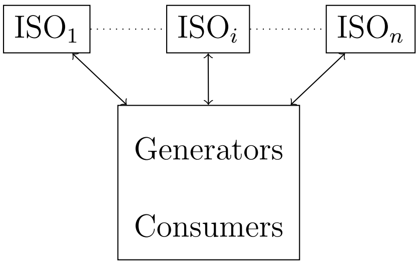


Figure 4.4: Hierarchical structure of Multi-ISO transmission planning problem. All ISOs are in separate upper level problems, and there is a single energy market in the lower level they interact with and it consists of generators and consumers in all regions.

If the EPEC converges, there is no guarantee that the equilibrium found is unique or the best possible equilibrium for all players involved (i.e., Pareto superior to all other equilibria). In the general case, each MPEC's constraint set defines a non-convex feasible region. So, not all MPEC local optima are necessarily globally optimal. Hence, nothing in general can be said about the existence or uniqueness of EPEC solutions [94]. In fact, [110] points out that non-unique solutions are common.

4.6 Cooperative transmission planning

The noncooperative ISO planning problem solution above is compared to a benchmark cooperative solution which is the least-cost co-optimized transmission/generation solution. Here, all the regional planners are assumed to fully cooperate with each other in the planning process. When there is a single lower-level energy market in which all players are competitive, the cooperative transmission planning model takes the form of a single cost minimization model. The equivalence between such a cost minimization model and a model where all players and their actions are modeled explicitly can be established by showing that their KKT conditions are the same [85]. This is in line with centralized transmission planning models such as [64] and [22].

The objective function is to minimize the total cost of the transmission and generation investments and the assumed operations for T_O years from year T_I onward:

$$\text{MIN} \quad \sum_{l} CZ_l z_l + \sum_{b,k} CX_{b,k} x_{b,k} + P \sum_{b,k,h} CY_{b,k} y_{b,k,h} + P \sum_{b,h} VOLL_b l_{b,h} \tag{4.28}$$

The constraint set is formed by concatenating the constraint sets of each of the regional transmission planner, i.e., the constraint set defining the market equilibrium and the generators' response to the transmission planners' investments. These include equations (4.1) - (4.9) and (4.11).

In effect, this is an Integrated Planning Model, except the interpretation here is that regional transmission planners fully cooperate with each other, generators are reacting competitively by making their investments simultaneously, and these reactions are correctly anticipated by the "proactive" transmission planner [111].

4.7 Case study

In this section, we (a) illustrate how our model can be applied to a small test case, (b) show how the transmission and generation investment results from a noncooperative model can be very different from a cooperative (cost-minimization) model, and (c) calculate the economic value each individual player in the system gains (or loses) if transmission planners from the different ISOs cooperate. The last point directly addresses the notion that there will be “winners” and “losers” when the planning paradigm changes. We then define and calculate the net monetary Value Of Cooperation (VOC) and show how this framework can be used to evaluate proposed side-payment agreements between control regions that could leave everyone better off.

4.7.1 Test case

To test our model, we used the CAISO 17-bus data set from [65]. We selected a subset of 12 hours from the dataset to represent yearly operations. The subset of hours was chosen to match the yearly averages, standard deviations, and geographical correlation of load and wind. Specifically, we used hour sampling techniques from [22] to minimize the total squared error of the above metrics between the samples and yearly data. We use a discount rate of 5% per year and we assume that transmission investments take 10 years to be built and come online since the time of the decision. Lastly, we assume the Value Of Lost Load (VOLL) to be \$1000/MWh.

4.7.2 Results and discussion

We consider the simplest case where there are two regional planners and they have a common follower (the energy market). We arbitrarily divide the region into two regions, roughly along the North-South axis.[8] We then solve the two-region EPEC using Gauss-Seidel diagonalization [94] where we solve each planner's MPEC assuming it to be a Nash player. Note that henceforth, we use "Regional Planner" instead of "ISO".

4.7.2.1 Changes in transmission and generation investments

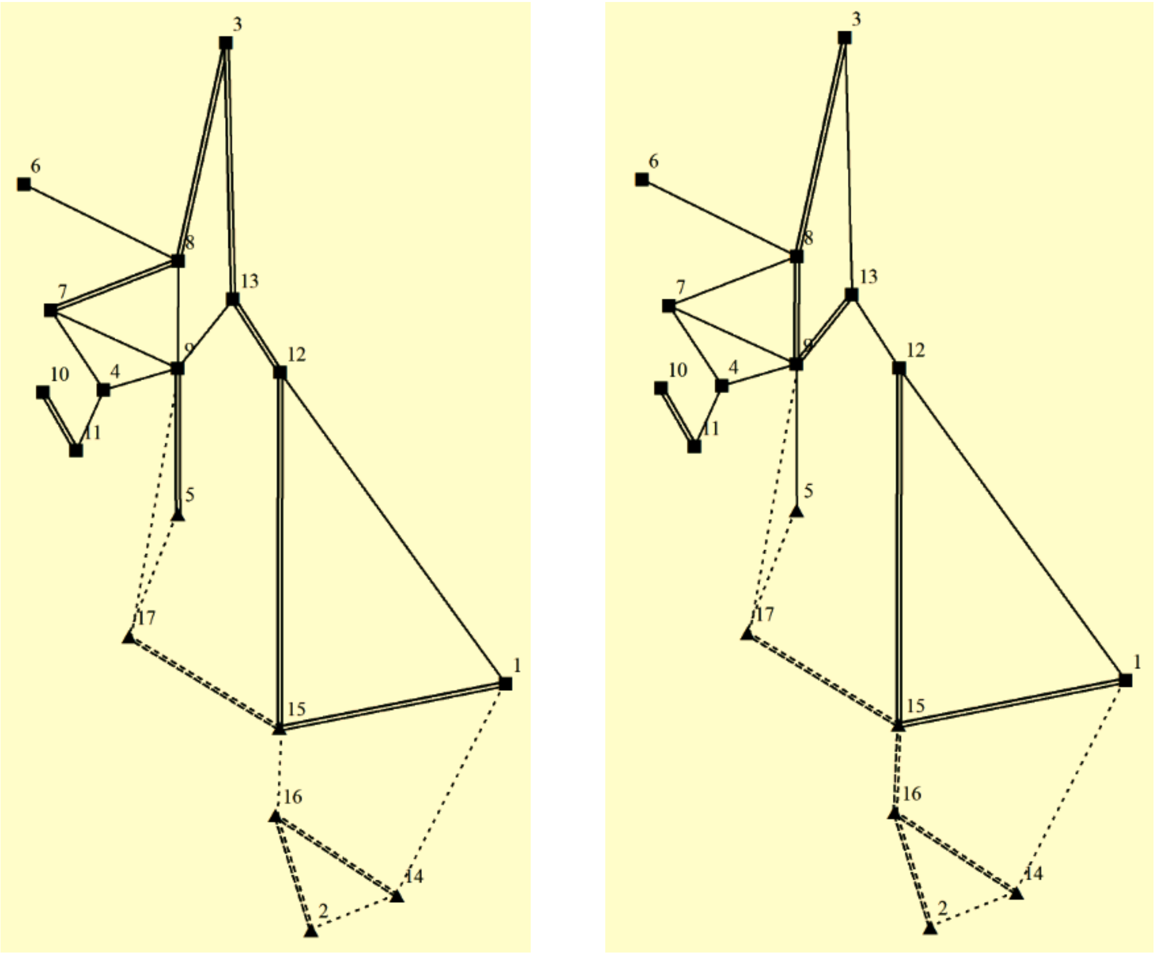
From Table 4.1, we see the following changes under cooperative planning relative to noncooperative planning. One extra line is built in Region 1 while 4 lines are dropped from Region 2's noncooperative plans and 2 different lines are built that would not have built by Region 2 on its own (see Figure 4.5). At the same time, we see a change in how generators' respond to these changes in transmission investments. From Table 4.2, we see that generators in Region 1 increase their overall investment by 1.3 GW while generators in Region 2 decrease theirs by 1.6 GW. Furthermore, the mix changes. With cooperative transmission plans, more combined cycle (CCGT) units are built as opposed to combustion turbines (CT) in Region 1. No load curtailment occurs in either solution.

---

[8] Note that this arbitrary geographical division is for illustrative purposes and not meant to reflect or represent any real planning agency in the State of California or elsewhere.

Region	line l	Non-Cooperative	Cooperative
1	5	✓	✓
	19	✓	✓
	20	✓	✓
	21*		✓
2	$2^\dagger$	✓	✓
	6	✓	✓
	7	✓	
	$8^\dagger$	✓	
	11	✓	
	14*		✓
	$16^\dagger$	✓	✓
	17	✓	✓
	22*		✓
	23	✓	

Table 4.1: Region-wise transmission investment. † indicates a seam line while * indicates a region's internal line that is built only in the cooperative framework.


3
6
8
7
13
9
12
10
4
11
5
17
1
15
16
14
2
3
6
8
7
13
9
12
10
4
11
5
17
1
15
16
14
2

(a) Transmission investments without interregional cooperation

(b) Transmission investments with interregional cooperation

Figure 4.5: Transmission investments change with cooperative transmission planning. ▲ and - - - indicate nodes and lines of Region 1. ■ and — represent Region 2. Parallel lines between two nodes indicate transmission investment. Lines connecting ▲ and ■ are seams lines. Only bus numbers are indicated for clarity.

Region	Δ (Cooperative - Non Cooperative)(GW)
1	CT: -1.3, CCGT: 2.6
2	CCGT: -1.6

Table 4.2: Generation Investment Changes

Even though Region 1's generators invest more with cooperation, their profit decreases compared to the noncooperative framework (Table 4.3). This is partly due to increased competition from cheaper generation in Region 2 which the cooperative solution's additional transmission capacity now makes more accessible to Region 1's consumers. Overall, Table 4.3 indicates that a cooperative framework invests in more transmission (in \$) than the noncooperative framework and in less generation (in \$) across both regions.

It is interesting to note the nature of some of this new transmission under the cooperative framework. We see that there is one line in Region 1 and two lines in Region 2 (indicated by † in Table 4.1), that are internal to each region (not seam lines) and are only built under the cooperative framework. These internal lines have interregional benefits and are only built if the regional transmission planners cooperate with each other. Surprisingly, investments in seams lines (indicated by † in Table 4.1) are not affected, as much as internal lines, by whether the cooperative or noncooperative framework is used. Only one seam line is built differently, as opposed to three internal lines that are built differently, under the two frameworks. Therefore, it

i	ΔCX_i (in \$ M)	ΔCZ_i (in \$ M)	$\Delta \overline{p}_i$ (\$/MWh)
1	117.74	19.52	-0.59
2	-122.95	-13.01	1.83

Table 4.3: Change in Annualized Investment Cost and Energy Prices by Region (Cooperative - Non Cooperative)

should not be assumed that the primary effect of cooperation is upon the economics of lines connecting regions; here, internal lines were more affected.

4.7.2.2 Value of Cooperation

We calculate the Value Of Cooperation (VOC), which is the benefit each (group of) player (consumers, producers, and the ISO itself) gains as a result of the two transmission planning entities cooperating with each other in the planning process. The concept of VOC is related to cooperative game theory's notion of the 'characteristic function' which calculates the total payoff for a set of players. This idea first appeared in Neumann and Morgenstern's seminal 1944 book on Game theory [112]. More recently, this concept appeared in a variety of studies, including transmission planning [88], water-resource sharing [113], and in analyzing competitive advantage in farmers' markets [114].

In this study, VOC is the difference between a player's surplus in the cooperative setting and the noncooperative setting. Hence, a player's VOC, if positive, indicates

Party	Region 1 VOC (in \$ M)	Region 2 VOC (in \$ M)
Consumers	536.97	-36.42
Producers	-229.72	107.84
ISO	-103.97	-114.61
Regional	203.29	-43.19
Interregional	160.10	

Table 4.4: Breakdown of Annualized Value of Cooperation [Δ Surplus (Cooperative-Noncooperative)]

that cooperation in transmission planning benefits the player while a negative VOC indicates a loss. While we cannot say anything in general about the nature of these individual surplus' changes, the total interregional surplus can only increase with cooperative planning. This is due to the fact that under our assumptions, by definition, the cooperative model maximizes total surplus. Table 4.4 indeed indicates that the interregional VOC is positive. Note that these are annualized surplus values over a period of T_O years' worth of market operations, in this case 30 years.

As expected, with cooperative transmission planning, the overall investment and operational cost to the system decreases and the total interregional surplus increases. Region 1's consumers benefit most from cooperation because the region's average hourly energy price falls by \$ 0.59/MWh with cooperative planning. This is due to increased access to cheaper generation from Region 2, where as expected, we see an increase in the average hourly energy prices (by \$ 1.83/MWh). Commensurate with this is an increase in Region 2's producer profit and a reduction in Region 1's profit as shown in Table 4.4.

We also find the total regional VOC to be 83% of the total transmission investment cost. That is, the benefits of cooperation are of the same magnitude as total transmission investment, and must therefore be viewed as significant.

4.7.2.3 Using this framework to evaluate side-payment agreements

This framework can be used to evaluate different side-payment agreements between the regions. For example, in this case study, we can see from Table 4.4 that Region 2's net surplus decreases if it cooperates with Region 1 in transmission planning (due to increased prices to consumers and lesser arbitrage opportunities for the ISO itself). Therefore, Region 2 would only cooperate if Region 1 agrees to compensate for its losses. So, Region 1 has to compensate Region 2 by at least an annualized amount of \$ 43.19 M to incent Region 2 to cooperate in transmission planning. With a side-payment exceeding this value, both regions could be better off.

For illustrative purposes, one practical way of accomplishing this transfer is for Region 1 to pay for a part or the entirety of the cost of reinforcing Region 2's seam lines. In this case, lines 2, 8, and 16 are Region 2's seam lines and in the cooperative solution, lines 2 and 16 are reinforced with an annualized cost of \$ 79.78 M. If Region 1 pays for these lines, it will still be left with an annualized net profit of \$ 123.51 M and Region 2 is better off by $ 36.59 M (compared to their respective noncooperative solutions).

4.7.2.4 Computational performance

All models were run on a Windows 7 PC with 4 GB of RAM and Intel Gen-3 Core-i5 processor. The cooperative models are MILPs and these were solved using CPLEX 12.6 in AIMMS [115].

For very small test-cases, CPLEX (V 12.3 and above) can be used to solve the non-cooperative MPECs which are non-convex MIQPs [116]. For larger cases, CPLEX's progress is extremely slow and we used a Multi-start Outer-Approximation algorithm in AIMMS [117] which is based on the outer-approximation algorithm proposed by [118] to solve the individual planner MPEC. For each MPEC, we ran the algorithm twice, first with 20 iterations and next with 30 iterations to help find good initial feasible solutions as suggested in [117]. For the multi-start algorithm, we ran the algorithm with 10 initial random starting points and chose the best solution from amongst them. In each iteration of the EPEC diagonalization, this solution was fixed for one planner and the other transmission planner's MPEC was solved in a similar manner until the convergence criterion was met.

4.8 Conclusion

In this study, we developed the optimization problems facing regional transmission planners while explicitly recognizing that there is little cooperation in planning across political boundaries. We showed how the multi-planner problem can be formulated as an EPEC. We also showed how this can be solved using an Outer-Approximation algorithm. For this case-study, the EPEC converged. Convergence is not guaranteed and even if it occurs, multiple equilibria might exist, as mentioned in Section 4.5.

We demonstrated the applicability of our model by running a small 17-bus test case. In this, we showed that the transmission plans can be very different with regional cooperation than without. Further, generation investments can change in reaction to these transmission investment changes. With this cooperation, consumers in some regions gain access to cheaper generation from other regions, lowering their average energy price. Additionally, there are three lines that are internal to the regions (not seam lines), which have interregional benefits, but are built only under when regional transmission planners cooperate with each other.

We also calculated the Value Of Cooperation (VOC) for each player involved, defined as the increase in their surplus when transmission planners from different regions cooperate with each other. We showed that the entire region benefits from cooperative transmission planning and in this test-case, the region-wide benefit is of the same order of magnitude as the transmission investment cost. Thus, the models' calculation of VOC can pave the way for interregional cooperation by identifying grid reinforcements that benefit the entire system, as well as side-payments that may incent each region to cooperate. Although it is natural to have “winners” and “losers” while moving from a noncooperative to a cooperative planning paradigm, in our case study it was possible to allocate the costs of new interregional transmission so that every region is made better off.

Chapter 5

McCormick Envelopes to Approximate Large-Scale Interregional Noncooperative Transmission Planning Models

5.1 Abstract

In the previous chapter, we described a non-convex MPEC model where an ISO non-cooperatively maximizes the profit of the players within its region. Then an EPEC was defined by combining these individual ISO MPECs. The resulting equilibrium

indicates the transmission investments made when two ISOs plan for transmission investment noncooperatively. In each ISO's MPEC, we exactly linearized all constraints, only leaving nonlinear terms in the objective function. We then solved the non-convex MIPs using the Outer Approximation algorithm [117] on a 17-bus test case. In this chapter, we show that these nonlinearities cannot be exactly linearized, and use McCormick envelopes [31] to demonstrate the impact of these approximations on the solution quality. We compare the above McCormick-based solution to the non-convex solution from the previous chapter, and examine the trade-off between accuracy, complexity of McCormick envelopes, and computational costs.

5.2 Introduction

Non-convex optimization problems are relatively difficult to solve to global optimality compared to linear programming problems, especially when considering integer variables. Out-of-box solvers can rarely be used to solve these non-convex MINLPs. Even for the small case in Chapter 4 with 17-bus case that includes 12 time steps, we found that CPLEX — which, from version 12.3 onwards, could solve MINLPs whose integer variables are binary — converges extremely slowly, if at all. Most non-convex MINLPs algorithms involve dividing the problem into a continuous and an integer sub-problem and then iteratively and sequentially solving each sub-problem (with information sharing) until local convergence is achieved. This method was used, for example, in the previous chapter, for solving the 17-bus, 12 time step case, using the outer approximation algorithm.

Moreover, long-term optimal investment problems are prone to scaling issues [119], due to the large difference in scales for parameters (e.g., hourly marginal operating cost vs. capital cost of investment). The issue of scaling is exacerbated by the use of the Big M technique [120], which adds very large scalar values to the constraints that are linearized. Most nonlinear solvers are fundamentally based on the Line Search algorithm [121] that relies on calculating the Hessian matrix at a given point [122]. When the Hessian matrix is ill-conditioned, solvers require the problem to be rescaled to avoid unbounded and infeasible problems. Indeed, we found the non-convex MPEC from Chapter 4 to be very sensitive to scaling.

Furthermore, while MPECs, in general, are non-convex problems, for which there exist algorithms that can guarantee local solutions (if they exist), convergence is however not guaranteed in EPECs. The reported solution may not be a global solution to all leaders [100] [123]. In light of these challenges in solving MPECs and non-convex MINLPs in general, we explore convex relaxations of the MPEC from Chapter 4. Specifically, we use a relaxation based on McCormick envelopes [31]. These relaxations could then be solved using out-of-box solvers such as CPLEX or Gurobi. It would also be easier to scale these relaxations up to larger test-cases.

In Section 5.3, we show that the nonlinearities in the objective function of the single-ISO MPEC, proposed in Chapter 4, cannot be exactly linearized. We also explain the physical interpretation of the reasoning behind this. Then in Section

5.5, we introduce McCormick envelopes. In Section 5.6, we develop these envelopes for the bi-linear terms in our single-ISO MPEC. Then, in Section 5.7, we evaluate the quality of this relaxation by comparing the primal solution (the recommended transmission investments) with those from the original single-ISO MPEC. In Section 5.8, we improve the quality of these envelopes by the piece-wise remodeling of bilinear terms. We measure the improvement in the quality of the envelopes for a numerical example and highlight the trade-off between this improvement and the increased size of the formulation.

5.3 All nonlinear terms in the objective function cannot be linearized

The inability to exactly linearize the objective function (4.10) is a direct consequence of Theorem 1 in Wu et al.'s seminal 1996 paper on folk theorems in transmission access [124]. The nonlinear terms in the objective function are $\sum_{b,h,k} p_{b,h} y_{b,h,k}$ (from generators surplus), equal to the sum of price times sales, and $\sum_{l \in i,h} (f^E_{l,h} + f^N_{l,h}) [\sum_{b \in B(L(i))} M_{b,l} p_{b,h}]$, which is the flow on that line times the price difference across it. Although the former term can be linearized using the KKT conditions of the lower-level problem,[1] the latter term, which is equivalent to the net payment from ISO to generators for moving power out of a bus, cannot. To understand why this term cannot be exactly linearized, let us look at the dual constraint (4.17) and the complementary slackness condition associated with constraint (4.3). Multiplying that dual constraint by $f^E_{l,h}$, we have:

---

[1] See [125] and [94] for examples on how to do this.

$$-f^E_{l,h}\sum_b p_{b,h}M_{b,l} + f^E_{l,h}\lambda^E_{l,h} - f^E_{l,h}\xi^-_{l,h} + f^E_{l,h}\xi^+_{l,h} = 0 \ \ \forall l \in E, h \tag{5.1}$$

But from complementary slackness conditions for the flow capacity constraint (4.3), we have:

$$0 \le \xi^-_{l,h} \perp -\underline{F}^E_{l,h} + f^E_{l,h} \ge 0 \ \ \forall l \in E, h \tag{5.2}$$

$$0 \le \xi^+_{l,h} \perp \overline{F}^E_{l,h} - f^E_{l,h} \ge 0 \ \ \forall l \in E, h \tag{5.3}$$

i.e., the shadow price of the constraint can be strictly positive only if flow on the line, $f^E_{l,h}$, equals either the maximum or minimum capacity limits on the line. So, equations (5.2) and (5.3) imply

$$\xi^-_{l,h}f^E_{l,h} = \xi^-_{l,h}\underline{F}^E_{l,h} \tag{5.4}$$

$$\xi^+_{l,h}f^E_{l,h} = \xi^+_{l,h}\overline{F}^E_{l,h} \tag{5.5}$$

Substituting the linear terms on the RHS of equations (5.4) -(5.5) for their corresponding LHS (bilinear) terms in (5.1) results in the following revision of (5.1):

$$-f^E_{l,h}\sum_b p_{b,h}M_{b,l} = -f^E_{l,h}\lambda^E_{l,h} + \underline{F}^E_{l,h}\xi^-_{l,h} - \overline{F}^E_{l,h}\xi^+_{l,h} \ \ \forall l \in E, h \tag{5.6}$$

If a line l is un-congested in an hour h, the corresponding variables $\xi^-_{l,h}$ and $\xi^+_{l,h}$ are zero and they drop out from the above equation, but the first term on the RHS remains. So, equation (5.6) suggests that it is possible to have a non-zero price difference across two buses even when lines directly connecting them are uncongested. The dual value of the Kirchhoff's Voltage Law (KVL), $\lambda^E_{l,h}$, is a free variable rather than non-negative, and therefore, an analogous trick cannot be used to linearize its product with flow on that line. So, the KKT conditions of the lower-level problem do not allow exact linearization of this term (using linearization principles used in [125]). KVL is one of the fundamental laws governing power flow. Therefore, the very nature of electricity when combined with artificial political boundaries (restricting complete cooperation and trade across adjoining regions) prevent us from studying this problem easily with linear models.

Cross-border energy arbitrage terms do not cancel out when there is strategic interaction among adjoining transmission planners. In contrast, the nonlinear terms do drop out in a competitive market model with a single transmission planner, as demonstrated next.

5.4 Why we do not see these nonlinear objective function terms in a competitive market model

A market where all players are competitive can be re-written as a single cost-minimization model [85], because one player's cost is another player's revenue, which cancel each other out, except at the system's "boundaries" (i.e. the system's inputs and outputs, such as raw material provision). These assumptions fail to hold when we consider the strategic reaction of individual players to other player's actions because the objective function of one player only includes either the payments or receipts, but not both.[2]

This becomes clearer when we consider the simple example of a 4-bus system with two regional players, as shown in Fig. 5.1. Green buses and lines are owned by the first regional ISO and the other buses and lines by the second.

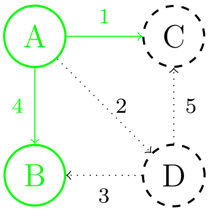


Figure 5.1: 4-bus example network with two regions. Green (solid) indicates buses and lines in Region 1 and Black (dashed) indicates Region 2.

Using the definitions above, the Consumers', Producers', and ISO Surplus of Region 1 are given below.

Producers' Surplus in Region 1 (green):

$$\sum_{\substack{b\in B_i\\k\in K(B_i)}} (p_b - CY_{b,k})\, y_{b,k} - \sum_{\substack{b\in B_i\\k\in K(B_i)}} CX_{b,k}x_{b,k} = \sum_{b\in B_i} p_b \sum_{k\in K(B_i)} y_{b,k} - \sum_{\substack{b\in B_i\\k\in K(B_i)}} CY_{b,k}y_{b,k} - \sum_{\substack{b\in B_i\\k\in K(B_i)}} CX_{b,k}x_{b,k} \tag{5.7}$$

---

[2] Exceptions to this exist on a case-by-case basis. For example, sometimes, if the players are Nash-Cournot, a complementarity problem can be re-written as an equivalent single optimization problem [126].

Applying the energy balance (KCL) constraint (4.2), the first term on the RHS can be rewritten, yielding:

$$\sum_{b\in B_i} p_b(D_b - l_b) + p_a(f_1 + f_2 + f_4) - p_b(f_4 + f_3) - \sum_{\substack{b\in B_i\\ k\in K(B_i)}} CY_{b,k}y_{b,k} - \sum_{\substack{b\in B_i\\ k\in K(B_i)}} CX_{b,k}x_{b,k} \tag{5.8}$$

Consumers' Surplus in Region 1:

$$\sum_{b\in B_i} (VOLL_b - p_b)(D_b - l_b) = \sum_{b\in B_i} VOLL_b(D_b - l_b) - \sum_{b\in B_i} p_b(D_b - l_b) \tag{5.9}$$

ISO Surplus in Region 1:

$$(p_c - p_a)f_1 + (p_b - p_a)f_4 - \sum_{l\in L_i} CZ_l z_l \tag{5.10}$$

Regional Social Welfare (PS + CS + ISO surplus), Region 1:

$$\begin{gathered}\cancel{\sum_{b\in B_i} p_b(D_b - l_b)} + p_a(\cancel{f_1} + f_2 + \cancel{f_4}) - p_b(\cancel{f_4} + f_3) - \sum_{\substack{b\in B_i\\ k\in K(B_i)}} CY_{b,k}y_{b,k} - \sum_{\substack{b\in B_i\\ k\in K(B_i)}} CX_{b,k}x_{b,k} + \\ \sum_{b\in B_i} VOLL_b(D_b - l_b) - \cancel{\sum_{b\in B_i} p_b(D_b - l_b)} + (p_c - \cancel{p_a})f_1 + (\cancel{p_b} - \cancel{p_a})f_4 - \sum_{l\in L_i} CZ_l z_l\end{gathered} \tag{5.11}$$

So, the Single-ISO MPEC objective function becomes:

$$\underbrace{p_c f_1}_{\substack{ISO_1 \text{ selling} \\ \text{on own line} \\ \text{exporting to} \\ \text{Region 2}}} + \underbrace{p_a f_2 - p_b f_3}_{\substack{ISO_1 \text{ selling \& buy-} \\ \text{-ing on } ISO_2 \text{ lines} \\ \text{(imports/exports} \\ \text{with Region 2)}}} + \sum_{b \in i} VOLL_b(D_b - l_b) - \sum_{\substack{b \in B_i \\ k \in K(B_i)}} CY_{b,k} y_{b,k} - \sum_{\substack{b \in B_i \\ k \in K(B_i)}} CX_{b,k} x_{b,k} - \sum_{l \in L_i} CZ_l z_l \tag{5.12}$$

The products of flow and prices do not all cancel out; price-flow terms for imports and exports (on lines connecting ISO$_1$ with ISO$_2$ remain). We see that these cross-border trade terms get canceled out when there is a single entity arbitraging across borders, or a single entity that owns and operates all the lines. If there is more than one ISO, and power exchanges between those ISOs, these terms remain in each ISO's objective function and make the problem nonlinear.

5.5 McCormick envelopes

McCormick envelopes are sets of linear under- and over-estimators used to create convex envelopes of multilinear terms. These were first proposed by G.P. McCormick in 1976 [31]. These envelopes are a convex relaxation of the bilinear term and can be used to generate bounds on the solution of the associated nonlinear Program (NLP) when bilinear terms appear in the objective function or constraint set.

For the simplest case where the bilinear term is the product of two bounded continuous variables (e.g. $w = xy$) , the associated simple McCormick envelopes are defined by the two under- and two over-estimators (see Figure 5.2) described by constraints

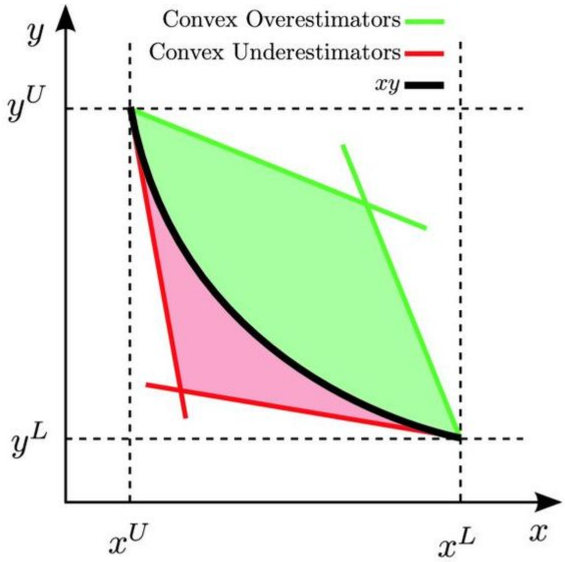


Figure 5.2: McCormick envelopes [3].

(5.15), (5.16) and (5.17), (5.18) respectively.[3] These four constraints together define the convex envelope within which the approximated value of the original bilinear term falls.

$$x^L \leq x \leq x^U \tag{5.13}$$

$$y^L \leq y \leq y^U \tag{5.14}$$

Constraints (5.13) and (5.14) define the lower and upper bounds on each of the variables in the bilinear term. Constraints (5.15) and (5.16) are under-estimators and (5.17) and (5.18) are the corresponding over-estimators of the bilinear term.

---

[3] This example and the associated figure are from [3].

$$w \geq x^L y + x y^L - x^L y^L \tag{5.15}$$

$$w \geq x^U y + x y^U - x^U y^U \tag{5.16}$$

$$w \leq x^U y + x y^L - x^U y^L \tag{5.17}$$

$$w \leq x y^U + x^L y - x^L y^U \tag{5.18}$$

It is clear from the above equations that the quality (tightness) of the envelopes depend to a large degree on the bounds of the variables themselves as well as the severity of the nonlinearity. The wider the domain of the variables, the larger the envelope, and the bigger the potential error in approximations.

5.6 McCormick envelopes for the bilinear terms

In the single-ISO MPEC from Section 4.4.3.3, the bilinear terms in the objective function are of the form $\sum_{(l,b)\in S_i} p_{b,h} f_{l,h}$ for every hour. Similar to the example from Section 5.4, this term captures the net monetary gain by the regional ISO i from its spatial arbitrage of electricity across its seams with neighboring ISOs. The variable $f_{l,h}$ indicates flow on a transmission line whose value in the optimization problem is bounded by thermal limits on the lines (see constraints (4.3) and (4.4)). The second variable, $p_{b,h}$, is the hourly Locational Marginal Price (LMP) for energy at bus b. This is the dual variable associated with the energy balance constraint (which is an equality constraint), and hence, is free and unbounded [122].[4] Acknowledging these as loose-bounds, we use a large scalar (big-M) for values of $\overline{P}$ and $\underline{P}$, the lower and upper bounds on $p_{b,h}$, respectively. Constraints (5.19) and (5.20) define the bounds on both variables.

$$\underline{P} \leq p_{b,h} \leq \overline{P} \quad \forall b, h \tag{5.19}$$

$$\underline{F}_l \leq f_{l,h} \leq \overline{F}_l \quad \forall l, h \tag{5.20}$$

Let us define[5]:

$$w_{l,b,h} = p_{b,h} f_{l,h} \tag{5.21}$$

This new variable $w_{l,b,h}$ is the bilinear term and its corresponding McCormick envelopes are given by constraints (5.22) - (5.25).

$$w_{l,b,h} \geq \underline{P} f_{l,h} + p_{b,h} \underline{F} - \underline{PF}_l \quad \forall l, b, h \tag{5.22}$$

$$w_{l,b,h} \geq \overline{P} f_{l,h} + p_{b,h} \overline{F} - \overline{PF}_l \quad \forall l, b, h \tag{5.23}$$

$$w_{l,b,h} \leq \overline{P} f_{l,h} + p_{b,h} \underline{F} - \overline{P}\underline{F}_l \quad \forall l, b, h \tag{5.24}$$

$$w_{l,b,h} \leq p_{b,h} \overline{F}_l + \underline{P} f_{l,h} - \underline{P}\overline{F}_l \quad \forall l, b, h \tag{5.25}$$

We now substitute the bilinear terms in the objective function with the new variable $w_{l,b,h}$. With this new substitution, the original single-ISO MPEC (section 4.4) becomes the new approximated single-ISO MPEC which takes the following form, and we refer to this problem as MCC_1 henceforth.

---

[4] Nevertheless, we know that $p_{b,h}$ refers to the energy prices at each bus. So, if historical price data is available, they can be used to derive these bounds.

[5] Flow on existing and new lines are combined here for notational simplicity.

$$\text{Max} \sum_{(l,b)\in s_i} w_{l,b,h} + \sum_{b\in i} VOLL_b(D_b - l_b) - \sum_{b,k\in i} CY_{b,k}y_{b,k} - \sum_{b,k\in i} CX_{b,k}x_{b,k} - \sum_{l\in L_i} CZ_l z_l \tag{5.26}$$

$$\text{s.t.} \quad (4.2)-(4.3),(4.5)-(4.9),(4.24) \tag{5.27}$$

$$(4.13)-(4.17),(4.19),(4.20),(4.25),(4.26) \tag{5.28}$$

$$(4.27) \tag{5.29}$$

$$(5.19),(5.22)-(5.25) \tag{5.30}$$

This is similar to the non-convex Single-ISO MPEC from Chapter 4 (section 4.4). The only differences are that the bilinear terms in the objective function are replaced by the new equivalent approximated variable, $w_{l,b,h}$, and equations (5.22) - (5.25) envelope these variables to constrain the bilinear term. This approximation is now linear and can be solved using out-of-the-box MILP solvers such as CPLEX and Gurobi. By definition, an approximated solution is sub-optimal (the original MPEC solution maximizes regional surplus). Hence, use of the line recommendations from the the McCormick approximation will under-estimate the regional surplus.

Player	Actual	MCC_1
1	1,20,21	1,9,19,20
2	2,16,22	4,7,8,10,11,12,13,14,15,17

Table 5.1: Comparing primal solutions from two MPECs - Lines chosen to be built

5.7 Quality of the single MCC envelope (MCC_1) for the 17-bus CAISO dataset

We use the 17-bus CAISO dataset from the previous chapter to compare the solutions from the full nonlinear single-ISO MPEC solution (which I will call the "original model") with the MCC_1 approximation — both solved under similar assumptions about the second players' actions. To compare the quality of the approximation, we take the upper-level solution (proposed transmission lines) from MCC_1 and impose these solutions on the original model to calculate the actual value of the objective function corresponding with those lines (which in general will have different flows and prices than MCC_1).

From Table 5.1, we see that the original model and MCC_1 primal solutions, i.e., recommendations of transmission line investments, are very different for the two ISOs. The difference is even more stark for ISO 2 where a total of 10 lines are

Player	MCC_1 % error
1	2.7%
2	6.4%

Table 5.2: Error in Objective value from two MPECs, calculated by imposing the upper level solution from the approximation upper level solution on the original single-ISO MPEC.

recommended from the approximated model as opposed to the 3 lines from the original solution. Note that in addition to monetary costs, each line also incurs political and bureaucratic costs. To measure the quality of the McCormick approximation, we measure the deviations in ISO surplus from the original model.

From Table 5.2, we see that for ISO 1, surplus is underestimated by 2.7% while for ISO 2, the quality of the solution is worse with an underestimation of 6.4%.

5.8 Tightening McCormick envelopes

The quality of McCormick envelopes can be improved by piece-wise modeling (dividing up the domain of some or all of the variables and constructing convex envelopes for each part separately). For the two variables in our bilinear term, the simplest way to do this is to separate each variable into positive and negative parts. This is done by constraints (5.31) - (5.36).

$$\underline{P} \leq -p^{-}_{b,h} \leq 0 \tag{5.31}$$

$$0 \leq p^{+}_{b,h} \leq \overline{P} \tag{5.32}$$

$$p_{b,h} = p^{+}_{b,h} - p^{-}_{b,h} \tag{5.33}$$

$$\underline{F}_l \leq -f^{-}_{l,h} \leq 0 \tag{5.34}$$

$$0 \leq f^{+}_{l,h} \leq \overline{F}_l \tag{5.35}$$

$$f_{l,h} = f^{+}_{l,h} - f^{-}_{l,h} \tag{5.36}$$

Constraints (5.33) and (5.36) split the variables $p_{b,h}$ and $f_{l,h}$ into non-negative and non-positive terms.[6] With these bounds, we can construct convex envelopes for each of the four new bilinear terms that make up the original one i.e., for each of the terms in the RHS of equation (5.37).

$$p_{b,h} f_{l,h} = (p^{+}_{b,h} - p^{-}_{b,h})(f^{+}_{l,h} - f^{-}_{l,h}) \tag{5.37}$$

The corresponding McCormick envelopes for the first of these four terms are given below: $w^{1}_{b,l,h} = p^{+}_{b,h} f^{+}_{l,h}$:

$$w^{1}_{b,l,h} \geq 0 \tag{5.38}$$

$$w^{1}_{b,l,h} \geq \overline{P} f^{+}_{l,h} + p^{+}_{b,h} \overline{F}_l - \overline{P}\overline{F}_l \tag{5.39}$$

$$w^{1}_{b,l,h} \leq \overline{P} f^{+}_{l,h} \tag{5.40}$$

$$w^{1}_{b,l,h} \leq p^{+}_{b,h} \overline{F}_l \tag{5.41}$$

---

[6] Ideally, only one of these split-terms will take on a non-negative value without additional constraints

Similarly, we can write McCormick envelopes for the three remaining new bilinear variables $w^2_{b,l,h}, w^3_{b,l,h},$ and $w^4_{b,l,h}$. These are:

$w^2_{b,l,h} = p^-_{b,h} f^+_{l,h}$:

$$w^2_{b,l,h} \geq 0 \tag{5.42}$$

$$w^2_{b,l,h} \geq -\underline{P} f^+_{l,h} + p^-_{b,h}\overline{F}_l + \underline{P}\,\overline{F}_l \tag{5.43}$$

$$w^2_{b,l,h} \leq -\underline{P} f^+_{l,h} \tag{5.44}$$

$$w^2_{b,l,h} \leq p^-_{b,h}\overline{F}_l \tag{5.45}$$

$w^3_{b,l,h} = p^+_{b,h} f^-_{l,h}$:

$$w^3_{b,l,h} \geq 0 \tag{5.46}$$

$$w^3_{b,l,h} \geq \overline{P} f^-_{l,h} - p^+_{b,h}\underline{F}_l + \overline{P}\,\underline{F}_l \tag{5.47}$$

$$w^3_{b,l,h} \leq \overline{P} f^-_{l,h} \tag{5.48}$$

$$w^3_{b,l,h} \leq -p^+_{b,h}\underline{F}_l \tag{5.49}$$

$w^4_{b,l,h} = p^-_{b,h} f^-_{l,h}$:

$$w^4_{b,l,h} \geq 0 \tag{5.50}$$

$$w^4_{b,l,h} \geq -\underline{P} f^-_{l,h} - p^-_{b,h}\underline{F}_l - \underline{P}\,\underline{F}_l \tag{5.51}$$

$$w^4_{b,l,h} \leq -\underline{P} f^-_{l,h} \tag{5.52}$$

$$w^4_{b,l,h} \leq -p^-_{b,h}\underline{F}_l \tag{5.53}$$

Equations (5.38) - (5.53) together make up the original nonlinear term via the following inequality:

$$p_{b,h} f_{l,h} = w^1_{b,l,h} - w^2_{b,l,h} - w^3_{b,l,h} + w^4_{b,l,h} \tag{5.54}$$

The updated optimization problem facing each individual ISO$_i$ is given below:

$$\begin{aligned} \text{Max} \sum_{(l,b)\in S_i} \left(w^1_{l,b,h} - w^2_{l,b,h} - w^3_{l,b,h} + w^4_{l,b,h}\right) + \sum_{b\in B_i} VOLL_b(D_b - l_b) - \\ \sum_{\substack{b\in B_i \\ k\in K(B_i)}} CY_{b,k} y_{b,k} - \sum_{\substack{b\in B_i \\ k\in K(B_i)}} CX_{b,k} x_{b,k} - \sum_{l\in L_i} CZ_l z_l \end{aligned} \tag{5.55}$$

$$\text{s.t.} \quad (4.2) - (4.3), (4.5) - (4.9)$$

$$(4.13) - (4.17), (4.19), (4.20)$$

$$(4.24) - (4.27)$$

$$(5.31) - (5.36), (5.38) - (5.53)$$

Ideally, the non-negative and non-positive components of p and f should be orthogonal, i.e., only one component should be non-zero. However, our simulations[7] resulted in non-orthogonal behavior with positive values for both components. For example, if the value of $f_{l,h}$ is 2000 MWh, the model may have returned $f^+_{l,h} = 2500$ and $f^-_{l,h} = 500$ instead of $f^+_{l,h} = 2000$ and $f^-_{l,h} = 0$. We refer to this as spurious splitting.

---

[7] Results not shown here.

5.8.1 Does spurious splitting matter?

Spurious splitting does not affect the solution of the optimization problem, provided that the following conditions are met:

- The split parts should always add up to the whole.
- The parts should never appear separately in the model, except to contribute to the whole.

If these two conditions are satisfied, the exact split of the variables does not matter. In our case though, the second condition does not hold. It is not the parts that contribute to the whole, but approximations of the parts in the form of $w^1_{b,l,h}...w^4_{b,l,h}$. The variables $p^+_{b,h}, p^-_{b,h}, f^+_{l,h}, f^-_{l,h}$ appear separately (from each other and in combination with other parameters) to set bounds on these approximations. For example, on the RHS of equations (5.39)-(5.41). So, there is an incentive for the model to spuriously split the terms resulting in a looser set of bounds in the constraints.

5.8.2 Additional constraints needed to correctly split the variables

The following additional constraints involving binary variables are needed to correctly split the terms.

$$0 \leq p^+_{b,h} \leq z_{b,h} p_{b,h} \tag{5.56}$$

$$0 \leq p^-_{b,h} \leq -(1 - z_{b,h})p_{b,h} \tag{5.57}$$

$$0 \leq f^+_{l,h} \leq y_{l,h} f_{l,h} \tag{5.58}$$

$$0 \leq f^-_{l,h} \leq -(1 - y_{l,h}) f_{l,h} \tag{5.59}$$

$$z_{b,h}, y_{l,h} \in \{0, 1\} \tag{5.60}$$

Constraints (5.56) and (5.57) use a binary variable $z_{b,h}$ to ensure that only one of the components of the variable $p_{b,h}$ takes on a non-zero value. Constraints (5.58) and (5.59) do the same for variable $f_{l,h}$.

However, it can be seen that there are bilinear terms in the above constraints that make the problem nonlinear again (which is exactly what we were trying to avoid using McCormick approximations in the first place). Fortunately, these bilinear terms are all products of binary and continuous variables (and not products of continuous variables) which can be exactly linearized using big-M techniques specified in [120]. Using these techniques, equation (5.56) will for example be replaced with the following four constraints.

$$0 \leq p^+_{b,h} \leq b_{b,h} \tag{5.61}$$

$$-z_{b,h}\underline{P}_{b,h} \leq b_{b,h} \leq z_{b,h}\overline{P}_{b,h} \tag{5.62}$$

$$p_{b,h} - (1 - z_{b,h})\overline{P}_{b,h} \leq b_{b,h} \leq p_{b,h} - (1 - z_{b,h})\underline{P}_{b,h} \tag{5.63}$$

$$b_{b,h} \leq p_{b,h} + (1 - z_{b,h})\overline{P}_{b,h} \tag{5.64}$$

Constraints (5.61) - (5.64) ensure that the bilinear term $z_{b,h}p_{b,h}$ takes on a value of 0 if $z_{b,h}$ is 0 and takes on the value of $p_{b,h}$ when $z_{b,h}$ is 1. We define a new variable $b_{b,h}$ which is equivalent to $z_{b,h}p_{b,h}$. Specifically, if $z_{b,h}$ is zero, constraint (5.62) restricts $b_{b,h}$ to be zero. If $z_{b,h}$ is 1, constraints (5.63) and (5.64) ensure that $b_{b,h}$ takes on the value of $p_{b,h}$.

Constraints (5.57) - (5.59) are also replaced by similar constraints corresponding to (5.61) - (5.64) and henceforth, we refer to the resulting piece-wise approximation as MCC_2.

5.9 Performance of piece-wise McCormick approximation

In this section, we look at how well the McCormick approximation, obtained by diving the variables $p_{b,h}$ and $f_{l,h}$ piece-wise into positive and negative segments (MCC_2), performs in relation to the original single-ISO MPEC solution and the MCC_1 approximation.

5.9.1 Changes in line investment and overall surplus

We see from Table 5.3 that in MCC_2, both ISOs end up building an equal or lesser number of lines when compared to MCC_1. The difference is drastic for ISO 2 which builds only two lines as opposed to the 10 lines recommended by MCC_1. This is closer in number to the original MPEC solution (3 lines). In the next paragraph, we

Player	Actual	MCC_1	MCC_2
1	1,20,21	1,9,19,20	1,5,19,20
2	2,16,22	4,7,8,10,11,12,13,14,15,17	8,23

Table 5.3: Primal Solutions: Comparison of the approximations' transmission investments with the original recommendations.

Player	MCC_1 % error	MCC_2 % error
1	2.7%	2.5%
2	6.4%	2.5%

Table 5.4: Percentage underestimation of Objective value: Imposing approximation upper level solution on original MPEC. Green indicates a reduction in error. For all four models, it is assumed that the other player builds no transmission lines.

measure the accuracy with which MCC_2 approximates the original MPEC solution's ISO surplus 5.4.

We get the values in Table 5.4 by imposing the upper-level transmission investments from MCC_2 for ISOs 1 and 2 on their respective non-convex MPECs (with the same assumptions about the other player). The values shown in the table are the percentage changes from the original MPEC's regional surplus predictions. We know that these new predicted surpluses will always be smaller than the actual surpluses (as the approximated solutions are suboptimal).

From Table 5.4, we see that the tighter approximation performs better than the simple approximation MCC_1. We see the error reduces to 2.5% in both cases from 2.7% and 6.4% for ISOs 1 and 2 respectively. We conclude that for MPECs, in this case study, piece-wise approximations predicts both regions' surpluses more accurately than the simple McCormick approximation.

5.9.2 Effect of approximations' quality on EPEC solution

The goal of this approximation is to be able to accurately predict the equilibrium reached by both regional transmission planners when they are acting strategically to maximize the profits of their individual regional players. To evaluate the quality of the approximation, we use diagonalization to solve two EPECs - one with the MCC_1 MPEC approximation, and the other with the MCC_2 MPEC approximation. We then take the equilibrium transmission investment recommendations from these EPECs and impose them on the original MPEC each ISO faces, and calculate the resulting regional surplus. Again, since these values are sub-optimal solutions, we might expect the objective value to be underestimated (since each MPEC is a maximization problem). However, since this is an equilibrium problem (not a maximization), this might not happen. The difference between these surpluses and the ISOs' actual surpluses - as calculated in Chapter 4 from the original EPEC - indicates the quality of our approximations.

Table 5.5 shows that if each ISO faces the MCC_1 approximation, ISO 1's surplus

Player	MCC_1 % error	MCC_2 % error
1	4%	3.5%
2	1.2%	1.7%

Table 5.5: Error in Objective value - Imposing approximated EPEC solution on EPEC

is under-estimated by 4% and ISO 2's surplus is under-estimated by 1.2%. With the tighter approximation, these errors decrease to 3.5% but increase to 1.7% for Regions 1 and 2, respectively. It is interesting to note that, although, as we see from Table 5.4, the tighter approximation, MCC_2, predicts regional surpluses better than MCC_1 given the same starting point, the same does not necessarily translate into a better EPEC solution (as evidenced by the increased error of 0.5% in predicting Region 2's surplus).

5.10 Increase in size of approximations

The number of constraints and variables increases as the complexity of the McCormick envelopes increases. For example, for each bilinear term in the objective function of the single-ISO MPEC, the additional number of variables and constraints required for the simple (MCC_1) and piece-wise McCormick envelopes (MCC_2) are shown in Table 5.6.

Per bilinear term	MCC_1	MCC_2
Additional variables	4	20 (8 binaries)
Additional Constraints	4	26

Table 5.6: Size of the problem increases with complexity of McCormick envelopes

We see that for each bilinear term in the original problem, there is a 4-fold increase in the number of variables and constraints if we use simple McCormick envelopes (MCC_1), whereas, with the piece-wise approach (MCC_2), there is about a 20-fold increase in number of variables and constraints. Some of these additional variables are binary, which increases the complexity of the MIP relaxation. The decision-maker needs to consider problem size and complexity when evaluating relaxations of the noncooperative transmission planning problem.

5.11 Conclusion

In Chapter 4, we saw that the optimization problem faced by regional ISOs, when they look to maximize the profit of the consumers, generators, and themselves, takes the form of a non-convex MINLP. While we used an Outer-Approximation algorithm to solve the MPEC, scaling the framework to larger datasets is difficult due to non-convexities and the mixed-integer nature of the problem.

In this chapter, we used McCormick envelopes to create convex relaxations of the aforementioned MPEC problem. First, we used loose bounds on one of the variables in the bilinear term $p_{b,h}$ to generate simple McCormick envelopes and evaluated the quality of the resulting approximation by comparing the primal solutions, as well as the error in surplus estimation of the regional ISOs. This was done using the same CAISO 17-bus dataset and two regional planners as used in Chapter 4. Next, we improved upon this approximation by constructing piece-wise McCormick envelopes based on tighter bounds on the two variables in the bilinear term. This tighter approximation was then used to solve the regional ISOs' problems, and we found that it provided a closer estimate of the actual regional surpluses. Although this accuracy comes at the cost of an additional 26 constraints and 20 variables (including 8 binary variables) for each bilinear term in the objective function, the tradeoff here is that we do not have to solve a MINLP. The approximation is a MILP which can be solved for large datasets using powerful out-of-the-box solvers. These solvers routinely handle problems with a large number of binary variables and constraints. Decision makers need to consider the computational speed-ups of these approximations and other advantages such as easier scaling up to larger datasets against the loss in accuracy of 1.7% - 3.5% (for this case-study). Additionally, depending on the computational resources available, these approximations can be improved (albeit with an increase in size of the associated MILPs) by further tightening the bounds on the variables in the bilinear term.

Chapter 6

Conclusion

In this thesis, our goal was to develop computational tools that can aid decision makers in effective transmission planning. We did this by focusing on two themes: bridging the gap between short-term operations and long-term planning, and exploring the effects of regionality on transmission planning.

We start by summarizing the contributions of this thesis in Section 6.1. In Sections 6.2 and 6.3, computational difficulties we faced are discussed. We then discuss the limitations of these studies, and future research directions in Sections 6.4 and 6.5 respectively.

6.1 Summary and contributions

The unit commitment (UC) problem is a very large mixed integer program that is used to determine generator schedules in daily system operations. Historically, the computational burden of unit commitment was so large that the effects of short-term operational constraints, such as ramp-rates and minimum-run constraints, could not be explicitly inculded in long-term transmission planning models (which by themselves are complex mixed integer programs [64]). In Chapters 2, we aimed to remedy this issue by presenting a tight unit commitment MILP formulation, whose relaxation performs better than currently used linear approximations from literature. In Chapter 3, we applied this to a U.S. Western Interconnection application and show that UC indeed changes long-term transmission and generation investments. Specific contributions of Chapters 2 and 3 are discussed below.

6.1.1 Improved approximations of unit commitment

In Chapter 2, we proposed a Mixed-Integer Tight Unit Commitment (TUC) formulation that defines a tighter constraint set for the unit commitment problem. This is achieved by selectively trimming the relaxed MILP without removing valid points in the original problem. We validated our results by simulating unit commitment operations on systems based on an 11-generator test-case over a period of 168 hours (1 week). We showed that, for all system sizes, the TUC formulation converges faster than the standard UC formulation while giving the same primal and dual solutions. We then showed that the relaxation of this formulation (TRUC) is tight enough to predict system costs with a $\geq 99\%$ accuracy for all system sizes. TRUC outperformed the following linear approximations common in literature:

1. A load duration curve (LDC) model, which orders hours in decreasing order of magnitude of load and dispatches generators according to a “merit-order” stack (i.e., cheapest-first). This approach ignores inter-temporal ramping and minimum-run constraints, and start-up and shut-down costs.

2. A variant of LDC, LDC’, which averages out the total start-up and shut-down costs into the marginal cost of generation.

3. A relaxed unit commitment formulation for the standard UC formulation (BCRUC) where the integrality constraints on unit status (running/not running) are relaxed.

For larger test cases, we also showed that TRUC predicts hourly energy prices and a new, small generator’s profits better than the linear approximations. In TRUC, we have a linear approximation of the Unit Commitment problem that can estimate the total system costs and energy prices, which are signals for generator investment, with a high degree of accuracy, while remaining a tractable linear programming problem. Sophisticated algorithms based on the Simplex and Inter-point methods exist that solve linear programs significantly faster than a comparatively sized MILP. With

TRUC representing operations within a large-scale planning model, decomposition techniques (such as Benders' algorithm) can be applied, as LPs can be used as subproblems.

In the same chapter, we showed how a Partially Relaxed TUC formulation (TPRUC) can reduce the computational burden of the full UC MILP while more accurately predicting price and total system cost. The partial relaxation allows power system planners and operators to select critical periods where variables remain binary in nature (e.g., fast-ramping periods). For example, in the smallest system ($1x$), we designated the 60 hours (out of 168) corresponding to the steepest changes in net-load as binary variables for shoulder and peaking units (e.g., CCGT, CT, and oil units). These plants and periods were selected because they were most likely to violate ramping constraints in a significant manner. By relaxing all other variables, the number of binary variables was reduced to 19% of its original quantity, with 99.9% fidelity in system cost and an RMSE of \$0.75/MWh. Depending on the system size, TPRUC also solves 30-56 times faster than the base case UC.

In summary, the main contributions of Chapter 2 are the Tight Unit Commitment (TUC) model and its approximations. We showed that the MILP formulation, TUC, solves faster than the standard formulation from the literature [32], while giving the same primal and dual solutions. We also showed that the linear relaxation, TRUC, estimates system costs and prices better than the linear approximations used in literature (LDC and LDC'), especially for larger system sizes. A way to incorporate operator insight into UC models (in TPRUC) was also shown. This model has only 19.4% of the number of binary variables in the standard formulation, yet predicts system costs and energy prices accurately.

In Chapter 3, we applied TRUC to a planning problem for which it would have been impractical to use a full UC formulation with binary variables. This application allowed us to consider unit commitment constraints without rendering the model impractical. In Chapter 3, we demonstrated, by applying TRUC on a two-stage multi-period investment model, that short-term operational constraints (e.g., ramping limits) can have an impact on transmission investment. More specifically, by comparing the dispatch from the UC and LDC models, we found that transmission investment differences are caused by the inflexibility of certain generators at an hourly time scale. For example, in one instance, when a LDC was used, coal units were started-up and shut-down for a few hours in the afternoon and then ramped up to their full capacity in the evenings. With UC constraints, coal generators are more accurately modeled as having slower ramps and longer start-up/shut-down times. Our results show that wind, solar and hydro generation (both deterministic and stochastic) and load profiles can widely affect long-term transmission and generation investments. Specifically, we find that flexible generation, such as CTs, is sometimes favored over less flexible CCGTs, in order to accommodate high ramp rates in load or renewable energy generation profile. As mentioned, transmission investments are also impacted by operational constraints. Transmission line investment provides the option of bring-ing generation from distant centers to load pockets, rather than building new local generation.

We also found that these results are sensitive to factors affecting the merit-order stack. For example, as carbon-tax is increased from \$0/ton to \$100/ton, coal, intuitively, becomes un-competitive and is not dispatched. However, in the medium-carbon tax range, when coal is neither completely base-loaded nor completely priced out, unit commitment has the largest potential to affect long-term investments. This is the carbon-tax range where coal is being cycled the most (compared to other carbon-tax ranges) and this is where ramping, start-up, shut-down, and minimum-run constraints have the most effect on long-term investments. A second factor affecting investments is the weight given to the scenarios is a stochastic model. We showed that under one set of weights, Stage 1 (here-and-now) transmission decisions are not affected while under a different set of weights the model recommends a different set of transmission and generation investments.

In summary, for first time in the literature, the analysis in Chapter 3 explicitly considered short-term intertemporal operational constraints within a generation and transmission optimization model. . The computational burden of integrating a full UC model into expansion models was previously too great because both are mixed integer programs. We address this by integrating a tight linear approximation of UC from Chapter 2 — which we showed more accurately estimates hourly energy prices, total system costs, and generator profits than other linear approximations from literature — with a two-stage stochastic planning model. We then showed that short-term UC constraints indeed have the potential to change long-term transmission and generation investments. This potential is the greatest when there are slow-moving, inflexible generators in the energy mix which are cycled.

6.1.2 Noncooperative vs cooperative transmission planning

In Chapter 4, we address the fact that, although, the United States' electricity grid, at a high level, is comprised of three interconnections, each interconnection is made up of multiple Independent System Operators (ISOs) or Regional Transmission Operators (RTOs). Further down, the western North American market is comprised of 38 balancing authorities who are responsible for maintaining and safely operating the power system for their regions. Their responsibility is to ensure that generators and consumers have access to the transmission system. Since electricity follows the laws of physics (e.g., Kirchhoff's Voltage Laws or KVLs) rather than geopolitical boundaries, long-term investments are a complex problem that should, in theory, be addressed in a coordinated fashion by all entities involved in planning and operating the system. But in practice, each ISO has its own transmission planning process.

Traditionally, production costing or single-shot cost-minimization/benefit-maximization optimization models were used in literature (and sometimes in practice) to identify potential transmission line investments. Following deregulation, equivalent models were still used to find optimal investments, with the assumption of perfect competition and information symmetry. In reality, rather than maximizing profits, non-profit ISOs make investments that benefit the players in their own region [127], while considering cross-border electricity trade (e.g., bilateral contracts and self-scheduling on the spot markets).[1] Until now, to the best of our knowledge, no model had adequately addressed this noncooperative nature of transmission planning.

In Chapter 4, we first look at a single regional planner's (ISO's) problem. We formulate the problem where the planner's objective is to identify candidate transmission investments that maximize the net surplus of regional players, including consumers, generators, and the ISO itself. The model identifies these investments anticipating that, in the future, generators and consumers will behave competitively both in the spot market and while making investment decisions. Furthermore, the ISO also assumes that all trades are competitive.

This structure naturally gives rise to a leader-follower game (in this case, a Mathematical Program with Equilibrium Constraints, or MPEC) with the ISO being the leader, while the generators and the players in the spot-market are the followers. We then showed how to combine multiple players' problems by integrating the follower's primal constraints, dual constraints, and the strong duality condition into the main problem. We exactly linearized the resulting nonlinear constraints generated by the MPEC, leaving only some nonlinearities in the objective function.

Later in the chapter, we extend this single-ISO framework into an Equilibrium

---

[1] This is a simplified assumption of reality.

Problem with Equilibrium Constraints (EPEC) where multiple regional ISOs all face the same optimization problem with a common follower — the spot market and generators making investments in all regions. This model attempts to find an equilibrium among two or more regional ISOs' MPEC problems, assuming Nash equilibrium behavior over their individual transmission investment strategies. Using a test-case with 17-buses, 12 hours, and 2 regional planners, we solve the EPEC using diagonalization (while solving the single-ISO MPEC using an Outer-Approximation algorithm). We compare the resulting set of transmission investments to those from a traditional cost-minimization optimization problem (i.e., central planning), and show that our game-theoretic approach can help quantify the changes in the profits of all entities (consumers, producers, and the ISO itself), when the ISOs fully cooperate with each other in the transmission planning process. Specifically, for our case study, we found this Value of Cooperation (VOC) to be 83% of the total transmission investment cost.

We found that if the regional planners cooperated with each other, cross-border trades increased, as cooperative transmission investments gave consumers in one region access to cheaper generation from another region. We also showed that this competition from one region's generation will then force cheaper generation investment in a neighboring region. Moreover, we were able to identify the lines internal to both regions that have interregional benefit. In this case, the cooperative model results in more transmission built, but in lines internal to each of the regional markets, and not between the markets.

Overall, we showed that cooperative transmission planning benefits both regions,[2] while exactly identifying the "winners" and "losers" (from the status-quo noncooperative planning). As long as side-payment agreements exist that can bring the players that lose (due to this planning paradigm change) on board, cooperative planning can benefit the region. We explore one such side-payment agreement in our case-study where the region that benefits overall from the cooperation agrees to shoulder some of the second region's costs of building transmission.

Using these formulations to identify winners, losers, and the effects of cooperation on each player can help ISOs not only operate more efficiently, but also negotiate beneficial side-payment agreements. Furthermore, this also helps the ISOs comply with federal regulations (such as FERC Order 1000, which mandates interregional cooperation in transmission planning).

In summary, the contribution of Chapter 4 is that for the first time in the literature, noncooperative transmission planning by adjoining regions is framed as a bi-level equilibrium model, where these regions make investments *without* a supra-player (regulatory body) directing the investments. We showed that the problem each region's planner faces takes the form of an MPEC, which can be re-cast as a non-convex MINLP. An outer-approximation algorithm was used to solve this MPEC, while solving the EPEC of all regional planners. The results from this framework were compared to those from a cooperative framework in which regional planners fully cooperate with each other in transmission planning. It was shown that cooperation can only benefit the entire region, and the resulting changes to surpluses of individual players from both regions were quantified.

---

[2] Subject to side-payments.

Although we were able to solve the single-ISO MPEC for a 17-bus system with 12 hours of operations, directly scaling these formulations up to larger test-cases and more hours is difficult, because non-convex MINLPs are some of the most challenging problems in optimization to solve to global optimality. In Chapter 5, to aid scaling up, we use McCormick envelopes to convexify and linearize the optimization problem. We first construct simple McCormick envelopes around the nonlinear term in the objective function. We solve the resulting EPEC (consisting of approximated MPECs), and compare the approximation's quality with the actual solution from Chapter 4.

The quality of McCormick envelopes depends, to a large degree, on the bounds of the variables. For example, in our single-ISO MPEC problem, one of the bilinear terms includes the dual variable associated with the energy balance constraint due to KCL (i.e., the hourly energy price of energy). Because the latter is an equality constraint, it is difficult to bound its associated dual variable. Tighter bounds on the variables could theoretically tighten the McCormick envelopes leading to a better solution. We separated the energy price and power flow variables on seam lines into positive and negative components, and constructed McCormick envelopes for each of the four bilinear terms. Further, we added constraints to guarantee orthogonality between the respective positive and negative components.

Using the tighter piece-wise McCormick envelopes resulted in improved solution quality in the single-ISO MPEC (measured by the difference in predicted regional surplus), but produced mixed results for the multiple-ISO EPEC. Overall, we found that McCormick can be a suitable convex approximation of the multi-regional noncooperative transmission planning problem if tight bounds are available on the variables that make up the bilinear term. Although energy prices are dual variables, they have a practical interpretation, and decision makers can generate tight bounds for energy prices based on historical data. Then, based on the available computational resources, piece-wise envelopes can be constructed for the bilinear terms in the objective function, where more pieces result in higher solution quality at the cost of creating additional variables. The resulting EPEC can be solved using diagonalization and out-of-box solvers such as CPLEX or Gurobi.

In summary, the contribution of Chapter 5 is that we showed McCormick envelopes to be a suitable tool that can aid in scaling up the noncooperative framework from Chapter 4 to large networks. Depending on the available computational resources, the quality of these envelopes can be improved, while re-casting the non-convex MINLP faced by each ISO as a MILP. We showed that, in this case study, an approximation with tighter McCormick envelopes (MCC_2) estimates the individual regional profits better than a simple McCormick approximation (MCC_1).

Next, we discuss some practical computational issues we encountered while running the formulations we used in this thesis.

6.2 Computational difficulties

Computing power has improved exponentially the past few decades. Yet, we encountered a number of challenges while solving the Unit Commitment and Transmission Planning models from these chapters. For example, in Chapters 2 and 3, we were able to initially include only 24 h of operations (with default CPLEX settings on a Windows Server 2012 PC with an AMD Opteron 6274 2.20GHz Processor and 112 GB RAM, these models took about 6 - 7 h to solve). But with tuning of solver parameters (which in general is problem specific), we were able to include more hours (72 h of operations) and solve the same model in 2 - 2.5 h. When scaling-up a model while facing computational limits, traditional single-level optimization models (i.e., models solved as a single instance) may be inadequate. To partially address computational limits, it is possible to use decomposition techniques (e.g., Benders' decomposition and Progressive hedging) with high-throughput computing facilities [66] [128].

In Chapters 4 and 5, we used an Outer Approximation algorithm to solve the single-ISO MPEC for 12 h of operations. As mentioned in Chapter 4, theoretically, CPLEX (from version 12.3 onwards) can optimally solve MINLPs whose integer variables are binary, when their non-convexities are concentrated in the objective function. However, practically, the computational cost was unreasonable for solving 3 hours of operations in a 17-bus model. Moreover, scaling is a major issue in the MPECs (due to the required bounds on dual variables and the presence of disjunctive constraints).

In summary, transmission planning models are computationally challenging by themselves. Their complexity increases when the embedded operations component links generation production between different hours using inter-temporal ramping and minimum-run constraints. We found that tuning solver parameters greatly helped computational times, and we were then able to simulate operations for more hours. We also found that CPLEX currently takes a long time to solve very simple non-convex MIPs.

6.3 When is the additional effort justified?

Simplifications have always been part of long-term power systems planning models - simplifications related to network resolution, operations depiction, market structure, political boundaries, etc. Deregulation and increasing penetration of variable renewable energy (VRE) has increased the need to include more operational detail into planning models as we showed in Chapters 2 and 3. However, this inclusion comes with additional data, modeling, and computational efforts. For example, more constraints need to be added to the formulation which increases the computational time, and additional data about each generator's operational characteristics such as start-up, shut-down times, and minimum-run capacities needs to be obtained.

Decision makers need to be aware of this effort and weigh their trade-offs against the potential benefits from using these more accurate models. For example, our linear Unit Commitment approximation, TRUC, has the potential to be most useful when the system has a mix of inflexible (slow-moving) generation and highly variable renewable energy sources in the mix. These are the conditions under which it is necessary to adequately account for the effects of flexibility (or inflexibility) of generators on the system, as this is when steep ramps are required to accommodate renewable energy that bid at very low prices. This effect can be significant enough to change the relative economic attractiveness of different generation and transmission investments. On the other hand, if the inflexible generation is base-loaded all the time or only used for peaks, then TRUC is unlikely to change operations enough relative to a model without UC constraints to affect investments.

Regarding the transmission planning models from Chapters 4, these models are a more accurate representation of reality than a traditional vertically integrated model, in that they explicitly consider the incentives faced by regional ISOs. Hence, the transmission recommendations from such models can be used by decision makers to identify the “winners” and “losers” of noncooperative or cooperative planning. But, there are computational challenges in solving these MPECs, which are MINLPs, that need to be addressed.

6.4 Limitations of the studies

The models and the analyses presented in these essays address important issues, such as the effect of short-term operations and political boundaries, on transmission planning. However, there are limitations to what our models currently address. For example, our models do not consider reactive power or transmission line losses. Now, we delve into the specific limitations of each chapter.

- *Chapter 2:* In the TUC formulation and its approximations, we do not model minimum-up and down time constraints. Our models implicitly assume these times to be 1 h, i.e., when turned off, there is no restriction on when these units can be started up again. In reality, tens of hours are sometimes required for a nuclear or coal unit to be switched on after being turned off. Start-up costs and marginal costs of generation also depend on the length of time the unit has been off [129]. In this study, we assume these costs are constant. While we do not include network constraints, such as transmission line thermal limits, in the formulations in this chapter (operations and load at a single bus are considered), these are included when TRUC is used in the next chapter. Additionally, we do not evaluate the performance of these formulations with variable renewable energy sources in the energy mix. Preliminary testing has shown us that high variability in net-load profile (from one hour to the next) could increase solve-times.
- *Chapter 3:* In Chapter 3, we do not consider Kirchhoff's Voltage Laws (KVLs) in the two-stage stochastic (and deterministic) planning model. These constraints have indeed been shown to affect long-term transmission plans [64]. Another limitation is that we use only 72 hours (three days) to represent yearly operations. Industrial scale generation production costing runs (without plan-

ning, multiple-stages, or stochasticity) generally simulate the entire 8760 hours of yearly operations.

- *Chapters 4 and 5:* The main limitation of our non-cooperative transmission planning models from Chapter 4 is scale. In our case-study, we used a 17-bus system representation of the region maintained by the California ISO (CAISO). But, in reality, these regions contain thousands of buses and transmission lines. Furthermore, we only consider 12 hours to represent yearly load and renewable conditions. But this non-cooperative MPEC is a non-convex MIP and solving these models is challenging. In fact, this was the motivation for the McCormick approximations in Chapter 5. In these approximations, we only divide each variable constituting the bilinear term into two variables. This can be improved by increasing the number of parts each variable (from the bilinear term) is divided into.

6.5 Future research

The essays in this thesis address some key challenges in long-term transmission planning. The following extensions can be used to address some of the limitations we mention in Section 6.4 as well as to explore future directions of work.

- *Including minimum-up and -down time constraints in unit commitment:* Including these constraints in the UC formulations from Chapter 2 would allow the models to represent generator shut-down times which are an important consideration in generator scheduling. With this, more resolution can be added to the generator fixed costs as well. For example, start-up costs depend on the length of time a generator is turned off.

- *More hours in the transmission planning models from Chapter 3:* One challenge in this direction is that most planning models use a sampling [22] or clustering methodology [64] to choose *non-chronological* hours to match yearly averages and geographical correlations between variable data such as load, wind, solar, and hydro profiles. But including inter-temporal operational constraints automatically necessitates the use of continuous swathes of hours (e.g., full days). In Chapter 3, we select 72 hours and normalize variable energy profiles to match yearly averages. We plan to improve upon this by exploring techniques, e.g., [130], that will allow us to capture continuous hours that match yearly (or seasonal) averages and geographical correlations between load and variable energy source outputs.

- *Scaling the noncooperative transmission planning framework:* For the non-cooperative single-ISO MPEC model from Chapters 4 and 5, we plan to explore the challenge of concurrently improving solutions for the single-ISO MPEC approximations, while using realistically scaled models.

- *Incorporating current cross-border practices into transmission planning:* Another avenue we would like to focus on is to incorporate current cross-border artefacts such as hurdle-rates, which have been previously described as economic "friction" on the system [131]. Incorporating these artefacts will help us truly understand the effects of non-cooperation between neighboring ISOs in the planning process, and hopefully pave the way to more cooperation in planning (which we showed can only benefit the system). This can also help in negotiating side-payment agreements by pin-pointing the exact effects of current policies and regulations, and the market-participants directly affected.

Appendix

g	α_g	β_g	γ_g	θ_g	UR_g	DR_g	C_g^{fuel}	C_g^{om}	Q_g^{max}	Q_g^{min}	Power factor
NUCLEAR	1	0	5	0.5	0.02	0.02	3.5	1.2	1	0.23	0.95
LIGNITE	3	0.015	2	0.2	0.038	0.038	8	2.4	0.35	0.23	0.94
SUBBITUMIN	2.6	0.03	2	0.2	0.044	0.044	8.5	1.8	0.35	0.21	0.95
BITUMINOUS	2.3	0.035	1.4	0.14	0.04	0.04	8	1.2	0.35	0.22	0.93
ANTHRACITE	2.2	0.06	1.9	0.19	0.118	0.118	7	1.2	0.55	0.18	0.96
CCGT 1	1.3	0.09	1.1	0.11	0.065	0.065	20	1.2	0.4	0.2	0.98
CCGT 2	1.3	0.09	1.1	0.11	0.065	0.065	20	1.2	0.4	0.2	0.98
CCGT 3	1.3	0.09	1.1	0.11	0.065	0.065	20	1.2	0.4	0.2	0.98
FUEL OIL 1	2.1	0.08	0.07	0.007	0.125	0.125	20	1.2	0.54	0.14	0.94
FUEL OIL 2	2.1	0.08	0.07	0.007	0.125	0.125	20	1.2	0.54	0.14	0.94
GAS	2	0.09	0.11	0.011	0.075	0.075	18	2	0.38	0.14	0.94

Table 6.1: Generator data (size $1x$) for Unit Commitment models from Chapter 2.

Zone	Alberta	Arizona/ NE N. Mexico	BANC	British Columbia	Colorado	Idaho	IID	LADWP	Mexico	Montana	N. California	N. Nevada	Pacific Northwest	San Diego	San Francisco	S. California	S. Nevada	Texas & N. Mexico	Utah	W. Wyoming	Wyoming & Colorado
Biogas	0	0	0	7609	0	1822	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Coal-PC	0	-3760483	0	0	449153	0	0	0	0	-422516	0	18554	0	0	-39926	-2909	0	39008	-552710	2248026	982300
Gas CCGT	1370208	-5376047	-9219	0	-680159	4890	-8572	-280973	488781	0	593475	-35903	-411173	9033933	-6071583	6211664	1014097	648127	-5030	0	147316
Gas CT-Frame	4714994	16421	0	0	0	0	0	-9904	0	0	777564	0	0	11047	-827972	26299	-45585	11851	0	0	0
Gas CT-Aeroderivative	-41986	-5290	8997	0	1162276	52992	0	2178	0	0	-4	0	445669	-60250	411296	3498	-206688	0	-15175	0	24133
Gas Reciprocating Engine	0	0	3079	0	76791	0	0	0	0	0	0	59938	208588	9	0	0	0	0	0	0	0
Geothermal	0	0	0	29813	0	46946	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hydro	0	0	0	-26053	-766	35324	0	0	0	499553	0	0	0	0	0	0	0	0	0	0	-1188
Solar PV-Fixed Tilt	0	0	0	0	0	0	0	0	0	5029	0	0	0	0	0	0	0	23045	0	0	0
Solar PV-Tracking	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	147	0	0	0
Steam Turbine	4427	0	0	0	0	0	0	-1905	0	0	0	0	-102	0	0	-5708	0	0	0	0	0
Wind	0	0	0	-11370	-59305	0	0	0	0	-1562858	0	0	0	0	0	0	0	-23192	0	0	-438693
Gas CCGT	-6686367	0	0	0	0	0	0	0	0	0	0	0	0	0	0	-93702	0	0	-3867956	0	-271648

Table 6.2: Changes in 1st stage energy mix (annual operations) in the deterministic case study from section 3.6. The plotted values were filtered for values below 400 GWh for ease of display.

Zone	Solar PV	Wind	Gas CCGT
Alberta	0	0	-454
British Columbia	0	0	715
Colorado	0	-783	404
Mexico	0	0	-298
Montana	0	54	0
Northern California	0	0	-363
Northern Nevada	0	0	288
San Francisco	0	0	-601
Southern California	0	0	-377
Southern Nevada	-2442	0	-581
Texas & New Mexico	0	161	-1880
Utah	0	0	162
Wyoming & Colorado	0	-259	-437

Table 6.3: 2nd stage generation investment changes (with UC - without UC) for Set 1 probabilities. Overall, we see that there is less investment across all technologies.

Zone	Geothermal	Solar PV	Wind	Biomass	Gas CCGT	Gas CT
Alberta	0	0	4429	0	12575	0
Arizona/North East New Mexico	0	5522	521	329	0	0
British Columbia	340	0	4721	0	687	0
Colorado	0	0	0	0	2804	0
Idaho	329	0	1649	0	0	0
IID	486	3405	0	19	0	0
Mexico	0	0	2936	0	951	188
Montana	0	0	7006	0	0	0
Northern California	0	0	0	0	354	0
Northern Nevada	792	0	0	0	5173	0
Pacific Northwest	832	0	6175	0	0	0
San Francisco	0	0	0	0	1367	0
Southern California	0	12665	5297	126	7348	0
Southern Nevada	0	3475	0	12	163	0
Texas & New Mexico	0	0	5730	224	430	0
Utah	375	0	0	0	7831	0
Wyoming & Colorado	0	0	19274	0	10689	0

Table 6.4: 2nd stage generation investment changes under Set 2 probabilities **without** Unit Commitment. Compare this with Table 6.5.

Zone	Geothermal	Solar PV	Wind	Biomass	Gas CCGT	Gas CT
Alberta	0	0	4429	0	12128	0
Arizona/North East New Mexico	0	5522	521	329	0	0
British Columbia	340	0	4721	0	1236	0
Colorado	0	0	0	0	2653	0
Idaho	329	0	1649	0	0	0
IID	486	3405	0	19	0	0
LADWP	0	0	0	0	0	0
Mexico	0	0	2936	0	844	0
Montana	0	0	7063	0	0	0
Northern Nevada	792	0	0	0	4976	0
Pacific Northwest	832	0	6175	0	0	0
San Francisco	0	0	0	0	770	0
Southern California	0	12665	5297	126	6971	0
Southern Nevada	0	3475	0	12	2597	0
Texas & New Mexico	0	0	1994	224	3342	0
Utah	375	0	0	0	7681	0
Wyoming & Colorado	0	0	18786	0	6391	0

Table 6.5: 2nd stage generation investment changes under Set 2 probabilities **with** Unit Commitment. Compare this with Table 6.4.

Bibliography

[1] J. L. Ho, B. F. Hobbs, P. Donohoo-Vallett, Q. Xu, S. Kasina, S. W. Park, and Y. Ouyang, "Planning transmission for uncertainty: Applications and lessons for the western interconnection," 2016.

[2] FERC, "Order no. 1000 - transmission planning and cost allocation," Accessed 11/25/2016. [Online]. Available: https://www.ferc.gov/industries/electric/indus-act/trans-plan.asp

[3] Northwestern University, "McCormick envelopes," accessed 03/18/2017. [Online]. Available: https://optimization.mccormick.northwestern.edu/index.php/McCormick_envelopes

[4] Edison Electric Institute, "Transmission," Accessed 04/12/2017. [Online]. Available: http://www.eei.org/issuesandpolicy/transmission/Pages/default.aspx

[5] Wikipedia, "Northeast blackout of 2003," Accessed 04/12/2017. [Online]. Available: https://en.wikipedia.org/wiki/Northeast_blackout_of_2003

[6] B. Sweet, "A post-mortem on india's blackout," 2012, Accessed 04/12/2017. [Online]. Available: http://spectrum.ieee.org/energywise/energy/the-smarter-grid/a-postmortem-on-indias-blackout

[7] M. Shahidehpour, "Investing in expansion: the many issues that cloud transmission planning," *IEEE Power and Energy Magazine*, vol. 2, no. 1, pp. 14–18, 2004.

[8] W. Pentland, "Perverse economics of the electric grid: As generation gets cheaper, transmission costs soar," Posted 01/02/2013; Accessed 04/22/2017. [Online]. Available: https://www.forbes.com/sites/williampentland/2013/01/02/the-perverse-economics-of-the-electric-grid/#1e070567702b

[9] S. Gordon, "Supergrid to the rescue [electricity supply security]," *Power Engineer*, vol. 20, no. 5, pp. 30–33, 2006.

[10] A. Purvins, H. Wilkening, G. Fulli, E. Tzimas, G. Celli, S. Mocci, F. Pilo, and S. Tedde, "A European supergrid for renewable energy: local impacts and far-reaching challenges," *Journal of Cleaner Production*, vol. 19, no. 17, pp. 1909–1916, 2011.

[11] R. McMahon, "For electric utilities, the future is here," USEA WEC North America Regional Energy Forum, 2015, Accessed 04/22/2017. [Online]. Available: https://www.usea.org/sites/default/files/event-/Richard%20McMahon%20-%202015%20WEC%20NA%20Regional%20Energy%20Forum.pdf

[12] Edison Electric Institute, “Transmission projects: At a glance,” 2016, Accessed 04/22/2017. [Online]. Available: http://www.eei.org/issuesandpolicy/transmission/Documents/Trans_Project_lowres_bookmarked.pdf

[13] E. Kahn, “Wind integration studies: Optimization vs. simulation,” *The Electricity Journal*, vol. 23, no. 9, pp. 51–64, 2010.

[14] J. Chang, J. Pfeifenberger, and M. Hagerty, “The benefits of electric transmission: identifying and analyzing the value of investments,” *WIRES report by The Brattle Group, Cambridge, MA*, 2013.

[15] NREL, “Potential wind capacity,” 2014, Accessed October 14, 2015. [Online]. Available: http://apps2.eere.energy.gov/wind/windexchange/windmaps/resource_potential.asp

[16] New England States Committee on Electricity, “Improving consistency in regional transmission planning,” 2015, Accessed 04/24/2017. [Online]. Available: http://nescoe.com/consistent-planning-bergeron-sep2015/

[17] T.-O. Léautier and V. Thelen, “Optimal expansion of the power transmission grid: why not?” *Journal of Regulatory Economics*, vol. 36, no. 2, pp. 127–153, 2009.

[18] Y. Gu, L. Xie, B. Rollow, and B. Hesselbaek, “Congestion-induced wind curtail-

ment: Sensitivity analysis and case studies," in *North American Power Symposium (NAPS), 2011.* IEEE, 2011, pp. 1–7.

[19] L. T. Lam, L. Branstetter, and I. M. Azevedo, "Chinas wind electricity and cost of carbon mitigation are more expensive than anticipated," *Environmental Research Letters*, vol. 11, no. 8, p. 084015, 2016.

[20] J. Manley, "India already has a problem with wasting renewable energy on the grid," Accessed 02/28/2017. [Online]. Available: https://www.greentechmedia.com/articles/read/how-can-india-avoid-wasting-renewable-energy

[21] M. Buygi, G. Balzer, H. Shanechi, and M. Shahidehpour, "Market-based transmission expansion planning," *IEEE Transactions on Power Systems*, vol. 19, no. 4, pp. 2060–2067, Nov 2004.

[22] A. H. van der Weijde and B. F. Hobbs, "The economics of planning electricity transmission to accommodate renewables: Using two-stage optimisation to evaluate flexibility and the cost of disregarding uncertainty," *Energy Economics*, vol. 34, no. 6, pp. 2089 – 2101, 2012.

[23] F. D. Munoz, B. F. Hobbs, J. L. Ho, and S. Kasina, "An engineering-economic approach to transmission planning under market and regulatory uncertainties: WECC case study," *IEEE Transactions on Power Systems*, vol. 29, no. 1, pp. 307–317, 2014.

[24] K. W. Hedman, M. C. Ferris, R. P. O'Neill, E. B. Fisher, and S. S. Oren, "Co-optimization of generation unit commitment and transmission switching with N-1 reliability," *IEEE Transactions on Power Systems*, vol. 25, no. 2, pp. 1052–1063, 2010.

[25] A. Street, F. Oliveira, and J. M. Arroyo, "Contingency-constrained unit commitment with $n-k$ security criterion: A robust optimization approach," *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1581–1590, 2011.

[26] F. H. Murphy, S. Sen, and A. L. Soyster, "Electric utility capacity expansion planning with uncertain load forecasts," *AIIE Transactions*, vol. 14, no. 1, pp. 52–59, 1982.

[27] A. Moreira, K. Rocha, and P. David, "Thermopower generation investment in Brazil-economic conditions," *Energy Policy*, vol. 32, no. 1, pp. 91–100, 2004.

[28] C. Nweke, F. Leanez, G. Drayton, and M. Kolhe, "Benefits of chronological optimization in capacity planning for electricity markets," in *Proc. IEEE Int. Conf. Power System Tech. (POWERCON)*, 2012, pp. 1–6.

[29] A. Rosso, J. Ma, D. Kirschen, and L. Ochoa, "Assessing the contribution of demand side management to power system flexibility," in *Proc. 50th IEEE Conference on Decision and Control - European Control Conference (CDC-ECC)*, 2011, pp. 4361–4365.

[30] B. Palmintier and M. Webster, "Impact of unit commitment constraints on generation expansion planning with renewables," in *Proc. IEEE PES General Meeting*, 2011, pp. 1–7.

[31] G. P. McCormick, "Computability of global solutions to factorable nonconvex programs: Part iconvex underestimating problems," *Mathematical programming*, vol. 10, no. 1, pp. 147–175, 1976.

[32] M. Carrion and J. Arroyo, "A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem," *IEEE Transactions on Power Systems*, vol. 21, no. 3, pp. 1371–1378, 2006.

[33] B. F. Hobbs, M. H. Rothkopf, R. P. ONeill, and H. P. Chao, *The Next Generation of Electric Power Unit Commitment Models.* Kluwer, 2001.

[34] R. O'Neill, "It's getting better all the time (with mixed integer programming)," 2007, Accessed 04/24/2017. [Online]. Available: http://www.hks.harvard.edu/hepg/ONeill_Richard.pdf

[35] M. Lynch, A. Shortt, R. Tol, and M. O'Malley, "The effect of operational considerations on the return of electricity generation investment," in *Proc. IEEE PES General Meeting*, 2013, pp. 1–5.

[36] A. Shortt, J. Kiviluoma, and M. O'Malley, "Accommodating variability in gen-

eration planning," *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 158–169, 2013.

[37] J. F. Benders, "Partitioning procedures for solving mixed-variables programming problems," *Numerische mathematik*, vol. 4, no. 1, pp. 238–252, 1962.

[38] T. Niknam, A. Khodaei, and F. Fallahi, "A new decomposition approach for the thermal unit commitment problem," *Applied Energy*, vol. 86, no. 9, pp. 1667 – 1674, 2009.

[39] D. Shi, D. Shawhan, N. Li, D. Tylavsky, J. Taber, R. Zimmerman, and W. Schulze, "Optimal generation investment planning: Pt. 1: network equivalents," in *Proceedings of the North American Power Symposium (NAPS)*, 2012, pp. 1–6.

[40] D. L. Shawhan, J. T. Taber, D. Shi, R. D. Zimmerman, J. Yan, C. M. Marquet, Y. Qi, B. Mao, R. E. Schuler, W. D. Schulze, and D. Tylavsky, "Does a detailed model of the electricity grid matter? Estimating the impacts of the Regional Greenhouse Gas Initiative," *Resource and Energy Economics*, vol. 36, no. 1, pp. 191 – 207, 2014.

[41] J. Wang, A. Botterud, R. Bessa, H. Keko, L. Carvalho, D. Issicaba, J. Sumaili, and V. Miranda, "Wind power forecasting uncertainty and unit commitment," *Applied Energy*, vol. 88, no. 11, pp. 4014–4023, 2011.

[42] R. Barth, H. Brand, P. Meibom, and C. Weber, "A stochastic unit-commitment model for the evaluation of the impacts of integration of large amounts of intermittent wind power," in *International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), 2006.*, 2006, pp. 1–8.

[43] S. Takriti, B. Krasenbrink, and L. S.-Y. Wu, "Incorporating fuel constraints and electricity spot prices into the stochastic unit commitment problem," *Operations Research*, vol. 48, no. 2, pp. 268–280, 2000.

[44] M. Conforti, G. Cornuéjols, and G. Zambelli, *Integer programming.* Springer, 2014, vol. 271.

[45] X. Xie, "CS295: convex optimization - lecture notes," http://www.ics.uci.edu/~xhx/courses/ConvexOpt/convex_sets.pdf, Accessed 04/08/2017.

[46] E. Balas, S. Ceria, G. Cornuéjols, and N. Natraj, "Gomory cuts revisited," *Operations Research Letters*, vol. 19, no. 1, pp. 1–9, 1996.

[47] K. Kianfar and Y. Fathi, "Generalized mixed integer rounding inequalities: facets for infinite group polyhedra," *Mathematical Programming*, vol. 120, no. 2, pp. 313–346, 2009.

[48] R. E. Davis, D. A. Kendrick, and M. Weitzman, "A branch-and-bound algorithm for zero-one mixed integer programming problems," *Operations Research*, vol. 19, no. 4, pp. 1036–1044, 1971.

[49] IBM Knowledge Center, “Branch and cut in CPLEX,” https://www.ibm.com/support/knowledgecenter/SSSA5P_12.4.0/ilog.odms.cplex.help/refcppcplex/html/branch.html, Accessed 04/07/2017.

[50] L. Yang, C. Zhang, J. Jian, K. Meng, and Z. Dong, “A novel projected two binary variables formulation for unit commitment problem,” *arXiv preprint arXiv:1606.05710*, 2016.

[51] M. G. Marcovecchio, A. Q. Novais, and I. E. Grossmann, “A branch and cut search for the deterministic optimization of the thermal unit commitment problem. Part I: Methodology,” 2011.

[52] M. Milligan, P. Donohoo, and M. OMalley, “Stochastic methods for planning and operating power system with large amounts of wind and solar power,” in *Proc. Int. Workshop Large-Scale Integration of Wind Power into Power Systems*, 2012.

[53] L. Wolsey, *Integer Programming.* Wiley, 1998.

[54] S. A. Gabriel, A. S. Kydes, and P. Whitman, “The National Energy Modeling System: a large-scale energy-economic equilibrium model,” *Operations Research*, vol. 49, no. 1, pp. 14–25, 2001.

[55] D. Anderson and R. Turvey, *Electricity Economics: Essays and Case Studies.* Johns Hopkins University Press, 1977.

[56] B. F. Hobbs, "Optimization methods for electric utility resource planning," *European Journal of Operations Research*, vol. 83, no. 1, pp. 1–20, 1995.

[57] California Energy Commission (CEC), "Cost of generation model user's guide," 2010, Accessed 04/24/2017. [Online]. Available: www.energy.ca.gov/2010publications/CEC-200-2010-002/CEC-200-2010-002.PDF

[58] J. Garcìa-González, "Decision support models in electric power systems, Lec. Notes, Master's Degree in Electric Power Industry, Universidad Pontificia Comillas, Madrid," *http://goo.gl/aGFzxa*, 2014.

[59] R. M. Lima and A. Q. Novais, "Symmetry breaking in MILP formulations for unit commitment problems," *Computers & Chemical Engineering*, vol. 85, pp. 162–176, 2016.

[60] Q. Chen, C. Kang, Q. Xia, and J. Zhong, "Power generation expansion planning model towards low-carbon economy and its application in China," *IEEE Transactions on Power Systems*, vol. 25, no. 2, pp. 1117–1125, 2010.

[61] D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to linear regression analysis.* John Wiley & Sons, 2015.

[62] J. A. Bloom, "Solving an electricity generating capacity expansion planning problem by Generalized Benders' Decomposition," *Operations Research*, vol. 31, no. 1, pp. 84–100, 1983.

[63] R. P. O'Neill, P. M. Sotkiewicz, B. F. Hobbs, M. H. Rothkopf, and W. R. Stewart, "Efficient market-clearing prices in markets with nonconvexities," *European Journal of Operations Research*, vol. 164, no. 1, pp. 269 – 285, 2005.

[64] F. Munoz, B. Hobbs, J. Ho, and S. Kasina, "An engineering-economic approach to transmission planning under market and regulatory uncertainties: WECC case study," *IEEE Transactions on Power Systems*, vol. 29, no. 1, pp. 307–317, 2014.

[65] F. D. Munoz, B. Hobbs, and S. Kasina, "Efficient proactive transmission planning to accommodate renewables," in *Proc. IEEE PES General Meeting*, 2012, pp. 1–7.

[66] F. D. Munoz, B. F. Hobbs, and J.-P. Watson, "New bounding and decomposition approaches for MILP investment problems: Multi-area transmission and generation planning under policy constraints," *European Journal of Operational Research*, vol. 248, no. 3, pp. 888–898, 2016.

[67] T. Li and M. Shahidehpour, "Price-based unit commitment: a case of lagrangian relaxation versus mixed integer programming," *IEEE Transactions on Power Systems*, vol. 20, no. 4, pp. 2015–2025, 2005.

[68] F. Zhuang and F. D. Galiana, "Towards a more rigorous and practical unit commitment by lagrangian relaxation," *IEEE Transactions on Power Systems*, vol. 3, no. 2, pp. 763–773, 1988.

[69] H. Ma, S. Shahidehpour, and M. Marwali, "Transmission constrained unit commitment based on benders decomposition," in *American Control Conference, 1997. Proceedings of the 1997*, vol. 4. IEEE, 1997, pp. 2263–2267.

[70] P. Van den Bosch and G. Honderd, "A solution of the unit commitment problem via decomposition and dynamic programming," Laboratory for Control Engineering, Department of Electrical Engineering, Delft University of Technology, Delft, Tech. Rep., 1985.

[71] E. Balas, S. Ceria, G. Cornuéjols, and N. Natraj, "Gomory cuts revisited," *Operations Research Letters*, vol. 19, no. 1, pp. 1–9, 1996.

[72] E. Balas, S. Ceria, and G. Cornuéjols, "A lift-and-project cutting plane algorithm for mixed 0–1 programs," *Mathematical programming*, vol. 58, no. 1-3, pp. 295–324, 1993.

[73] M. Shahidehopour and Y. Fu, "Benders decomposition: applying benders decomposition to power systems," *IEEE Power and Energy Magazine*, vol. 3, no. 2, pp. 20–21, 2005.

[74] F. Li and R. Bo, "DCOPF-based LMP simulation: algorithm, comparison with ACOPF, and sensitivity," *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 1475–1485, 2007.

[75] A. Castillo *et al.*, "Essays on the ACOPF problem: Formulations, approxima-

tions, and applications in the electricity markets," Ph.D. dissertation, Johns Hopkins University, 2016.

[76] A. Olson, A. Mahone, E. Hart, J. Hargreaves, R. Jones, N. Schlag, G. Kwok, N. Ryan, R. Orans, and R. Frowd, "Halfway there: Can California achieve a 50% renewable grid?" *IEEE Power and Energy Magazine*, vol. 13, no. 4, pp. 41–52, 2015.

[77] J. L. Ho, B. F. Hobbs, P. Donohoo-Vallett, Q. Xu, S. Kasina, S. Park, and Y. Ouyang, "Planning transmission for uncertainty: Applications and lessons with the western interconnection," Submitted to the Western Energy Coordinating Council (WECC), Tech. Rep. MSU-CSE-00-2, 2015.

[78] S. P. S. Group, *WECC long term planning scenario report*, 2013, Accessed 11/18/2015.

[79] Wikipedia, "Regional transmission organization," Accessed 10/15/2015. [Online]. Available: https://en.wikipedia.org/wiki/Regional_transmission_organization

[80] MISO, "Miso transmission expansion plan 2014," 2014, Accessed 10/15/2015). [Online]. Available: https://www.misoenergy.org/Library/Repository/Study/MTEP/MTEP14/MTEP14%20Full%20Report.pdf

[81] ERCOT, "ERCOT system planning: 2014 regional transmission plan report,"

2014, Accessed 10/15/2015. [Online]. Available: http://www.ercot.com/news/presentations/

[82] Federal Energy Regulatory Commission and others, “Order no. 1000–transmission planning and cost allocation,” FERC, 2012.

[83] Western Electricity Coordinating Council, “2013 Interconnection-wide plan summary,” 2013, Accessed 04/24/2017. [Online]. Available: https://www.wecc.biz/Reliability/2013Plan_PlanSummary.pdf

[84] “EIPC modeling results: Futures & sensitivities,” 2010, Accessed 11/18/2015. [Online]. Available: http://www.eipconline.com/modeling-results.html

[85] O. Ozdemir, F. D. Munoz, J. L. Ho, and B. F. Hobbs, “Economic analysis of transmission expansion planning with price-responsive demand and quadratic losses by successive LP,” *IEEE Transactions on Power Systems*, 2015.

[86] C. O’Malley, “2 of 3 MISO-SPP seams projects likely doomed,” 2015, Accessed on 10/10/2016. [Online]. Available: https://www.rtoinsider.com/miso-spp-interregional-transmission-17298/

[87] Corina Rivera Linares, “FERC approves order conditionally accepting compliance filings by ISO-NE, NYISO, PJM involving Order 1000 interregional requirements,” 2015, Accessed 04/25/2017. [Online]. Available: http://www.transmissionhub.com/articles/2015/05/ferc-approves-order-

conditionally-accepting-compliance-filings-by-iso-ne-nyiso-pjm-involving-order-1000-interregional-requirements.html

[88] D. Gately, "Sharing the gains from regional cooperation: A game theoretic application to planning investment in electric power," *International Economic Review*, vol. 15, no. 1, pp. 195–208, 1974.

[89] J. Contreras and F. Wu, "Coalition formation in transmission expansion planning," *IEEE Transactions on Power Systems*, vol. 14, no. 3, pp. 1144–1152, Aug 1999.

[90] D. Huppmann and J. Egerer, "National-strategic investment in european power transmission capacity," *DIW Berlin Discussion Paper*, 2014.

[91] Z.-Q. Luo, J.-S. Pang, and D. Ralph, *Mathematical programs with equilibrium constraints.* Cambridge University Press, 1996.

[92] H. Von Stackelberg, *Market structure and equilibrium.* Springer Science & Business Media, 2010.

[93] Wikipedia, *Bilevel Optimization*, Accessed 11/15/2015. [Online]. Available: https://en.wikipedia.org/wiki/Bilevel_optimization

[94] S. A. Gabriel, A. J. Conejo, J. D. Fuller, B. F. Hobbs, and C. Ruiz, *Complementarity modeling in energy markets.* Springer Science & Business Media, 2012, vol. 180.

[95] B. Hobbs, C. Metzler, and J.-S. Pang, “Strategic gaming analysis for electric power systems: an mpec approach,” *IEEE Transactions on Power Systems*, vol. 15, no. 2, pp. 638–645, May 2000.

[96] A. G. Bakirtzis, N. P. Ziogos, A. C. Tellidou, G. Bakirtzis *et al.*, “Electricity producer offering strategies in day-ahead energy market with step-wise offers,” *IEEE Transactions on Power Systems*, vol. 22, no. 4, pp. 1804–1818, 2007.

[97] S. J. Kazempour, A. J. Conejo, and C. Ruiz, “Strategic generation investment using a complementarity approach,” *IEEE Transactions on Power Systems*, vol. 26, no. 2, pp. 940–948, 2011.

[98] S. Wogrin, E. Centeno, and J. Barquín, “Generation capacity expansion in liberalized electricity markets: a stochastic mpec approach,” *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 2526–2532, 2011.

[99] D. Pozo, E. E. Sauma, and J. Contreras, “A three-level static milp model for generation and transmission expansion planning,” *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 202–210, 2013.

[100] D. Ralph and Y. Smeers, “EPECs as models for electricity markets,” in *Power Systems Conference and Exposition, 2006. PSCE’06. 2006 IEEE PES.* IEEE, 2006, pp. 74–80.

[101] C. De Jonghe, B. F. Hobbs, and R. Belmans, “Optimal generation mix with

short-term demand response and wind penetration," *IEEE Transactions on Power Systems*, vol. 27, no. 2, pp. 830–839, 2012.

[102] Y. Chen, B. F. Hobbs, S. Leyffer, and T. S. Munson, "Leader-follower equilibria for electric power and NOx allowances markets," *Computational Management Science*, vol. 3, no. 4, pp. 307–330, 2006.

[103] S. Stoft, "Problems of transmission investment in a deregulated power market," *Competitive electricity markets and sustainability*, pp. 87–130, 2006.

[104] R. Boţ, G. Kassay, and G. Wanka, "Strong duality for generalized convex optimization problems," *Journal of Optimization Theory and Applications*, vol. 127, no. 1, pp. 45–70, 2005.

[105] P. Belotti, "Disjunctive cuts for nonconvex MINLP," in *Mixed Integer Nonlinear Programming.* Springer, 2012, pp. 117–144.

[106] C. DAmbrosio and A. Lodi, "Mixed integer nonlinear programming tools: an updated practical overview," *Annals of Operations Research*, vol. 204, no. 1, pp. 301–320, 2013.

[107] D. Pozo and J. Contreras, "Finding multiple nash equilibria in pool-based markets: A stochastic epec approach," *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1744–1752, Aug 2011.

[108] E. W. Weisstein, "Gauss-seidel method," *Wolfram Research, Inc.*, 2002.

[109] S. Jin and S. Ryan, “A tri-level model of centralized transmission and decentralized generation expansion planning for an electricity market part II,” *IEEE Transactions on Power Systems*, vol. 29, no. 1, pp. 142–148, Jan 2014.

[110] A. Ehrenmann, “Equilibrium problems with equilibrium constraints and their application to electricity markets,” Ph.D. dissertation, Citeseer, 2004.

[111] E. E. Sauma and S. S. Oren, “Proactive planning and valuation of transmission investments in restructured electricity markets,” *Journal of Regulatory Economics*, vol. 30, no. 3, pp. 261–290, 2006.

[112] J. Von Neumann and O. Morgenstern, *Theory of games and economic behavior.* Princeton university press, 2007.

[113] D. Whittington, X. Wu, and C. Sadoff, “Water resources management in the nile basin: the economic value of cooperation,” *Water policy*, vol. 7, no. 3, pp. 227–252, 2005.

[114] A. Lindgreen, M. Hingley, R. Lawson, J. Guthrie, A. Cameron, and W. C. Fischer, “Creating value through cooperation: An investigation of farmers’ markets in new zealand,” *British Food Journal*, vol. 110, no. 1, pp. 11–25, 2008.

[115] J. Bisschop and R. Entriken, *AIMMS: The modeling system.* Paragon Decision Technology, 1993.

[116] C. Bliek1ú, P. Bonami, and A. Lodi, "Solving mixed-integer quadratic programming problems with IBM-CPLEX: a progress report," 2014.

[117] M. Hunting, "Solving convex MINLP problems with AIMMS," *An AIMMS white paper, Paragon Decision Technology, BV*, 2012.

[118] I. Quesada and I. E. Grossmann, "An LP/NLP based branch and bound algorithm for convex MINLP optimization problems," *Computers & chemical engineering*, vol. 16, no. 10-11, pp. 937–947, 1992.

[119] "ALGLIB project, about variable scaling," http://www.alglib.net/optimization/scaling.php, accessed 03/20/2017.

[120] L. C. Coelho, "Linearization of the product of two variables," 2013, Accessed 10/15/2015. [Online]. Available: http://www.leandro-coelho.com/linearization-product-variables/

[121] C. T. Kelley, *Iterative methods for optimization.* SIAM, 1999.

[122] J. W. Chinneck, "Practical optimization: a gentle introduction," 2006, Accessed 04/24/2017. [Online]. Available: http://www.sce.carleton.ca/faculty/chinneck/po.html

[123] S. Wogrin, "Generation expansion planning in electricity markets with bilevel mathematical programming techniques," Ph.D. dissertation, Universidad Pontificia Comillas de Madrid, 2013.

[124] F. Wu, P. Varaiya, P. Spiller, and S. Oren, “Folk theorems on transmission access: Proofs and counterexamples,” *Journal of Regulatory Economics*, vol. 10, no. 1, pp. 5–23, 1996.

[125] S. J. Kazempour, A. J. Conejo, and C. Ruiz, “Generation investment equilibria with strategic producers Part I: formulation,” *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 2613–2622, 2013.

[126] H. Hashimoto and P. T. Harker, *A Spatial Nash Equilibrium Model.* Springer Berlin Heidelberg, 1985.

[127] M. Awad, K. E. Casey, A. S. Geevarghese, J. C. Miller, A. F. Rahimi, A. Y. Sheffrin, M. Zhang, E. Toolson, G. Drayton, B. F. Hobbs *et al.*, “Using market simulations for economic assessment of transmission upgrades: application of the California ISO approach,” *Restructured Electric Power Systems*, pp. 241–270, 2010.

[128] F. D. Munoz and J.-P. Watson, “A scalable solution framework for stochastic transmission and generation planning problems,” *Computational Management Science*, vol. 12, no. 4, pp. 491–518, 2015.

[129] M. Shahidehpour and M. Marwali, *Maintenance scheduling in restructured power systems.* Springer Science & Business Media, 2012.

[130] P. Nahmmacher, E. Schmid, L. Hirth, and B. Knopf, “Carpe diem: A novel

approach to select representative days for long-term power system modeling," *Energy*, vol. 112, pp. 430–442, 2016.

[131] J. H. Eto, D. R. Hale, and B. C. Lesieutre, "Toward more comprehensive assessments of FERC electricity restructuring policies: A review of recent benefit-cost studies of RTOs," *The Electricity Journal*, vol. 19, no. 10, pp. 50–62, 2006.

Vita

Saamrat Kasina (full name, Bala Gurudutta Saamrat Kasina) was born on September 19, 1988, in Kakinada, Andhra Pradesh, India. He attended the Indian Institute of Technology (IIT), Guwahati, for his Bachelors degree in Biotechnology. During his bachelors, he interned at India's largest environmental engineering firm working at a hazardous waste management plant. In 2010, he joined the Department of Geography and Environmental Engineering (DoGEE) at The Johns Hopkins University as a graduate student. In December 2011, he was awarded a Master of Science in Engineering (M.S.E.) degree in Environmental Engineering with a concentration in Environmental Economics and Management. In August 2012, he started pursuing a Ph.D. at The Johns Hopkins University under the direction of Dr. Benjamin F. Hobbs. His doctoral research focuses on exploring the effects of short-term operational constraints and interregional cooperation on long-term transmission planning. Part of his research was done in collaboration with the Consortium for Electric Reliability Technology Solutions (CERTS) of the Department of Energy (DOE), and the Sandia National Laboratories, Albuquerque, New Mexico.